COMPUTATIONAL URBAN ANALYTICS FOR WALKABILITY: ÇANKAYA, ANKARA CASE

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF ARCHITECTURE
IN
ARCHITECTURE

FEBRUARY 2021

Approval of the thesis:

COMPUTATIONAL URBAN ANALYTICS FOR WALKABILITY: ÇANKAYA, ANKARA CASE

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ABSTRACT

COMPUTATIONAL URBAN ANALYTICS FOR WALKABILITY: ÇANKAYA, ANKARA CASE

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February 2021, 146 pages

The complexity of the built environment and the number of components acting upon the cities are increasing and in constant transformation. Analyzing the quality of urban spaces is becoming difficult due to the scale and level of interconnectivity between urban data. However, advances in technologies, particularly in computational urban analytics methods, have the potential to facilitate the collection, measurement, and analysis of urban metrics relevant to urban design. Walkability is an important measure related to sustainable urban mobility with its potentials to be evaluated computationally. The main goal of the research is to explore the methods of computational urban analytics in assessing walkability at different measurement scales, which are neighborhood and street, and for a specific target group, older adults (over 60). The study consists of three stages implementing in the neighborhoods of Çankaya, Ankara. In the first stage of the study, 115 neighborhoods were assessed based on the macro-scale urban features, while in the second stage, nine neighborhoods of those 115 were investigated according to the micro-scale urban features. In the third stage, these nine neighborhoods were reconsidered for estimation of the walkability level for older adults. The exploratory analysis is comprised of the big data approach, semantic segmentation, trip generation, and geometrical operations on 3D digital models. The results showed that the walkability level of a neighborhood could differ based on the considered factors. It was determined that the scope of computational urban analytics methods on walkability assessment was limited by the accuracy and accessibility of urban data.

Keywords: Big Data, Urban Analytics, Urban Features, Walkability

ÖZ

YÜRÜNEBİLİRLİK İÇİN SAYISAL KENT ANALİTİĞİ: ÇANKAYA, ANKARA ÖRNEĞİ

Ardıç, Sabiha İrem
Yüksek Lisans, Mimarlık
Tez Yöneticisi: Doç. Dr. İpek Gürsel Dino

Şubat 2021, 146 sayfa

Yapılı çevrenin karmaşıklığı ve şehirlere etki eden bileşenlerin sayısı artmakta ve bu bileşenler sürekli etkileşmektedirler. Kentsel verilerin büyüklüğü ve aralarındaki ilişkinin düzeyi nedeniyle kentsel alanların kalitesini analiz etmek zorlaşmaktadır. Ancak, teknolojik gelişmeler, özellikle hesaplamalı kent analitiği yöntemleri, kentsel verilerin toplanmasını, ölçülmesini ve analiz edilmesini kolaylaştırma potansiyeline sahiptir. Yürünebilirlik sürdürülebilir kentsel hareketlilik açısından önemli bir ölçüttür ve sayısal olarak değerlendirilmeye uygundur. Araştırmanın ana amacı sayısal kent analitiği yöntemlerini, farklı ölçeklerde (mahalle ve sokak) ve belirli bir hedef kitle (60 yaş ve üstü yetişkinler) için yapılan yürünebirlik değerlendirmelerinde deneyimlemektir. Çalışma Ankara'nın Çankaya ilçesine bağlı mahallelere uygulanan üç aşamadan oluşmaktadır. Çalışmanın ilk aşamasında 115 mahalledeki yürünebilirlik seviyesi makro ölçekli kentsel özelliklere göre değerlendirilirken, ikinci aşamada seçilen dokuz mahallenin sokak ölçeğinde yürünebilirliği mikro ölçekli kentsel özelliklere göre incelenmiştir. Üçüncü aşamada ise dokuz mahalle, yaşlı bireyler için yürünebilirlik düzeyini tahmin etmek amacıyla tekrar ele alınmıştır. Bu keşifsel analiz çalışması büyük veri yaklaşımı, anlamsal bölümleme, rota oluşturma ve üç boyutlu dijital modeller üzerinde yapılan geometrik operasyonlardan oluşmaktadır. Sonuçlar bir mahallenin yürünebilirlik düzeyinin dikkate alınan faktörlere bağlı olarak farklılık gösterebileceğini sunmuştur. Sayısal kent analitiği metotlarının yürünebilirlik analizlerindeki kapsamının kentsel verilerin doğruluğu ve ulaşılabilirliği ile sınırlığı olduğu tespit edilmiştir.

Anahtar Kelimeler: Büyük Veri, Kent Analitiği, Kentsel Özellikler, Yürünebilirlik

To My Family, Güler - Temel Ardıç and Ceren - Sefa Aydemir,

ACKNOWLEDGMENTS

There is an immense amount of effort and support behind the path towards this dissertation. At this point, I would like to thank many people who have supported me so far. This research would not have been possible without their guidance, contribution, and all-around surrounding helpfulness.

I owe my deepest gratitude to my supervisor, my mentor Assoc. Prof. Dr. Ipek Gürsel Dino for her endless support and visionary guidance. It was my privilege to be encouraged and challenged by her ingeniously to achieve the better and the advanced since the beginning of this study. I believe that it is an extreme opportunity to be guided by her knowledge and wisdom in my academic life.

I would like to thank my jury members Assoc. Prof. Dr. Ela Alanyalı Aral, Assoc. Prof. Dr. Olgu Çalışkan, Assoc. Prof. Dr. Derya Güleç Özer, and Assoc. Prof. Dr. Yasemin Afacan, who took the time to review my thesis and gave invaluable feedback and sincere contributions.

I would also like to offer my thanks to ACE Architecture team, especially Sedef Yıldız and Orçun Ersan. Although it was challenging to simultaneously experience professional and academic life, I managed to, thanks to their unlimited support and understanding.

I am grateful to my friends for their companionship and endless support since the first day of the university. We have shared countless moments and stories throughout our long friendship. Elif Ceren Yılmaz and Elif Çağlayan Özçelik were always there for me despite the distances, and Kubilay Şahinler was always a source of motivation and support for me while studying just across my chair. Without sharing and fun, nothing would have been worth doing it, and I would like to thank them for that.

But foremost, no words can express my gratitude to my family, Güler Ardıç, Temel Ardıç, Ceren Aydemir, and Sefa Aydemir, for their constant support, love, generous patient, and understanding, not only throughout this study but in life overall. I would not be able to come this far without their support, and for that, I believe this is the best place to express my gratitude to them. I am more than blessed to have them in my life, and I owe them a lot. They are my greatest treasure in life, and I dedicate this thesis to them.

Finally, I owe deep gratitude to whom I have mentioned their names here, together with many others I have not, supporting me and being with me. Thank you all!

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LIST OF ABBREVIATIONS

ABBREVIATIONS

AwaP	Area-weighted Average Perimeter
C	Complexity
E	Enclosure
GH	Grasshopper
GP	Geotagged Photos
HS	Human Scale
I	Imageability
NH	Neighborhood
OSM	Open Street Map
POI	Point of Interest
PT	Public Transportation
QGIS	Quantum Geographic Information System
QoL	Quality of Life
R	Ranking
RH	Rhinoceros
SM	Social Media
UF	Urban Feature
WI	Walkability Index
WIEP	Walkability Index for Elderly People
WINS	Walkability Index at Neighborhood Scale
WISS	Walkability Index at Street Scale

CHAPTER 1

INTRODUCTION

The first chapter of the thesis presents an introduction to the thesis study, including three sections that are (1) the motivation of the research, (2) research questions, and (3) the structure of the thesis.

1.1 The Motivation of the Research

Analysis has significant importance in the well-informed design process to build design components more rigor or evaluate them against specific criteria. It is widely interpreted as a process or method of disintegrating any complex entity to its creator elements and a study evaluating each component in detail to re-form, synthesize, or understand it better (Blakey, 1850, as cited in Karimi, 2017). Design can be defined as an intrinsically complex problem, comprised of various elements and facets (Karimi, 2017). In that sense, analysis can be considered as an assistive and necessary part of the design process to solve a complex problem, and evaluate its outcomes. When design is accepted as a purposeful problem-solving process, rational thinking and reasoning degree must be extended through the process.

According to Daley (1984); Darke (1984); and Hillier, Musgrove, and O'Sullivan (1984), the whole or some parts of the design process require intuition, creativity, or novelty, not entirely governed by logical or scientific discourses (as cited in Karimi, 2017). Both arguments do not mean that design can be considered as an entirely discursive or logical process. Nevertheless, some parts or stages of design should be informed by analytical knowledge arisen from non-intuitive actions such as reasoning, induction, or analysis. In the urban design process mentioned by Karimi, analytical investigation can be utilized in two ways. Firstly, analysis can feed the design process by informing designers with the information they might not be able to gather intuitively before generating the ideas. Secondly, by applying analytical methods, a more reliable evaluation of the design ideas can be conducted (Karimi, 2017).

Besides its importance, analysis in the urban design process has confronted multiple challenges due to the increasing complexity of the cities and the built environment. The components acting upon the cities are growing and transforming constantly. Thus, analyzing the urban spaces is becoming difficult with traditional approaches such as on-site audit tools, surveys, or interviews due to the scale of urban data and interconnectivity between urban data. However, advances in technologies, particularly computational methods and tools, have the potential to facilitate the collection, measurement, and analysis of urban data for a well-informed design process. Consequently, urban planning should develop new analysis techniques in collaboration with other fields of study, and a new concept, urban analytics. This concept, which is originated from urban analysis, takes advantage of rich digital datasets that encompass various aspects of city life and computational approaches (Batty, 2019).

Another challenge that urban design faces is the increase in the population of the cities and urbanization of the world's population by the end of the 21st century (Higham, Batty, Bettencourt, Greetham, & Grindrod, 2017). These will lead to the rising demand for services and infrastructure as most human interaction, energy consumption, waste generation, innovation, entertainment, transportation, and education services occur in the cities. Thus, new development agendas for future cities must emphasize sustainable solutions while planning the cities. Moreover, in urban analytics, there is a potential to formulate urban sustainability problems regarding each urban domain, generate analytical solutions, make realistic assumptions, develop scientific methods, and evaluate the findings (Bibri & Krogstie, 2018).

The growth of the population and the cities leads to an increase in demand for transportation services, including vehicular traffic volumes. This situation causes high levels of environmental pollution and decrease in the quality of life (QoL) in the cities. Thus, sustainable mobility strategies must be adopted as a part of urban sustainability solutions for future cities. The urban planning approaches must be shifted towards pedestrian mobility and walkability (Berzi, Gorrini, & Vizzari, 2017). Many research projects have been conducted to evaluate and develop the walkability level of the cities by different disciplines such as medicine, sociology, psychology, geography, urban planning, and architecture. It has become a significant factor for public health, QoL, sustainable mobility strategies, and built environment over the years. There are defined urban features utilized by existing studies to associate walkability in the built environment. Most of the studies have focused on walkability indices based on city and street scale separately. While a part of the literature has ignored macro-scale features of walkability, the other part does not consider micro-scale features that affect the pedestrian experience. However, a combined and sequential approach can be developed for walkability analysis of a city.

This research highlights the importance of analytical investigations in the urban design process to generate ideas and evaluate the outcomes. In this study, it is suggested to take advantage of urban analytics to overcome the challenges of evaluating the quality of urban spaces due to the complexity of the cities. According to Wang (2018), digital advances in technology do not only possess the social values and design originalities of man-machine dialogues but also provide quantitative property and database outcomes, which can be more effectively merged into the urban design process (as cited in Guan, Keith, & Hong, 2019). Thus, it is preferred to utilize accessible urban data with the help of digital advances in technology. As an indicator of urban space quality, “walkability” is reviewed due to its importance in sustainable mobility strategies. Urban mobility is one of the priority themes for European (EU) cities, which strives to improve the QoL in cities by promoting active mobility solutions such as walking and cycling (European Commission, n.d.). Considering these motivations, as mentioned above, computational urban analytics tools and existing methodologies for walkability evaluations have been reviewed. The urban features utilized by the existing walkability studies have been examined and categorized as perceptual and physical aspects. The urban features have been listed according to data type, collection, computation, and visualization methods used in the literature. The research study for walkability evaluation has been divided into three stages, at neighborhood scale, street scale and for elderly people. The urban features with accessible urban data were based on these three stages. This research study investigates the potentials of computational urban analytics in the assessment of walkability at neighborhood and street scale, and for older adults. It is aimed to experience the methods and tools to collect and measure the urban data. The neighborhoods of Çankaya, Ankara in Turkey have been selected as a case study area of the proposed methodology.

1.2 Research Questions

The study aims to explore the computational urban analytics methods in the assessment of walkability at neighborhood and street scale for well-informed urban design. In this regard, the current study addressed the following research questions:

- To what extend computational urban analytics can be utilized in the walkability assessment?
- Which computational methods and tools can be involved in walkability assessment?
    - Which data sources can be used to extract urban data?
    - Which methods and tools can be utilized to collect urban data?
    - Which methods and tools can be utilized to compute the urban data?

- Which urban features can be measured to evaluate walkability at neighborhood and street scale?
- Which urban features can be measured to evaluate walkability for elderly people?
- Can a combined and sequential approach be developed to evaluate walkability at the neighborhood and street scale?
- How does the walkability level of a neighborhood differ according to the scale of the analysis?
- What are the limitations and future research directions of the study?

To address the above-mentioned research questions, a comprehensive methodological approach has been required for this study. The methodological approach utilized in this research is exploratory analysis, which includes data collection, data computation and spatial analysis. The data sets gathered for the research are composed of quantitative and secondary data. A case study area was selected to develop an exploratory analysis and implementation of it. The methodology of this research will be explained in Chapter 4.

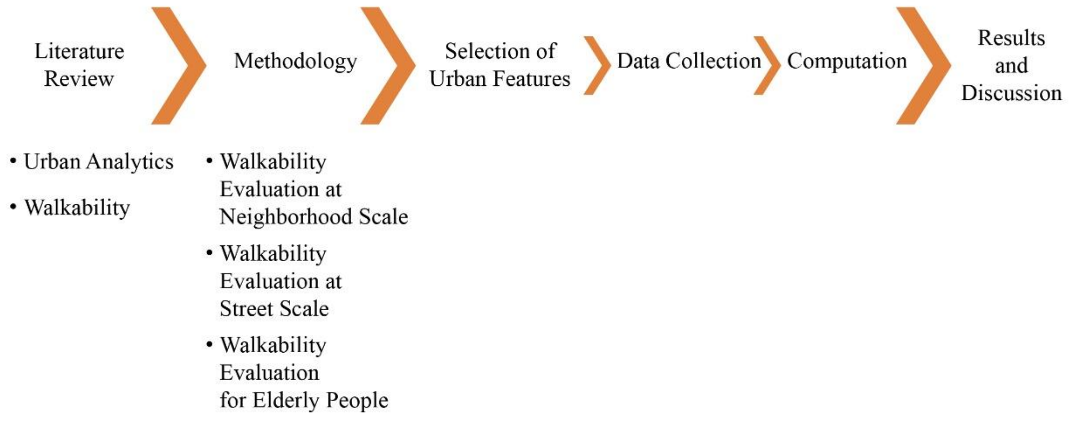

Figure 1-1. Research Process Illustration

1.3 Structure of the Thesis

The thesis consists of six chapters. The content and organization of the chapters will be briefed in this present introduction section for a finer comprehension of the research study. The current introduction chapter also includes the motivation of the research and research questions. Chapter two and chapter three have explanations and definitions based on the literature review. While the main concept of chapter two is urban analytics, the main term of chapter three is walkability. The first part of the second chapter includes definitions of urban analytics. The second part is about developing urban analytics from the use of analytical methods in the urban design process through the emergence of urban analytics. The emphasis has been given to urban big data analytics in the third and fourth sections. While the definitions and explanations can be found in the third section, the existing studies based on the applications of analytical methods for sustainable urban mobility have been exemplified in the fourth section. In the first section of chapter three, what the term walkability means and its perceptual scope over the years have been reviewed. Then, the significance of the walkability for sustainable urban mobility has been explained with the examples from the existing studies. In the last section, existing studies regarding walkability evaluation have been reviewed. Firstly, the urban features utilized by the existing walkability studies have been examined and categorized as perceptual and physical aspects. Then, macro and micro-scale urban features used in the walkability studies have been explained. Later, the methods utilized in the existing walkability studies have been described based on their data collection, computation, and visualization approaches.

Chapter four clarifies the methodology that has been used in this research. In the first part, the general framework of the research has been displayed through a case study area. Since the analysis has been conducted in three stages, in the second part of chapter four, walkability evaluation at the neighborhood scale has been described, in the third part, walkability evaluation at street scale has been expressed, and in the last section walkability evaluation for older adults has been explained. For each stage of the analysis, selected urban features have been defined, and the metrics of these features have been shown. Moreover, through the second and third sections, data collection and computation methods of each urban features have been explained in detail.

Chapter five presents walkability evaluation results through a case study area. In the first section, the results of walkability evaluation at the neighborhood scale have been discussed through the maps. Then, the results of walkability evaluation at street scale based on the selected neighborhoods have been negotiated through the visuals. After that, chapter five has been finalized with the results of the walkability assessment for older adults. Finally, the last chapter evaluates the overall research with a conclusion. In the beginning of this chapter, the outcomes of the proposed methodology have been discussed. Then, the limitations of the research have been stated. In the last section, suggestions for future studies have been mentioned to display the potentials of the study to be developed.

CHAPTER 2

URBAN ANALYTICS

The second chapter of the thesis presents a literature review on urban analytics, including four main aspects that are (1) definition of urban analytics, (2) historical background of urban analytics, (3) big data approach in urban analytics, and (4) urban big data analytics for sustainable urban mobility.

2.1 Definition of Urban Analytics

Batty and his colleagues explain urban analytics as "methods of mathematical and symbolic modeling that generate insights into existing data as well as predictions of future data" (Batty, Hudson-Smith, Hugel, & Roumpani, 2015). McArdle defines urban analytics in the scope of a research project called "Urban Analytics" as the science of examining data related to urban space to enable insight into how the data is operated and utilized (McArdle, n.d). Moreover, Batty (2019) describes urban analytics together with Michael Goodchild's explanation as following:

> "Urban analytics is fast emerging as the core set of tools employed to deal with problems of big data, urban simulation, and geodemographics, while Michael Goodchild defines it as 'new kind of urban research, one that exploits the vast new data resources that are becoming available from social media, crowd-sourcing, and sensor networks…'." (Batty, 2019, p. 403)

According to Goodchild's quote, urban analytics is regarding the new available big data, emerged in the last decade and can be embedded into multiple systems of urban research projects (Batty, 2019). Likewise, urban analytics is also related to using new and emerging forms of data (Singleton, Spielman, & Folch, 2017). They present the widespread availability of urban data as a new phenomenon and state that it ensures developing a new multi-disciplinary research area called "urban analytics." It is prescribed as “the practice of using new forms of data combined with computational approaches to gain insight into urban processes.” These approaches involve computational and statistical techniques to work on cities (Singleton, Spielman, & Folch, 2017). These techniques based on fundamental concepts of data science can be exemplified as data mining, machine learning, statistical analysis, regression analysis, database querying, data warehousing, or a combination of these (Bibri et al., 2018). Thus, urban analytics can be considered as a methodological toolkit, including these techniques, and it has the potential to develop the new tools, technologies, and processes to analyze data-rich cities (Singleton et al., 2017).

When the current studies are examined, the concept of “city analytics” is also encountered, and it is recognized that it has similar content with urban analytics. The new aspects of city analytics are explained by the fact that it is settled in a challenging and interdisciplinary space by interacting with multiple sectors (transport, energy, security, well-being, commerce, governance, environment, and resilience) and key professions (architecture, engineering, policy-making, and urban planning), and includes disparate new types of data such as CCTV, social media, city sensors, retail, utility and population censuses (Higham et al., 2017). Although both are utilized to define the same notion, the use of “urban analytics” as a phrase is found broader than “city analytics” in the literature. Thus, for this thesis study, “urban analytics” is preferred to be referred.

2.2 Historical Background of Urban Analytics

The evolution of urban analytics will be reviewed from the use of analytical methods in the urban design process through the emergence of urban analytics. The analytical tools and models, such as transport models, economic models, and planning models, take significant place to create an analytical understanding of the city. However, they have not been developed specifically for urban design. They have been used in the disciplines associated with urban design.

Besides using digital modeling in representation of design, with the advances in computer programs, new techniques have been utilized to analyze specific aspects of design (Morello, Carneiro, & Desthieux, 2010). Parametric design or computational design might be considered as examples of these approaches since they enable designers to change design parameters, visualize, and analyze the results dynamically. Among most of the developments in this field, GIS (Geographical Information Systems) occupies a fundamental place on analytical approaches in urban planning and transportation (Birkin, 1996; Nyerges, 2004). The potential of overlaying layers, including geo-referenced data and the ability to analyze these layers quantitatively, have made GIS a substantive tool in urban design.

The above-mentioned applications of analytical methods and tools have difficulties in integrating with the urban design process and providing a reliable evaluation. The primary reason for these difficulties is the shortfall of an urban theory, which could connect the physical features of the urban system with its functional, social and behavioral aspects directly and uneventfully (Hillier, 2008; Penn, 2008; Sailer, Budgen, Lonsdale, Turner, & Penn, 2008). This lack of theoretical approaches leads to a distance between the analysis of things and their implementation in design. Therefore, these approaches might cause a failure in producing tangible analytical tools or methods integrated into to design process since analysis and design are separated from each other. Moreover, these applications are rarely multi-disciplinary and multi-scalar. This limits their implementation to only particular areas of urban space without strong connections with other disciplines such as transportation, engineering, or socio-economics. They require a large amount of data, time, and resources to generate and conduct the models, making their use in design difficult and impractical (Karimi, 2017).

Batty refers to a new understanding of how cities function, and how urban data can be utilized to derive new theories (2013). This new understanding might provide solutions to the abovementioned problems, which are the need for a link between the physical, functional, social, and behavioral aspects of the urban space. They also require integration between analysis and design process, multi-disciplinary and multi-scalar methods, and a way to deal with a large amount of urban data. Batty mentions that their focus will continue to be on applying quantitative, computational, design, and visual methods to the spatial and morphological structure of cities and regions (2017). Singleton, Spielman, and Folch mention the advantages of these methods through an example. According to them, it is possible to monitor activities of a small group of pedestrians with the naked eye in a limited time; however, the flow of all pedestrians within an entire shopping mall over a day cannot be observed without the assistance of analytical technologies (Singleton et al., 2017).

The term “urban analytics” as an academic activity has entered into the literature under these necessities. According to Batty, it is originated from ‘urban analysis’, but it is more than that since the term analytics involves a set of methods that can be utilized to discover, perceive and foresee properties and features of any system, in our case, cities (Batty, 2019). As mentioned in the previous section, urban analytics benefits from data science and statistics. Thus, the research, including computational and statistical approaches, and dealing with urban data can be a part of urban analytics studies. Indeed, most of the methods or procedures belonging to urban analytics are not unexplored; however, their togetherness and relation with the urban systems can be considered as a new research area. There are several research groups interested in urban analytics all around the world. There is a research program called as Urban Analytics defined by Turing Institute in 2018. The program focuses on the mechanism, structure, relationships, and developments of agents, technology, and infrastructure within and between the cities across spatial and time-based scales (Urban analytics, 2018). Another research group founded by the National University of Singapore is Urban Analytics Lab. They describe their mission to benefit from spatial data for urban applications, develop 3D geo-information in the context of smart cities, and interpret big geospatial data and digital twins in the built environment (Urban Analytics Lab: Singapore, 2020). The last example is Urban Analytics Lab of Berkeley University, where they work on urban data for sustainable urban solutions by modeling, simulating, and visualizing (Urban Analytics Lab, n.d.). In general, the research groups have similar purposes, which are improving the QoL in cities and designing future cities by using data science. In this thesis study, it is aimed to utilize big data approach in the context of urban analytics. Thus, in the next section, definitions and explanations regarding urban big data analytics will be provided.

2.3 Urban Big Data Analytics

At present, the amount of data created in a single second is equal to data available on the entire Internet at the beginning of this century. This massive amount of data is produced by sensors, mobile phones, social networks, surveys, online payments, Global Navigation Satellite Systems (GNSS), online activities, public transport ticketing, and location-based services (Semanjski, Bellens, Gautama, & Witlox, 2016). This massive data is being referred to as big data. The term big data is utilized to describe huge and complex data sets that conventional data processing operations cannot qualify anymore. Changing from a data-scarce to a data-rich environment provides a shift from "small data" research that sought to answer specific questions based on the limited data to "big data" research that aimed to explore relationships and correlations between a series of variables and contexts (Witlox, 2015). Laney (2001) characterized big data with the 3Vs definition. Volume, first of all, refers to the magnitude of data either in terms of bigger than previously, or too big to handle with existing abilities. With characterizing by Velocity, it is intended to show its timeliness since it can be gained in close-to-real time from online sources. It is also defined by Variety, which demonstrates its various sources since it can be categorized as structured, semi-structured, and unstructured (Goodchild, 2013). In 2016, Patgiri and Ahmed mentioned 6V's and 1C, which are Veracity, Value, Validity, Variability/Volatility, Virtual, Visualization/Visibility, and Complexity (2016). Technology and analytical methods are required to make genuine use of such big data. Companies and researchers have been working on the development of different tools and software in order to understand, evaluate and extract the values of big data. In general, they have combined more than one analytic tool to conduct a big data task, including statistical functions, mining tools and predictive modeling (Stavros, Petros-Angelos, Nathanail, & Mitropoulos, 2019).

The availability and accessibility of geo-referenced big data have initiated a new area to evaluate urban characteristics at different spatial scales. How the urban space can be quantitatively measured, how it changes over time, and how these measures can be utilized to compare different cases with the help of big data analytics are critical aspects of the study area. Besides the spatial metrics, big data analytics can evaluate the influence of the spatial configuration on humans; in other words, human spatial behavior. It can be observed with the help of intelligent sensors, remote sensing data, smartphones, smart cards, and social media, as well as various sources of voluntary geographic information in the context of big data analytics (Goodchild, 2007; Jiang & Thill, 2015). By extracting knowledge from data regarding human behavior, it is aimed to empower citizens and authorities in making more informed decisions (Semanjski & Gautama, 2015). The most vital role for big data within urban analytics is its ability to support decision making and inform the design process. In this thesis, it is aimed to review approaches in urban big data analytics based on walkability and sustainable mobility studies. Thus, in the next section, existing studies covering urban big data analytics for sustainable mobility will be examined.

2.4 Urban Big Data Analytics for Sustainable Urban Mobility

The level of urbanization is on the inevitable increase, and it seems to continue in the foreseeable future. In 1800, only 2% of the world population lived in urban areas while in 1900, 14%, in 1950, 29%, in 2000, 47%, and in 2008, over 50% (Wu, Xiang, & Zhao, 2014). By 2050, it is estimated at 70%, and by 2092, 100% (Batty, 2011). Therefore, it is predictable that this increase in urbanization brings a number of problems related to sustainability (Grimm et al. 2008; Pickett et al. 2011; Liu, He, Zhou, & Wu, 2014; Wu, 2014). In urban analytics, it is significant to address these urban sustainability problems in various urban domains to allocate solutions and strategies. The urban sustainability problems can be related to energy, mobility, built environment, healthcare, education, safety, or their combinations. Mobility is one of the important domains of urban life affecting sustainability since it leads to problems regarding air pollution, traffic safety, urban development patterns, car dependency, QoL, and so forth.

The role of urban big data analytics addresses the problems of providing or supporting a solution for these problems to build awareness and knowledge on demand for mobility of people and transportation of goods, as well as to develop tools to manage and assess mobility performance. In the era of rapid technological development and endless production of data, smartphones, personal computers, autonomous vehicles, GPS (Global, Positioning System), SDR (Software-defined radio) devices, Bluetooth, UGC (User-generated content) platforms, urban sensors, Internet of Things (IoTs) and administrative records have become sources of big data. These data sources can be either machine-based (social media), human-based, or organization based (Stavros et al., 2019). Stavros et al. have studied the existing works regarding big data applications for sustainable urban mobility. They have reviewed 20 case studies published within 2016-2018. According to them, the most common methods of data collection in mobility are using sensors, such as road sensors, vehicle sensors, and park sensors. They have indicated additional means as cameras, GPS, mobile phones, surveys, image collectors, and smart cards. They have also mentioned the necessity of processing big data to understand and export solutions. The most common tools specified by them are Hadoop, Spark, Matlab, and programming model MapReduce for processing big data sets (Stavros et al., 2019).

Possible benefits of big data integration to the urban design process range from gathering real-time data and reducing the duration of the design process to more informed and agile decision making (Semanjski et al., 2016). In that sense, Semanjski et al. (2016) have integrated user-generated content into the Policy 2.0 platform for sustainable mobility planning. Policy 2.0 has been defined as a data-driven decision making and planning concept that actively includes citizens in a collaborative content generation to provide increased QoL and co-creation of more sustainable communities. They reported on collaborative content generation created in Leuven, Belgium, as a part of a sustainable mobility campaign. The campaign was motivated by the integration and active participation of all stakeholders into the mobility planning process. The data was collected with the help of a smartphone application for the Android platform called Routecoach. The application was utilized to learn from user-generated content and coach users towards more sustainable route choices. Collected data were transferred into the Policy 2.0 platform and utilized to calculate four sustainable mobility indicators, which are carbon dioxide (CO_2) emissions, particulate matter with less than 2.5 micrometers in diameter emissions ($PM_{2.5}$), calories burned by the user (kcal), and cost per trip in euros (€). Both data collection approaches and integration of big data into sustainable mobility planning in this study can be considered as part of urban analytics studies. Conventionally, data for mobility planning are collected with household surveys or interviews, and participants are asked to indicate their usual mobility behavior during a week. However, it has been identified that this way of reported mobility behavior does not agree with the actual one. Moreover, such data collection methods require more time, resources, and processing periods (Stopher & Greaves, 2007).

Another benefit of the big data approach utilized in sustainable urban mobility studies is its potential to predict travelers' activities. Predicting travelers' activities is a crucial matter to measure current sustainable mobility performance and direct travelers through more sustainable mobility choices. During the last decade, a large number of research studies based on data deriving from social media have been conducted to observe and foresee travelers' activities. Social media platforms, also known as Social Networking Services or Social Networking Sites, are the product of Web 2.0, and their usage is increasing day by day due to the increased dependence on smartphones and tablets (Hanna, Rohm, & Crittenden, 2011; Rashidi, Abbasi, Maghrebi, Hasan, & Waller, 2017). Facebook, Flickr, Foursquare, Google+, Instagram, LinkedIn, Pinterest, Tumblr, and Twitter are among the most widely used examples of these platforms. For the mobility studies, the spatial information of geotagged and the discursive content of the posts can be considered as the most commonly exploited SM-originated information (Chaniotakis, Antoniou, & Pereira, 2016). The most common methods and applications of SM-originated data followed by their goals, specifically for mobility studies, are presented in Table 2-1, as stated by Chaniotakis et al. (2016).

Table 2-1. Common methods and applications of SM-originated data & their goals in transport research (Chaniotakis et al., 2016)

Common methods and applications of SM-originated data	**Their goals in transport research**
Identification of spatial and temporal mobility patterns	Identification of the movement of the population
Investigation of the applicability of the social-media-originated data for travel demand modeling	Definition of the cities' boundaries
Identification of users' activities	Design of the Origin-Destination (O-D) matrices
Definition of urban settings and related characteristics (e.g., points of interest, boundaries, land uses)	Investigation of the users' mobility patterns
Investigation of riders' satisfaction	Exploration of the users' social networks and their effect on transportation-related behavior
Examination of the relationship between social networks and mobility	

In sustainable urban mobility, it is fundamental to develop objective targets and scientifically grounded indicators for each problem to evaluate the current situation, monitor progress, implement strategies, allocate resources, and increase the participation of the citizens. Urban big data analytics supports the goals of sustainable urban mobility studies with big data and its applications. Due to its importance, the use of big data applications for sustainable urban mobility was reviewed in this section. In this thesis study, walkability is taken into account as a part of sustainable urban mobility. Thus, the scope and importance of walkability as an urban metric will be explained in 3.2. Walkability as Sustainable Urban Mobility section. The methods and approaches utilized in the existing walkability research studies will be represented in 3.3.2. Methods for the Walkability Evaluation section.

CHAPTER 3

WALKABILITY: CONCEPTS AND DEFINITIONS

The third chapter of this thesis presents a literature review on walkability, with its three main aspects that are (1) definition of walkability, (2) walkability for sustainable urban mobility, and (3) walkability evaluation, including urban features and methods for walkability evaluation.

3.1 Definition of Walkability

In this thesis study, walkability was considered as an urban metric measured in the urban analytics context. Therefore, importance was given to what the term walkability means and its perceptual scope over the years.

The act of walking was compulsory before the automobile era. The pre-industrial city streets had to be designed to be walkable since everyone had to walk or use slow-moving vehicles such as carts, wagons, or carriages for daily life activities. The distribution of activities had to be well-organized, the density of housing had to be comparatively high, and each component of the city had to be connected by a continuous pedestrian path network. The cities in the middle ages were significant in terms of walkability. Generally, all the necessities of urban living were gathered into an area no more than 800 meters from the central square (Guan et al., 2019). Industrial cities of the 19th century had succeeded in maintaining the high walkability because horse-drawn carriages or streetcars were not affordable for most workers. With industrialization, advances in transportation technology and demand for high-speed transportation have negatively influenced the pedestrianized environment. As a result, the necessity of a walkable city was ignored by the end of the 1920s with the appearance of automobiles and the emergence of Modernism. The streets lost their human-scale, transparency, and public life due to high-speed traffic and imposed barriers (Southworth, 2005). In the late post-industrial city, it was challenging for pedestrians to move freely due to discontinuous cul-de-sacs, large block sizes, spaced and segregated land use patterns, over-scaled streets, and lack of sidewalks (Southworth & Ben-Joseph, 2003, 2004).

During the post-modern era, sustainable urban design has emerged since the necessity of human-scaled and environmentally supported urban space for the livability of the residents was recognized. This has occurred in many forms, such as urban metabolism, compact cities, the charter of the new urbanism, resilient cities, smart cities, and so forth. The rising awareness of public health, climate change, and ecological conservation led to more consideration of walkability in the post-modernist era (Guan et al., 2019).

Learning from past experiences, it can be stated that walkability, which can be defined as a metric associated with built environment, provides a comfortable and safe walking experience, connects people with varied destinations within a reasonable amount of time and effort, and offers visual interest throughout the walking path (Southworth, 2005). Thus, walkability is not a simple measure of the distance between origin and destination points (Jaskiewicz, 2011). In that sense, Southworth mentions the following six criteria that a walkable environment should have (2005, p. 249):

> 1. Connectivity of path network, both locally and in the larger urban setting;
>
> 2. Linkage with other modes: bus, streetcar, subway, train;
>
> 3. Fine-grained and varied land use patterns, especially for local serving uses;
>
> 4. Safety, both from traffic and social crime;
>
> 5. Quality of path, including width, paving, landscaping, signing, and lighting; and
>
> 6. Path context, including street design, visual interest of the built environment, transparency, spatial definition, landscape, and overall exploration.

These above-mentioned criteria are summarized as urban features associated with walkability. In the following sections, it will be demonstrated that walkability has been taken into account based on different urban features in the literature. Beyond the scope of walkability over the years, its definition and criteria, why walkability is significant for sustainable urban mobility will be explained in the next section.

3.2 Walkability as Sustainable Urban Mobility

Walkability can be considered as a foundation for a sustainable city. It contributes to sustainability level of cities based on several aspects such as human, social, economic, and environmental. Human sustainability means maintaining the individual wealth comprised of health, education, skills, knowledge, leadership, and access to services (Goodland, 2002). Walkability can promote mental and physical health by providing cardio-vascular fitness, reduced stress, stronger bones, weight control, mental alertness, and creativity. Moreover, it is the most accessible and affordable way to be physically active (Southworth, 2005). The lack of physical activity may cause numerous health problems like obesity, depression, osteoporosis, and cardiovascular disease (Frank, Engelke, & Schmid, 2003). Among these problems, obesity has become dangerous for the whole world. According to WHO (World Health Organization), more people are obese than underweight in every region except sub-Saharan Africa and Asia (World Health Organization, n.d.). Modern lifestyle and working conditions require very little necessity for physical activity. Thus, exercise should be included in individuals' daily routines to achieve the minimum recommended level of physical activity. Providing a walkable environment is one way to achieve this amount of physical activity at the population-level. Therefore, several studies making connections between health and mobility planning have been conducted. Besides urban design, there are many studies associated with walkability and health issues published by medicine and public health disciplines, as presented in Appendix A.

Social sustainability means maintaining the resilience of society. It consists of social cohesion, social equality, social support, human rights, cultural competence, livability, connectedness between groups of people, reciprocity, tolerance, compassion, patience, forbearance, fellowship, love, honesty, discipline, and ethics (Goodland, 2002). In that sense, walking is not only a purely utilitarian mode of travel for daily commuting, but it also provides social and recreational value. Thanks to its accessibility by a majority of the population across classes and ages, it can be considered as a socially equitable mode of transport. Moreover, it promotes sociability and social capital. Leyden, who mentions a study in Galway, Ireland, states that people who live in neighborhoods with high walkability are more likely to know each other and socially engaged (2003). Thus, in walkability studies, several urban features related to social issues have been associated with characteristics of built environment and walkability. Some examples of these studies, including social issues, can be found in Table 3-1.

Table 3-1. Some studies and related UFs associating social issues and walkability

Year	Researchers	UFs related to social issues
2001	Ball et al.	companionship
2007	Evenson et al.	perceived safety
2004	Humpel et al.	safety
2005	Alfonzo	
2005	Duncan & Mummery	
2015	Quercia, Aiello, & Davies	
2016	Tekel & Özalp	
2003	Bourdeaudhuij et al.	satisfaction with neighborhood
2008	Mehta	sense of belonging
		sense of safety
2006	Lee & Moudon	social
2019	Nasrin & Afifah	social and environmental friendliness
2002	Craig et al.	social dynamics
2005	Hoehner, Ramirez, Elliott, Handy, & Brownson	social environment
2017	Chiang, Sullivan, & Larsen	social safety
2002	Giles-Corti & Donovan	social support
2007	Moudon, Lee, & Schmid	
2006	Handy, Cao, & Mokhtarian	socializing
2019	Seles & Afacan	surveillance
2004	Addy, Wilson, Kirtland, Ainsworth, & Sharpe	trustability of neighborhood

Economic sustainability refers to providing long-term economic growth without bringing negative influences on social, environmental, and cultural aspects of the community while preserving economic capital (Goodland, 2002). Besides the primary factors affecting the choice of motorized or non-motorized transport, such as distance and connectivity, travel cost is also likely influential (Saelens, Sallis, & Lawrence, 2003). Walking is the most affordable transportation mode; thereby, it contributes to the individual and global budget by saving transportation costs and energy consumption. Boarnet and Crane (2001) explain the effects of the built environment on walking with an economic perspective. According to them, the built environment influences travel costs by affecting travel time and other qualities of travel. A similar approach is valid in discrete choice models of travel behavior. With these models, travel time and cost are tried to be minimized for the choice of travel modes (Boarnet et al., 2001).

Lastly, environmental sustainability, which is the management of the physical environment, gives importance to living within ecological concerns, conserving natural resources, and fulfilling the needs of communities while saving the resources for future generations' needs (Goodland, 2002). In sustainable urban mobility, it is aimed to decrease the negative impacts of transportation services on the environment. Since walking is described as a "green" mode of transportation, the walkability level of the cities is crucial in terms of environmental sustainability. Like other active transportation modes, it can reduce traffic congestion and decrease fuel consumption while eliminating air and noise pollution. There are several studies that mention the environmental benefits of active transportation modes. According to Hong (2018), walking and cycling require less space in terms of infrastructure, they produce fewer emissions per capita or per travel distance of passenger, and they lead to lower life cycle costs. Forman (2014) states some solutions in his book Urban Ecology – Science of Cities to increase walkability and protect ecological values in an urban environment. These solutions can be briefed into urban ecological principles encouraging the design and planning of walkable cities. Aligning the design of walkable cities with political interests such as the Paris Agreement towards reducing the risks of climate change can realize the long-term objectives of keeping people on walking and low carbon modes of travel (Guan et al., 2019).

As stated above, walkability has the potentials to promote sustainable urban mobility in several aspects. In this thesis study, it is taken into consideration as an urban metric to be measured by computational and analytical methods due to its importance for sustainable urban mobility. To understand relations between the built environment and walkability, existing studies regarding walkability evaluation will be elaborated in the following section.

3.3 Walkability Evaluation

In this thesis study, a framework for computational walkability analysis is proposed. Therefore, it is essential to review a wide range of existing walkability studies. The existing studies have been examined based on the utilized urban features and methodologies. In the following sections, these urban features and methodologies used in the studies will be explained comprehensively.

3.3.1 Urban Features for the Walkability Evaluation

Walkability is a measure that has been examined by several disciplines such as medicine, sociology, psychology, geography, urban planning, and architecture since it is considered as an important indicator for health, QoL, sustainable urban mobility, and built environment. In order to associate walkability with conditions of the built environment, existing studies utilize some features of urban design, environment, transportation, infrastructure, and human perception. These features will be addressed as “urban features” throughout this thesis. Therefore, the existing studies published by different disciplines related to walkability have been examined for the literature review of this thesis study to determine the urban features utilized before and to describe the general framework of the walkability studies. For the literature review, 85 walkability studies have been reviewed, and in the 76 of them, walkability has been measured according to defined urban features. In the rest of them, the proposed features to evaluate walkability level are just defined and explained based on the theoretical background of the study without any measurement. Throughout these studies, urban features, their definitions, variables, measurement methods, and observed relation with walkability are examined. Based on the literature review, how urban features have been categorized in different studies, which urban features have been used, and which methods for walkability evaluation have been utilized will be explained later in this section.

Firstly, existing studies from different disciplines mentioned above have the potential to evaluate walkability from different perspectives. It is seen in the examined literature review that even though there are urban features named similarly or the same, they might have different meanings according to the research context. Thus, urban features are not only reviewed based on their names, but also their definitions, variables and methods that are crucial to perceive the relation with walkability. Moreover, even the studies included in this thesis can show that there is a wide range of features mentioned in the literature. Therefore, it is essential to categorize them so that relation of urban features to the built environment and walkability can be comprehended. For instance, Ewing and Clemente (2013) mention urban features regarding walkability under three categories, which are: physical features, urban design qualities, and individual reactions, as seen in Figure 3-1. As they state, physical features individually are not sufficient to provide the experience of walking down a particular street, and they do not detect people's overall perceptions of the street environment. Moreover, urban design qualities are considered different from individual reactions since they can be assessed objectively by outside observers, while individual reactions cannot (Ewing & Clemente, 2013). Mostly studies belonging to medicine and health disciplines classify urban features according to their objectivity and subjectivity level and mention them as perceived and physical neighborhood characteristics. To illustrate, Lin and Moudon (2010) explain each built environment attributes with both objectively and subjectively measured variables.

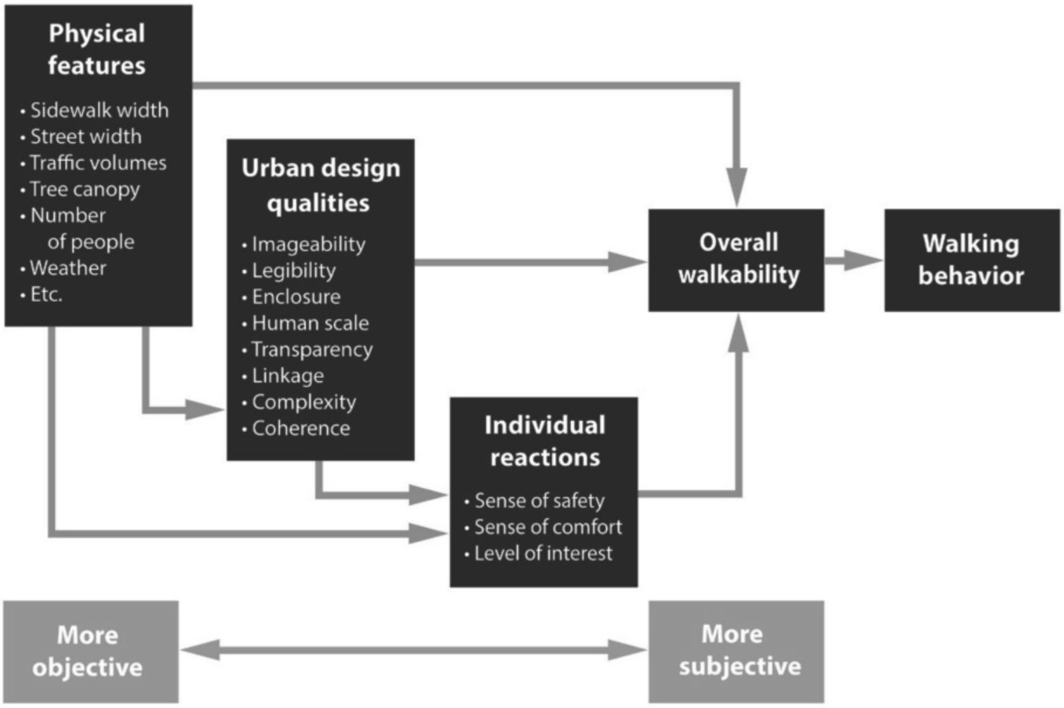

Figure 3-1. Urban features (Ewing et al., 2013)

Ewing and his colleagues' study identifies features according to the scale of measurement area, such as streetscape features defined as micro-features of the street environment that affect the pedestrian experience (Ewing, Hajrasouliha, Neckerman, Purciel-Hill, & Greene, 2016). According to Ledraa (2015), most walkability studies have focused on walkability indices based on city and street scales separately. While a part of the literature has ignored the macro-scale features of walkability, the other part does not consider micro-scale features (Ledraa, 2015). A detailed explanation of macro and micro-scale features will be described in section 3.3.1.1. Macro and Micro-Scale Urban Features.

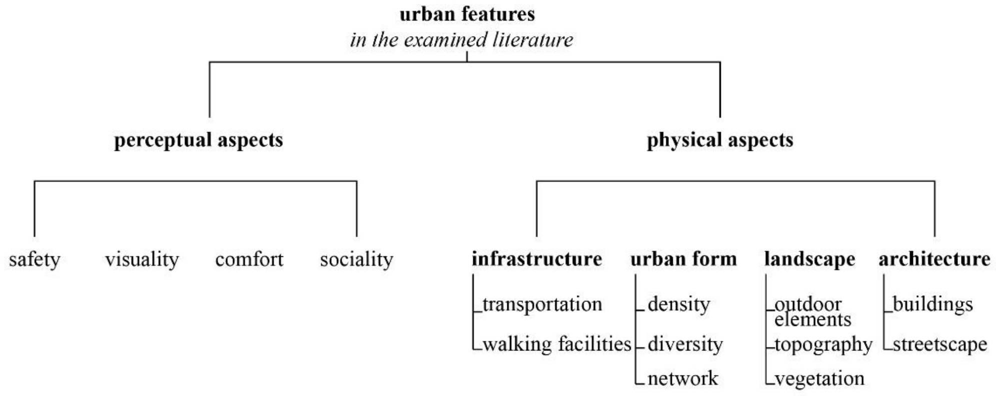

Figure 3-2. The categorization of urban features based on the literature review

In the examined studies, the urban features have been mostly framed under two or three categories like physical features-urban design qualities-individual reactions (Ewing et al., 2013), subjective-objective features (Lin et al., 2010) and macro-micro features (Ledraa, 2015). However, a more complex network is required to categorize the urban features related to walkability due to their interconnected relations, as shown by Ewing et al. (2013). Thus, the hierarchical categorization of the urban features based on the literature study is presented in Figure 3-2. Furthermore, the features belonging to each category have been displayed in a network graph (Figure 3-3). In accordance with the definitions and variables of the urban features, some of them are connected to more than one category. To illustrate, complexity is defined as the visual richness of a place (Ewing, Clemente, Handy, Brownson & Winson, 2006; Ewing et al., 2013), and its variables explained as number of buildings, number of dominant building colors, number of accent colors, number of pedestrians moving, existence of outdoor dining and public art. Hence, in the network, it is related to visuality, buildings, and sociality.

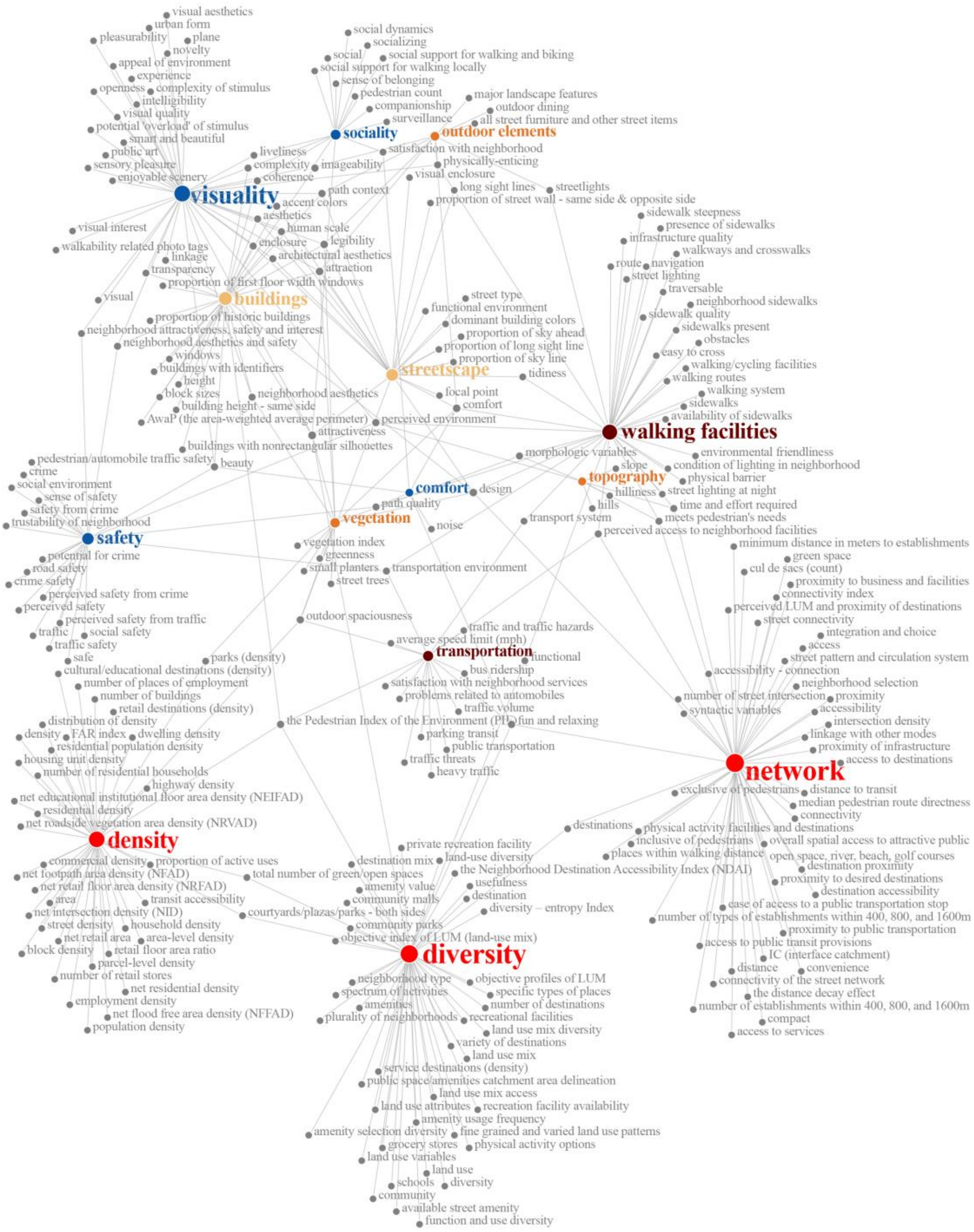

Figure 3-3. The network diagram of the urban features and categories based on the literature review, visualized in Graph Commons

As seen in Figure 3-2, the urban features are classified under fourteen categories. Firstly, they are separated as perceptual and physical aspects. Then, perceptual aspects have four categories, which are *safety*, *visuality*, *comfort* and *sociality*. "*Safety"* features are about a person's ability to feel safe from the social and physical factors (Mehta, 2008), such as crime and traffic safety. "*Visuality*" points out the features with respect to the perceived visual quality of urban space (Moudon, Lee, & Schmid, 2007), such as aesthetics, attractiveness, sensory pleasure, experience, novelty, and so on. The category "*comfort*" contains features referring to the presence of physical features of the urban space so that a person can feel comfortable (Tekel & Özalp, 2016), such as street furniture, outdoor dining, path quality, and so forth. "S*ociality*" consists of features related to the social environment of neighborhoods, such as satisfaction, social support, companionship, sense of belonging, surveillance, number of pedestrians on the street, and so forth.

Physical aspects consist of four top-categories which are infrastructure, urban form, landscape and architecture. The categories regarding infrastructure are *transportation* and *walking facilities*. "*Transportation*" refers to the features related to other transportation modes affecting walkability such as public transportation capacity, traffic volume and average speed limit, and so on. "Walking facilities" comprises features displaying the development level of transportation infrastructure for walking, such as sidewalks, street lighting, signs, tidiness, environmental friendliness, navigation, obstacles, and so on.

The categories regarding urban form are *density*, *diversity* and *network*. "*Density*" consists of features measured as the variable of interest (population, dwelling units, employment, and building floor area, etc.) per unit of area (Ewing & Cervero, 2010) such as employment, residential, parcel-level, commercial density, and so forth. "*Diversity*" involves features expressing the distribution of different land uses and their variety, such as diversity, dissimilarity index, entropy, vertical mixture, land use mix, variety of destinations, usefulness, amenities, plurality of neighborhoods, and so forth. "*Network*" includes every feature related to street pattern, especially connectivity and proximity. Connectivity refers to features about the directness or ease of travel between origin and destination points that are directly related to street network (Saelens et al., 2003), such as street intersection, street pattern, integration, convenience, and so on. "*Proximity*" includes features monitoring walking distances to destinations in terms of accessibility level, such as convenience, exclusiveness and inclusiveness of pedestrians, accessibility, access to destinations, proximity to destinations, compactness, and so on.

The categories regarding landscape are *outdoor elements*, *topography*, and *vegetation*. "*Outdoor elements*" is associated with the existence of street furniture, major hand-made landscape elements, and outdoor dining areas. "*Topography*" indicates the features of the land and its form such as slope and hilliness. "*Vegetation*" indicates features showing the organization of natural elements, such as order of trees, greenness, vegetation index, and so forth.

Lastly, the categories regarding architecture are *buildings* and *streetscape*. "*Buildings*" addresses to characteristics of buildings' such as block size, height, façade quality, floor area, architectural aesthetics, and so on. "*Streetscape*" features consider the overall quality of a street, such as enclosure, human scale, proportion of sky ahead-line, existence of long sight lines and so on.

In one of the earliest studies, Cervero and Kockelman (1997) mention density, diversity, and design as three dimensions, or "three Ds", of the built environment as indicators for travel demand. These three dimensions are considered to be positively associated with the choices of shared-ride, transit, and non-motorized modes (Cervero & Kockelman, 1997). The 3Ds are followed later by destination accessibility and distance to transit (Ewing et al., 2001; Ewing et al., 2009). With the need of more research focused on walkability, the Walkability Index was developed by Frank et al. (2009), adopted by some studies afterward (Van Dyck et al. 2010; Sundquist et al. 2011; Saelens et al. 2012; Reyer et al. 2014). For the Walkability Index (WI), intersection density, net residential density, retail floor area ratio, and land use mix are required to be calculated, and the equation can be seen below (Frank et al., 2009).

$$Walkability = [(2 \, x \, z - intersection\ density) + (z - net\ residential\ density) + (z - retail\ floor\ area\ ratio) + (z - land\ use\ mix)]$$

Equation 3-1. Walkability Index equation (Frank et al., 2009)

Until Ewing and his colleagues' study in 2006, urban features related to travel behavior and physical activity research have been mostly gross qualities such as neighborhood density, street connectivity, distance to parks, and so forth. According to them, features like the number of travel lanes and the presence of marked crosswalks provide crude measures to assess the walkability. Therefore, they prefer to utilize urban design qualities, which were declared by classical readings in the urban design field (Ewing, Handy, Brownson, Clemente, & Winston, 2006). These urban design qualities are stated as imageability, coherence, enclosure, human scale, complexity, legibility, linkage, and tidiness. In 2013, Ewing and Clemente published a book named "*Measuring Urban Design Metrics for Livable Places"* which is a continuation of the previous study. After that, Ewing et al. (2016) addressed the variables of these features as streetscape features, and they made the assessment directly based on these variables. The same features and some of their variables were utilized afterward by some studies (Jahanmohan, 2016; Tekel et al., 2016; Yin, 2017; Yin & Wang, 2016; Zhu, Hua & Dogan, 2019).

As mentioned previously, in the literature, the urban features are also categorized as macro and micro scale. Since the proposed methodology will be conducted at both neighborhood and street scales, macro and micro scale urban features will be explained in detail in the next section.

3.3.1.1 Macro and Micro-Scale Urban Features

Influences of the built environment on walking behavior can be understood and examined on different levels or scales (Choi, 2012). Therefore, urban features differ as macro-scale and micro-scale according to level or scale of the area. Macro-scale features are mostly measured at the urban planning and larger-scale urban design level, while micro-scale features at the street and building level. These features related to the built environment discussed in different studies and literature range from the regional planning level through the urban planning and design level, and down to the micro-level of urban design and architecture (Choi, 2012). In one of the studies, Southworth explains these features by the attitudes of different disciplines as follows:

> "While transportation planners have focused on abstract "macro" variables like capacity, demand, volume, rate of flow, trip origin/destination analysis, congestion patterns, and regional land use patterns, urban designers and landscape architects have looked at "micro" variables, the form and use of local places." (Southworth, 2005, p. 247)

Ledraa (2015) considers the difference between these features according to their variables' like being quantitative or qualitative. Macro-scale features such as population and building densities, street length per hectare, block and street intersection densities, mixed land use, and street network patterns are accounted as quantitative measures, while micro-scale features such as pedestrian route quality, continuous sidewalks, street trees, building facades, accessibility, destinations, streetscape aesthetics, and perception of safety, liveliness, cleanliness, sense of place and enclosure are delineated as qualitative factors (Ledraa, 2015).

As mentioned before, Ledraa (2015) states that while a part of the existing studies has neglected macro-scale features of walkability, others do not take micro-scale features into consideration. Moreover, according to Choi (2012), evaluation of the built environment attributes at the street and building-level seems to be insufficient in current research on walkability. Also, when it comes down to the micro-level of urban design and architecture, the features utilized are often limited to design qualities such as street width, aesthetics, landscape design (e.g., presence of trees), or street furniture (Choi, 2012). Therefore, it is necessary to discuss their importance to capture walkability at both the city and street level. In this respect, Choi (2012) states that the investigation of walkability factors that are more thoroughly carried out at street and neighborhood level can contribute to a better understanding of how and why walking behavior is influenced by these factors. Thus, micro-scale features are required to be developed and more explored for the provision of better evidence for well-informed urban design. Furthermore, when the detail level of the features increases, the degree of their impacts on walking behavior would increase (Choi, 2012). To illustrate this argument, Choi gives the following example:

> "For example, in cases where the degree of land-use diversity or density measured at the area or neighborhood level is the same, the effectiveness of their influence on both the quantity and the quality of walking activity may differ slightly, according to how they are designed at the street and building level in accordance with the qualities, such as design of the ground level, number and position of building entrances, design related to sidewalk-ground level interaction, building types, etc."(Choi, 2012, p. 45)

In this regard, it is also necessary to mention Jan Gehl's argument (2010), which is the provision of possibilities is provided at the macro level, but the battle is fought at the micro-level (as cited in Choi, 2012, p.45). As a different aspect, Talen (2002) emphasizes the importance of capturing walkability at the street level since an individual is more subjected to the micro-features of the environment while walking than driving. During this walking experience, the environment can provide one to sense the social and natural life of a place, yet it is impossible to assess this experience with macro-scale features (Owen, 1993). However, the macro-scale features are also necessary to perceive the situation of the city in terms of density, diversity, mixed land use, connectivity, accessibility, and street network patterns. Hence, they should not be disregarded for walkability assessment at the city scale or higher scales.

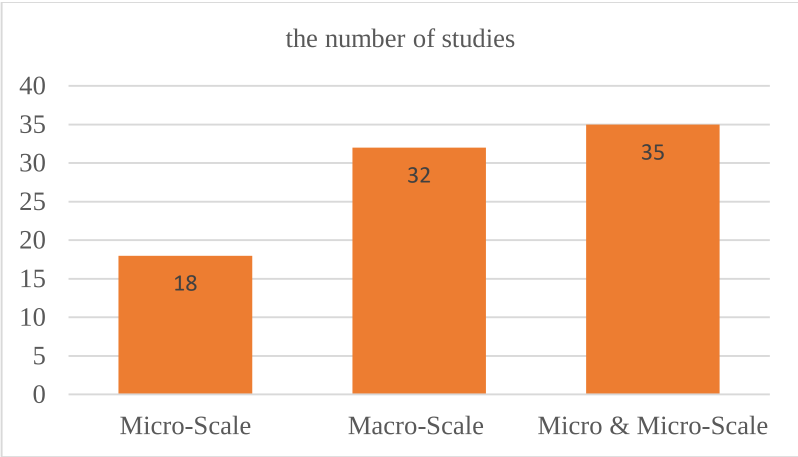

Figure 3-3. The graph showing the number of walkability studies including micro and macro scale features based on the existing studies in the literature review (Appendix B)

In the few examined studies, the features are categorized as macro or micro-scale by the authors themselves (Cervero et al., 1997; Choi, 2012; Ledraa, 2015; Saelens, Sallis, Black, & Chen, 2003; Southworth, 2005). For the ones not described, they are defined as macro or micro-scale features according to their definitions, variables, and the scale of the case area throughout the literature review. After then, each study was categorized in terms of using macro, micro, and macro-micro scale features. From the graph in Figure 3-3, it can be stated that in 32 out of 85 studies, only macro-scale features, in 18 of them only micro-scale features, whereas in 35 of them both macro and micro-scale features are utilized. From this result, it can be deduced that the macro-scale features own the majority in the examined studies. While most of the micro-scale features belong to perceptual aspects, macro-scale features are defined mostly under the density, diversity and network categories with a few exceptions. As an exception, Choi (2012) utilizes two features (land-use diversity and connectivity) belonging to diversity and network categories at different levels like global, local, street, and building level.

To conclude, urban features can be described as micro and macro-scale according to their definitions and the scale of the implementation area. It is essential to consider both of them with respect to the research context while deciding the urban features to evaluate walkability. In the next section, walkability studies will be briefly explained based on the methodologies mentioned in the literature.

3.3.2 Methods for the Walkability Evaluation

Methods for walkability evaluation will be explained under three parts, which are data collection, computation, and visualization methods, through the examined studies. Distribution of the different methods utilized in the studies are displayed in Figure 3-4, 3-5, and 3-6. As 9 out of 85 studies do not have any implementation process, there is a category named as "not applicable" for these studies in the graphs.

3.3.2.1 Data Collection

The data collection approaches assessed in the selected studies are generalized as five methods, which are gathering from database, gaining data from survey/ interview/audit instrument, web-scraping, field observation/fieldwork, and video/photograph rating. According to Figure 3-4, enabling data from databases and survey/interview/audit results are the most common methods to collect data between the selected studies, whereas web-scraping, field observation / fieldwork and video/photograph rating are the least common ones.

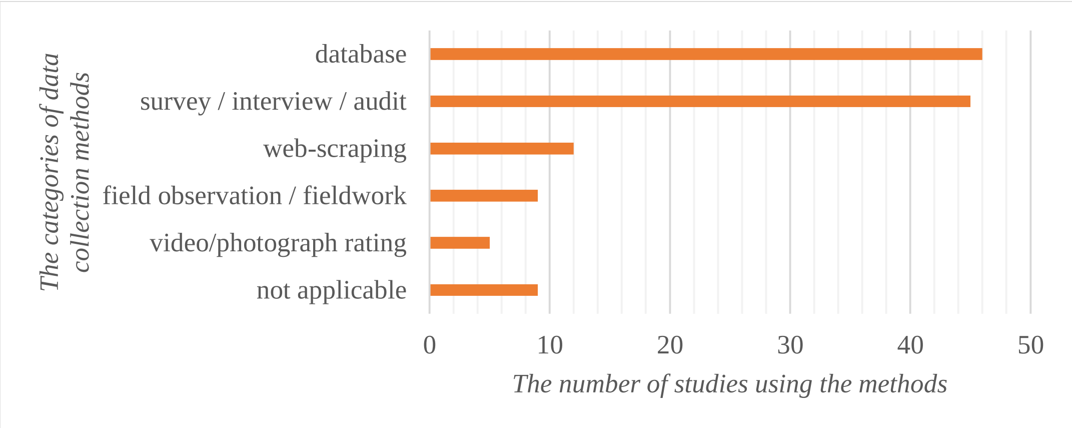

Figure 3-4. The graph showing data collection methods based on the existing studies in the literature review (Appendix B)

According to the selected studies, the most common data sources are existing databases, which are varied as open databases (e.g., OpenStreetMaps), databases belonging to governments, municipalities, or institutions, and GIS databases (e.g., ESRI).

In general, by survey/interview/audit instruments, two main types of data are aimed to be gathered. Firstly, home addresses of participants are geo-coded so that the locations of residential units can be clarified. Secondly, participants respond to questions regarding their perceptions of the physical environment. In the selected studies, different types of surveys and interviews are conducted to gather data, such as face-to-face interviews, telephone interviews/surveys, mail-out surveys, self-reported surveys, and open-ended question surveys. While survey and interview methods include mostly self-reported perceptions of the physical environment by local residents (Bourdeaudhuij, Sallis, & Saelens, 2003; Humpel et al., 2004; Saelens et al., 2003), audit instruments used by trained raters are based on more objective measures. In other words, audit tools are developed to measure the street-scale or fine grain attributes of the physical environment objectively. The characteristics of the environment that are relevant to walking will vary according to climate, landscape, built form, and cultural traditions; therefore, audit tools should be sensitive to such differences and tailored accordingly (Millington et al., 2009). To illustrate, in Australia, the Systematic Pedestrian and Cycling Environmental Scan (SPACES) (Pikora et al., 2002), and in the United States, the St. Louis Instrument (Brownson et al., 2004) and the Irvine-Minnesota Inventory (Boarnet et al., 2006) were developed. However, the context of the environments for which these tools have been developed differs from urban areas in many European towns and cities. Thus, Millington et al. had to design a new assessment tool, which is the Scottish Walkability Assessment Tool (SWAT), to evaluate walkability in Scotland, UK (Millington et al., 2009). Pikora and colleagues (2002) developed a Systematic Pedestrian and Cycling Environmental Scan (SPACES) instrument to get data about the micro-scale street features while Clifton and colleagues (2006) devised another pedestrian environment audit instrument, known as the Pedestrian Environment Data

Scan (PEDS), which provides a comprehensive method to evaluate the effects of urban form on pedestrian behavior at both the neighborhood macro-scale and the street micro-scale. As a different approach, Lee and Moudon (2003) undertook a comprehensive review of the 31 audit tools with over 200 built environment macro- and micro-scale features to devise a model called the Behavioral Model of Environments (BME). Likewise, Ledraa (2015) developed an audit tool by reviewing four published audit tools, SPACES, PEDS, BME and the St. Louis audit tools.

Web-scraping and collecting data through applications are newly used methods in the selected studies. In this respect, thanks to the increasing popularity of social media web sites and the parallel diffusion of smart devices embedded with a camera, high-speed Internet connection, and GPS, massive social media sources of geo-referenced data about user behaviors have recently become available (Berzi et al., 2017). Lu (2017), Berzi et al. (2017), and Quercia et al. (2015) retrieve data from social media platforms (Flickr and Foursquare); Yin et al. (2015 & 2016) utilize images from Google Street View, and Duncan et al. (2011) gather data regarding the features of physical environment from Walk Score API. Quercia et al. (2015) also get the ranking data regarding eight different categories (road safety, easy to cross, sidewalks, hilliness, navigation, safety from crime and smart and beautiful) from Walkonomics, a web platform and a mobile application that maps and rates the pedestrian-friendliness of streets in England, San Francisco, Toronto, and Manhattan.

Field observation / fieldwork and video/photograph rating methods appear in Figure 3-4. For these methods, generally, experts are asked to visit the site or watch the video clips and photographs and rate each street segment according to defined criteria. To illustrate, in Oreskovic and colleagues' research, two of the co-authors rated photographs from Google Street View based on transparency level of the facades, variations in building height and plane, and presence of street focal point (Oreskovic, Charles, Shepherd, Nelson, & Bar, 2014).

These new methods, web-scraping and gathering data from open databases, can show that when data becomes more ubiquitously available and accessible through the advance of technology, the new techniques to gather it have to be developed and utilized more. The following inferences can explain the change in data collection methods in time:

> "Planners and social scientists have been using survey, interview, and field work to collect empirical data for years (Ruppert, 2013). Recent studies suggested to attend to new forms of empirical data and conceptions (Lury and Wakeford, 2012; Ruppert, 2013). 'Big data' and computational analytics create important opportunities for interdisciplinary approach to study new phenomena or to study old questions with new data and insights (Arribas-Bel, 2014; Ruppert, 2013). They have a potential to help study social phenomena in ways never before imagined and possible (Arribas-Bel, 2014; Watts, 2007)." (as cited in Yin, Cheng, Wang, & Shao, 2015, p. 337)

As can be seen from Figure 3-4, traditional data collection methods like using surveys, interviews, or fieldwork have been still employed while the new methods are emerging. However, in the future, these new methods and newer ones might be substituted for the conventional methods.

3.3.2.2 Computation

The computational methods assessed in the selected studies are generalized as four methods, which are statistical analysis, spatial analysis, machine learning techniques, and 3D digital modeling. According to Figure 3-5, statistical and spatial analysis are the most common methods to compute the data, whereas using machine learning techniques and 3D digital modeling are the latest and least common ones in the selected literature.

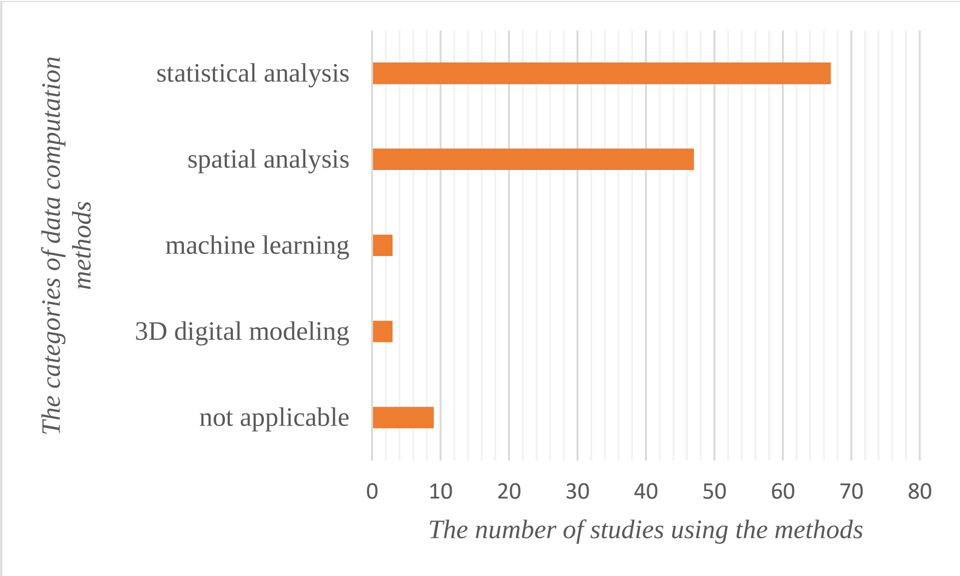

Figure 3-5. The graph showing computation methods based on the existing studies in the literature review (Appendix B)

Various types of statistical analyses, such as regression analysis, multivariate modeling, factor analysis, and so forth, are applied in walkability research. In some cases, the data retrieved from surveys, interviews, audit instruments, field observation, databases, or expert ratings is directly computed by statistical analysis (Ainsworth, Wilcox, Thompson, Richter, & Henderson, 2003; Cervero et al., 1997; Craig, Brownson, Cragg, & Dunn, 2002; Ewing et al., 2006; Giles-Corti & Donovan, 2002; Hajna, Dasgupta, Halparin, & Ross, 2013) whereas there are also studies constructing a statistical model based on the data found by GIS calculations (Boarnet, Forsyth, Day, & Oakes, 2011; Duncan & Mummery, 2005; Handy, Cao, & Mokhtarian, 2006; Moudon et al., 2007; Troped, Wilson, Matthews, Cromley, & Melly, 2008). Thus, it can be stated that GIS analysis methods are applied to walkability studies to serve several aims. Firstly, it is used to calculate some indexes and scores such as Walkability Index, Walkability Score, entropy, connectivity, and dissimilarity index before investigating the statistical relations between the different features as mentioned above. Secondly, GIS enables network analysis (Tilt, Unfried, & Roca, 2007) and cluster analysis (Berzi et al., 2017). Lastly, GIS has the potential to provide specific measurement and analysis through its plug-ins such as WBC Analyst (Lee & Moudon, 2006), AwaP, and IC tools (Majic & Pafka, 2019).

Another computational method in walkability studies is Space Syntax analysis, which is based on the Theory of Social Logic of Space or Space Syntax (Hillier & Hanson, 1984; Hillier, 1996; Medeiros, 2013). It contributes substantially to the debate when aligned with the reading strategies of urban forms whose bases are derived from the systemic view. The theory offers techniques for understanding and representing space, including the structure of the street network, providing materials that allow the researcher to investigate the city through its urban articulations (Barros, Martínez, & Viegas, 2017). In a study conducted by Handy (1996), the urban form was used only like a different urban grid, but the systemic conception of urban form was not approached. In order to try to fill this gap, Barros, Martinez, and Viegas (2017) used the Space Syntax Theory because it is based on a systemic conception that allows understanding the interrelations more broadly. Likewise, Özer and Kubat (2014) utilized Space Syntax analysis based on integration and choice feature of the built environment since it estimates not only current but also potential movement levels.

Big data analytics like machine learning technology, evolved from artificial intelligence on computational learning and pattern recognition, can also help to develop current approaches to measure urban features related to walkability (Yin et al., 2016). Yin and Wang (2016) utilized two machine learning methods, which are Artificial Neural Network (ANN) and Support Vector Machine (SVM), to develop an algorithm to identify sky areas for measuring the proportion of sky on the sampled street blocks to evaluate visual enclosure. As the first step, they analyzed texture and color on images using ANN, then they combined detection and segmentation with feature extraction to analyze image structure and extract features such as adjacent regions and their areas and locations, and lastly, these extracted features were used as input for the third step on classification using SVM (Figure 3-6). These data-driven prediction methods contribute to learn and analyze for planning and to design an urban built environment based on big data like Google Street View images.

Similarly, Yin et al. (2015) found that applying machine learning technology on Google Street View imagery can help to determine the presence of pedestrians with a reasonable level of accuracy to help get an objective estimate of pedestrian volume.

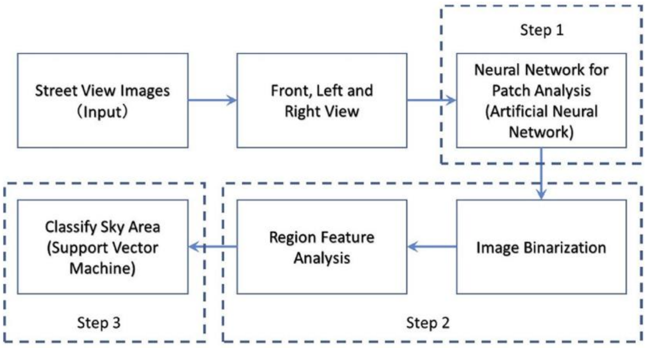

Figure 3-6. Machine learning process to identify sky areas (Yin et al., 2016)

While 2D models have been widely used in planning, it is limited in terms of visualizing and analyzing physical objects that need to be understood in their solid forms with sensory information such as texture, shape, and size or in vertical dimensions and spatial relations such as elevation, heights, volume, and space (Yin & Shiode, 2014). 3D models are built on 2D data and 3D models for buildings, trees, and other objects to create virtual environments. Such models can help make the complex spatial relationship within the urban fabric easier to understand to human by delivering information in an intuitively comprehensive form, and thus improve the ability of decision-makers and designers to make a decision. (Day, 1994; Shiode, 2001). 3D digital models enable interactive control of visual exploration and explanation of spatially referenced data by accessing accurately represented studied subjects and their properties as real-world objects (Kwan & Lee, 2005). Such models are especially important for planning and design activities with a focus on view assessment (Yin & Hastings, 2007; Yang, Putra, & Li, 2007), which is important for walkability analysis. In this manner, Yin (2017) utilized the ArcScene tool, which is a 3D GIS tool, to evaluate the proportion of sky and long sightline while Zhu, Hua, and Dogan created a 3D digital model by Grasshopper (GH) and Rhinoceros (RH) to assess transparency and enclosure level of the street segments.

3D digital modeling at the city scale has been expanded in recent years thanks to the development in gaming and military simulation industries and advances in computer technology. The complex models with a more accurate and realistic representation of the built environment using architectural models, photogrammetry and laser scanning, procedural modeling, etc., such as Autodesk and CityEngine models, have been developed. These models can help generate objectively measured micro-scale features related to walkability. More complicated models with detailed façade information are helpful for other streetscape measures such as the proportion of windows and building colors as well (Yin, 2017).

3.3.2.3 Visualization

Visualization is an important process in urban analysis for better communication of the data to designers and decision-makers. Through the visualization, new knowledge can be generated for designers and decision-makers (Ensari & Kobaş, 2018). Thus, the selected studies were examined to clarify existing visualization methods in walkability studies. In the studies, only four types of visuals are observed, which are tables, maps, graphs, and perspectives. According to Figure 3-7, tables are the most common representation procedure, and then maps and graphs take the second place. Perspective drawings gathered from 3D digital models are the newcomers.

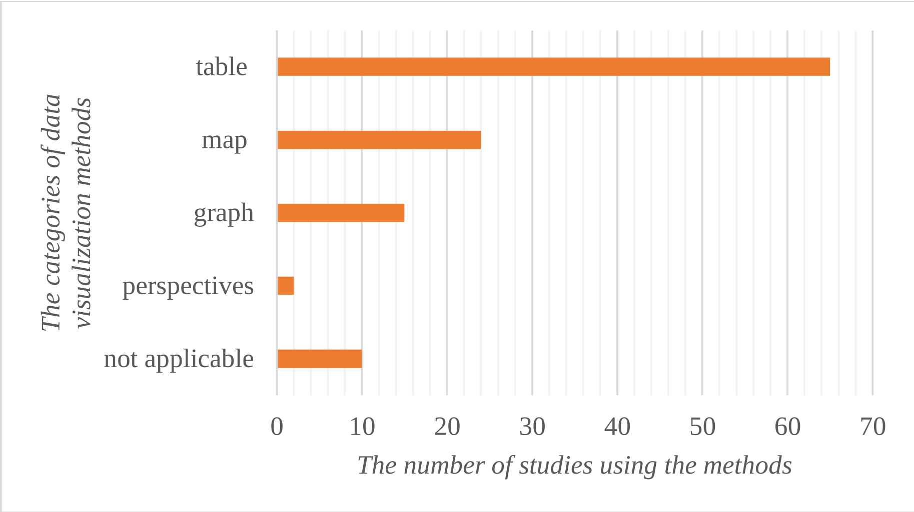

Figure 3-7. The graph showing visualization methods based on the existing studies in the literature review (Appendix B)

In most of the studies, the results of the statistical analysis are preferred to be shown by only tables (Addy, Wilson, Kirtland, Ainsworth, & Sharpe, 2004; Agampatian, 2014; Ainsworth et al., 2003; Bahrainy, Khosravi, Aliakbari, & Khosravi, 2015; Ball, Bauman, Leslie, & Owen, 2001). However, the intelligibility of these tables by the ones not having any knowledge about statistics is questionable. Therefore, supporting these statistical results by maps and graphs is an encouraging way for visualization of big data. Mapping techniques also have the potential to assess visualization of a rich set of urban data human perception, which is deemed as valuable as automated analytical processes (Schreck & Keim, 2013). The studies based on GIS analysis mostly prefer to produce maps for each urban features evaluated for walkability such land-use, proximity, street junction, density, and so forth, and then, they also visualize Walkability Score or Index based on a map (Agampatian, 2014; Lu, 2017; Zhu et al., 2019). As a different approach, Nourian and Sariyildiz (2012) utilized a GH visual programming environment to express their configurative approach promoting pedestrian mobility.

Besides tables, graphs are also favored to explain the statistical relationship between features or variables. To illustrate, Tilt and colleagues express the relationship between vegetation index (NDVI), objective accessibility, and body mass index

(BMI) through a graph (Tilt et al., 2007); Mehta (2008) compares the number of pedestrian and blocks for each street with bar graph; Yan and colleagues show the distribution of land-use based on clusters with a graph (Yan, Voorhees, Clifton, & Burnier, 2010); Tekel and Özalp (2016) visualize expert rates with the help of graphs for each urban features; and lastly, Majic and Pafka display the variation between AwaP (the area-weighted average perimeter) and IC (interface catchment) compared for several cities by a graph as well.

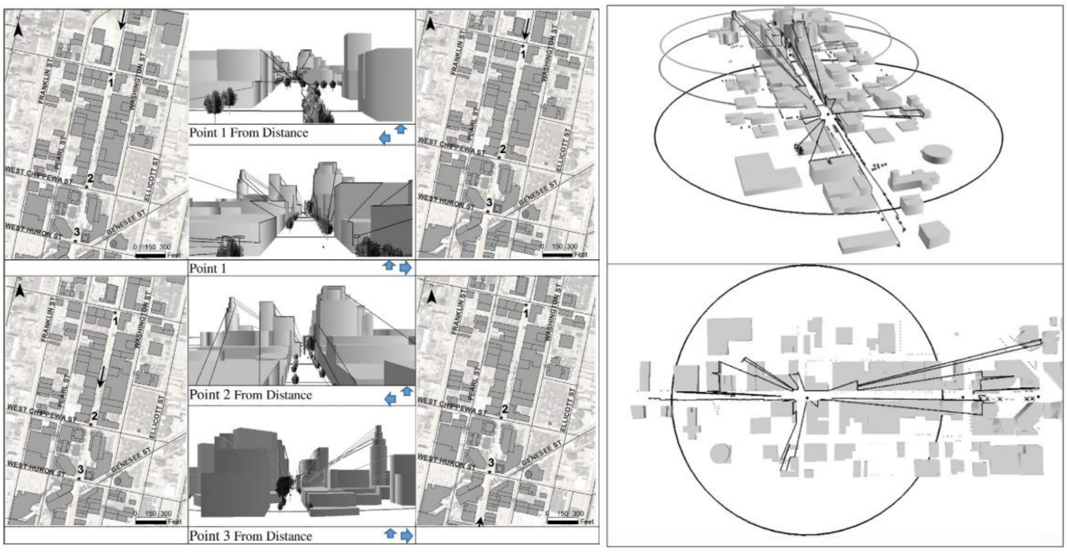

Figure 3-8. Illustrations of the line of sight analysis (Yin, 2017)

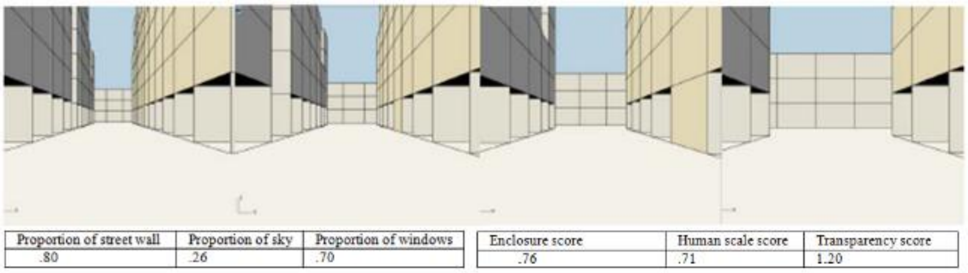

Figure 3-9. A group of images for a street model with its quantitative information (Zhu et al., 2019)

The studies evaluating 3D dimensional features such as enclosure, human scale, the proportion of skyline, and long sightlines began to prefer digital modeling to measure them objectively. Using perspectives also provide a better communication method for human understanding of the built environment, which is an important factor for walkability evaluation. Therefore, it is inevitable to assess visualization of the data with the various scenes from these models. Yin (2017) illustrates the line of sight analysis with the perspectives and lines computed by the digital model (Figure 3-8). Likewise, Zhu, Hua, and Dogan (2019) provides images of a street section at the level of pedestrians' view to indicate variables (e.g., the proportion of street wall, sky, and windows) and features (e.g., enclosure, human scale, and transparency) of the study (Figure 3-9).

CHAPTER 4

METHODOLOGY: EXPLORATORY ANALYSIS

The aim of the study is to explore the computational urban analytics methods in the assessment of walkability for well-informed urban design. As previously mentioned, a comprehensive literature review on urban analytics and walkability studies has been conducted. In consideration of this learning, an exploratory analysis for walkability is developed. A case study area is selected to implement the analysis. This walkability evaluation is designed in three sequential stages. Firstly, an approach is proposed for walkability evaluation at the neighborhood scale, and then an analysis is enhanced at the street scale. Finally, walkability evaluation at the street scale is reconsidered for elderly people. The fourth chapter of this thesis explains the methodological approaches utilized throughout these stages. In the first part, the general framework of the research has been displayed. In the following three parts, walkability evaluation has been described and implemented through a case study area, including explanations of the urban features, data collection, and computation methods for each stage.

4.1 Developing an Exploratory Analysis for Walkability through a Case Study Area

In the literature, walkability has been considered from different perspectives. As previously explained, walkability studies have been applied at different scales such as city, neighborhood, street, and building. The urban features utilized for these studies can be categorized as macro and micro-scale features according to the level or scale of the study. Besides the scale, walkability studies have been differentiated concerning the characteristics of the target groups such as gender, age, nationality, or profession. Both perceptual and physical aspects of the urban features may differ based on these characteristics. They influence on people’s walking habits, abilities, and types of destination points. The different urban features were included into the existing studies based on specific target groups. As a result, it can be stated that focusing on either a specific scale or target group requires particular urban features to be evaluated. Each urban feature might have different urban metrics, depending on it, different data sources, data collection, and computation methods. Focusing on a limited area or a specific target group might negatively affect the improvement and use of the analysis for future studies. Hence, this study aims to develop a general framework applicable to various cases. This exploratory analysis is composed of three sequential stages. In the first two stages, the walkability assessment is enhanced pursuant to the scale of the case area, while in the last stage, a specific target group, which is elderly people, is taken into consideration.

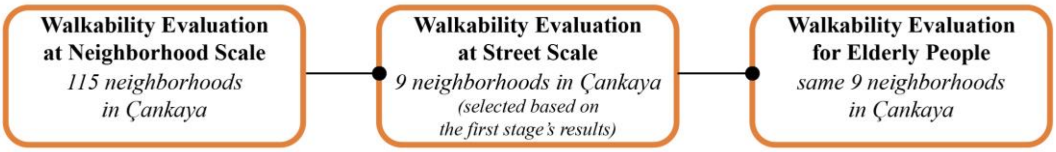

Figure 4-1. The diagram displaying research's stages

In the first stage, it is determined to evaluate walkability at the neighborhood scale. For this stage, urban features are selected among the macro-scale features. The case area should be consist of more than one neighborhood. It is intended to calculate a walkability level for each neighborhood. The neighborhoods are sorted according to natural breaks classification method. As a result, there are three categories for the neighborhoods, which are high, medium, and low walkable. In the second stage, as a case area, three neighborhoods are selected from each category. The urban features are chosen among the micro-scale features. The walkability level of each neighborhood are calculated based on the walkability level of the streets in the neighborhoods. The differences between the streets with respect to their walkability level are also displayed. In the last stage, same nine neighborhoods are considered as case area. Additional urban features are described to assess the walkability for elderly people. As a result, the walkability level for elderly people is calculated for each neighborhood.

In order to implement the analysis, a case study area, Çankaya, was selected. Çankaya is one of the central districts in Ankara. It has 124 neighborhoods; however, 115 neighborhoods were included in the study due to the data availability. For the second and third stage, 9 neighborhoods out of 115 were selected based on the first stage's results. The detailed workflow and explanations for each stage will be given throughout the next three section.

4.2 Walkability Evaluation at Neighborhood Scale

This section elaborates on the first stage of the analysis, which was applied to the 115 neighborhoods in Çankaya. The workflow of this stage was briefed as follows:

1. Selecting and defining the urban features
2. Specifying the regarding urban metrics for each urban feature
3. Describing required data for each urban metric
4. Reviewing the data sources for the required data
5. Collecting the data from the selected sources
6. Processing the data to gather the big data
7. Computing the big data for each urban feature
8. Defining the walkability index at neighborhood scale
9. Sorting the neighborhoods according to their walkability level based on the natural breaks classification method

Each operation shown in Figure 4-2 will be explained in detail in the following three sections.

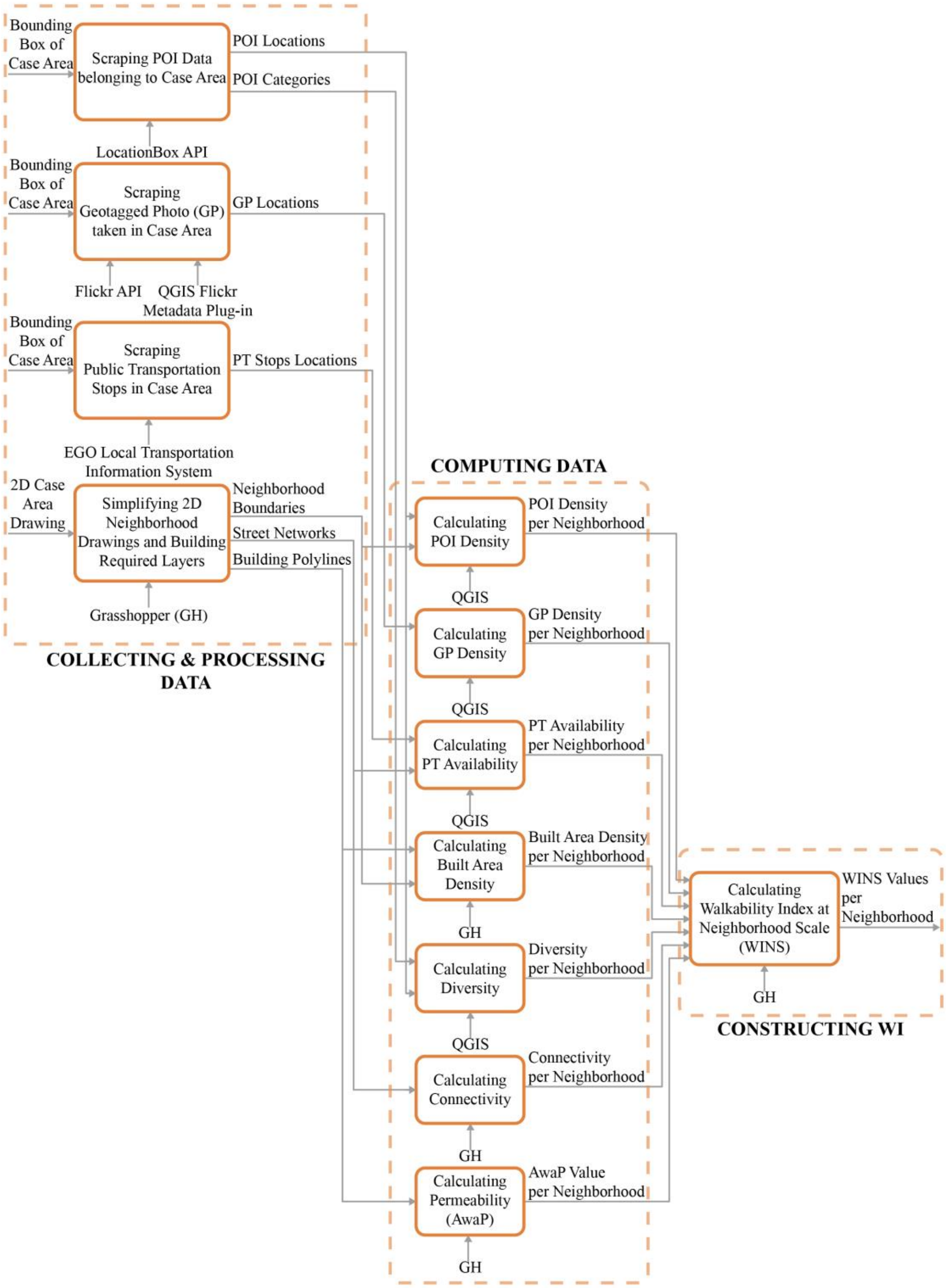

Figure 4-2. The workflow diagram displaying the stages of walkability evaluation at neighborhood scale

4.2.1 Selected Urban Features

In the first stage of the analysis, the urban features to be utilized in the assessment were determined. While selecting these features, three issues were taken into consideration. First of all, in the literature review, different built environmental aspects and their relations with walkability were investigated. The urban features were categorized as perceptual and physical aspects, and there are sub-categories for each aspect (Figure 3-2). Then, the network graph was presented to display the relations of the features with these categories (Figure 3-3). Therefore, the importance was given to select urban features from each category to evaluate the walkability comprehensively. Secondly, in the literature review, macro and micro-scale features were defined in detail. Hence, the urban features for the first stage of the analysis were chosen among the macro-scale features. Lastly, the availability of the data, which can be collected and computed by urban analytics methods, was a fundamental criteria while designating the urban features. In accordance with these criteria, six urban features, attractiveness, public transport availability, density, diversity, connectivity, and permeability, were selected to be included into the walkability index at neighborhood scale.

Attractiveness: In the examined literature, several studies have utilized attractiveness as an urban feature to evaluate walkability. Each of them has their definition and measurement method. To illustrate, Handy et al. (2006) defined attractiveness as a perception of the neighborhood’s appearance, high level of upkeep in the area, variety in housing styles, and presence of big street trees. Ozer and Kubat (2014) described it as being attractive or unattractive; decent or inferior; rich or plain; special or ordinary; nice or bizarre; modern or old-style; surprising or dull; clean or dirty. Berzi et al. (2017) explain attractiveness with one of the Jeff Speck’s criteria for the assessment of urban environments’ walkability level. It means having several distinctive areas of attraction for both the citizens and visitors (Speck, 2013). They associated attractiveness with the presence of point of interests (POIs) and events, the quality of architectural streetscape, and the vitality of urban space’s social context. POIs show locations where human activities take place and which attract people to visit somewhere like restaurants, shops, museums, universities, or parks (Gao, Janowicz, and Couclelis 2017). Berzi et al. (2017) state that they were preferred to use geo-referred social media data for walkability evaluation as it is directly based on user's experience of the urban space without a need of infrastructure for the sensors, surveys, or observations. In the research study, two urban metrics are decided to measure, which are POI's density and geotagged photos' (GPs') density. POI's density is taken into consideration to identify the areas with high number of activity and event; while, GPs' density is taken to point out the areas which are visually attractive for the citizens and visitors of the city.

Public Transportation (PT) Availability: The availability of public transportation is considered as significant feature for walkability by several studies in the literature. To illustrate, Craig et al. (2002) investigated the connectivity of the PT with other modes of transportation while Hoehner et al. (2005) the presence of PT. Both of the study collects the data regarding the PT availability with qualitative methods such as field observation and telephone interview. Carr, Dunsiger, and Marcus calculated the total number of bus stops within 1 mile for each residential address to measure the PT availability. They found significant correlations between the walkability and PT (2010). Van Dyck et al. (2009) examined the PT system with the calculation of PT stops in radius of 800 m from each origin point. In the research study, number of PT stops to the total length of street network is accepted as the urban metric for PT availability.

Density: Density is a variable of built environment affecting the travel, and one of the "three Ds" coined by Cervero and Kockelman (1997). Ewing and Cervero (2010) define it as the variable of interest per unit of area. In the existing studies, the area is taken gross or net, and the variable of interest is one of the following features: population, residential area, employment, building floor area, commercial area, household and so on. The variable of interest can be described according to the scope of the research and data availability. In this thesis study, built area density is taken as the urban metric for density, and the relation between the walkability level is accepted as positive with respect to the existing studies.

Diversity: Diversity is also one of "three Ds" mentioned by Cervero and Kockelman (1997). Ewing and Cervero (2010) explain it as a measure regarding the number of different land uses in a given area. It affects walkability positively as diversity tends to attract people to walk through the area. In the literature, it is possible to encounter with the different terms measuring the same thing such as usefulness, land-use mix, variety of destinations, functionality and amenity value. There is an index called as entropy, which utilized by the existing studies (Agampatian, 2014; Barros et al., 2017; Dygryn et al., 2010; Ewing et al., 2010; Frank et al., 2009; Hajna et al., 2013; Leslie et al., 2007; Troped et al., 2008). The entropy index displays the land-use diversity of a given area. If the value of entropy index is close to zero, a positive walkability result is expected; whereas, if it is close to one, walkability will be influenced negatively. In this thesis study, entropy index is utilized for the walkability assessment.

Connectivity: Connectivity is defined as the measure that appraising the degree to how much roads, sideways, pedestrian walkways and trails are connected (Marshall, 2005). A high connectivity means a well-connected network offering shorter and many alternative routes, which in turn increase the walkability level. Agampatian (2014) and Leslie et al. (2007) measured the connectivity by the number of intersections per a unit area. In the study, a ratio between the total number of intersections in the street network and its total length is considered as the urban metric of connectivity.

Permeability: Permeability can be defined as the degree to which a particular urban morphology is accessible by public space (Marshall, 2005, pp. 88–89). It provides the ease of movement through an urban space as well as alternative routes between any two points. Pafka and Dovey (2017) proposed an urban metric, the area-weighted average perimeter (AwaP), as a measure of permeability. It conceives the perimeters and areas of all buildings within a given study area. While low AwaP level states high permeability, high level shows low permeability within the study area. The permeability influences the walkability positively as it allows the movement. It can be stated that the AwaP and walkability are inversely related (Pafka & Dovey, 2017).

4.2.2 Data Collection

In the first stage of the analysis, six urban features, attractiveness, PT availability, density, diversity, connectivity and permeability, were taken into consideration to evaluate walkability at neighborhood scale. In accordance with their definitions and urban metrics, required data types are determined. The required data, their sources and collection methods for each urban metric are shown in Table 4-1. They all can be described as quantitative and secondary data. Big data approach was taken for the data collection due to the complexity and huge amount of data as part of computational urban analytics methods.

Table 4-1. Data types, sources and collection methods utilized in the first stage of the analysis

Urban Feature	Urban Metric	Data	Data Source	Data Collection Method
attractiveness	POIs' density	number of POIs per neighborhood	LocationBox API	web-scraping
		2D drawings of neighborhood boundaries	Çankaya Municipality	obtaining from local authority
	GPs' density	locations of geotagged photos	Flickr API	web-scraping
		2D drawings of neighborhood boundaries	Çankaya Municipality	obtaining from local authority
PT availability	PT density	number of PT stops per neighborhood	EGO Local Transportation Information System	obtaining from local authority information system
		total length of the streets per neighborhood	Çankaya Municipality	obtaining from local authority

Table 4-2 (continued)

density	built area density	2D drawings of buildings	Çankaya Municipality	obtaining from local authority
		2D drawings of neighborhood boundaries		
diversity	entropy index	number of POIs per neighborhood	LocationBox API	web-scraping
		POIs categories		
connectivity	intersection density	2D drawings of street network	Çankaya Municipality	obtaining from local authority
permeability	AwaP	2D drawings of buildings	Çankaya Municipality	obtaining from local authority

For attractiveness, two urban metrics, POIs' and GPs' density, were utilized. POI data was gathered through LocationBox API services. LocationBox is a company that provides a set of tools for developers to create location-based applications. LocationBox API was used instead of Google API for the POI data due to Google's restrictions on requests. The locations of the POI data were obtained from the API with POI search requests. The responses consisted of outputs like user key, response format, latitude and longitude of the center point, the radius of the area bounding the search results, and category of POI. Many requests were sent for the Çankaya area based on 1499 different categories. The responses were gathered in XML format with parameters like id, name, address, phone number, latitude and longitude of the POIs. The metadata, including 40270 POIs, was classified according to their neighborhoods regardless of the categories to which they belong.

Figure 4-3. An example from Flickr metadata set

For GP data, Flickr API was selected since it is a social media platform where people upload photos mostly showing the attractive urban areas or events (Berzi et al., 2017). It has also higher accessibility than other user-generated content (UGC) platforms, and provides reliable geo-references with its GPS coordinate data. This spatial temporal data is provided thanks to modern camera devices storing location information in EXIF tags which include the longitude and latitude of the photo, the time it was taken and the time it was uploaded. The GP data were gathered from Flickr API by using QGIS Flickr Metadata plug-in developed by Mátyás Gede. The input parameters for the operation were Flickr API key and bounding box for the area. The result of the operation consisted of 31842 geotagged photos for Çankaya area. The output parameters included photo id, latitude and longitude, date, accuracy, title, tags and url. The time period of the photos varies between the 1950-2020.

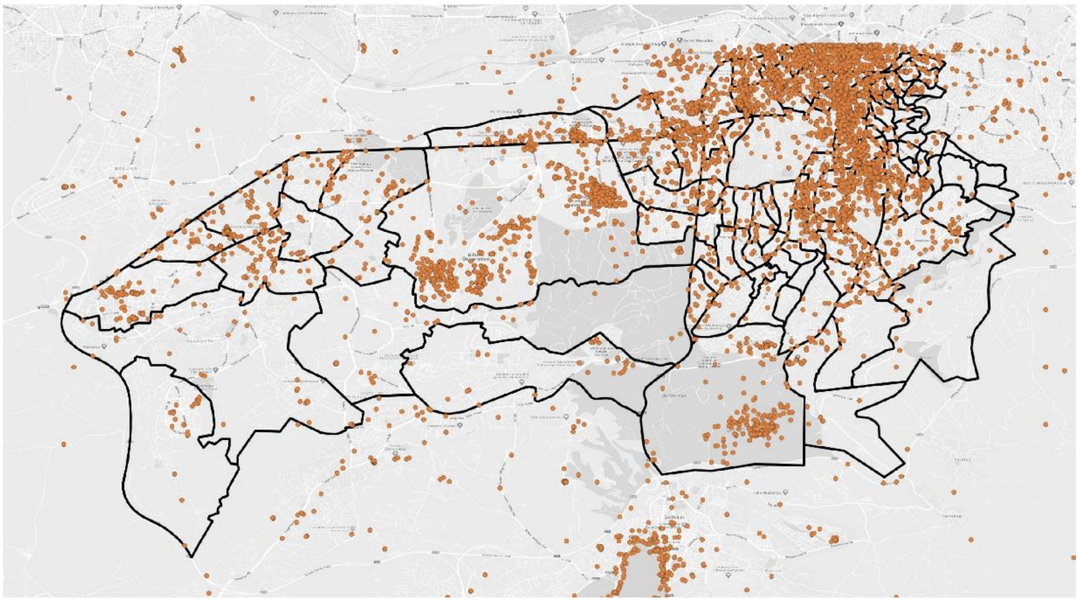

Figure 4-4. The map of the geotagged Flickr photos taken between 1950-2020 in Çankaya, visualized in QGIS

For PT availability, location of PT stops were gathered from EGO Local Transportation Information System. The total number of PT stops locating in the case area is 1504, and they were classified based on their neighborhood in XLSX format. The total length of the streets per neighborhood was calculated from the 2D drawings of the street network, gathered from Çankaya Municipality.

For diversity, POI data was preferred to calculate the entropy index. As mentioned previously, the POI data has 1499 different categories. To decrease the number of categories, they were grouped under the following 24 categories: accommodation, commercial, commercial service, culture, depot, education, entertainment, food, food service, governmental, health, industrial, local government, military, office, political, public service, recreational, religious, research, residence, sport, transportation, and union. As a result, 40270 POIs were sorted according to their category and neighborhood in XLSX format.

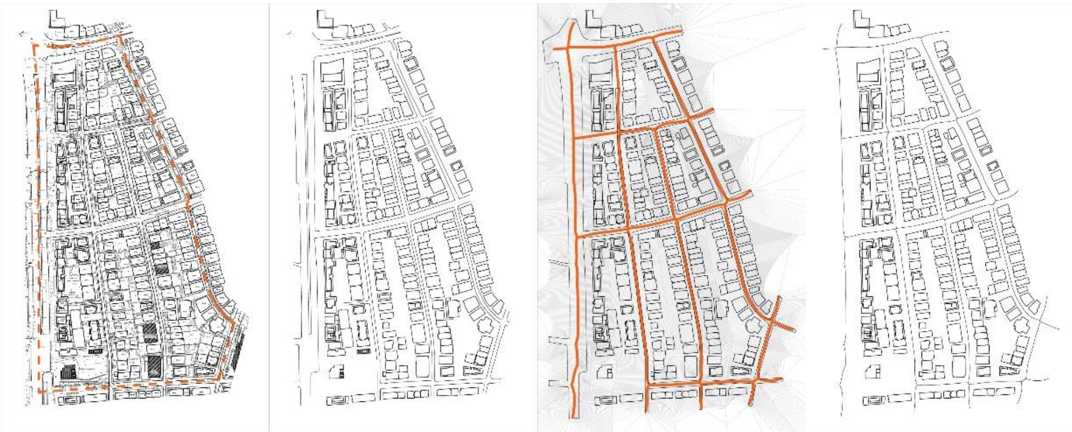

Figure 4-5. The maps showing the operations applied to the base map of Meşrutiyet neighborhood

For density, connectivity, and permeability, the base maps of the neighborhoods were obtained from Çankaya Municipality. The drawings cover 534 x 694 m² area, and are in .ncz format. Thus, they were converted to .dxf files, and combined based on the neighborhoods boundaries. The number of layers were reduced to decrease the file sizes. Only layers including buildings and streets were remained. Then, the centerlines of the streets were produced by *voronoi* component in GH (Figure 4-5). For density and permeability polylines of the buildings were utilized whereas the centerlines of the streets were used for connectivity.

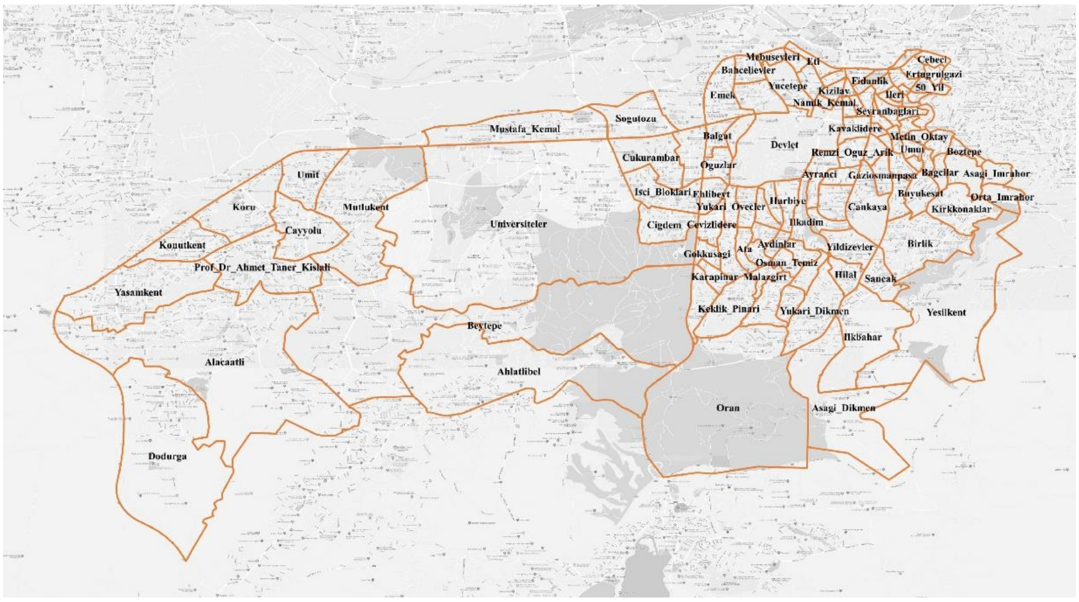

Figure 4-6. The boundaries of the 115 neighborhoods in Çankaya, visualized in QGIS

For POIs' density, GPs' density and built area density, the total area of each neighborhood was calculated based on their boundaries as shown in Figure 4-6. The calculations and geometrical operations for urban features will be explained in the next section.

4.2.3 Computation Process

The computational methods will be explained for each urban feature in this section. The methods comprise of basic mathematical operations in Excel, geometrical functions in QGIS, and geometrical operations in GH. The equations formulated for the computational process are briefed in Table 4-2.

First of all, the areas of the polygons showing the boundaries of the neighborhoods were calculated by *area* function in QGIS. POIs' density for each neighborhood was calculated by dividing the total number of POIs per neighborhood to the neighborhood area. The number of GPs belonging to each neighborhood was found by *contains* function in QGIS. Then, GPs' density per neighborhood was calculated by dividing the total number of GPs per neighborhood to the neighborhood area.

Secondly, the PT availability was figured out by the proportion between the total number of PT stops and the total length of the street network per neighborhood. For the third urban feature, density, the built area density was calculated by dividing the total floor area of the buildings in the neighborhood to the neighborhood area. The area of the buildings and neighborhood were listed by *area* component in GH. After, the entropy index for diversity was calculated in Excel based on the equation in Table 4-2. For the connectivity, the number of intersections on the centerlines of the street network was found by *multiple curves intersection* component in GH. Then, the number of intersections per neighborhood was divided to the total length of the neighborhood street network, which is calculated by *length* component in GH. Lastly, for permeability, the total length of the buildings' perimeters and the area of them were calculated. The value for each neighborhood was found by operating the equation in Table 4-2.

Table 4-3. Equations for the first stage of the analysis

Urban Feature	Urban Metric	Equation
attractiveness	POIs' density	$\frac{\#\text{POIs}}{\text{neighborhood area}}$
	GPs' density	$\frac{\#\text{geotagged photos}}{\text{neighborhood area}}$
PT availability	PT density	$\frac{\#\text{PT stops}}{\text{total length of street network}}$
density	built area density	$\frac{\text{total floor area of the buildings}}{\text{neighborhood area}}$
diversity	entropy index	$-\sum_{i=1}^{n}\left(\left(\frac{Pij}{Pj}\right)\ln\left(\frac{Pij}{Pj}\right)\right)/\ln n$ n: number of land-use categories Pij: number of land-use units (from i category) in zone j Pj: sum of land-use units (from all categories) in zone j 0 = maximum specialization 1= maximum diversification (Agampatian, 2014)
connectivity	intersection density	$\frac{\#\text{intersections in street network}}{\text{total length of street network}}$

Table 4-4 (continued)

permeability	AwaP	$$\sum_{i=1}^{n} Pi\ x\ \frac{Ai}{At}$$ n: total number of blocks Pi: the perimeter of the block i Ai: the area of the block i At: the total area of blocks (Pafka & Dovey, 2017)

The values resulted from each computation were brought together in an excel file. They were standardized, and z-scores were calculated for each urban feature since the units of the values were different from each other. A walkability index was created according to the relations between the urban features and walkability.

$$\begin{aligned} WINS = z(POIs\ density) + z(GPs\ density) + z(PT\ density) \\ + z(built\ area\ density) + z(entropy\ index) \\ + z(intersection\ density) - z(AwaP) \end{aligned}$$

Equation 4-1. Walkability Index (where z stands for z-score normalization) for the analysis at neighborhood scale

With respect to this index, walkability levels of each neighborhood were estimated. Then, these values were transferred to QGIS to classify the neighborhoods and visualize the results on the maps. The neighborhoods were classified in three category (high-medium-low) based on the natural breaks classification method in QGIS. The results of the walkability evaluation at neighborhood scale will be explained in Chapter 5.

4.3 Walkability Evaluation at Street Scale

This section elaborates on the second stage of the analysis, which was applied to the 9 neighborhoods in Çankaya. The nine neighborhoods were selected according to the results of the first stage. The neighborhoods were listed based on their walkability levels in three categories (high-medium-low). The three neighborhoods were selected from each category. Among the most walkable neighborhoods, Meşrutiyet, Kızılay, and Mebusevleri were chosen. From the medium level walkable category, Yücetepe, Ön Cebeci, and Maltepe were taken. Among the least walkable neighborhoods, Çankaya, 50. Yıl and İleri were selected. The workflow of this stage was briefed as follows:

1. Selecting and defining the urban features
2. Specifying the regarding urban metrics for each urban feature
3. Describing required data for each urban metric
4. Reviewing the data sources for the required data
5. Collecting the data from the selected sources
6. Processing the data to create 3D digital models of the neighborhoods
7. Creating 3D digital models of the neighborhoods
8. Computing on 3D digital models and images for each urban feature
9. Defining the walkability index at street scale
10. Sorting the streets and neighborhoods according to their walkability level at street scale

Each operation shown in Figure 4-7 will be explained in detail in the following three sections.

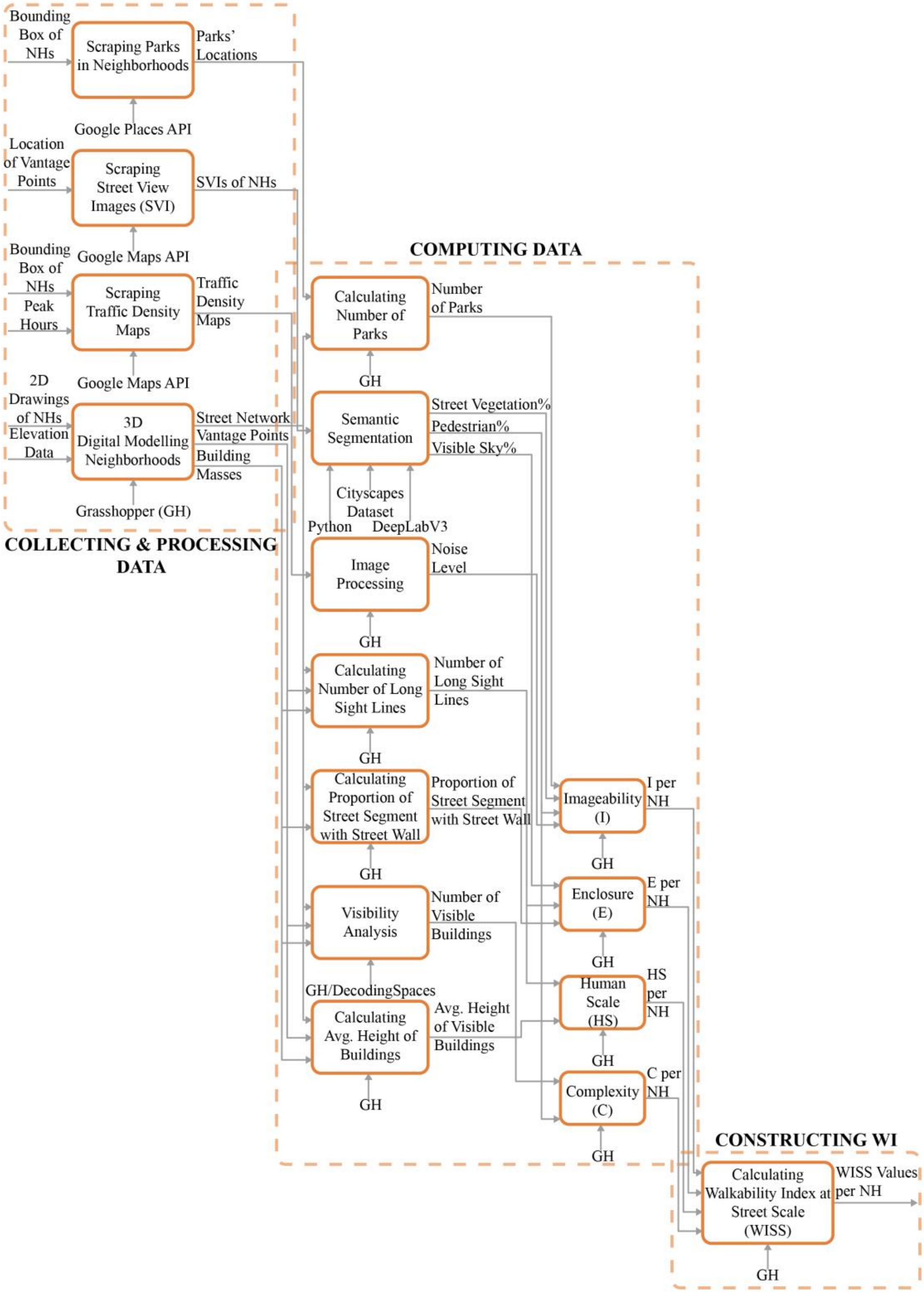

Figure 4-7. The workflow diagram displaying the stages of walkability evaluation at street scale

4.3.1 Selected Urban Features

Like the first stage of the analysis, the urban features utilized in the assessment were reviewed and decided for the second stage. While selecting these features, existing studies in the literature were reviewed. The importance was given to choose micro-scale features evaluating the perception of the streets by pedestrians. In that sense, it can be stated that Ewing and Clemente's book "*Measuring Urban Design Metrics for Livable Places"* is an extensive and fundamental source. They listed classic works in urban design addressing perceptual qualities, and then defined fifty-one perceptual qualities of the built environment. Yet, of these fifty-one qualities, eight were selected for their study based on their importance in the literature: imageability, enclosure, human scale, transparency, complexity, coherence, legibility, and linkage. Of the eight, the first five were successfully measured in a manner that passed tests of validity and reliability (Ewing & Clemente, 2013). These five features were also utilized in other walkability studies (e.g., Ewing, Hajrasouliha, Neckerman, Purciel-Hill, & Greene, 2016; Tekel & Özalp, 2016; Yin & Wang, 2016; Yin, 2017; Zhu, Hua, & Dogan, 2019). As in the first stage, the availability of the data and their potential to be collected and computed by urban analytics methods are also significant while determining the urban features. Therefore, four urban features, imageability, enclosure, humans scale, and complexity, were selected to be included into walkability index at street scale.

Imageability: Imageability is the feature of a place that makes it identical, noticeable, and memorable. The urban spaces having high imageability can capture attention and evoke the feelings of the pedestrians. The qualities that make a street imageable are not only one element by itself rather the combination of many (Ewing & Clemente, 2013). Hence, all elements in a streetscape, such as buildings, open spaces, landscape features, and people's presence, and their togetherness, are significant for imageability. Landmarks are also considered as a component of imageability. It is stated that the term landmark does not have to denote a spectacular public structure or object (Lynch, 1960). Ewing and Clemente elaborated on the number of courtyards, plazas, and parks, significant landscape features, the proposition of historic buildings, shapes of the buildings, presence of outdoor dining, number of people, and noise level of a street to measure the imageability in their study (2013). In this research study, the urban metrics were defined concerning the data availability and their potentials to be evaluated computationally. The selected urban metrics are the number of parks, the percentage of street vegetation, pedestrians, and noise level.

Enclosure: Enclosure means the level at which streets and other open public spaces are visually defined by the vertical built environment elements like buildings, walls, trees, etc. When the height of vertical elements is proportionally related to the open spaces' width, the urban area's quality gives the sense of a room. The vertical objects, interrupting pedestrians' lines of sight, define and shape the open spaces (Ewing & Clemente, 2013). According to Cullen (1961, p.29), the enclosure is significant to instill a sense of position, and it embodies the idea of hereness. Jacobs and Appleyeard (1987, p. 118) state that the buildings are required to define or enclose space rather than stay in the area. Ewing and Clemente (2013) associate the urban setting with a building. They liken buildings to the outdoor room walls, the street and sidewalks to the floor, and the sky to an invisible ceiling. When the density is low, buildings become less critical in enclosing the space, and street trees prioritize. The layout of the street network can also affect the sense of enclosure. To illustrate, a rectangular grid with continuous streets leads to long sight lines that may decrease the enclosure sense (Ewing & Clemente, 2013). They stated that the enclosure had been taken into consideration both qualitatively and quantitatively in many urban design guidelines and several land development codes. Thus, they evaluated the number of long sight lines, the proportion of street segment with the street wall, and the proportion of visible sky to measure the enclosure in their study (2013). In this research study, the urban metrics were chosen concerning data availability and their potentials to be evaluated computationally. The selected urban metrics are the proportion of visible proportion sky, the number of long sight lines, and the proportion of street segment with the street wall.

Human Scale: Human scale refers to a combination of built environment elements matching humans' size and proportions. These elements can consist of buildings' details, pavement texture, street trees, and street furniture. In contrast to tall buildings, wide streets, large spaces, moderate-sized buildings, narrow streets, and small spaces can create a human-scaled environment (Ewing and Clemente, 2013). In that sense, Alexander et al. (1977) mention that buildings having more than four stories are out of human scale, Lennard and Lennard (1987) set the threshold at six levels while Blumenfeld (1953) places it at three stories. Besides the buildings, street trees can also affect the scale of the streetscapes. Arnold states (1993) that a canopy of leaves and branches provides a simultaneous sense of the smaller space where tall buildings or wide streets exist. Additionally, any small-scale elements, depth of setbacks on tall buildings, presence of car parking, the ornamentation of buildings, and spacing of windows and doors can provide a human-scaled environment (Ewing and Clemente, 2013). Thus, they measured the number of long sight lines, the proportion of street segment with windows, average height of the buildings, number of small planters, and number of street furniture to estimate the human scale level in their research (2013). In this thesis, the urban metrics were selected based on the data availability and their potentials to be measured computationally. The selected urban metrics are the average height of the visible buildings, and the number of long sight lines.

Complexity: Complexity displays the visual richness of urban space. The complexity of a place is related to the diversity of the built environment, precisely, the numbers and kinds of buildings, architectural variety and ornamentation, landscape elements, street furniture, signage, and human activity (Ewing and Clemente, 2013). According to Rapoport (1990), complexity refers to the number of recognizable changes to which a viewer is subjected per unit time. Therefore, a higher level of complexity is required to hold pedestrians' interest rather than drivers. Moreover, Gehl (1987, p.143) mentions that streets high in complexity provide exciting things to look at and have a psychological influence on people to perceive the walking distance as shorter. Gehl (1987, p.25) also states that people are attracted to other people, and they tend to place themselves near others. Hence, it can be stated that presence of people is also significant for the complexity. In accordance with these explanations, Ewing and Clemente counted the number of buildings, number of basic building colors, accent building colors, outdoor dining, pieces of public art, and people to assess the complexity in their study (2013). In this research study, the urban metrics were determined concerning the data availability and their potentials to be evaluated computationally. The considered urban metrics are the number of visible buildings and the percentage of pedestrians.

4.3.2 Data Collection

In the second stage of the analysis, four urban features, imageability, enclosure, human scale, and complexity, were considered to evaluate walkability at street scale. In accordance with their definitions and urban metrics, required data types are determined. The required data, their sources and collection methods for each urban metric are shown in Table 4-3. Like the first stage, they all can be described as quantitative and secondary data.

Table 4-5. Data types, sources and collection methods utilized in the second stage of the analysis

Urban Feature	Urban Metric	Data	Data Source	Data Collection Method
imageability	number of parks	location of parks	Google Places API	web-scraping
		street network	Open Street Map (OSM)	downloading through the application
	percentage of street vegetation	street view images	Google Maps API	web-scraping
	percentage of pedestrians			
	noise level	traffic density maps	Google Maps API	web-scraping

Table 4-6 (continued)

enclosure	proportion of visible sky	street view images	Google Maps API	web-scraping
	number of long sight lines	2D drawings of the area (including elevation information)	Çankaya Municipality	obtaining from local authority
	proportion of street segment with street wall			
human scale	average heights of the visible buildings	2D drawings of the area (including elevation information)	Çankaya Municipality	obtaining from local authority
	number of long sight lines			
complexity	number of visible buildings	2D drawings of the area (including elevation information)	Çankaya Municipality	obtaining from local authority
	percentage of pedestrians	street view images	Google Maps API	web-scraping

As can be seen in Table 4-3, for the second stage of the analysis, four data sources, Google Places API, OSM, Google Maps API, and Çankaya Municipality, were utilized. The locations of parks in and around the neighborhoods were scrapped from the Google Places API. In order to generate the trips, the maps of each neighborhood were downloaded from OSM by using GH Urbano Plug-in, which is developed by Dogan, Samaranayake, Saraf, and Yang in 2019. Then, the locations of the parks were transferred to the RH file as points. These points were defined as amenities with *create amenity* component in GH.

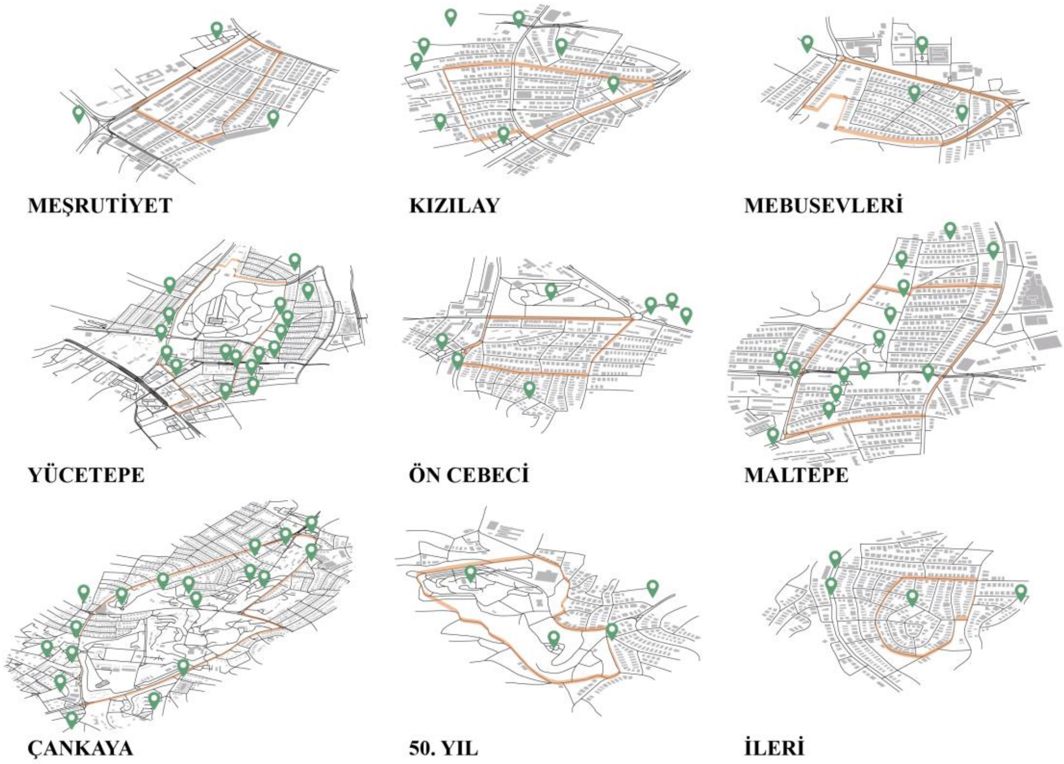

Figure 4-8. Neighborhoods' maps showing the location of parks

Google Maps API provides several features for developers, and one of them is Street View Imagery. It represents an alternative source of data on the built environment, and is utilized in several kinds of research. To illustrate, Anguelov et al. (2010) used street view to create 3D models, Yin et al. (2015) used it to estimate the pedestrian volume, Rundle, Bader, Richards, Neckerman and Teitler (2011) used it audit neighborhood environments, and Yin et al. (2016) used it to measure visual enclosure for street walkability. Therefore, in this thesis, a street view image for each street in the neighborhoods was taken to estimate the percentage of vegetation, pedestrian, and sky visibility. Another feature enabled by Google Maps API is Traffic Layer displaying the real-time traffic information on the map. Besides the real-time data, it also provides average data based on the selected day and time. To evaluate the noise level caused by traffic density, maps with a traffic layer for each neighborhood were downloaded. The maps were taken based on the peak hours to increase the accuracy of the data. Three weekdays (Monday-Wednesday-Friday) and Saturday were selected. The maps showing the average traffic data were gathered for the time 8 am-6 pm hours for the weekdays while for 2 pm for the weekend.

Figure 4-9. The maps of Meşrutiyet neighborhood showing the traffic layer

The urban metrics, like the number of long sight lines, the proportion of street segment with the street wall, the average height of the visible buildings, and the number of visible buildings, were estimated by geometrical operations. Therefore, 3D digital models of the neighborhoods, including the altitude information of the buildings' top levels and topography, were required. For 3D digital modeling, 2D drawings obtained from Çankaya Municipality were processed. In the previous stage, the drawings of the building and street network were organized. However, all elevation information in 2D drawings were composed of separated text objects, and there were not any data about which text object belongs to which point or polyline. To be able to model the topography and extrude building polyline based on their heights, some operations were progressed in GH. First of all, the text objects were deconstructed to their characters. Then, these characters were matched based on the list length of the character groups. These two character groups (e.g. 890 and 98) were combined by placing a comma between them (e.g., 890.98). These connected text objects were converted to the number in GH. The points of the deconstructed text objects were utilized as topography points, and the surface was created by patch component in GH. For building heights, the combined text objects were matched with buildings' polylines based on the distance between the center point of the polyline and deconstructed text objects' points. Then, each polyline was extruded according to the number on it. Lastly, street networks were projected on the topography in GH.

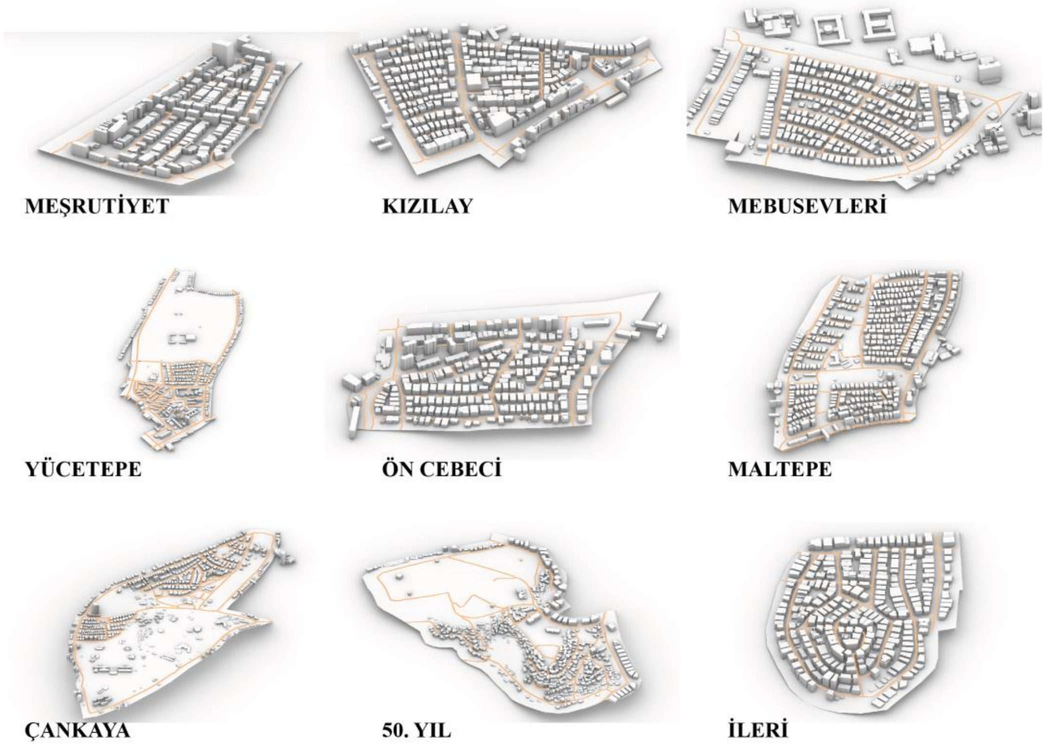

Figure 4-10. The digital models of the neighborhoods

As a result, the digital models of each neighborhood consist of 3D street networks, topography surfaces, and building masses. How the computational operations were run on these models and how street view images were utilized to measure the urban metrics will be explained in the next section.

4.3.3 Computation Process

The computational methods followed in the second stage of the analysis will be explained for each urban feature in this section. They consist of trip generation, semantic segmentation, image processing, visibility analysis, and geometrical operations in GH. The methods and equations for the computational process are shown in Table 4-4.

The parks are places providing high-level imageability to the urban areas. Therefore, the number of these open spaces was calculated for each street. The locations of the parks were marked on the 3D digital models. Then, the number of parks visible from each street was counted through the digital models, and the average value for each neighborhood was computed.

Table 4-7. Methods and equations for the second stage of the analysis

Urban Feature	Urban Metric	Method	Equation
imageability	number of parks	geometrical operations	-
	percentage of street vegetation	semantic segmentation	-
	percentage of pedestrians	semantic segmentation	-
	noise level	image processing	$\frac{\text{\#black pixels in the image}}{\text{\#all pixels in the image}}$
enclosure	proportion of visible sky	semantic segmentation	-
	number of long sight lines	geometrical operations	-
	proportion of street segment with street wall	geometrical operations	$\frac{\sum_{b=1}^{n} FLb}{SL}$ n: number of buildings FL_b: façade length of the building b SL: street length
human scale	average heights of the visible buildings	visibility analysis, geometrical operations	-
	number of long sight lines	geometrical operations	-
complexity	number of visible buildings	visibility analysis	-
	percentage of pedestrians	semantic segmentation	-

Semantic segmentation is a deep learning method detecting objects in an image while simultaneously creating a high-quality segmentation mask for each sample (He, Gkioxari, Dollar & Girschick, 2017). They developed a method called Mask R-CNN, consisting of two stages: Faster R-CNN and FCN. In the first stage, the predictions about the regions where an object on the input image are generated. The second stage predicts the object's class, refines the bounding box, and creates a pixel-level mask of the object based on the first stage estimation (He, Gkioxari, Dollar & Girschick, 2017). For this thesis study, the workshop Artificial Intelligence for Resilient Urban

Planning organized by City Intelligence Lab (CIL), Austrian Institute of Technology, was followed. Their prepared Google Colab setup, including code in Python programming language, was utilized and organized for this thesis case. As a pre-trained model, DeepLabV3 was gathered, and the CityScapes dataset was used. In the CityScapes data set, there are eight groups for objects in the images: flat, human, vehicle, construction, object, nature, sky, and void (The Cityscapes Dataset, n.d). The classes belonging to each group can be shown in Table 4-5.

Table 4-8. Groups and classes in Cityscapes dataset (The Cityscapes Dataset, n.d)

Group	**Classes**
flat	road, sidewalk, parking, rail track
human	person, rider
vehicle	car, truck, bus, on rails, motorcycle, bicycle, caravan, trailer
construction	building, wall, fence, guard rail, bridge, tunnel
object	pole, pole group, traffic sign, traffic light
nature	vegetation, terrain
sky	sky
void	ground, dynamic, static

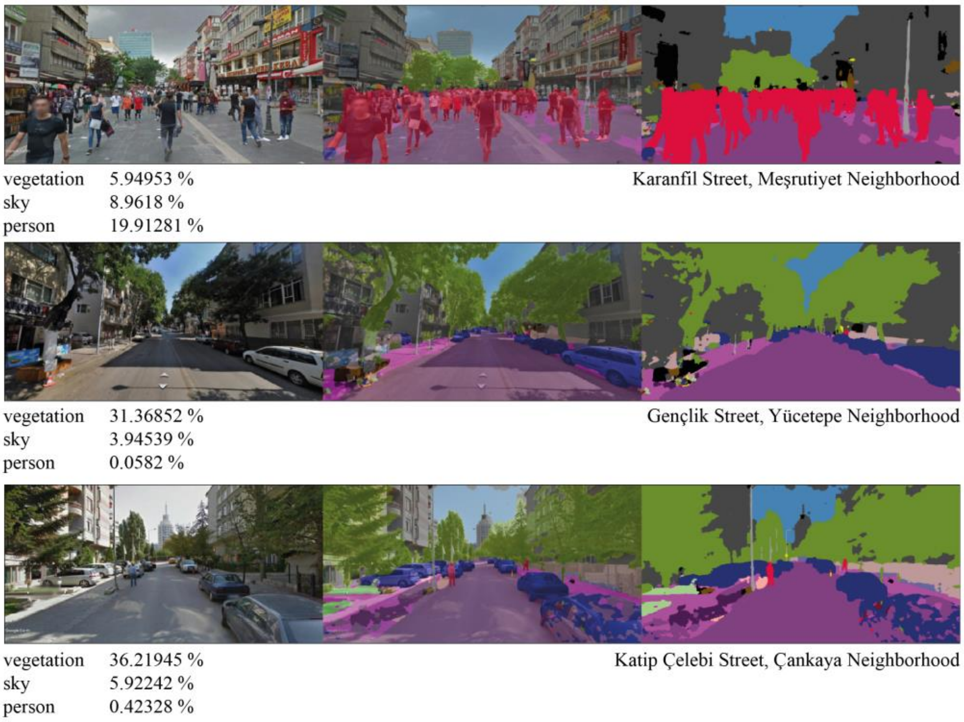

Figure 4-11. The sample input and output images of three streets from semantic segmentation process

The Mask R-CNN model was applied to the 141 street view images taken from the nine neighborhoods' streets. The output data comprised of the percentages of each class in the sample images. The urban metrics, the percentage of pedestrians, street vegetation, and visible sky, were measured with this method. The sample images, including input and output images, for three neighborhoods can be seen in Figure 4-11. The urban metric values for each neighborhood were calculated using the average percentages of the neighborhoods' streets.

To evaluate the noise level on the streets, traffic congestion was tried to be measured. As explained previously, the maps, including the traffic data layer, were obtained for different periods from Google Maps API. In the original maps, lines from red to green color display the traffic density from high to low level. Thus, these maps were converted to gray-scale color based on red color density using Adobe Photoshop. Afterward, the points based on the size of the images were generated by *rectangular grid* component in GH. The images were processed based on these points by using *image sampler* component in GH. The output of this component gave the RGB codes of each point. The pixels having 0, 0, 0 RGB code (black) were selected from the list. Lastly, the total number of the black points was divided by the total number of points for each map, and the average value was calculated for each neighborhood.

To calculate the number of long sight lines, the proportion of street segment with the street wall, average heights of the visible buildings, and the number of visible buildings, 3D digital models were utilized. As previously mentioned, the digital models were created in RH and GH environment by using 2D drawings obtained from Çankaya Municipality.

First of all, visibility analysis was conducted to calculate the number of visible buildings on each street. The analysis was performed with the DeCodingSpaces Toolbox plug-in for GH, a collection of analytical and generative components for algorithmic architectural and urban planning. It was developed by Computational Planning Group (CPlan), Abdulmawla, Bielik, Dennemark, Fuchkina, Miao, Knecht, König, Aichinger, Schneider, Veselý, and Buš from six partner institutions

(DeCodingSpaces, n.d). They developed *3D isovist* component by constructing 2d isovist to the third dimension. Benedikt defines an isovist as the set of all points visible from a vantage point in space and the built environment (Benedikt, 1979). The vantage points were constructed for the visibility analysis by dividing the street centerlines into 100 m intervals and moving up 1.67 meters to represent the human eye-level viewpoint (Yin, 2017). Then, the buildings were converted to mesh objects and defined as obstacles meshes. View direction vectors were generated towards the streets between the vantage points. The visibility analysis was conducted with *isovist 3d* component in GH. One of the output parameters is object visibility, which returns a list of hit numbers for each mesh. Then, these meshes were dispatched based on their visibility. For each street, the number of visible buildings was calculated by summing the number of visible buildings from each vantage point. For the neighborhood value, the average number of visible buildings from all the streets was calculated.

Figure 4-12. The vantage points and view direction vectors in Meşrutiyet neighborhood

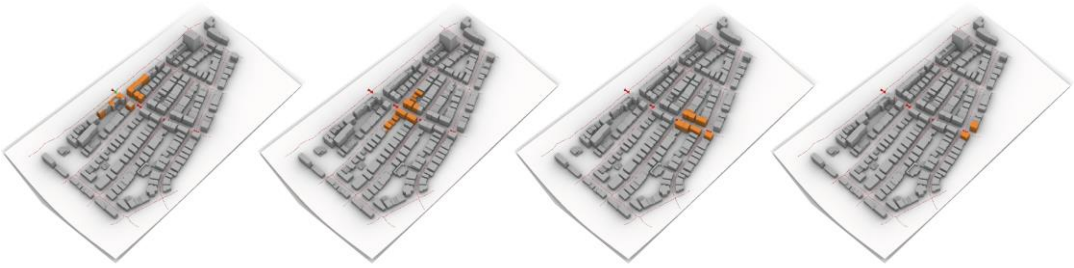

Figure 4-13. The visible buildings walking towards Meşrutiyet Street

For the human-scale feature, the average buildings' heights of these visible buildings were considered since the pedestrians are influenced by the heights of the buildings in their vision while walking. In order to calculate the building heights, the breps of the visible buildings were deconstructed, and the center points of the top surfaces were taken. Then, the lines were generated from these points to the topography below. The intersection points were found between the lines and topography by *surface curve intersection* component. Lastly, these two sets of points were deconstructed, and the buildings' heights were found by subtracting their z values. The average buildings' heights were calculated for each street, and then for each neighborhood.

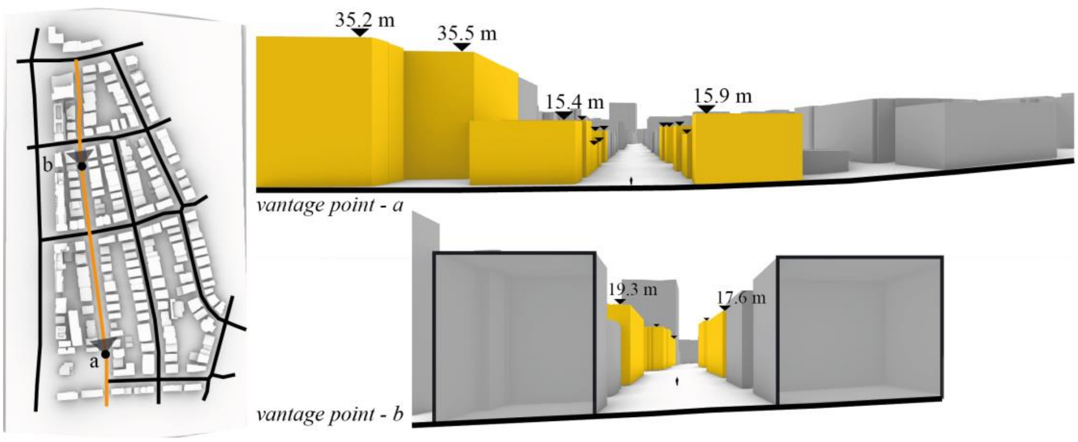

Figure 4-14. The diagram showing the heights of the visible buildings from vantage point a and b on Karanfil Street

As previously mentioned, Ewing and Clemente measured the number of long sight lines to evaluate the enclosure and human-scale qualities of the streets. They estimated it during the field observation with video recording (2013). The number of long sight lines is another visibility related urban metric that can be measured through the 3D digital models (Yin, 2017). According to Purciel and Marrone (2006), the long sight lines exist in three directions, front, left, and right. The lines can have a maximum of 305 meters length as one can see at least 1000 ft. (about 305 meters) into the distance at any point on a street while walking down. In this thesis study, observation points were placed on the 200 m intervals of the streets with a height attribute of 1.67 meters again. As the horizontal range of the human vision is 210 degrees, 210° arcs were generated, and the origin points of the arcs were defined as the observation points. Then, they were divided in three directions, front, left, and right, by 70°. Afterwards, five points were taken on each 70° arcs, and the lines with 305 meters length were created between the observation points and them. These lines and buildings' breps were intersected with *brep curve intersection* component. The lines that were not crossed with any breps were selected. The number of directions including any long sight lines refers the number of long sight lines on the street. Hence, the streets can take either the value of 0, 1, 2 or 3 as the number of long sight lines. For the neighborhoods, their average value was calculated.

Figure 4-15. The long sight line analysis in Meşrutiyet neighborhood

The proportion of street segment with the street wall is another urban metric affecting the enclosure of the space. As previously mentioned, buildings' facades can be considered as the walls of outdoor spaces if the buildings' heights are over 5 ft. (1.52 meters) and their set back is no more than 10 ft. (3.04 meters) from the sidewalk path edge (Ewing & Clemente, 2013). Thus, their proportion to the length of the street is significant while measuring the enclosure. In this thesis study, it was estimated based on the 3D digital models of the neighborhoods. As there is no data regarding the sidewalk boundaries, the street centerlines were moved through the buildings 20 meters to intersect the buildings and lines. Then, the curves were generated from the intersection of the buildings and moved reference lines. The total length of these curves was divided by the total length of the street. These operations were conducted twice for both sides of the street. The proportion of street segment with the street wall was calculated for the neighborhoods by taking the average of each street in the neighborhoods.

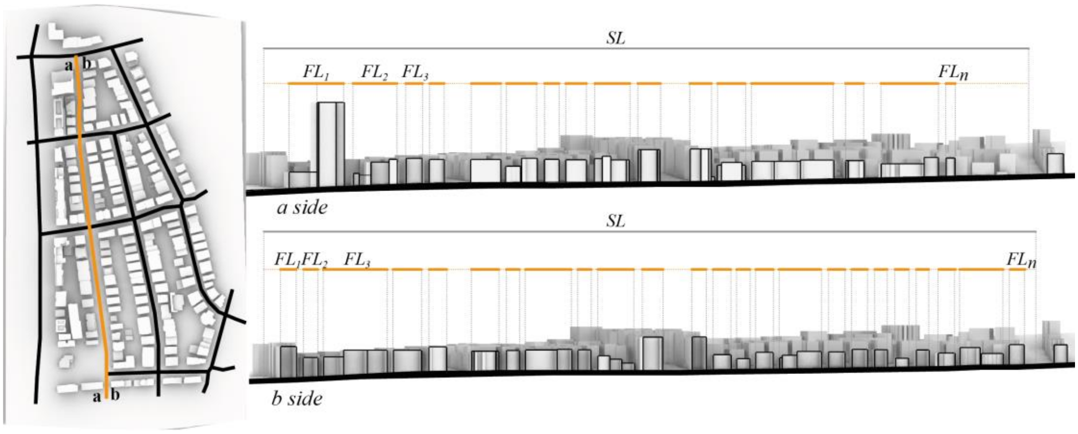

Figure 4-16. The diagram showing the proportion of street segment with street wall in Karanfil Street

$$The\ proportion\ of\ street\ segment\ with\ streeet\ wall = \frac{\sum_{b=1}^{n} \mathrm{FLb}}{\mathrm{SL}}$$

n: number of buildings

FL_b: façade length of the building b

SL: street length

Equation 4-2. The equation for the proportion of the street segment with the street wall

As each urban metric's units are different from each other, the values were transformed to z-score value in Excel. The z-scores were summed up for each urban feature based on the index shown in Table 4-6.

Table 4-9. The urban features' indexes

Urban Feature	Index
imageability	$= z(number\ of\ parks) + z(street\ vegetation\%) + z(pedestrian\%) \quad - z(noise\ level)$
enclosure	$= -z(proportion\ of\ visible\ sky) - z(\#long\ sight\ lines) + z(proportion\ of\ street\ segment\ with\ street\ wall)$
human scale	$= -\ z(average\ height\ of\ visible\ buildings) - z(\#long\ sight\ lines)$
complexity	$= z(\#visible\ buildings) + z(pedestrian\%)$

$$WISS = z(Imageability) + z(enclosure) + z(human\ scale) + z(complexity)$$

Equation 4-3. Walkability Index (where z stands for z-score normalization) for the analysis at street scale

The walkability levels of each street in each neighborhood were estimated based on these indexes. The average of the streets' walkability levels was calculated for each neighborhood so that a comparison can be made between different neighborhoods. The results of the walkability evaluation at the street scale will be explained in Chapter 5.

4.4 Walkability Evaluation for Elderly People

As previously mentioned, there are walkability studies focusing on a specific target groups in the literature. Evaluating the walkability level of an urban area for older adults has also been studied as they are getting to travel more on their foot for longer distances and for various reasons (Sundling, 2015; Tacken, 1998). Therefore, more policies and decisions should be taken into account to respond their needs. Moreover, the built environment is required to be evaluated based on these necessities. The third stage of the analysis proposes a walkability index to evaluate the walkability for older adults. The analysis was conducted on the same neighborhoods with the previous stage: Meşrutiyet, Kızılay, Mebusevleri, Yücetepe, Ön Cebeci, Maltepe, Çankaya, 50. Yıl and İleri. The third stage of the analysis can be considered as extension to the second stage since the regarding urban features for older adults' walkability was added to WISS. The workflow of this stage was briefed as follows:

1. Selecting and defining the urban features for elderly people walkability
2. Specifying the regarding urban metrics for each urban feature
3. Describing required data for each urban metric
4. Reviewing the data sources for the required data
5. Collecting the data from the selected sources
6. Attaching the data to the existing models of the neighborhoods
7. Computing on the models for each urban feature
8. Defining the walkability index for elderly people
9. Sorting the streets and neighborhoods according to their walkability for older adults

Each operation shown in Figure 4-17 will be explained in detail in the following three sections.

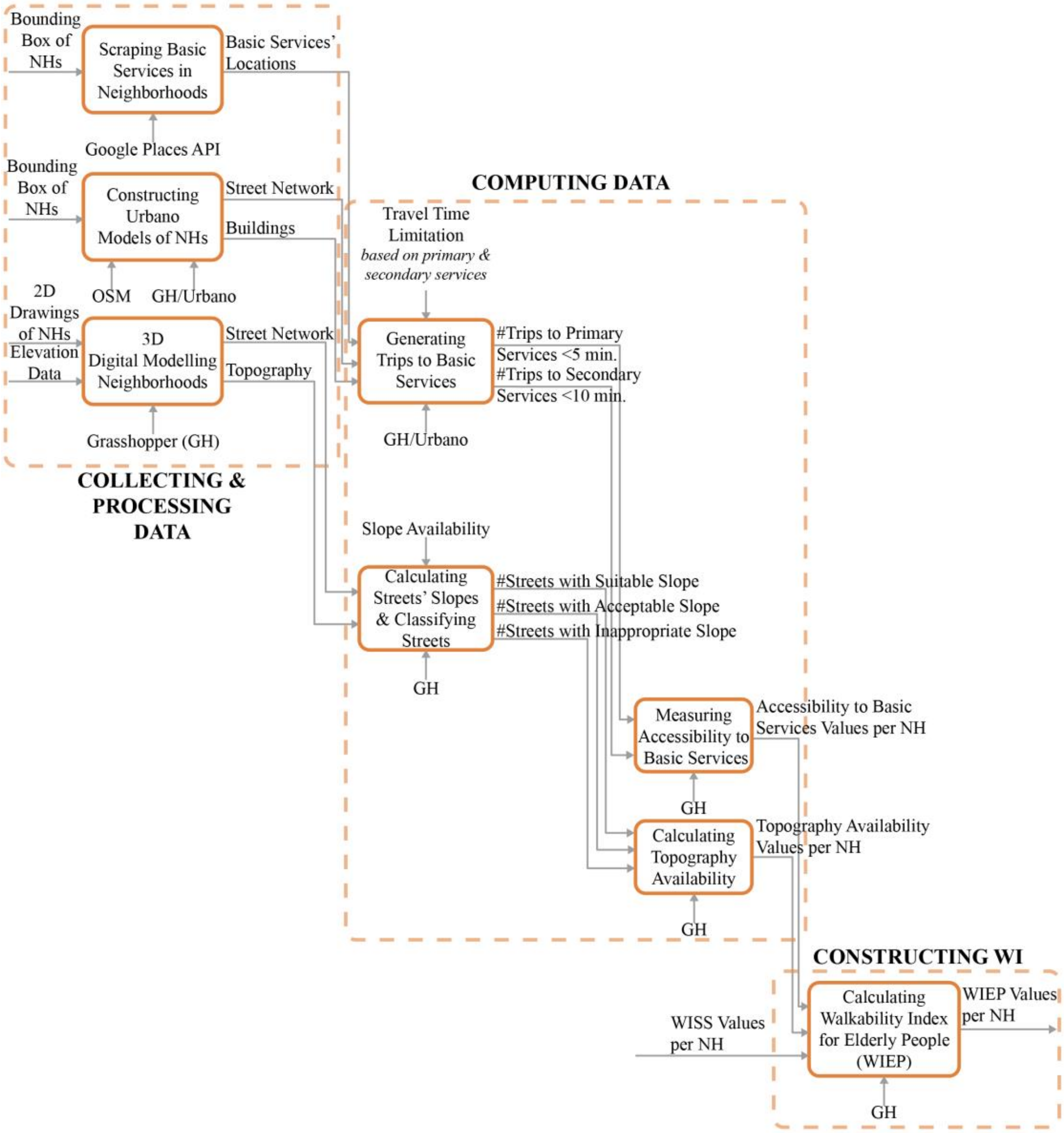

Figure 4-17. The workflow diagram displaying the stages of walkability evaluation for elderly people

4.4.1 Selected Urban Features

The urban features of the walkability assessment for older adults were defined based on their needs. While selecting these features, existing studies focusing on elderly people in the literature were reviewed. As the factors influencing walkability have been reviewed extensively for the previous stages, the importance was given to select the urban features among the critical issues for older adults. The studies, including the individuals, have tried to associate older adults' physical activity levels with built environment characteristics. To illustrate, Wendy et al. (2005) measured older women's physical activity level with a pedometer. They associated the participants' physical activity level with neighborhood characteristics such as socioeconomic status, built years of the buildings, and proximity to business and facilities. Alves et al. (2020) investigated the slopes and stairs in public spaces besides the factors significant for all target groups like pedestrian surface quality, sidewalk existence and width, traffic street intersections, existence of obstacles, land mix-use, presence of trees/vegetation and urban furniture, street lighting, and diversity of information signs. They also indicated the age-friendly routes based on the locations of the places which elderly people frequently visit. In this thesis study, as an addition to the previous urban features measured at the street scale, topography availability and accessibility to the basic services were taken into account as urban features affecting elderly walkability.

Topography availability: It refers to the slope of the surfaces. The sloped streets can be accepted one of the difficulties while walking for all age groups, yet especially for older people (Alves et al., 2020). In the literature, few studies have evaluated how inclined topography affecting the walkability of older adults (Meeder, Aebi & Weidmann, 2017; Ferraro, Pinto-Zipp, Simpkins & Clark, 2013). According to Meeder et al. results, 1% increase in slope can make walking 10% less attractive. Alves et al. (2020) adopted three types of walking inclines based on the Portuguese Institute for Mobility and Land Transports:

- x < 5% : Suitable
- 5% < x < 8% : Acceptable
- x > 8% : Inappropriate

According to them, older adults do not force themselves extremely up to 5% of inclination. They consider inclines between 5% and 8% acceptable for elderly people, and over 8% are defined as steep slopes. It requires the highest level of physical effort and leads to a major increase in heart rate and muscle fatigue (Alves et al., 2020). Moreover, according to Type Zoning Regulation for Planned Areas published on 3rd of July, 2017, the inclines of the pedestrian ramps can range between the 5% and 8%. Thus, for this research, the classification of the inclines was accepted as indicated above.

Accessibility to the basic services: Another significant factor influencing the older adults' walkability is their accessibility to the basic services. Alves et al. mention two types of basic services: primary and secondary. They exemplify primary services with pharmacy, supermarket and day care center; whereas, secondary services with postal service, bank and park (2020). The primary services should be located within 400 m of elderly people's houses, which accounting for a 5-min walking. The secondary services should be located within 800 m in other words a 10-min walking (Cartstens, 1993, as cited in Alves et al., 2020). For this research, some additions and changes in categorization of the services were made with respect to the local context. Pharmacies, hospitals, supermarkets, bakeries, and groceries were accepted as primary services while mosques, postal offices, banks and parks as secondary services.

4.4.2 Data Collection

In the third stage of the analysis, two urban features, topography availability and accessibility to the basic services, were added to the walkability index at street scale to evaluate walkability for older adults. In accordance with their definitions and urban metrics, required data types are reviewed. The required data, their sources and collection methods for each urban metric are shown in Table 4-7. As can be seen in the table, the previous models and collected data were utilized for this stage except the locations of the basic services.

Table 4-10. Data types, sources and collection methods utilized in the third stage of the analysis

Urban Feature	Urban Metric	Data	Data Source	Data Collection Method
topography availability	average slope of the streets	2D drawings of the area (including elevation information)	Çankaya Municipality	obtaining from local authority
accessibility to the basic services	accessibility to the primary and secondary services	location of primary and secondary services	Google Places API	web-scraping
		street network, buildings	Open Street Map (OSM)	downloading through the application

To measure the average slope of the streets, 3D digital models created in the second stage were utilized. As explained previously, topography for each neighborhood were modeled based on the elevation points obtained from Çankaya Municipality.

To evaluate the accessibility to the basic services, Urbano models, which were created in the previous stage as well, were utilized to generate the trips to the basic services. The locations of primary and secondary services for each neighborhood were scrapped from the Google Places API. Then, their locations were defined in RH by constructing points for each, and they were defined as amenities in GH.

How these urban metrics were measured through the digital models will be explained in the next section.

4.4.3 Computation Process

The computational methods applied in the third stage of the analysis will be explained for each urban feature in this section. They include geometrical operations and trip generation in GH. The methods and equations for the computational process are shown in Table 4-8.

Table 4-11. Methods and equations for the third stage of the analysis

Urban Feature	Urban Metric	Method	Equation
topography availability	average slope of the streets	geometrical operations	$S\% = \frac{\lvert Zs - Ze \rvert x\ 100}{\mathrm{SL}}$ S: Slope of the street Zs: z value of the street's start point Ze: z value of the street's end point SL: the length of the street
accessibility to the basic services	accessibility to the primary services	trip generation	$\frac{\#trips\ \leq 5\ min}{\#\text{origin points}}$
	accessibility to the secondary services		$\frac{\#trips\ \leq 10\ min}{\#\text{origin points}}$

The topography availability for older adults' walkability was evaluated by classifying the streets based on their incline percentages. Concerning the calculated street inclines' ranges, the determined points were given to each street. The slopes of the streets were calculated through the digital 3D models of the neighborhoods. The centerlines of the streets were projected onto the topography surface in GH. The start and endpoints of the projected centerlines were selected, and they were deconstructed in GH. The z values of the points were subtracted from each other, and it was converted to the absolute value. Then, to calculate the percentage, the absolute value was multiplied by 100 and divided by the street's length. The list of the streets' inclines was dispatched based on the defined ranges. The points were given to the streets based on the values in Table 4-9. Lastly, the arithmetic mean of the values was calculated for each neighborhood.

Table 4-12. The points given to the streets based on the inclines percentages

Inclines Percentages	Description	Point
x < 5%	suitable	0
5% < x < 8%	acceptable	1
x > 8%	inappropriate	2

For the computational process of basic services' accessibility, the trips between the origin points and the location of the basic services were generated. However, each building was assumed as an origin location as the data including the residential addresses of older adults is not available. Hence, origin input parameter of *router* component is defined by the buildings obtained from OSMs. There were two types of destination points: primary and secondary services. Firstly, the trips were generated for the primary services, and the resulting trips were sorted based on their travel time. For primary services, the number of trips taking 5 minutes or less was found. Secondly, the trips were built for the secondary services, and listed based on their travel time as well. For secondary services, the number of trips taking 10 minutes or less was calculated. It is accepted that the more available trips between the blocks and basic services means higher accessibility for the neighborhood.

$$
\begin{aligned}
&WISS\ for\ elderly\ people \\
&\qquad = z(Imageability) + z(enclosure) + z(human\ scale) \\
&\qquad + z(complexity) \boldsymbol{-} \boldsymbol{z}(\boldsymbol{topography\ availability}) \\
&\qquad + \boldsymbol{z}(\boldsymbol{accessibility\ to\ the\ basic\ services})
\end{aligned}
$$

Equation 4-4. Walkability Index for elderly people (where z stands for z-score normalization)

The calculated values of the urban features were transformed to z-score value in Excel as well. The features were added to the WISS to compare the walkability level of the neighborhoods for elderly people. The results of the walkability evaluation for older adults will be given in Chapter 5.

CHAPTER 5

RESULTS

This chapter presents the results of the exploratory analysis including walkability assessment at neighborhood-street scale and for older adults. The analysis consisting of three stages was implemented to the neighborhoods of Çankaya district in Ankara. While 115 neighborhoods were evaluated for the first stage of the analysis, 9 neighborhoods were taken into account for the second and third stages. The findings of the each stage will be presented separately; thereafter, comparative results of 9 neighborhoods will be displayed with respect to the scale of the analysis and target group.

5.1 The Results of Walkability Evaluation at Neighborhood Scale

The first stage of the analysis aims to assess the neighborhoods' walkability concerning macro-scale urban features. In that sense, attractiveness, PT availability, density, diversity, connectivity, and permeability were measured based on urban metrics. The big data approach was utilized while collecting and evaluating the data. As explained in Chapter 4, the computational process was carried on each urban metrics, and the values were found for each urban metric and neighborhood. The values were converted to a z-score, and the WINS was calculated based on their relation with walkability. The spatial associations between the findings and their correspondent neighborhoods were visualized in QGIS.

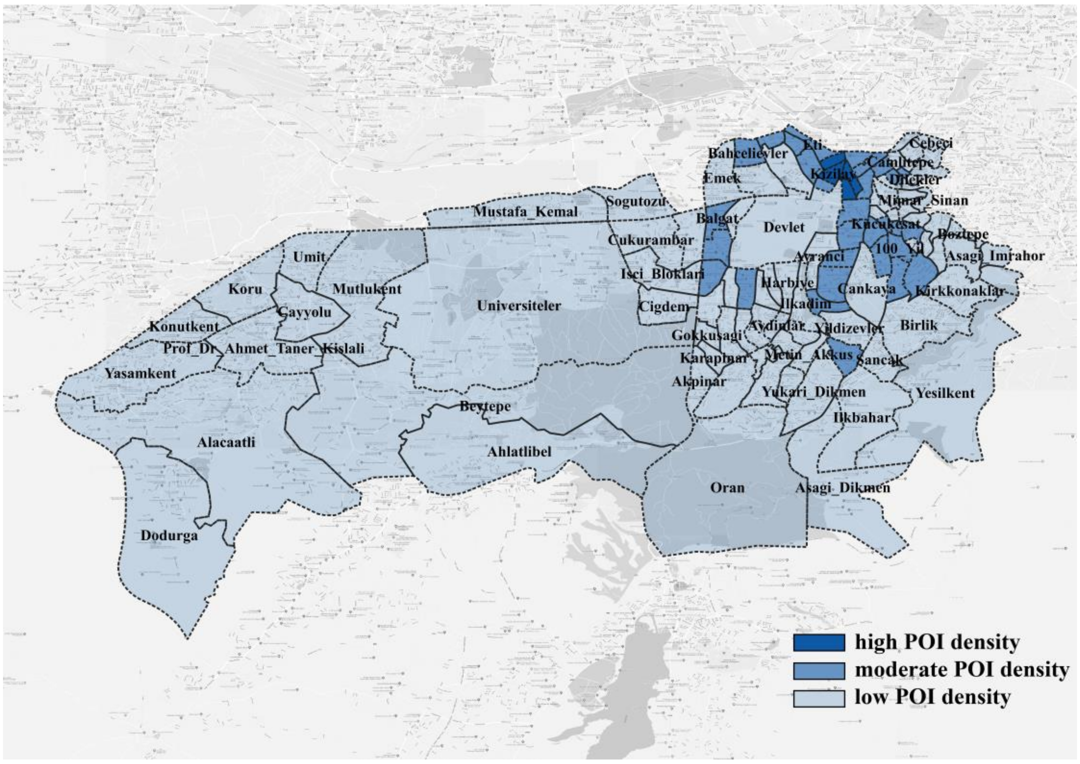

Figure 5-1. The POI density distribution in Çankaya, visualized in QGIS

Table 5-1. The table of POI density results

category name	**min. value (z-score)**	**max. value (z-score)**	**# neighborhood per category**	**neighborhood% per category**
high POI density	1.1	4.5	5	4.35%
moderate POI density	0.0	1.1	30	26.09%
low POI density	-0.7	0.0	80	69.57%

The majority of Çankaya neighborhoods (69.57%) have low POI density. According to Figure 5-1, the low POI dense neighborhoods are the ones in the periphery of the district, in the new development area, having a bigger land area, and comprised of residential buildings. The most POI dense neighborhoods (Cumhuriyet, Kızılay, Kocatepe, Korkutreis, and Meşrutiyet) are locating in the city center with a high number of attraction point. The high POI density makes urban areas attractive to visit; therefore, it is significant to compare the walkability level of the neighborhoods.

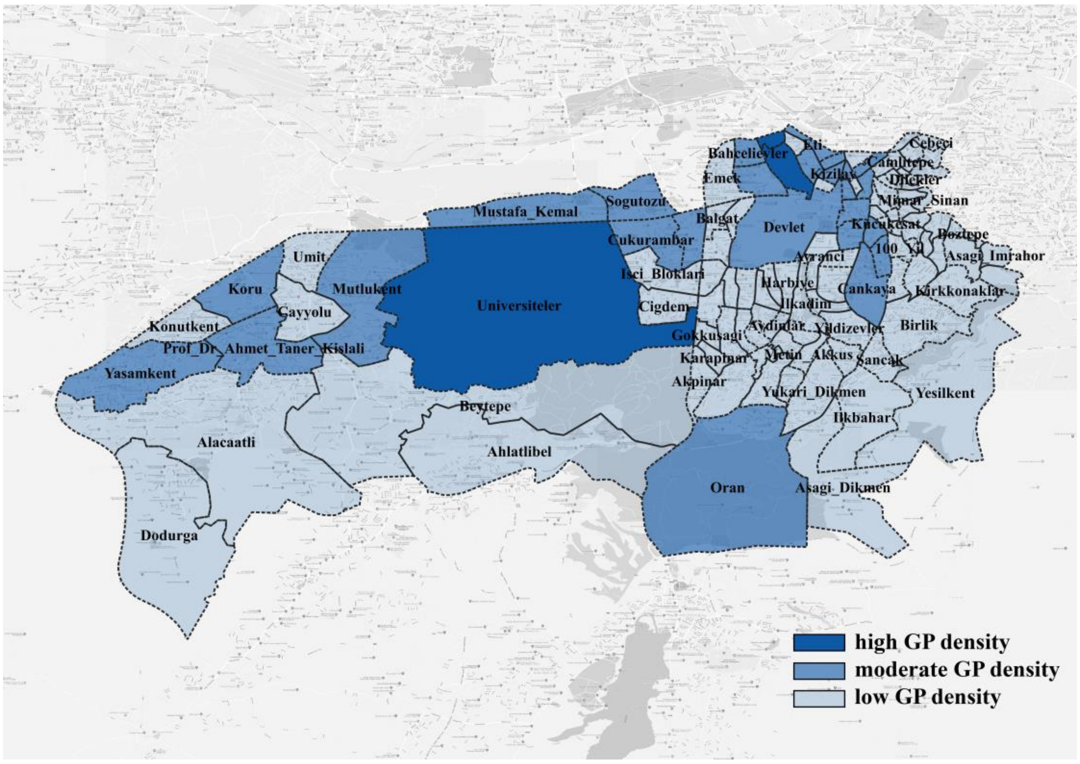

Figure 5-2. The GP density distribution in Çankaya, visualized in QGIS

Table 5-2. The table of GP density results

category name	min. value (z-score)	max. value (z-score)	# neighborhood per category	neighborhood% per category
high GP density	2.411	6.010	3	2.61%
moderate GP density	-0.020	2.411	25	21.74%
low GP density	-0.465	-0.020	87	75.65%

Another urban metric of attractiveness is GP density, which was measured based on the SM-originated data. GP density shows the places which people found attractive to take the photo and visit. It is seen that the most of the neighborhoods (75.65%) have low GP density. The results make sense when the viewpoints of Ankara are considered. One of the most GP dense neighborhoods is Yücetepe, where Anıtkabir is locating, and the other is Mebusevleri, which is next to it. Another most GP dense neighborhood is Üniversiteler, which consisting of three big university campuses: METU, Hacettepe, and Bilkent University. The reasons behind this high value might be the architectural quality of the university campuses, the forest area covering most of the neighborhood, and the characteristics of the population living there. Most of the neighborhood's residents are comprised of students. The majority of the social media platform sharing is from a young population since they use smartphones and applications more widely (Cranshaw, Schwartz, Hong & Sadeh, 2012).

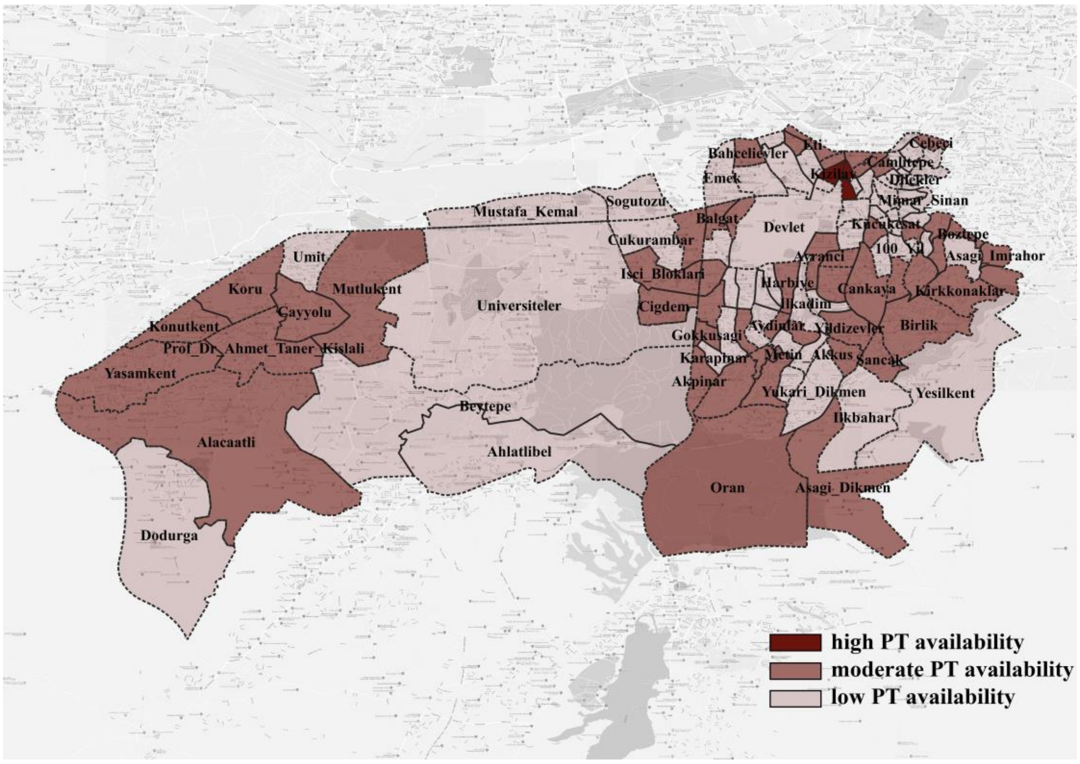

Figure 5-3. The PT availability distribution in Çankaya, visualized in QGIS

Table 5-3. The table of PT availability results

category name	min. value (z-score)	max. value (z-score)	# neighborhood per category	neighborhood% per category
high PT availability	2.2	5.6	3	2.61%
moderate PT availability	-0.1	2.2	51	44.35%
low PT availability	-1.1	-0.1	61	53.04%

The PT availability is vital for walkability as it promotes active transportation. The high level of PT might make people leave their cars at home. The majority of the neighborhoods in Çankaya stands at moderate (44.35%) and low (53.04%) level PT availability. Only three neighborhoods (Cumhuriyet, Kızılay, and Meşrutiyet) in the city center show high-level PT availability.

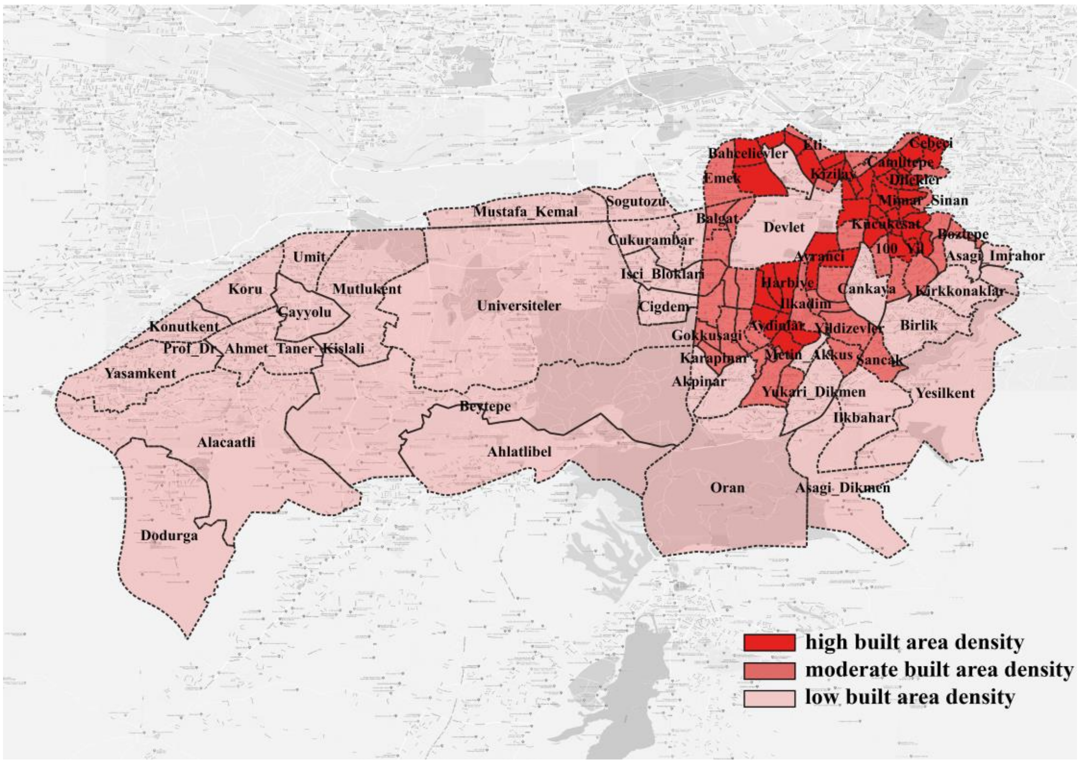

Figure 5-4. The built area density distribution in Çankaya, visualized in QGIS

Table 5-4. The table of built area density results

category name	min. value (z-score)	max. value (z-score)	# neighborhood per category	neighborhood% per category
high built area density	0.5	1.7	45	39.13%
moderate built area density	-0.7	0.5	36	31.3%
low built area density	-1.8	-0.7	34	29.57%

The high built area density makes the distance shorter between the origin and destination points. Hence, it is an essential urban metric for walkability. Compared to the other urban metrics, the distribution of built area density is seen as more balanced. The percentage of the neighborhoods per category is close to each other. In the low built area dense neighborhoods, the high rise buildings exist mostly, while the high and moderate built area dense neighborhoods are consist of low-rise buildings. Therefore, the total built area density might show different results.

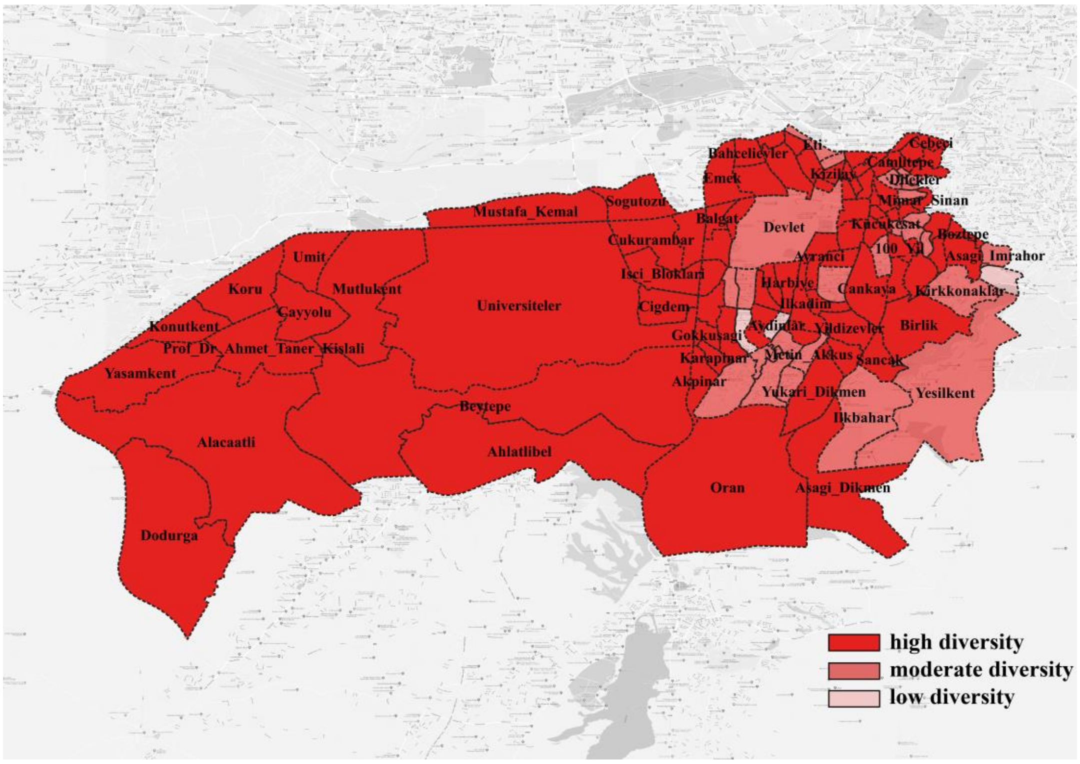

Figure 5-5. The diversity distribution in Çankaya, visualized in QGIS

Table 5-5. The table of diversity results

category name	min. value (z-score)	max. value (z-score)	# neighborhood per category	neighborhood% per category
high diversity	-0.3	1.2	85	73.91%
moderate diversity	-3.0	-0.3	27	23.48%
low diversity	-4.7	-3.0	3	2.61%

The diversity feature presents the functional usefulness of the neighborhoods. The high level of diversity means that people can find their needs in the neighborhoods where they live. The majority of the neighborhoods (73.91%) in Çankaya has high diversity, which is a promising result for the walkability assessment.

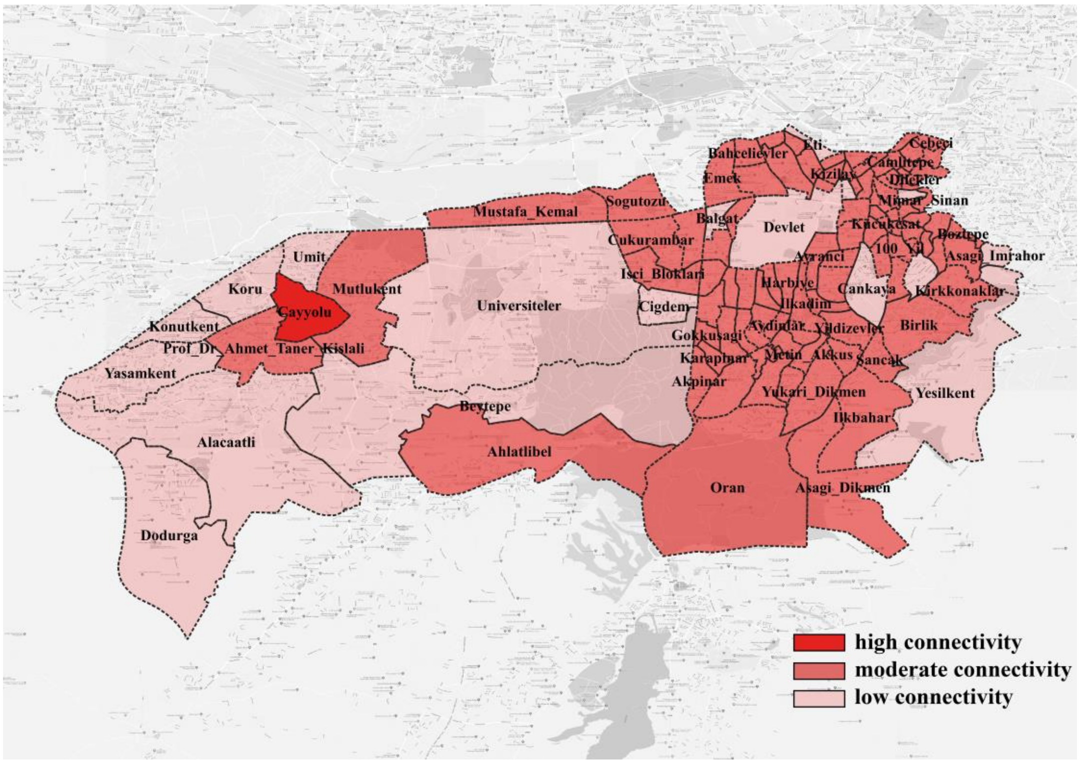

Figure 5-6. The connectivity distribution in Çankaya, visualized in QGIS

Table 5-6. The table of connectivity results

category name	min. value (z-score)	max. value (z-score)	# neighborhood per category	neighborhood% per category
high connectivity	2.3	5.6	1	0.87%
moderate connectivity	-0.7	2.3	95	82.61%
low connectivity	-2.8	-0.7	19	16.52%

The connectivity metric considers the proportion of intersection points in the street network with the street network's total length. The high level of connectivity ensures shorter distances as well. Most of the neighborhoods (82.61%) in Çankaya shows the moderate connectivity. The low connective neighborhoods are among the ones new developing or having a bigger land area.

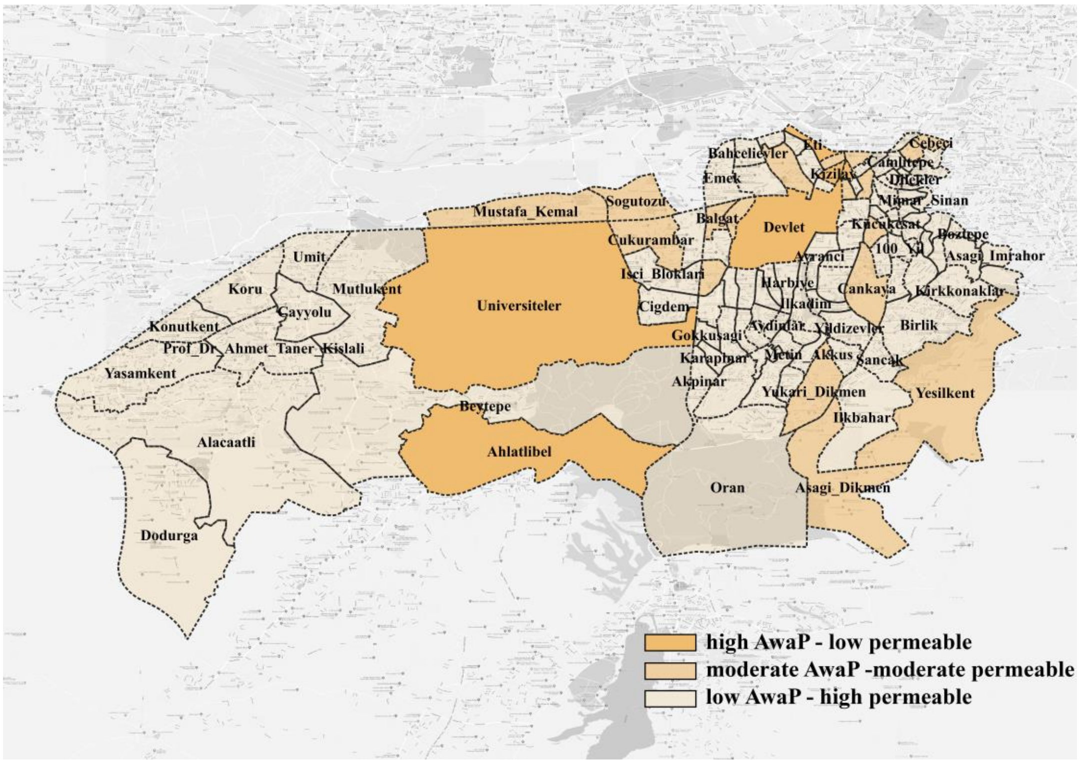

Figure 5-7. The permeability distribution in Çankaya, visualized in QGIS

Table 5-7. The table of permeability results

category name	min. value (z-score)	max. value (z-score)	# neighborhood per category	neighborhood% per category
high permeability	-1.0	0.2	91	79.13%
moderate permeability	0.2	2.0	18	15.65%
low permeability	2.0	4.2	6	5.22%

The last urban metric included in the first stage of analysis is permeability. It refers to the degree of urban areas' accessibility level by public space. The low AwaP value means the high-level permeability, whereas the high AwaP refers to the low-level permeability. According to Table 5-7, most of the neighborhoods (79.13%) have low AwaP values and are highly permeable. Besides the perimeter and area of the blocks, the boundaries of the gated communities might have influenced the accessibility of urban spaces. Therefore, if this input was included in the analysis, the results would show differences.

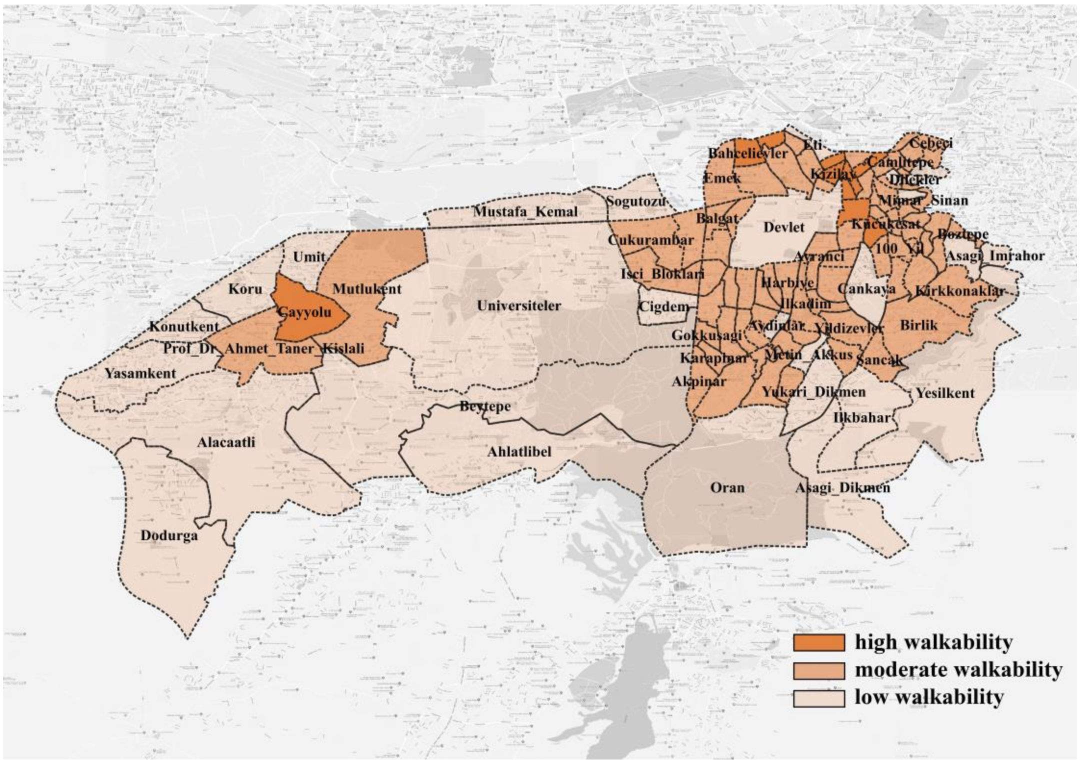

Figure 5-8. The walkability distribution in Çankaya, visualized in QGIS

Table 5-8. The table of walkability results at neighborhood scale

category name	min. value (z-score)	max. value (z-score)	# neighborhood per category	neighborhood% per category
high walkability	1.1	4.5	11	9.57%
moderate walkability	0.0	1.1	75	65.22
low walkability	-0.7	0.0	29	25.22%

The WINS was calculated based on the urban metrics' results. The spatial associations between the walkability levels and their correspondent neighborhoods were performed in QGIS and displayed in Figure 5-8. According to the results, the majority of Çankaya neighborhoods have a moderate walkability level with 65.22%. This result is promising for the development of Ankara in the context of sustainable mobility. It is seen that the neighborhoods near the city center are more walkable than the others. The walkability of some neighborhoods like Devlet and Çankaya stands at a low level since there are governmental settlements in these neighborhoods. Likewise, Üniversiteler neighborhood is comprised of three big university campuses, and its walkability level is low. These bounded urban areas should have been considered while evaluating the walkability level.

Table 5-9. The table displaying the z-scored values for nine neighborhoods (R: Rank, POI-D: POI density, GP-D: GP density, PT-A: PT availability, BA-D: built area density, DV: diversity, C: connectivity, AwaP: the area-weighted average perimeter, WINS: walkability index at neighborhood scale)

R	NH name	POI -D	GP-D	PT-A	BA-D	DV	C	AwaP	WINS
1	Meşrutiyet	4.03	1.15	5.63	1.06	0.74	-0.85	0.71	11.05
2	Kızılay	4.5	0.14	5.43	1.73	0.42	-0.37	3.57	8.28
3	Mebusevleri	0.97	6.01	-0.59	0.8	-0.06	0.32	-0.46	7.92
12	Yücetepe	-0.62	5.01	-0.71	-1.01	1.22	-0.11	1.09	2.69
13	Ön Cebeci	0.08	-0.28	0.31	0.9	0.89	0.56	-0.18	2.64
14	Maltepe	0.38	1.03	-0.29	0.75	0.52	-0.32	-0.31	2.38
87	Çankaya	-0.28	1.03	0.07	-0.76	-0.07	-0.97	0.6	-1.59
88	50. Yıl	-0.64	-0.43	-0.72	-0.44	0.55	-0.24	-0.25	-1.67
89	İleri	0.32	-0.45	-1.13	1.54	-2.36	-0.28	-0.66	-1.7

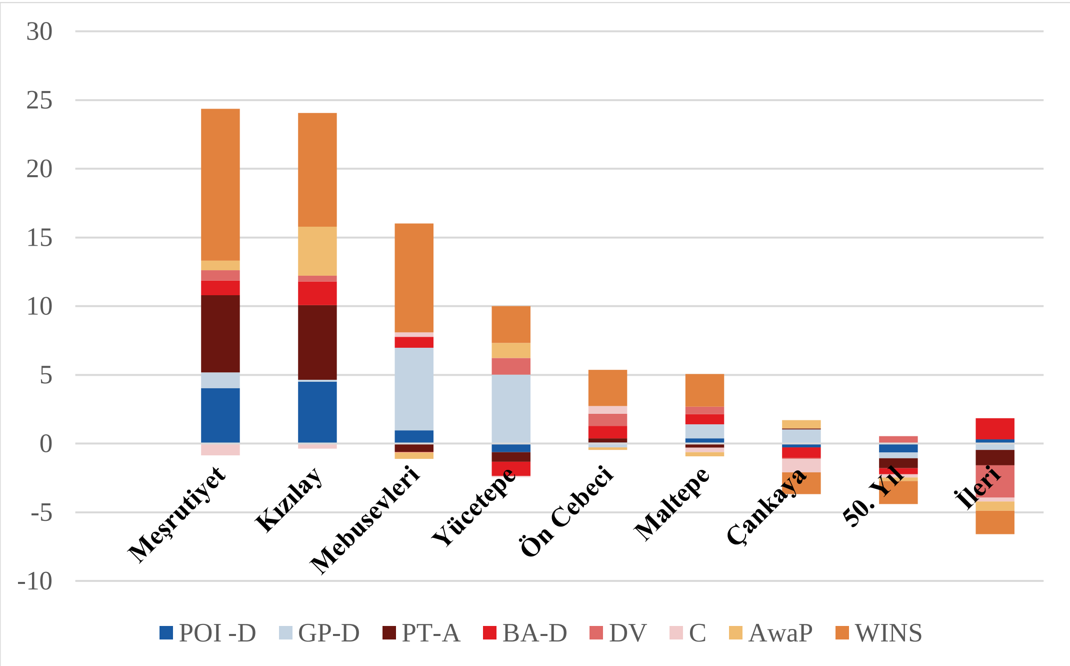

Figure 5-9. The graph displaying the z-scored values for nine neighborhoods (R: Rank, POI-D: POI density, GP-D: GP density, PT-A: PT availability, BA-D: built area density, DV: diversity, C: connectivity, AwaP: the area-weighted average perimeter, WINS: walkability index at neighborhood scale)

According to the WINS results, the neighborhoods were sorted into three categories. The first three neighborhoods were selected from each category to evaluate them at a street scale. The selected neighborhoods and their results in the first stage are presented in Table 5-9.

The first stage of the analysis was subjected to some limitations, and they might affect on the results. These limitations and suggestions for further studies will be explained in Chapter 6.

5.2 The Results of Walkability Evaluation at Street Scale

The second stage of the analysis aims to assess the neighborhoods' walkability concerning the micro-scale urban features measured based on the streets' qualities. In that sense, imageability, enclosure, human scale, and complexity were estimated with respect to their correspondent urban metrics. As explained in Chapter 4, the computational methods like trip generation, semantic segmentation, image processing and geometrical operations on 3D digital models were applied to find the results. In order to calculate the WISS for each neighborhood, the average values of the urban features were found. The values were converted to a z-score, and the WISS was calculated based on their relation with walkability. The results of the geometrical operations and trip generation were visualized in GH (Figure 5-10, 11, 12, 13, and 14). The values of the urban metrics, number of parks, number of long sight lines, proportion of street segment with street wall, average height of the visible buildings and the number visible buildings, for each street were remapped in the domain of zero to one. Then, the classification of the streets were visualized based on these remapped values. The results of each urban metric and urban features are presented in Table 5-10, 11, 12, and 13.

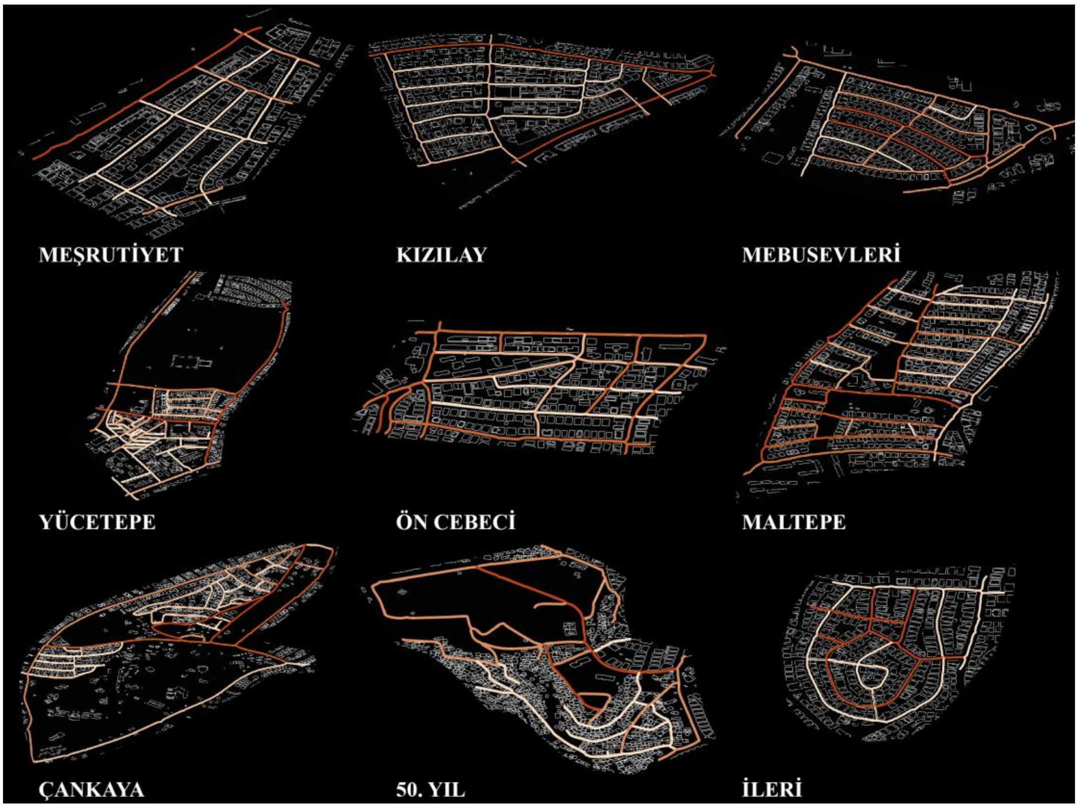

Figure 5-10. The maps displaying the number of parks visible from the streets, visualized in GH

The above maps display the number of parks visible from the streets. Courtyards, squares and parks are significant urban spaces to be memorable for pedestrians. Hence, the provided views to the parks increase people's demand to walk. As seen in the maps, the streets next to or along the parks have higher value than other streets.

Table 5-10. The table displaying the z-scored values of imageability and its urban metrics for nine neighborhoods

R	NH name	number of parks	vegetation%	pedestrian%	noise level	I
1	Mebusevleri	-0.24	1.51	-0.49	-0.98	1.76
2	Maltepe	2.23	0.35	-0.38	0.47	1.73
3	50.Yıl	-0.71	-0.61	-0.43	-2.29	0.54
4	Çankaya	0.04	0.95	-0.49	-0.02	0.52
5	Ön Cebeci	0.95	0.62	-0.39	0.74	0.44
6	Kızılay	-0.5	0.27	0.31	0.85	-0.77
7	Meşrutiyet	-0.92	-2.08	2.75	0.84	-1.09
8	Yücetepe	0.32	-0.67	-0.44	0.7	-1.49
9	İleri	-1.17	-0.34	-0.43	-0.29	-1.65

In Table 5-10, the z-scored values of number of visible parks, vegetation%, pedestrians% and noise level are shown for each neighborhood. The nine neighborhoods were sorted based on the imageability ranking. Number of parks, vegetation and pedestrian percentages affect the imageability positively while the noise level has negative influence on it. According to the results, Mebusevleri is the most imageable neighborhood whereas İleri is the least among these 9 neighborhoods. The high level of street vegetation and low level of noise contributed to the imageability level of Mebusevleri. The lack of parks, the low level of street vegetation and pedestrian percentage lead to decrease in the imageability of İleri neighborhood.

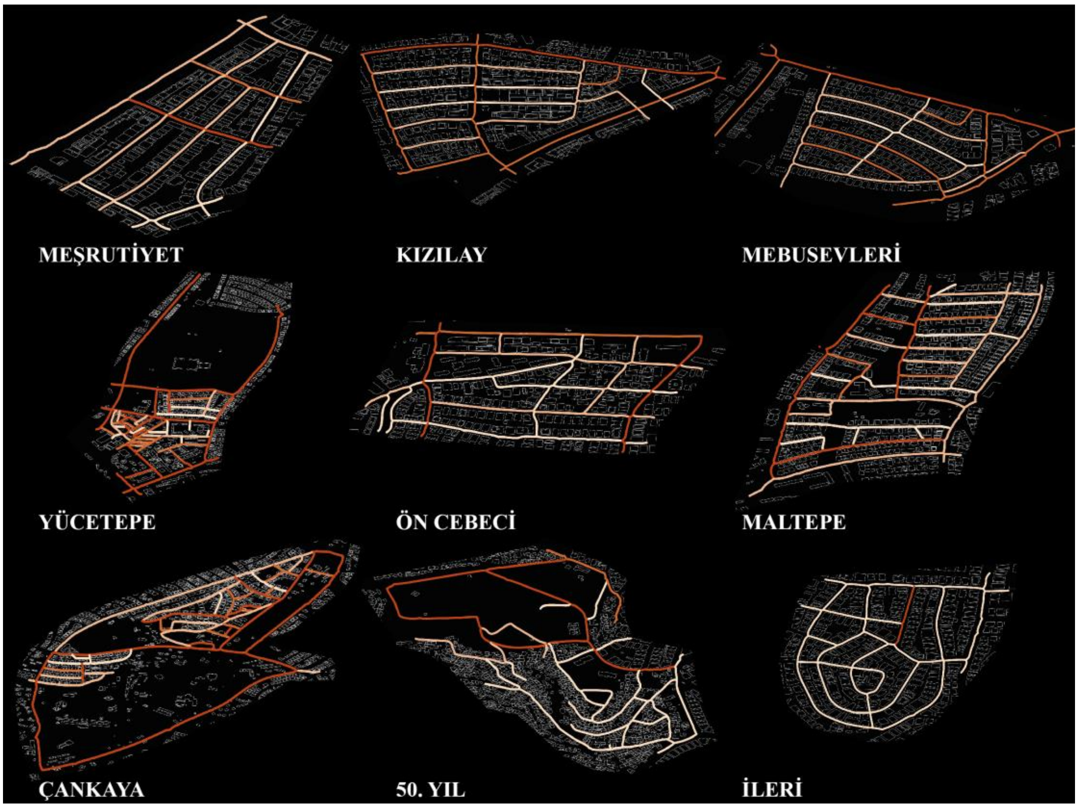

Figure 5-11. The maps displaying the number of long sight lines in the streets, visualized in GH

The presence of long sight lines is one of the urban metrics affecting the sense of enclosure negatively. The above maps show the number long sight lines seen while walking down the streets. As explained previously, the streets are marked by 0, 1, 2, or 3 according to the number of directions having long sight lines. The streets in red color have long sight lines in three directions while the ones in white color do not have long sight lines in any direction.

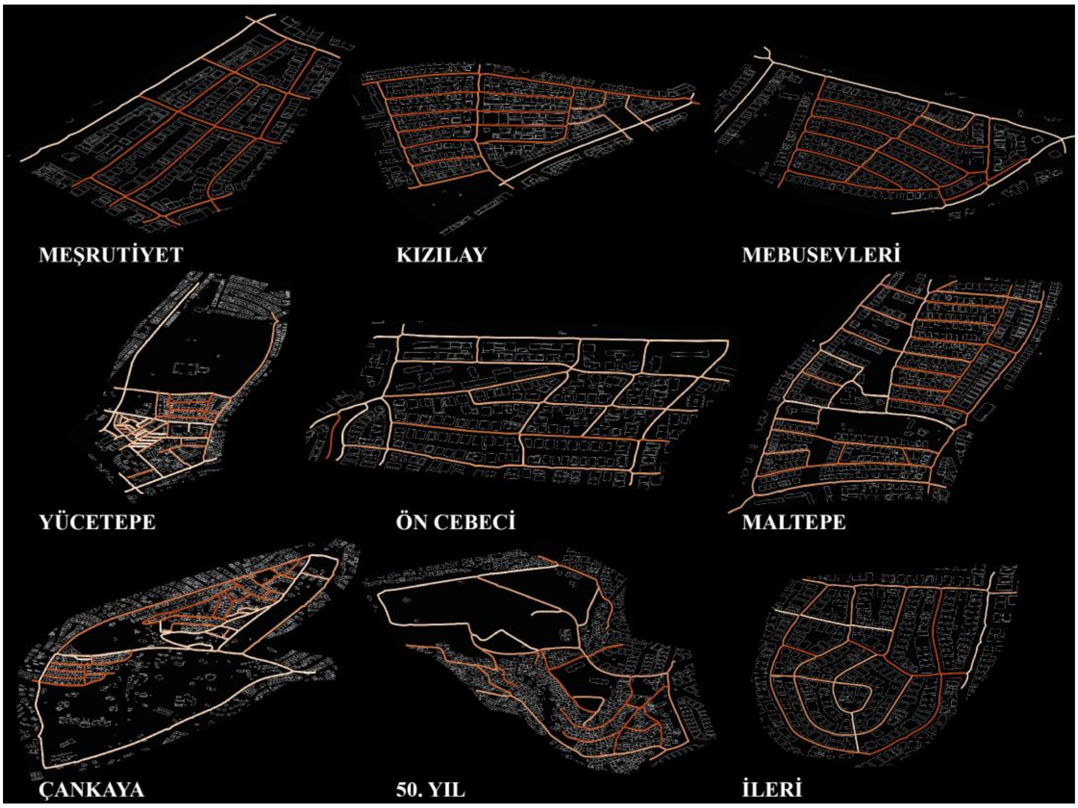

Figure 5-12. The maps displaying the street wall proportion in the streets, visualized in GH

The proportion of street segment with street wall is an urban metric which contributes the sense of enclosure. The above maps present the comparative situation of the streets in each neighborhood based on the proportion of street segments with street walls.

Table 5-11. The table displaying the z-scored values of enclosure and its urban metrics for nine neighborhoods

R	NH name	visible sky%	#long sight lines	proportion of street segment	E
1	İleri	-0.43	-2.15	0.51	3.09
2	Kızılay	-1.12	0.27	1.08	1.93
3	Maltepe	-0.74	0.06	0.97	1.66
4	Meşrutiyet	-0.17	-0.3	0.9	1.37
5	Ön Cebeci	-0.45	0.27	0.64	0.81
6	Mebusevleri	-0.65	0.63	-0.19	-0.17
7	Çankaya	0.06	1.29	-0.92	-2.27
8	50.Yıl	2.09	-1.06	-1.37	-2.4
9	Yücetepe	1.41	0.99	-1.63	-4.02

Table 5-11 shows the z-scored values of visible sky percentage, the number of long sight lines, and the proportion of street segments with street walls displayed for each neighborhood. The nine neighborhoods were sorted based on the enclosure ranking. The percentage of visible sky and the proportion of street segment with street wall impress enclosure positively whereas the presence of long sight lines alters it negatively. Pursuant to the results, İleri gathered the highest value of enclosure while Yücetepe took the last place in the ranking. The low value of long sight lines provided an increased sense of enclosure to İleri neighborhood. There was only one street in the neighborhood with long sight lines in three directions while the others do not have any lines. Yücetepe has the lowest street segment proportion with the street wall among the nine neighborhoods due to two main streets along the Anıtkabir. This led to a decrease in the enclosure value even though its percentage of visible sky got the second-highest rate.

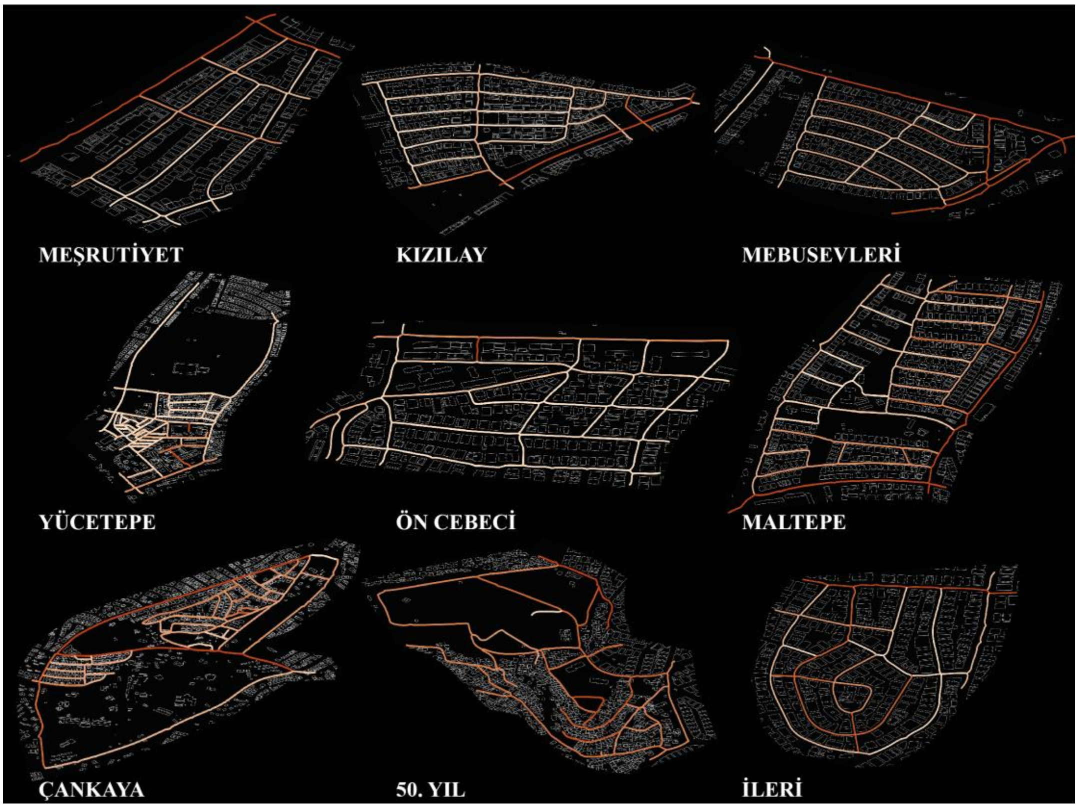

Figure 5-13. The maps displaying the average height of the buildings in the streets, visualized in GH

The height of the buildings visible for pedestrians affects the sense of human scale. The high rise buildings reduce the human scale in the built environment. The maps in Figure 5-13 exhibit that the main streets or boulevards, colored in red, do not contribute to human scale due to the buildings' height. To illustrate, the sections of the Atatürk Boulevard both in Meşrutiyet and Kızılay neighborhoods took the first place among other streets in terms of the average height of the buildings.

Table 5-12. The table displaying the z-scored values of human scale and its urban metrics for nine neighborhoods

R	NH name	avg. height of visible buildings	#long sight lines	HS
1	50.Yıl	-1.81 (7.31 m)	-1.06	2.87
2	İleri	-0.63 (11.88 m)	-2.15	2.78
3	Mebusevleri	-0.55 (12.21)	0.63	-0.08
4	Maltepe	0.02 (14.43 m)	0.06	-0.08
5	Ön Cebeci	0.2 (15.12 m)	0.27	-0.48
6	Yücetepe	-0.21 (13.52 m)	0.99	-0.78
7	Çankaya	-0.15 (13.75 m)	1.29	-1.14
8	Meşrutiyet	1.7 (20.96 m)	-0.3	-1.4
9	Kızılay	1.42 (19.86 m)	0.27	-1.69

Table 5-12 exhibits the z-scored values of the buildings' average height and the number of long sight lines for each neighborhood. The nine neighborhoods were aligned based on the human scale ranking. Both the average height of the buildings and the presence of long sight lines are inversely related to human scale. According to the results, 50. Yıl got the highest value of human scale while Kızılay had the lowest rate. 50. Yıl is a neighborhood consists of squatters and one-story houses, so it is expected to receive the highest value. Kızılay neighborhood is encircled by three main streets: Atatürk Boulevard, Gazi Mustafa Kemal Boulevard, and Necatibey Street. Hence, the average height of the buildings on these wide streets stands at a higher level than the ones in other neighborhoods. Indeed, Meşrutiyet is in the first place in terms of the buildings’ height; however, Kızılay streets had more long sight lines, which put it on the last row regarding human scale.

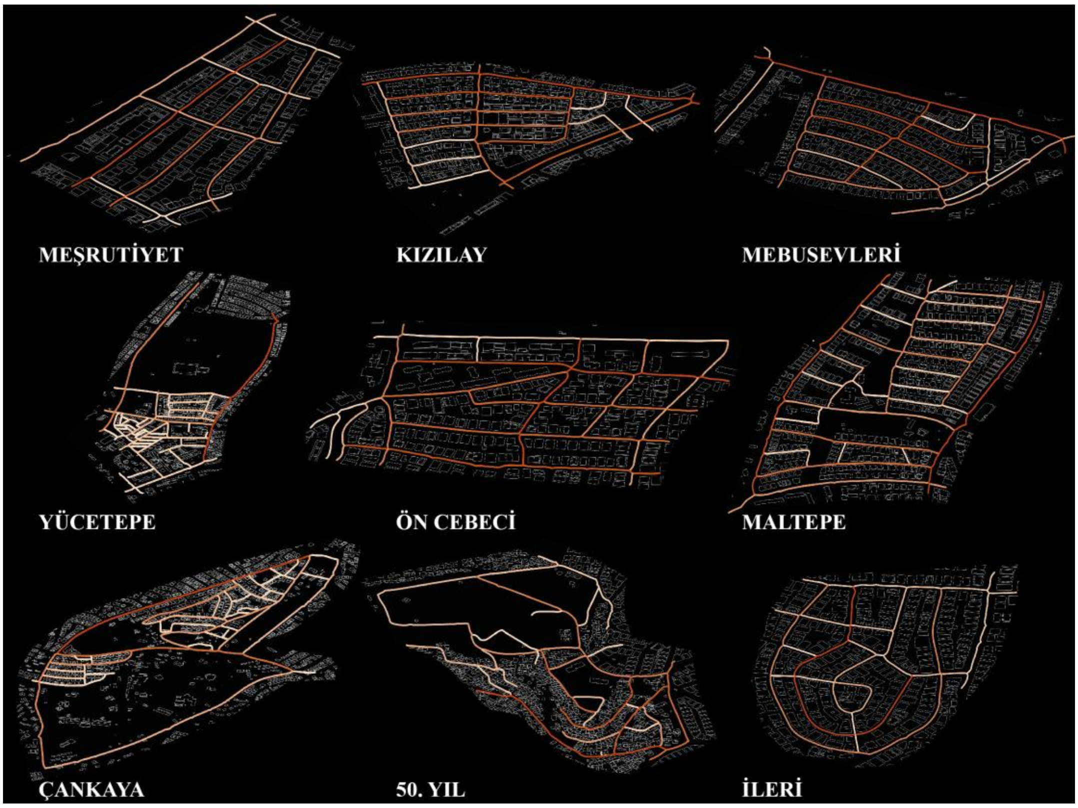

Figure 5-14. The maps displaying the number of visible buildings in the streets, visualized in GH

The more buildings pedestrians encounter while walking, the more complexity they perceive. Hence, the number of visible buildings increases the value of complexity. The configuration of the buildings and streets affect the number of visible buildings. The streets along the urban void such as Iran Street next to Seğmenler Park in Çankaya or Ziya Gökalp Street next to Kurtuluş Park in Ön Cebeci cause a decrease in the average value of the neighborhoods in terms of visible blocks.

Table 5-13. The table displaying the z-scored values of complexity and its urban metrics for nine neighborhoods

R	NH name	#visible buildings	pedestrian%	C
1	Meşrutiyet	0.11	2.75	2.87
2	Kızılay	1.2	0.31	2.78
3	İleri	1.01	-0.43	-0.08
4	Mebusevleri	1.04	-0.49	-0.08
5	50.Yıl	0.16	-0.43	-0.48
6	Ön Cebeci	-0.07	-0.39	-0.78
7	Maltepe	-0.29	-0.38	-1.14
8	Çankaya	-1.16	-0.49	-1.4
9	Yücetepe	-2	-0.44	-1.69

In Table 5-13, the number of visible buildings' and the percentage of pedestrians' z-scored values are presented for each neighborhood. The nine neighborhoods were sorted based on the complexity ranking. Both of the urban metrics provide a high level of complexity to the built environment. In accordance with the results, Meşrutiyet is the most complex neighborhood, whereas Yücetepe the least complex neighborhood. Meşrutiyet is a neighborhood locating at the center of the city and having many amenities. Moreover, some sections of the two streets in Meşrutiyet (Karanfil and Konur) are pedestrianized, which probably contributes to the pedestrians' high percentage on the streets. Hence, it is expected to gather the highest value in terms of complexity. The few buildings in Yücetepe led to a decrease in complexity. Anıtkabir and its garden create a void in the middle of the neighborhood, so the number of visible buildings is not as many as in other neighborhoods. In addition, most of the buildings' function is housing, and there are not as many commercial activities as in Meşrutiyet and Kızılay. Thus, the pedestrians' percentage on the streets is lower than in these neighborhoods.

Table 5-14. The table displaying the z-scored values of urban features (imageability, enclosure, human scale, complexity) and WISS for nine neighborhoods

R	NH name	I	E	HS	C	WISS
1	İleri	-1.65	3.09	2.78	0.58	4.8
2	Maltepe	1.73	1.66	-0.08	-0.66	2.65
3	Mebusevleri	1.76	-0.17	-0.08	0.55	2.06
4	Meşrutiyet	-1.09	1.37	-1.4	2.86	1.74
5	Kızılay	-0.77	1.93	-1.69	1.5	0.97
6	50.Yıl	0.54	-2.4	2.87	-0.28	0.73
7	Ön Cebeci	0.44	0.81	-0.48	-0.46	0.31
8	Çankaya	0.52	-2.27	-1.14	-1.65	-4.54
9	Yücetepe	-1.49	-4.02	-0.78	-2.44	-8.73

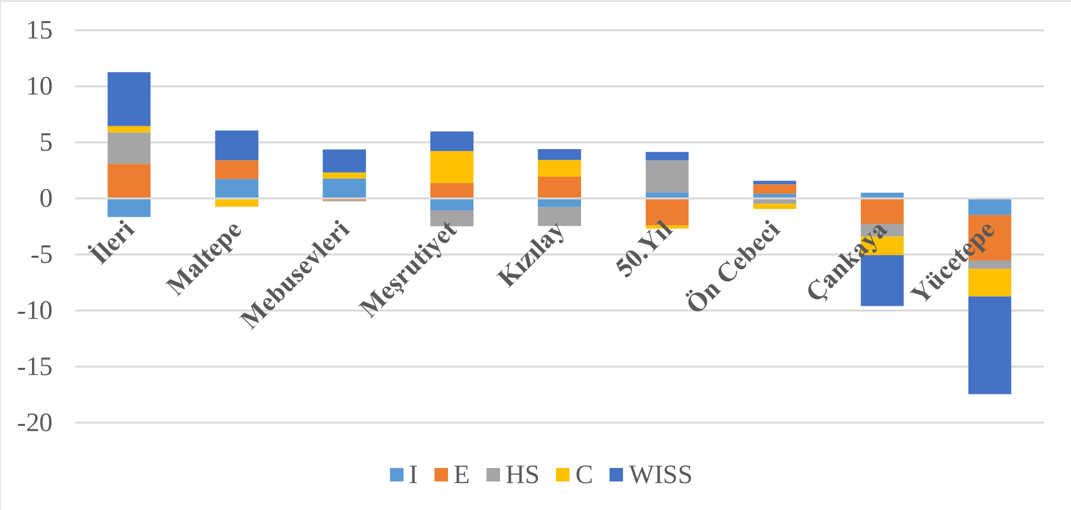

Figure 5-15. The graph displaying the z-scored values of urban features (imageability, enclosure, human scale, complexity) and WISS for nine neighborhoods

Table 5-14 presents the z-scored values of micro-scale urban features and walkability at street scale. The WISS was calculated based on these urban features' results. The nine neighborhoods were sorted with respect to WISS rates. According to the results, İleri was estimated as the most walkable neighborhood while Yücetepe was the least walkable one. The neighborhoods show different characteristics based on these micro-scale features. For instance, İleri has one of the lowest values in terms of imageability; however, the high level of the enclosure and human-scale make it the most walkable neighborhood at street scale. In this thesis study, all urban features were weighted by one in the walkability indexes. If some criteria weighted them, these results might show differences. Furthermore, İleri was the least walkable neighborhoods according to the results of the neighborhood scale. In that sense, it can be stated that walkability can vary based on measurement scale and factors.

Like the first stage of the analysis, this second step was also encountered with some limitations, and they might influence the results. These limitations and suggestions for further studies will be explained in Chapter 6.

5.3 The Results of Walkability Evaluation for Elderly People

The last stage of the analysis aims to evaluate the neighborhoods' walkability for older adults. In that sense, topography availability and accessibility to basic services were measured concerning their correspondent urban metrics. As explained in Chapter 4, computational methods like trip generation and geometrical operations on 3D digital models were conducted to estimate the urban metrics' value. The two factors affecting the walkability for older adults were measured, and then the results were added to WISS in order to calculate the WIEP for each neighborhood. Although, topography availability and accessibility to basic services were accepted as significant urban features for elderly people walkability, the WIEP was defined as a combination of previously measured micro-scale urban features and them.

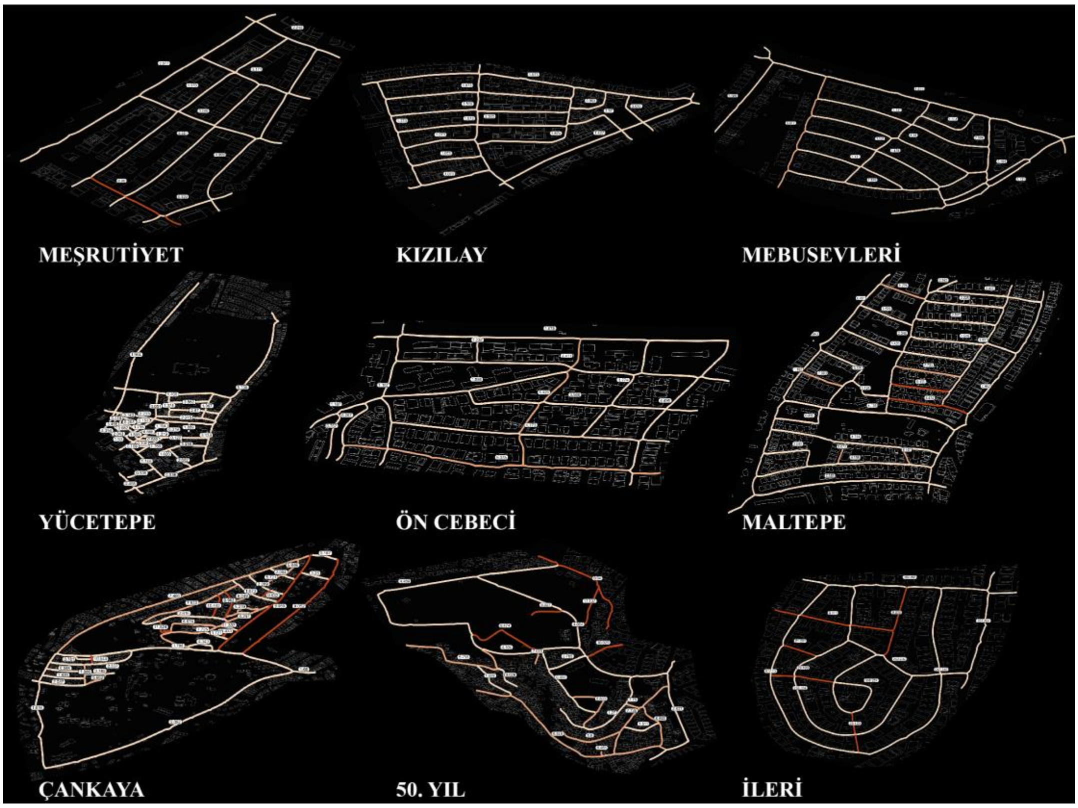

Figure 5-16. The maps displaying slope differences in the streets, visualized in GH

The above maps exhibit the classification of the streets in terms of slope degree. As explained before, the streets were defined according to incline percentages: suitable, acceptable, and inappropriate. The points (0, 1, or 2) were given to the streets based on these definitions. In the maps, red streets represent inappropriate slopes, orange ones reflect the acceptable ones, and white lines show suitable inclines. The average values of the given points for each neighborhood were calculated to include them in WIEP.

Table 5-15. The table displaying the number of origin points, routes to primary and secondary services, and the exact values of accessibility to basic services

R	NH name	#origin points	#routes to primary services	#routes to secondary services	accessibility to basic services
1	50.Yıl	265	126	217	1.29
2	Mebusevleri	394	93	315	1.04
3	İleri	610	131	481	1
4	Kızılay	577	135	240	0.65
5	Maltepe	921	117	363	0.52
6	Meşrutiyet	380	115	8	0.32
7	Ön Cebeci	565	157	23	0.32
8	Yücetepe	1604	147	188	0.21
9	Çankaya	1938	105	9	0.06

Table 5-15 shows the number of origin points, routes to primary and secondary services, and the exact values of accessibility to basic services. In order to measure the accessibility and make a comparison between the neighborhoods, the number of routes were proportioned by the number of origin points. According to output data, 50. Yıl obtains the most accessibility to basic services for older adults whereas Çankaya has the least accessibility to main needs.

Table 5-16. The table displaying the z-scored values of topography availability, accessibility to basic services, and sum of them for nine neighborhoods

R	NH name	topography availability	accessibility to basic services	walkability for older adults
1	Mebusevleri	-0.83	1.08	1.91
2	Kızılay	-1.07	0.12	1.19
3	50.Yıl	1.41	1.73	0.32
4	Yücetepe	-1.07	-0.98	0.09
5	Ön Cebeci	-0.62	-0.71	-0.09
6	Maltepe	-0.06	-0.2	-0.14
7	Meşrutiyet	-0.37	-0.69	-0.32
8	İleri	1.54	1	-0.54
9	Çankaya	1.07	-1.35	-2.43

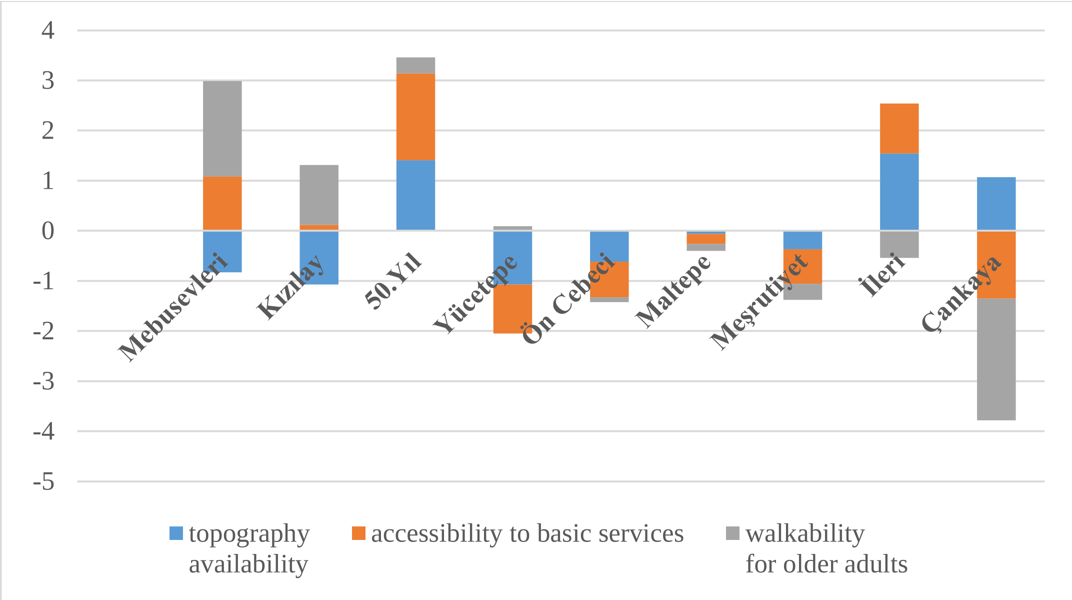

Figure 5-17. The graph displaying the z-scored values of topography availability, accessibility to basic services, and sum of them for nine neighborhoods

In Table 5-16, the z-scored values of topography availability and accessibility to basic services are shown for each neighborhood. The nine neighborhoods were sorted based on the sum of these urban features. Topography availability negatively influences the walkability while accessibility to basic services positively affects it. If only these two urban features are taken into consideration, Mebusevleri can be defined as the most walkable neighborhood for older adults, while Çankaya is the least walkable one. The low value of slope percentage and a high degree of accessibility to basic services provide a high walkability level for older adults in Mebusevleri. In Çankaya, the streets' inclines are not proper as much as the streets in other neighborhoods. Besides, the basic services are more distributed than other neighborhoods, and as a result, the number of time limited routes is not sufficient.

Table 5-17. The table displaying the z-scored values of WISS and WIEP for nine neighborhoods

R	NH name	WISS	walkability for older adults	WIEP
1	İleri	4.8	-0.54	4.26
2	Mebusevleri	2.06	1.91	3.97
3	Maltepe	2.65	-0.14	2.51
4	Kızılay	0.97	1.19	2.16
5	Meşrutiyet	1.74	-0.32	1.42
6	50.Yıl	0.73	0.32	1.05
7	Ön Cebeci	0.31	-0.09	0.22
8	Çankaya	-4.54	-2.43	-6.97
9	Yücetepe	-8.73	0.09	-8.64

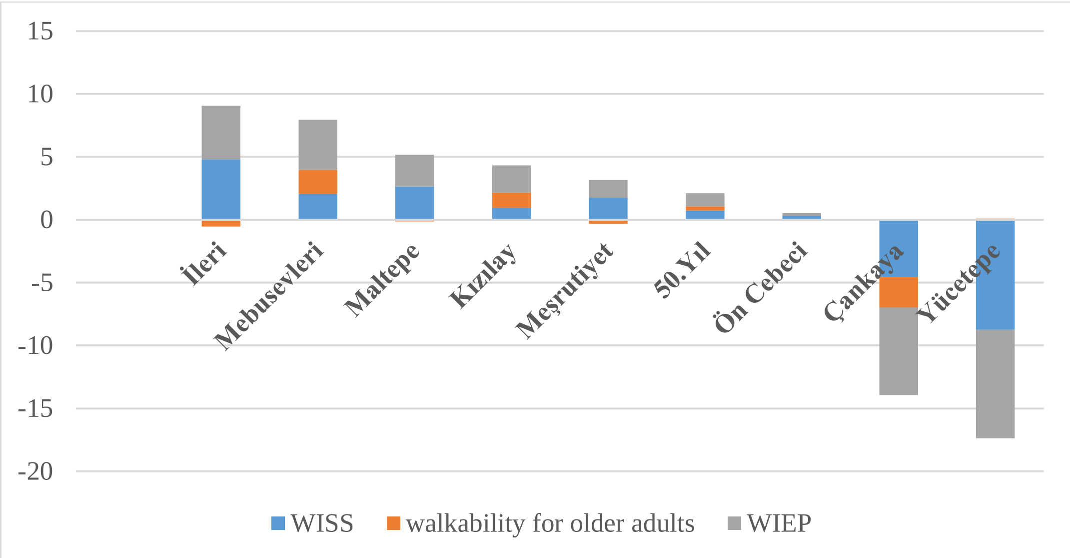

Figure 5-18. The graph displaying the z-scored values of WISS and WIEP for nine neighborhoods

Table 5-17 presented the results of WISS and WIEP for nine neighborhoods. The neighborhoods were listed based on the WIEP rates. Besides topography availability and accessibility to basic services, previously measured micro-scale urban features were considered. When the neighborhoods were sorted based on the WIEP, the ranking was altered. İleri neighborhoods retook the first place although it was in 8th place concerning the urban features selected for elderly people. Indeed, the additional urban features for older adults only changed Mebusevleri, Kızılay, and Maltepe's ranks.

The last stage of the analysis was limited to measuring two urban features. If more factors regarding older adults' walkability were taken into account, the results might show differences. Hence, these possible influences of the limitations will be explained and discussed in Chapter 6.

CHAPTER 6

CONCLUSION

The present research was designed to experience the computational methods in urban analytics for walkability assessment. It was aimed to estimate the walkability level at different scales and for a specific target group. In this regard, an exploratory urban analysis was conducted at three stages and implemented in the neighborhoods of Çankaya. Firstly, the walkability levels of the neighborhoods were evaluated based on the macro-scale urban features. Secondly, the selected nine neighborhoods were assessed based on the micro-scale urban features. Lastly, they were reconsidered by focusing on the requirements of older adults' walkability. The methodological approaches of the study included big data, machine learning algorithms, and other computational operations on 3D digital models. The results were presented for each stage, and the comparative discourse was expressed based on the findings. The exploratory analysis was conducted to experience the computational urban analytics methods; therefore, it does not assert that the results are accurate, and the analysis was completed.

This chapter will focus on the exploratory analysis's conclusions through the utilized methods and general framework of the research. In that sense, the outcomes of the proposed methodology will be reviewed through the research questions, the promising contributions of the study for the research field will be explained, and the limitations of the present study will be recognized and discussed. Eventually, the suggestions for further studies will be remarked at the end of this chapter.

6.1 The Outcomes of the Proposed Methodology

The outcomes of the proposed methodology will be summarized through the research questions. The main research question was to what extend computational urban analytics can be utilized in the walkability assessment. This study has found that computational urban analytics can contribute to the walkability assessment at different measurement scales and for specific target groups. The level of the contribution depends on data availability and accessibility. Besides, urban analytics methods can be utilized to gather the required data. The urban features used in the existing walkability studies have been reviewed and classified. It can be stated that the urban characteristics from different categories can be measured computationally. To illustrate, in this thesis study, both perceptual and physical aspects of the built environment were estimated by computational methods. For the perceptual aspects, more people's reactions can be tracked using SM-originated data rather than conducting a survey. For physical aspects, wider case areas can be studied without being there by information modeling rather than site visiting. It can be stated that the extent of the study is only limited by the amount and variety of data. However, the availability of public data is increasing day by day, and consequently, the potential of computational urban analytics is extending. At present, the development of open data platforms differs from country to country or local government to local government. For instance, OSM and Google data are more current and processed in the USA than in Turkey. These differences might bring some limitations to studies depending on the implementation area.

The second question was which computational methods and tools can be involved in walkability assessment, and consisting of three minor questions regarding data sources, collection, and computing. In terms of data sources, several open data platforms could be used based on the required data. The data sources utilized in this research were LocationBox API, Flickr API, Google API, OSM, Çankaya Municipality, and EGO Local Transportation Information System. In general, open data platforms, private companies, local or national governments, and social media platforms can be considered as main data sources to extract urban data. There are private services providing urban data like LocationBox, and many social media platforms sharing different types of data like Flickr. Hence, the selection of data sources depends on the required data type, limits of the authorization, study region, and context. If the data is not accessible directly through the data sources, then a sort of data collection method must be figured out. In this regard, knowledge of programming language would be beneficial. In this study, POI data was scrapped through LocationBox and Google API by making HTTP requests. The geotagged photos were extracted using the QGIS Flickr Metadata plug-in, and OSM data was gathered by Urbano plug-in in GH. The increase in the use of computational methods in urban analytics provides the development of new tools. Hence, there are many available methods and tools to compute the urban data. The selection of these methods and tools relies on the abilities of the researchers and data type. In the present study, mathematical operations, spatial analysis, geometrical operations, visibility analysis, trip generation, image processing, and semantic segmentation were applied to compute the urban data. The mathematical operations and standardization were conducted on Excel. The spatial analysis and visualization at the neighborhood scale were performed in QGIS. Geometrical operations like intersection, area, length, and slope calculation were practiced in RH and GH. The visibility analysis was run on the DeCodingSpaces plug-in in GH. The time-based routes were generated with the help of the Urbano plug-in in GH. The images of the traffic density maps were processed in GH as well. Semantic segmentation was applied by using Python in Google Colab.

The third and fourth questions were related to the urban features considered in walkability analysis at different scales and for a specific group of people. In the study's literature review part, the existing walkability studies have been reviewed based on considered urban features. They were described as macro or micro-scale features. Besides, the urban features dealing with larger-scale urban design issues can be included in the neighborhood scale analysis. In contrast, the ones relying on the streets' or buildings' characteristics can be involved in the street scale analysis.

In that sense, the study elaborated the urban components like attractiveness, PT availability, density, diversity, connectivity, and permeability at the neighborhood scale of the analysis, whereas the features like imageability, enclosure, human scale, and complexity were taken into account at the street scale analysis. For older adults' walkability, topography availability, and accessibility to basic services were considered as significant factors, so they were measured at the last stage of the analysis.

The fifth question was whether a combined and sequential approach could be developed to evaluate walkability at the neighborhood and street scale. In order to evaluate the walkability comprehensively, the case areas should be considered from different perspectives. The study should assess the design decisions taken both at the large urban and street scale. Therefore, the study proposed an exploratory analysis, including three stages. The selected neighborhoods from different walkability levels, according to the first stage's results, were investigated at the street scale. Thereby, it was seen that the levels of walkability could alter based on the considered factors. In addition, the data gathered in the first stage of the analysis contributed to the models in the second stage. Eventually, it is believed that such an approach is essential in order to make a walkability assessment in a broad urban area when the limited time and workforce are considered.

The sixth question was how the walkability level of a neighborhood differs according to the analysis scale. The study has found that the walkability level of a neighborhood can increase or decrease based on the considered factors. According to the results, the İleri neighborhood has the least WINS value among the nine neighborhoods, whereas its WISS value is the highest among them. The walkability level of the İleri neighborhood has increased when streets' qualities considered. In contrast, the Yücetepe neighborhood is at the fourth place in WINS results, yet it takes the last place in WISS ranking. It is expected to obtain different results due to the distinct variables. Nevertheless, some limitations might have led to these differences. The last question was about these limitations and future research directions of the study, and they will be explained in the next two sections.

6.2 The Limitations of the Research

The accuracy and generalizability of these results are subjected to certain limitations even though the study has shown the potentials of the computational urban analytics methods in assessing walkability. The first limitation is about the use of SM originated data. The use of SM is a precious source of data for urban research; in particular, Flickr was utilized by several walkability studies (Berzi et al., 2017; Lu, 2017; Quercia et al., 2015). However, it has limitations such as data bias and the accuracy level due to the nature of social network data. These limitations might cause data bias towards the place and amount of the data (Cranshaw et al., 2012; Sun, Fan, Li, & Zipf, 2015). The users of the social media platforms are mostly comprised of young population (Cranshaw et al., 2012), so this might lead to an increase in the number of GP taken on the specific locations like the Üniversiteler neighborhood. Moreover, the SM platforms, including Flickr, do not bring the private user accounts' shares. This might lead to a loss of information; however, it can be ignored as long as the obtained data is sufficient to make a measurement.

The second limitation is related to the street view images utilized in semantic segmentation. To evaluate the percentages of the pedestrians, visible sky, and street vegetation, a street view image was collected from each street. More images could be gathered to increase the accuracy level of the measurement; however, the number of images in Google Street View was limited. In addition, the time and season variables of the street views would be beneficial to prevent data bias. The street images can show different qualities based on the time and season. The data regarding the height and location of the point where the photo taken would be necessary to make more consistent measurements. The resolution and angle of the images are other parameters that might affect the results. Although these variables were tried to be fixed manually while extracting the images, the more accurate results would be obtained if they were included as input parameters.

The third limitation is regarding the lack of available urban data in Turkey. More data would provide the consideration of more features to assess the walkability. For instance, in the Netherlands, there are several governmental and local open data platforms serving the data concerning population, built environment, and transportation. Besides, some international applications like OSM and WalkScore do not have sufficient and up to date data for Turkey. If more data available, the detail level of the 3D digital models would be higher. To illustrate, the façade characteristics of the buildings would be transferred, and the transparency of the streets could be estimated. Other built environment components like street furniture or lighting elements would be added to the digital models in addition to the buildings and streets. The more accessible data would also reduce the time and workforce to collect the required data.

The last limitation was about determining the weights of the features included in the walkability index. The study assumed the weights of all features as one. However, indicating different weights would alter the results. The weights were decided based on the survey results or expert's opinions in some of the existing walkability studies. A similar approach would be applied to the research for further studies.

The suggestions for further studies based on these limitations, will be briefed in the next section.

6.3 Suggestions for Further Studies

The current study has provided a broad range of data regarding the built environment to develop future research. Besides, it has encountered several limitations in need of further investigation. Concerning the limitations of street view images, another method to collect the sample images could be preferred. More street views could be taken on-site visit based on the defined time ranges and fixed parameters. This would increase the accuracy level of the semantic segmentation process.

Secondly, the semantic segmentation algorithm could be developed so that the qualities of the buildings' facades could be detected through the facades' visuals. Thereby, the transparency feature of the streets could be involved to WISS.

Furthermore, the detail level of the 3D digital models would be enhanced so that more measurements with respect to other urban elements influencing the street walkability like street furniture and lighting could be conducted.

Additionally, the urban features involved in the walkability index would be weighted based on the selected criteria in further studies. This would ensure more consistent results according to the importance of the urban components.

Lastly, these computed big data could be investigated by various data analysis methods such as Bayesian Belief Network Analysis or regression in order to question the relationship between the urban features and walkability.

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APPENDICES

A. Examples of Walkability Studies Associated with Medicine and Public Health

Journal	Year	Researchers	Title of the publication
American Journal of Health Promotion	2003	Bourdeaudhuij, Sallis, & Saelens	Environmental Correlates of Physical Activity in a Sample of Belgian Adults
	2004	Humpel et al.	Associations of Location and Perceived Environmental Attributes With Walking in Neighborhoods
	2007	Tilt, Unfried & Roca	Using Objective and Subjective Measures of Neighborhood Greenness and Accessible Destinations for Understanding Walking Trips and BMI in Seattle, Washington
American Journal of Preventive Medicine	2002	Craig, Brownson, Cragg, & Dunn	Exploring the Effect of the Environment on Physical Activity A Study Examining Walking to Work
	2004	Humpel, Owen, Iverson, Leslie, & Bauman	Perceived Environment Attributes, Residential Location, and Walking for Particular Purposes
	2005	Hoehner, Ramirez, Elliott, Handy, & Brownson	Perceived and Objective Environmental Measures and Physical Activity Among Urban Adults
	2008	Troped, Wilson, Matthews, Cromley, & Melly	The Built Environment and Location-Based Physical Activity
	2013	Hajna, Dasgupta, Halparin, & Ross	Neighborhood Walkability: Field Validation of Geographic Information System Measures
American Journal of Public Health	2003	Giles-Corti & Donovan	Relative Influences of Individual, Social Environmental, and Physical Environmental Correlates of Walking
	2004	Addy, Wilson, Kirtland, Ainsworth, & Sharpe	Associations of Perceived Social and Physical Environmental Supports With Physical Activity and Walking Behavior
Annals of Behavioral Medicine	2003	Saelens, Sallis, & Lawrence	Environmental Correlates of Walking and Cycling: Findings from the Transportation, Urban Design, and Planning Literatures
Health & Place	2007	Cerin, Leslie, Owen, & Frank	Destinations that Matter: Associations with Walking for Transport
	2009	Van Dyck, Deforche, Cardon, & De Bourdeaudhuij	Neighborhood Walkability and Its Particular Importance for Adults with a Preference for Passive Transport
	2010	Lin & Moudon	Objective versus Subjective Measures of the Built Environment, Which Are Most Effective in Capturing Associations with Walking?

International Journal of Environmental Research and Public Health	2011	Duncan, Aldstadt, Whalen, Melly, & Gortmaker	Validation of Walk Score® for Estimating Neighborhood Walkability: An Analysis of Four US Metropolitan Areas
	2017	Chiang, Sullivan, & Larsen	Measuring Neighborhood Walkable Environments: A Comparison of Three Approaches
	2019	Al Shammas & Escobar	Comfort and Time-Based Walkability Index Design: A GIS-Based Proposal
Journal of Epidemiol Community Health	2005	Li, Fisher, Brownson, & Bosworth	Multilevel Modeling of Built Environment Characteristics related to Neighborhood Walking Activity in Older Adults
Journal of Physical Activity and Health	2006	Ewing, Clemente, Handy, Brownson, & Winson	Identifying and Measuring Urban Design Qualities Related to Walkability
	2007	Granner, Sharpe, Hutto, & Addy	Perceived Individual, Social, and Environmental Factors for Physical Activity and Walking
Obesity	2007	Evenson, Scott, Cohen, & Voorhees	Girls' Perception of Neighborhood Factors on Physical Activity, Sedentary Behavior, and BMI
Preventive Medicine	2001	Ball, Bauman, Leslie, & Owen	Perceived Environmental Aesthetics and Convenience and Company Are Associated with Walking for Exercise among Australian Adults
	2005	Duncan & Mummery	Psychosocial and Environmental Factors Associated with Physical Activity among City Dwellers in Regional Queensland
	2008	Frank, Kerr, Sallis, Miles, & Chapman	A Hierarchy of Sociodemographic and Environmental Correlates of Walking and Obesity
	2009	Rosenberg et al.	Neighborhood Environment Walkability Scale for Youth (NEWS-Y): Reliability and Relationship with Physical Activity
Social Science & Medicine	2003	Pikora, Giles-Corti, Bull, Jamrozik, & Donovan	Developing a Framework for Assessment of the Environmental Determinants of Walking and Cycling

B. The Existing Walkability Studies in the Literature Review

Year	Authors	Title of the Publication
2004	Addy, Wilson, Kirtland, Ainsworth, & Sharpe	Associations of Perceived Social and Physical Environmental Supports With Physical Activity and Walking Behavior
2014	Agampatian	Using GIS to Measure Walkability: A Case Study in New York City
2003	Ainsworth, Wilcox, Thompson, Richter, & Henderson	Personal, Social, and Physical Environmental Correlates of Physical Activity in African-American Women in South Carolina
2019	Al Shammas & Escobar	Comfort and Time-Based Walkability Index Design: A GIS-Based Proposal
2005	Alfonzo	To Walk or Not to Walk? The Hierarchy of Walking Needs
2016	Aranoa, Allo, & Serrano	Walkability City Tool (WCT): Measuring Walkability
2015	Bahrainy, Khosravi, Aliakbari, & Khosravi	The Impact of Built Environment on Walkability, Case Study: North-West of Shiraz
2001	Ball, Bauman, Leslie, & Owen	Perceived Environmental Aesthetics and Convenience and Company Are Associated with Walking for Exercise among Australian Adults
2017	Barros, Martínez, & Viegas	How Urban Form Promotes Walkability?
2017	Berzi, Gorrini, & Vizzari	Mining the Social Media Data for a Bottom-Up Evaluation of Walkability
2016	Bhadra, Sazid, & Esraz-Ul-Zannat	A GIS Based Walkability Measurement within the Built Environment of Khulna City, Bangladesh
2003	Bourdeaudhuij, Sallis, & Saelens	Environmental Correlates of Physical Activity in a Sample of Belgian Adults
2010	Brownson, Baker, Housemann, Brennan, & Bacak	Environmental and Policy Determinants of Physical Activity in the United States
2010	Carr, Dunsiger, & Marcus	Walk Score™ As a Global Estimate of Neighborhood Walkability
2007	Cerin, Leslie, Owen, & Frank	Destinations that Matter: Associations with Walking for Transport
1997	Cervero & Kockelman	Travel Demand and the 3Ds: Density, Diversity, and Design

2017	Chiang, Sullivan, & Larsen	Measuring Neighborhood Walkable Environments: A Comparison of Three Approaches
2012	Choi	Walkability as an Urban Design Problem :Understanding the Activity of Walking in the Urban Environment
2002	Craig, Brownson, Cragg, & Dunn	Exploring the Effect of the Environment on Physical Activity a Study Examining Walking to Work
2019	Dovey & Pafka	What is Walkability? The Urban DMA
2005	Duncan & Mummery	Psychosocial and Environmental Factors Associated with Physical Activity among City Dwellers in Regional Queensland
2011	Duncan, Aldstadt, Whalen, Melly, & Gortmaker	Validation of Walk Score® for Estimating Neighborhood Walkability: An Analysis of Four US Metropolitan Areas
2010	Dygryn, Mitas, & Stelzer	The Influence of Built Environment on Walkability Using Geographic Information System
2007	Evenson, Scott, Cohen, & Voorhees	Girls' Perception of Neighborhood Factors on Physical Activity, Sedentary Behavior, and BMI
2010	Ewing & Cervero	Travel and the Built Environment
2013	Ewing & Clemente	Measuring Urban Design Metrics for Livable Places
2006	Ewing, Clemente, Handy, Brownson, & Winson	Identifying and Measuring Urban Design Qualities Related to Walkability
2016	Ewing, Hajrasouliha, Neckerman, Purciel-Hill, & Greene	Streetscape Features Related to Pedestrian Activity
2015	Forsyth	What is a Walkable Place? The Walkability Debate in Urban Design
2006	Frank et al.	Many Pathways from Land Use to Health: Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality
2009	Frank et al.	The Development of a Walkability Index: Application to the Neighborhood Quality of Life Study
2008	Frank, Kerr, Sallis, Miles, & Chapman	A Hierarchy of Sociodemographic and Environmental Correlates of Walking and Obesity

2005	Frank, Schmid, Sallis, Chapman, & Saelens	Linking Objectively Measured Physical Activity with Objectively Measured Urban Form Findings from SMARTRAQ
2002	Giles-corti & Donovan	Socioeconomic Status Differences in Recreational Physical Activity Levels and Real and Perceived Access to a Supportive Physical Environment
2003	Giles-corti & Donovan	Relative Influences of Individual, Social Environmental, and Physical Environmental Correlates of Walking
2007	Granner, Sharpe, Hutto, & Addy	Perceived Individual, Social, and Environmental Factors for Physical Activity and Walking
2018	Gu, Han, Cao, Chen, & Jiang	Using Open Source Data to Measure Street Walkability and Bikeability in China: A Case of Four Cities
2019	Guan, Keith, & Hong	Designing Walkable Cities and Neighborhoods in the Era of Urban Big Data
2013	Hajna, Dasgupta, Halparin, & Ross	Neighborhood Walkability: Field Validation of Geographic Information System Measures
2006	Handy, Cao, & Mokhtarian	Self-Selection in the Relationship between the Built Environment and Walking: Empirical Evidence from Northern California
2005	Hoehner, Ramirez, Elliott, Handy, & Brownson	Perceived and Objective Environmental Measures and Physical Activity among Urban Adults
2004	Humpel et al.	Associations of Location and Perceived Environmental Attributes With Walking in Neighborhoods
2004	Humpel, Owen, Iverson, Leslie, & Bauman	Perceived Environment Attributes, Residential Location, and Walking for Particular Purposes
2004	Humpel, Marshall, Leslie, Bauman, & Owen	Changes in Neighborhood Walking Are Related to Changes in Perceptions of Environmental Attributes
2016	Jahanmohan	Identifying and Measuring Urban Design Qualities Related to Walkability - Special Reference to Jaffna Down Town
2003	King et al.	The Relationship Between Convenience of Destinations and Walking Levels in Older Women
2005	King et al.	Objective Measures of Neighborhood Environment and Physical Activity in Older Women

2006	Krizek & Johnson	Proximity to Trails and Retail : Effects on Urban Cycling and Walking
2015	Ledraa	Evaluating Walkability at the Neighborhood and Street Levels in Riyadh Using GIS and Environment Audit Tools
2006	Lee & Moudon	Correlates of Walking for Transportation or Recreation Purposes
2018	Lefebvre-Ropars & Morency	Walkability: Which Measure to Choose, Where to Measure It, and How?
2007	Leslie et al.	Walkability of Local Communities: Using Geographic Information Systems to Objectively Assess Relevant Environmental Attributes
2005	Li, Fisher, Brownson, & Bosworth	Multilevel Modeling of Built Environment Characteristics related to Neighborhood Walking Activity in Older Adults
2010	Lin & Moudon	Objective versus Subjective Measures of the Built Environment, Which Are Most Effective in Capturing Associations with Walking?
2017	Lu	The Development and Deployment of Walkability Assessment Models for Built Environments
2019	Majic & Pafka	AwaP-IC—An Open-Source GIS Tool for Measuring Walkable Access
2008	Mccormack, Giles-corti, & Bulsara	The Relationship between Destination Proximity, Destination Mix and Physical Activity Behaviors
2008	Mehta	Walkable Streets: Pedestrian Behavior, Perceptions and Attitudes
2007	Moudon, Lee & Schmid	Attributes of Environments Supporting Walking
2018	Motomura, Fontoura, & Kanashiro	Understanding Walkable Areas: Applicability and Analysis of a Walkability Index in a Brazilian City
2019	Nasrin & Afifah	Walkability Assessment Tool for a Developing Country
2012	Nourian & Sariyildiz	Designing for Pedestrians: A Configurative Approach to Neighborhood Planning and Design, Promoting Pedestrian Mobility, Using an Interactive Computational Design Method for ‘Polycentric Distribution of Built Space’ according to Walkability, Attractions and Topographic Features
2014	Oreskovic, Charles, Shepherd, Nelson, & Bar	Attributes of Form in the Built Environment that Influence Perceived Walkability

2007	Owen et al.	Neighborhood Walkability and the Walking Behavior of Australian Adults
2014	Ozer & Kubat	Walkability: Perceived and Measured Qualities in Action
2003	Pikora, Giles-corti, Bull, Jamrozik, & Donovan	Developing a Framework for Assessment of the Environmental Determinants of Walking and Cycling
2015	Quercia, Aiello, & Davies	The Digital Life of Walkable Streets
2008	Rodríguez, Aytur, Forsyth, Oakes, & Clifton	Relation of Modifiable Neighborhood Attributes to Walking
2009	Rosenberg et al.	Neighborhood Environment Walkability Scale for Youth (NEWS-Y): Reliability and relationship with physical activity
2003	Saelens, Sallis, & Lawrence	Environmental Correlates of Walking and Cycling: Findings From the Transportation, Urban Design, and Planning Literatures
2003	Saelens, Sallis, Black, & Chen	Neighborhood-Based Differences in Physical Activity: An Environment Scale Evaluation
2019	Seles & Afacan	Exploring the Relationship between Health and Walkability
2005	Southworth	Designing the Walkable City
2005	Suminski, Poston, Petosa, Stevens, & Katzenmoyer	Features of the Neighborhood Environment and Walking by U.S. Adults
2016	Tekel & Özalp	Effect of Physical and Perceptual Quality on Walkability and Walkers' Satisfaction: Case Study of Atatürk Boulevard in Ankara
2016	Tiemann, Scott, & Atkins	Sidewalks, Streets and Walkability
2007	Tilt, Unfried, & Roca	Using Objective and Subjective Measures of Neighborhood Greenness and Accessible Destinations for Understanding Walking Trips and BMI in Seattle, Washington
2008	Troped, Wilson, Matthews, Cromley, & Melly	The Built Environment and Location-Based Physical Activity
2009	Van Dyck, Deforche, Cardon, & De Bourdeaudhuij	Neighborhood Walkability and Its Particular Importance for Adults with a Preference for Passive Transport

2018	Xia, Li, & Chen	Assessing Neighborhood Walkability Based on Usage Characteristics of Amenities under Chinese Metropolises Context
2010	Yan, Voorhees, Clifton, & Burnier	“Do You See What I See?”– Correlates of Multidimensional Measures of Neighborhood Types and Perceived Physical Activity – Related Neighborhood Barriers and Facilitators for Urban Youth
2016	Yin & Wang	Measuring Visual Enclosure for Street Walkability: Using Machine Learning Algorithms and Google Street View Imagery
2017	Yin	Street Level Urban Design Qualities for Walkability: Combining 2D and 3D GIS Measures
2015	Yin, Cheng, Wang, & Shao	Big data' for Pedestrian Volume: Exploring the Use of Google Street View Images for Pedestrian Counts
2019	Zhu, Hua, & Dogan	Evaluating Street Quality for Walkability from 3D Models