

IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS

DOCTORAL THESIS

ALGORITHMIC SIGNALS, SENTIMENT SPACE, AND
SOCIETAL WELL-BEING THROUGH THE AI LENS: A
CASE STUDY OF TÜRKİYE

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İSTANBUL, 2025

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**by
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**A thesis submitted to the School of Graduate Studies in partial
fulfillment of the requirements for the degree of Doctor of
Philosophy in Economics**

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İSTANBUL, 2025

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ÖZ

YAPAY ZEKA MERCEĞİNDEN ALGORİTMİK SİNYALLER, DUYARLILIK ALANI VE TOPLUMSAL REFAH: TÜRKİYE ÖRNEĞİ

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Bu tez, toplumsal yaşam kalitesi ve refahı değerlendirmek için duyarlılık analizi, makine öğrenimi ve coğrafi mekânsal ağ analitiği yoluyla Türkiye'deki finansal dalgalanma ve mekânsal eşitsizliği araştırmaktadır.

Çalışma, farklı veri setleri ve metodolojiler kullanarak üç alanı analiz etmektedir. Finansal analiz için, Ocak 2015'ten Şubat 2024'e kadar günlük Türk Lirası-USD döviz kurları ve borsa verileri, uluslararası medya (The Economist, The New York Times, The Guardian) ve yerel kaynakların (Yeni Şafak, Türkçe Twitter) duyarlılık analizi ile birlikte incelenmiştir. Tahmin için doğal dil işleme teknikleri ve denetimli makine öğrenimi modelleri, açıklanabilirlik için ise XAI teknikleri kullanılmaktadır. Mekânsal analiz için OpenStreetMap verileri ve belediye kayıtları kullanılarak İstanbul'un 38 ilçesinde 15 dakikalık şehir çerçevesinde ulaşım, yeşil alanlar, kamu hizmetleri, güvenlik altyapısı ve ekonomik faaliyetler olmak üzere beş kentsel boyutta yürüme erişilebilirliğini ölçen bileşik bir yaşanabilirlik endeksi oluşturulmuştur.

Sonuçlar, uluslararası medya duyarlılığının Türk Lirası oynaklığı ile yerel haber kaynaklarına göre daha güçlü ilişkiler gösterdiğini ortaya koymaktadır. Benzer şekilde, borsa tahminleri için, uluslararası haber duyarlılığı modeller arasında öngörülebilirliği tutarlı bir şekilde artırırken, yerel duyarlılık daha az rol

oynamaktadır. Toplu öğrenme yöntemleri, bireysel ağaç tabanlı tekniklere kıyasla daha üstün tahmin doğruluğu elde etmektedir. Kentsel erişilebilirlikle ilgili olarak, birçok İstanbul sakini hizmetlere 15 dakika içinde erişebilirken, ulaşım ve eğlence tesislerine erişim eşit değildir. Merkez ilçeler (Fatih, Beyoğlu, Kadıköy) en yüksek erişilebilirlik seviyelerini sergilerken, çevre bölgeler önemli ölçüde geride kalmaktadır.

Araştırma, ekonomik stres ve istikrarı yakalayan finansal duyarlılık analizi ile kent sakinlerinin duygusal ve fiziksel refahını ölçen kentsel duyarlılık analizini entegre ederek, finansal dalgalanma ve mekânsal eşitsizliğin Türkiye'deki toplumsal yaşam kalitesini nasıl etkilediğini anlamak için bütünsel bir çerçeve sunuyor.

Anahtar Kelimeler: Borsa, Döviz Kuru, Makine Öğrenimi NLP, Kentsel Erişilebilirlik, Kentsel Yaşam Kalitesi, Refah.

ABSTRACT

ALGORITHMIC SIGNALS, SENTIMENT SPACE, AND SOCIETAL WELL-BEING THROUGH THE AI LENS: A CASE STUDY OF TÜRKİYE

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This thesis investigates financial volatility and spatial inequality in Türkiye through sentiment analysis, machine learning, and geospatial network analytics to assess societal quality of life and wellbeing.

The study analyzes three domains using diverse datasets and methodologies. For financial analysis, daily Turkish Lira-USD exchange rates and stock market data from January 2015 to February 2024 are examined alongside sentiment analysis of international media (The Economist, The New York Times, The Guardian) and domestic sources (Yeni Şafak, Turkish Twitter). Natural language processing techniques and supervised machine learning models are employed for prediction, and XAI techniques are used for explainability. For spatial analysis, OpenStreetMap data and municipal records are used to construct a composite livability index across Istanbul's 38 districts, measuring walking accessibility in five urban dimensions: transport, green spaces, public services, safety infrastructure, and economic activity within the 15-minute city framework.

The results indicate that international media sentiment demonstrates stronger associations with Turkish Lira volatility than domestic news sources. Similarly, for stock market predictions, international news sentiment consistently improves predictability across models, while local sentiment plays a lesser role. Ensemble

learning methods achieve superior predictive accuracy compared to individual tree-based techniques. Regarding urban accessibility, while many Istanbul residents can access services within 15 minutes, access to transport and recreational facilities remains uneven. Central districts (Fatih, Beyoğlu, Kadıköy) exhibit the highest accessibility levels, while peripheral areas lag significantly.

The research integrates financial sentiment analysis that captures economic stress and stability with urban sentiment analysis that measures residents' emotional and physical wellbeing, providing a holistic framework for understanding how financial volatility and spatial inequality collectively impact societal quality of life in Türkiye.

Keywords: Machine Learning NLP, Stock Market, Exchange Rate, Urban Accessibility, Urban Quality of Life, Well-being.

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It is with profound reverence and boundless gratitude that I recognize my brother, Ismael, whose extraordinary devotion, countless sacrifices, and unwavering belief in my potential have been the cornerstone of my intellectual and personal development. His selfless dedication to my academic aspirations has been a source of immeasurable strength, and I am deeply cognizant that the foundations of my scholarly achievements rest upon his remarkable support. To his entire family, I extend my heartfelt appreciation for their collective embrace and encouragement throughout my academic journey.

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LIST OF SYMBOLS AND ABBREVIATIONS

XAI	Explainable Artificial Intelligence
AI	Artificial Intelligent
TUIK	Turkish Statistical Institute
NLP	Natural Language Processing
API	Application Programming Interface
ML	Machine Learning
FindBERT	Financial Domain Bidirectional Encoder Representations from Transformers
BERT	Bidirectional Encoder Representations from Transformers
QOL	Quality of Life
OLI	Overall Livability Index
LI	Livability Index
ROC	Receiver Operating Characteristic
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
TP	Total Positive
TN	Total Negative
FP	False Positive
FN	False Negative

CHAPTER I

INTRODUCTION

Human well-being represents the fundamental foundation upon which societal prosperity rests (Chan et al., 2024). It is a multidimensional construct that encompasses physical health, psychological equilibrium (Gong et al., 2024), social integration, and material sufficiency components that collectively determine individual and community thriving (Khalil, 2012). Macroeconomic conditions, like price stability, play a decisive role in shaping well-being through various pathways that influence both objective circumstances and subjective perceptions of life quality (Aretz, 2022).

Economic volatility, elevated or unpredictable inflation rates, undermine well-being through multiple mechanisms (Bloom, 2009). Financially, price instability erodes purchasing power among fixed-income households, diminishing access to essential goods and services while potentially triggering resource allocation decisions that compromise health and nutrition (IMF, 2023). Psychologically, economic uncertainty generates chronic stress responses, exacerbating anxiety disorders and diminishing cognitive capacity for long-term planning. Emotionally, financial precarity frequently manifests in heightened familial tension, relationship strain, and decreased life satisfaction indicators (Cupák et al., 2024). These consequences transcend purely financial calculations, embedding themselves within the social fabric through community fragmentation, increased crime rates, and deteriorating public health metrics approach (Bachmann & Bayer, 2013).

Conversely, economic stability creates conditions where individuals experience sufficient security to engage in activities promoting overall socioeconomic and psychic well-being (Cupák et al., 2024). Stable prices facilitate budget predictability, enabling households to allocate resources toward health-promoting behaviors, educational advancement, and meaningful leisure pursuits. This stability fosters

psychological resilience through reduced financial stress and expanded temporal horizons for personal development (Friel et al., 2014). When inflation remains moderate and predictable, individuals report higher subjective well-being scores across diverse measurement instruments, which reflects the profound link between economic environments and human flourishing.

The spatial organization of urban environments constitutes another imperative determinant of resident well-being (Wilson, 1984). Quality of life (QOL) is one of the key concepts for successful urban planning and is therefore often addressed in planning policies worldwide (Khalil, 2012). This recognition emerges from extensive empirical evidence demonstrating correlations between neighborhood characteristics and well-being indicators. Inaccessible environments generate significant opportunity costs through extended commuting requirements, while accessible urban configurations maximize time available for wellbeing-enhancing activities (Chan et al., 2024).

Accessibility of transport infrastructure (Chan et al., 2024), commercial, urban amenities (Yang & Chen, 2025), recreational facilities (Ojonugwa, 2024), and green spaces (Gong et al., 2024) is widely recognized as an important element to the well-being of urban residents. This relationship manifests through several pathways: physical health improves through walkable environments that encourage routine physical activity; mental well-being enhances through reduced transportation stress and increased exposure to natural elements; social cohesion strengthens through accessible public spaces facilitating spontaneous community interaction; and economic opportunity expands through efficient access to employment centers across socioeconomic strata (Baumann & Brooks-Cederqvist, 2023).

The intersection between economic stability and urban accessibility creates powerful synergistic effects on well-being. When residents experience both macroeconomic and financial security and spatial convenience, their capacity for well-being is enhanced. Economic stability provides the financial foundation for utilizing proximate amenities, while thoughtful urban design ensures these amenities remain accessible regardless of economic fluctuations (Dobrowolska & Kopczewska, 2024; Bachmann & Bayer, 2013).

While the concept of well-being is broad and multifaceted, this study operationalizes well-being through two primary approaches as illustrated in Figure 1.1. First, we examine financial security and financial stress through news sentiment and X, the defunct (Twitter) analysis in exchange rate and stock markets, which captures the economic pressures that influence individual and collective well-being outcomes. Please see Chapters 3 and 4 for detailed descriptions and explanations. Second, we assess urban accessibility using five essential urban dimensions, which affect residents' quality of life and their ability to access essential services and opportunities in the urban environment. Detailed explanations are presented in Chapter 5.

In the subsequent sections of this chapter, we present (1) a sequential elaboration of the identified research gap and corresponding research questions, (2) the underlying motivation and relevance of this investigation to both national and global economic priorities, (3) the specific objectives guiding this study, (4) the anticipated significance and contributions of this work, and (5) the organizational structure and layout of the dissertation.

1.1. Research Gap

The central theme of this thesis is societal well-being, addressed through two distinct empirical tracks. The first investigates whether news sentiment can predict financial market movements in Türkiye. The second assesses urban quality of life in Istanbul using the 15-minute city framework. These components are unified through a conceptual framework that treats both financial sentiment and urban accessibility as reflections of physical, emotional, psychological, and economic well-being.

Despite the increasing use of sentiment analysis in finance and geospatial techniques in urban studies, existing research does not connect these approaches within a single study. Studies that apply natural language processing to financial markets have concentrated on developed economies, often excluding countries with emerging financial systems such as Türkiye. Moreover, most existing models overlook the behavioral aspects of investor decisions, which are central to financial volatility in such contexts. The literature tends to treat sentiment data as purely informational, which overlooks the psychological mechanisms emphasized in behavioral finance.

Likewise, research on urban accessibility rarely positions spatial proximity as a proxy for societal well-being or psychological stability, and typically isolates urban infrastructure from broader well-being outcomes.

Research in Türkiye remains limited in both strands. In financial markets, the predictive role of media sentiment, including distinctions between local, international, and social media sources, has not been systematically examined using machine learning or natural language processing methods. There is no research that integrates news sentiment and spatial accessibility data to examine how economic signals and urban conditions jointly reflect societal well-being. There is also no study applying these methods using natural language processing and geospatial analytics together in the context of Türkiye or its urban representation through Istanbul.

1.2. Research Questions

This thesis investigates two central questions grounded in the broader objective of analyzing societal well-being. First, it asks whether sentiment derived from news sources can predict exchange rate volatility and stock market performance in Türkiye. This question tests both the Efficient Market Hypothesis, which assumes all available information is reflected in asset prices, and behavioral theories, which suggest that market movements are influenced by psychological reactions to news content. A set of hypotheses in Chapter 2 differentiates between the predictive power of international, local, and social media sources. These hypotheses aim to test whether international media exert a stronger influence on market outcomes compared to domestic or user-generated sources, and whether news sentiment overall contributes more to prediction than social media sentiment.

The second research question concerns the relationship between urban accessibility and quality of life across Istanbul's 38 districts. Using the 15-minute city framework, the analysis evaluates accessibility across five key dimensions: transport and mobility, green and recreational spaces, public service infrastructure, urban safety, and economic opportunity. These dimensions are operationalized through spatial data and combined into a single livability index. The question focuses on whether disparities in accessibility can be interpreted as differences in societal well-being,

using physical proximity as a proxy for emotional, psychological, and economic security. The approach treats Istanbul not only as an urban system but also as a spatial representation of national urban development patterns and inequalities.

1.3. Objectives of the Study

This thesis examines societal well-being through the analysis of financial market sentiment and urban accessibility patterns in Türkiye. The research investigates how news sentiment influences exchange rate volatility and stock market movements, while also measuring spatial disparities in access to essential services across Istanbul's districts.

The objective is to examine how financial market sentiment affects societal well-being through exchange rate mechanisms. This research analyzes Turkish Lira/US Dollar exchange rate volatility from 2015 to 2024, a period when currency depreciation triggered widespread economic hardship for Turkish citizens. News and Twitter sentiment serve as an emotional barometer affecting investor and consumer confidence. The analysis predicts how negative sentiment translates into currency instability, which subsequently erodes purchasing power, increases inflation, raises import prices, and reduces real wages all direct determinants of financial well-being for the average citizen.

The study investigates societal well-being through stock market dynamics as reflections of economic and financial health. Using the same news, Twitter, and sentiment analysis, this research examines how media narratives predict Turkish stock market movements. Stock market performance functions as both an indicator of economic stability and a direct influence on public financial security through investment returns, pension funds, and corporate hiring capacity.

The research examines the comparative influence of international versus local media on Turkish financial markets by analyzing power dynamics in global information flows and their effects on market psychology. The study predicts how emotional content in financial news generates market volatility, undermines economic planning

capabilities for businesses and households, and ultimately impacts the financial security dimension of societal wellbeing.

The study addresses physical dimensions of societal well-being through urban accessibility patterns in Istanbul. It quantifies how the spatial distribution of essential services within 15-minute walking distance affects quality of life across Istanbul's 38 districts. The analysis examines five dimensions of urban accessibility: transportation networks, green spaces, public services, safety infrastructure, and economic opportunities. These physical environment factors determine residents' daily stress levels, time allocation efficiency, physical health outcomes, and social connection opportunities. The resulting district-level well-being index measures how urban design and service distribution create fundamental inequalities in lived experience, complementing the financial well-being analysis with spatial determinants of overall life satisfaction.

The research synthesizes financial and spatial well-being frameworks into an integrated theory of societal welfare by establishing conceptual connections between sentiment-driven financial markets and physical urban accessibility. Negative market sentiment creates financial instability that manifests in higher rental prices, which subsequently forces citizens to accept less accessible housing locations. This cycle reduces access to essential services, increases transportation costs, and diminishes quality of life through multiple reinforcing mechanisms. The relationship between financial security and urban quality of life reveals how economic stress and spatial constraints jointly determine overall societal well-being through interconnected pathways that transcend traditional disciplinary boundaries in economics and urban planning.

Finally, the study contributes methodological innovations that enable evidence-based policy development for societal well-being enhancement. Through explainable AI techniques, including Shapley values, feature importance analysis, and interpretable machine learning models, this research transforms complex predictive frameworks into transparent decision support tools. These methodological advances permit precise identification of which factors most strongly influence both financial stability and urban accessibility. The resulting analytical clarity enables targeted policy

interventions in financial market regulation, urban planning, and public service distribution that can effectively improve societal well-being across both economic and spatial dimensions. Figure 1 illustrates the thesis's framework.



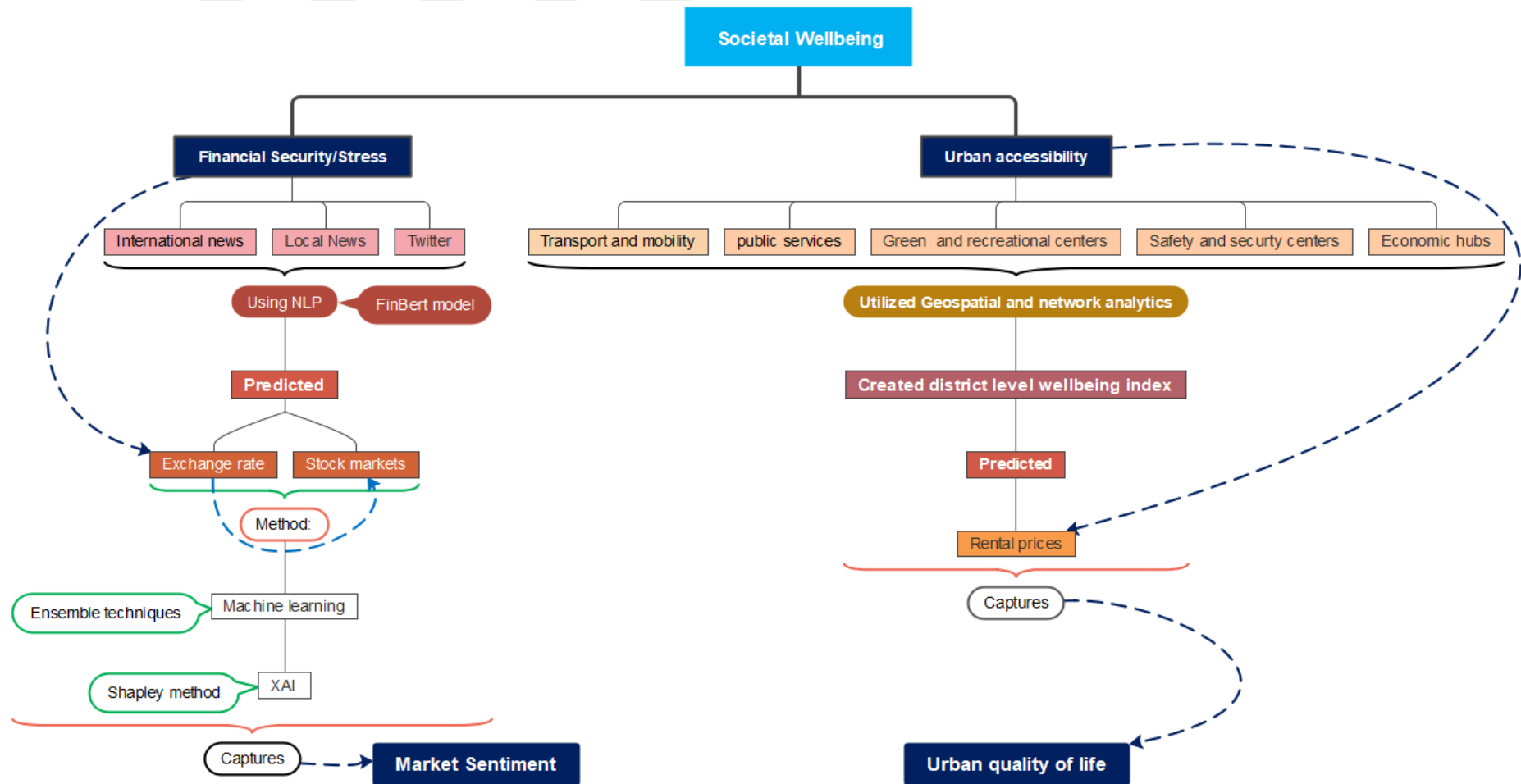


Figure 1.2. Thesis Framework Follow Chart

1.4. Motivation and Relevancy to National and Global Priorities

In recent years, the expansion of digital communication technologies and social platforms has led to the generation of vast volumes of unstructured data that reflect social, economic, and political behavior in real time. Thus, modern economies are increasingly shaped by digital transformations that have redefined how information is generated, processed, and used for policy and decision-making. In earlier decades, macroeconomic forecasting and financial modeling relied primarily on structured datasets such as time series, cross-sectional, or panel data, which were updated infrequently and often lacked contextual depth. While these sources remain relevant, they are limited in their ability to capture the complexity and immediacy of market reactions during periods of heightened uncertainty. Expressed in other ways, traditional datasets often suffer from both temporal frequency and contextual richness. In contrast, the rapid growth of unstructured data, including news reports, social media content, blogs, satellite imagery, and online commentary, offers new opportunities to observe and quantify the behavioral and informational dynamics that influence volatility detection in financial markets and macroeconomic trends (Gentzkow et al., 2019).

The ability of Natural language processing tools to transform such unstructured textual inputs into predictive signals has been made possible through advances in natural language processing tools and machine learning techniques. These tools allow for the extraction of sentiment, attention, and discourse features from large corpora of text that reflect real-time public opinion and institutional narratives. Unlike linear models that rely on predetermined variable relationships, machine learning can detect nonlinear patterns and interactions among a broader set of inputs. Moreover, the incorporation of explainable AI methods has provided a structured way to trace the reasoning behind each prediction, which is useful in domains where model transparency affects credibility and adoption (Doshi-Velez & Kim, 2017). In financial applications, explainability enables analysts and regulators to interpret how specific sentiments or events contribute to the volatility forecast.

Modern cities constitute pivotal engines of global economic development, primary hosts for burgeoning populations, and critical crucibles for innovation and

technological advancement. This concentration of human activity and capital, however, presents profound challenges for equitable living conditions and sustainable growth, demanding sophisticated governance frameworks. Recognizing this imperative, the Republic of Türkiye has explicitly prioritized enhancing urban habitability and citizen welfare within its successive national development plans; these strategic documents consistently emphasize integrated spatial planning, improved service delivery infrastructure, and the fostering of inclusive, resilient urban environments as core objectives for national progress. Moreover, the global community, through the United Nations 2030 Agenda for Sustainable Development (UN, 2015), has established a universal framework designed explicitly to guide the transformation towards inclusive, safe, resilient, and sustainable cities and communities, thereby directly addressing urban well-being. Thus, this methodological approach is motivated not only by technical considerations but also by national development priorities and global development plans.

The use of such data-driven, predictive tools directly supports the strategic priorities outlined in the Eleventh Development Plan of Türkiye (2019–2023). The plan was developed during a period of heightened uncertainty marked by global power realignments, trade tensions, technological rivalry, and increased volatility in international markets. It recognizes that economic policy must now operate under conditions where conventional forecasting tools are no longer sufficient, and where decision-making requires continuous adaptation to evolving global dynamics (Republic of Türkiye Presidency, 2019).

To tackle these challenges, the plan identifies five fundamental development pillars, each of which establishes a strategic direction for public investment and institutional reform:

- **Stable and Strong Economy:** This pillar emphasizes the need for sustainable growth, macroeconomic stability, and improved resilience to external shocks. The use of machine learning for forecasting contributes to this goal by improving the detection of potential volatility and supporting proactive economic management.
- **Competitive Production and Productivity:** The second pillar supports technological transformation and the digitalization of economic activity. It advocates for the adoption of advanced tools, including artificial intelligence, in

finance, manufacturing, and public administration. This directly aligns with the methodological innovations in this study, which incorporate sentiment-based forecasting into economic analysis.

- **Qualified Human Capital and Strong Society:** This pillar promotes inclusive access to health, education, and labor market opportunities. While the present study focuses on financial dynamics, it also incorporates spatial data on education and health accessibility within urban environments, which contributes to this pillar's objective of building a more equitable society.
- **Livable Cities and Sustainable Environment:** The fourth pillar addresses urban infrastructure, environmental resilience, and spatial well-being. This is directly related to the urban accessibility dimensions in this study, which assess access to public transportation, green spaces, economic hubs, security centers, and essential services.
- **Rule of Law, Democratization, and Good Governance:** The final pillar calls for greater transparency, institutional accountability, and evidence-based policymaking. The inclusion of explainable AI techniques enhances the interpretability of the models used in this study and supports decision-making that is both data-driven and publicly accountable.

In addition to national priorities, this research complements and aligns with the goals of the United Nations 2030 Agenda for Sustainable Development, most notably SDG 11, which calls for inclusive, safe, resilient, and sustainable cities. Sustainable Development Goal 11 (SDG 11), dedicated to sustainable cities and communities, provides the principal international lens through which urban accessibility, a fundamental determinant of well-being, is assessed. This research engages directly with Goal 11's mandate by developing a multidimensional accessibility framework. The framework operationalizes core concepts embedded within specific SDG 11 targets, focusing on equitable access to essential urban services and opportunities. Consequently, the dimension of Mobility and Public Transport corresponds to Target 11.2, which mandates access to safe, affordable, accessible, and sustainable transport systems for all. The dimension concerning Green Spaces and Recreational Facilities aligns with Target 11.7, which calls for universal access to safe, inclusive, and accessible green and public spaces. Furthermore, the dimensions evaluating

accessibility to Economic and Financial Hubs, Security and Safety Centers, and Education and Health Centers collectively address the integrated planning requirements of Target 11.3; this target aims to enhance inclusive and sustainable urbanization through participatory and integrated human settlement planning and management.

While SDG 11 provides the primary architectural framework, the research inherently connects to broader sustainable development objectives due to the interconnected nature of urban well-being. Accessibility to Education and Health Centers constitutes a direct contribution to SDG 4 (Quality Education), particularly Targets 4.1, 4.3, and 4.5 on inclusive and equitable education, and to SDG 3 (Good Health and Well-being), notably Target 3.8 on universal health coverage. Equitable access to Economic and Financial Hubs underpins SDG 8 (Decent Work and Economic Growth), specifically concerning full employment and decent work (Target 8.5) and entrepreneurship (Target 8.3). The dimension of Security and Safety Centers resonates with SDG 16 (Peace, Justice, and Strong Institutions), particularly Target 16.1 on reducing violence and related death rates and Target 16.3 on promoting the rule of law.

Therefore, this multidimensional assessment of macroeconomic predictions via text analytics and urban accessibility serves as a vital analytical tool for evaluating progress towards sustainable economic and urban development as articulated by national and global development plans.

1.5. Significance and the Contribution of the Study

This thesis offers significant contributions to the understanding and measurement of societal well-being in Türkiye. Conceptually, it establishes a unified framework that connects financial market sentiment with spatial accessibility as dual determinants of well-being. Methodologically, the research applies novel combinations of natural language processing, explainable AI techniques, and geospatial network analytics to examine well-being dimensions that traditional economic metrics cannot capture. The study maintains rigor through scrutiny of model assumptions and predictions, using explainable AI to transform "black box" algorithms into transparent analytical

tools. The practical relevance emerges from the sentiment indices and unified livability metrics that quantify previously unmeasured aspects of economic and spatial wellbeing. These innovations yield direct policy implications for financial market regulation, urban planning, and public service distribution to address well-being disparities across both economic and geographic dimensions.

The contribution lies in its methodological shift from conventional economic measurements. While traditional economic analyses rely primarily on time series data to measure financial well-being, this study employs text analytics on news media and social platforms. This approach captures psychological dimensions of market behavior not accessible through numerical data alone. The resulting sentiment metrics reveal emotional responses to economic conditions that precede measurable market movements, thus enhancing predictive capabilities while providing richer contextual understanding of financial well-being determinants.

The research advances methodological approaches for financial market analysis through machine learning algorithms that predict market sentiment effects on currency exchange rates and stock performance. Traditional econometric and time series models show limited capacity to capture non-linear relationships in financial markets during high volatility periods. Machine learning models overcome these limitations through their ability to identify patterns within large, unstructured datasets without linear relationship assumptions. This research addresses the "black box" limitation with explainable artificial intelligence (XAI) techniques that make machine learning predictions interpretable, maintaining analytical rigor while enhancing transparency.

The study develops a sentiment index derived from textual data through transformer models and advanced natural language processing techniques (NLP). This index converts emotional content from international and local news sources into numerical values for inclusion in financial forecasting models.

The research establishes a Unified Livability Index for Istanbul's 38 districts with network and geospatial analytics. Istanbul serves as an ideal case study with its population exceeding 16 million residents, representing nearly one-fifth of Türkiye's

total population. The city's demographic, economic, and social diversity mirrors national patterns to such an extent that the common axiom "Istanbul is Türkiye and Türkiye is Istanbul" reflects its status as a microcosm of the country. This contribution addresses shortcomings in traditional well-being measures that focus on income and consumption rather than spatial dimensions of quality of life. The index includes multiple aspects of urban accessibility: transportation networks, public services, green spaces, safety infrastructure, and economic opportunities, all measured through 15-minute walking distance parameters. This approach serves as the first expansive spatial well-being assessment for Istanbul with network analytics and provides urban planners and policymakers with precise metrics to identify service gaps and accessibility inequalities.

Finally, this thesis combines financial and spatial approaches to well-being measurement into one conceptual framework. Economic research typically treats financial markets and urban planning as separate domains, which limits understanding of how these systems affect the overall quality of life. This research shows how sentiment-driven financial volatility and urban accessibility constraints worsen socioeconomic disparities. The framework identifies feedback mechanisms between financial stress and spatial inequality, and shows how market sentiment affects housing affordability, which then influences access to essential services and overall well-being

1.6. The Layout of the Study

The study is organized into five chapters:

Chapter 1 establishes the conceptual and theoretical framework for well-being measurements. It introduces the research context, reviews relevant literature on financial market sentiment, urban accessibility, and well-being metrics, defines objectives, and outlines the significance of the study.

Chapter 2 investigates exchange rate dynamics through textual data from news headlines and social media (Twitter) discourse using Natural Language Processing techniques, machine learning techniques, and explainable (XAI) machine learning

methods to predict exchange rate volatility, examine its effects on society, and perform interpretability of the impacts.

Chapter 3 extends the applications of textual sentiment to Turkish stock markets (BIST100) and examines how news sentiment influences market behavior utilizing the same techniques as in the first Chapter 1.

Chapter 4 examines urban dimensions of well-being and analyzes how economic instability affects daily life for Istanbul residents. The study evaluates urban connectivity and reachability across five domains through geospatial and network analytics: Transportation Networks, Green Infrastructure, Public Service Distribution, Urban Security, and Economic Opportunity Landscapes. A unified livability index has been developed to perform comparative analysis across Istanbul's 38 districts and discuss geographical disparities and distributional asymmetry of resources. The chapter further ties and connects these findings to rental market dynamics and demonstrates how inflation affects household economic pressures.

Chapter 5 presents a unified conclusion of the three chapters (2, 3, and 4), policy recommendations, limitations of the research, and directions for future study.

CHAPTER II

THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

2.1. How Inflation Uncertainty Creates Psychological and Financial Stress

This chapter examines the impact of inflation and economic uncertainty on psychological and financial stress, explores the dimensions of quality of life and urban accessibility along with their measurement approaches, and applies these concepts to the Turkish context by providing a concise, synoptic overview of the country's macroeconomic fluctuations and currency volatility over the past decade.

Inflation, defined as the sustained increase in the general price level of goods and services, exerts profound effects on both economies and societies. The insidiousness of inflation, with its capacity to erode purchasing power and redistribute wealth in ways that often exacerbate inequality, has been sharply noted by Milton Friedman, who aptly observed, "Inflation is taxation without legislation" (Friedman, 1970). This economic phenomenon operates through multiple channels, disrupting economic stability by distorting price signals, undermining savings, and creating uncertainty for businesses and consumers alike. While low and predictable inflation can stimulate spending and investment, high and volatile inflation acts as what the IMF (2023) terms a "silent thief," diminishing the real value of incomes and savings, which affects those on fixed wages or reliant on cash holdings.

Moreover, apart from its material consequences, inflation carries considerable psychological weight and plays a paramount, central role in shaping economic behavior. Expectations account for approximately one-third of economic behavior, while monetary and fiscal policies constitute the remaining determinants (Akerlof & Shiller, 2009). Economic uncertainty fosters a pessimistic outlook, a bleak horizon, and an opaque business climate, which undermines investment by eroding

confidence in future returns (Bloom, 2009). This psychological impact manifests in what economists term a "wait-and-see" approach (Bachmann & Bayer, 2013).

The "wait-and-see economy" refers to an economic environment characterized by postponement behavior, where both businesses and households delay significant expenditures due to uncertainty. In such conditions, businesses demonstrate reluctance toward capital investments, while consumers exhibit heightened caution regarding discretionary spending. Households postpone major purchases such as automobiles, appliances, and vacation planning. Concurrently, firms display hesitancy in expanding their workforce and implementing capital expenditure projects, which creates a broader pattern of economic conservatism amid perceived instability¹.

Thus, the "wait-and-see" phenomenon represents a pernicious friction in macroeconomic systems. When economic agents collectively adopt postponement behaviors, the resultant observation inevitably reveals adverse outcomes. This widespread hesitation, in conjunction with the effects of fiscal policy instruments (taxation structures) and government expenditure patterns, functions to impede economic expansion and attenuate growth trajectories². Therefore, uncertainty and predictability of the economic horizon climate are fundamental factors in market psychology, as John Maynard Keynes presciently noted, "The state of long-term expectation is often steady until it is not," which pictures how sudden shifts in confidence can have destabilizing effects on economic activity (Keynes, 1936).

¹ <https://www.apolloacademy.com/this-is-a-wait-and-see-economy/>

² <https://www.linkedin.com/pulse/wait-see-economy-david-kelly-colwe/>



Figure 2.1. Wait-and-See Situation

Türkiye's post-2015 economic situation provides a compelling case study of these theoretical principles in action. As one of the world's largest emerging markets, which is ranked among the top 20 economies globally, Türkiye's strategic position at the crossroads of Europe and Asia magnifies the significance of its economic stability (World Bank, 2023). The roots of Türkiye's inflation crisis emerged from the combined effects of structural vulnerabilities and consistent external pressures, beginning with the 2015 geopolitical turmoil and the failed coup attempt in 2016. These events triggered a steady depreciation of the Turkish lira, exacerbated by unorthodox monetary policies and a reluctance to raise interest rates in line with global trends³.

The consequences of this policy approach became starkly apparent by 2022, when inflation surged to over 85%, the highest level in 24 years, driven by soaring energy prices, supply chain disruptions, and a weakening currency⁴. This inflationary spiral has disproportionately affected low- and middle-income households, who spend a

³ <https://www.euronews.com/2022/11/09/everything-is-overheating-why-is-Türkiye-s-economy-in-such-a-mess>

⁴ <https://www.aljazeera.com/economy/2022/1/7/just-how-bad-is-inflation-in-Türkiye-it-depends-on-who-you-ask>

larger share of their income on essential goods such as food and housing⁵. The erosion of purchasing power has created a feedback loop between economic instability and social inequities, leading to a deterioration in public health and education outcomes as households cut back on non-essential expenditures (Movsisyan, 2024).

The business sector, mainly the small and medium-sized enterprises (SMEs), has borne the brunt of this economic turbulence. These firms, lacking substantial financial buffers, have struggled to adapt to rising input costs and fluctuating demand, resulting in widespread closures and job losses⁶. Moreover, the inflationary environment has prompted a significant shift in financial behavior, with many Turks turning to cryptocurrency as an alternative store of value⁷. This adaptation reflects a broader erosion of trust in traditional monetary instruments and highlights the psychological toll of persistent inflation.

Research indicates that unexpected inflation strongly correlates with reduced life satisfaction and heightened stress levels (Cupák et al., 2024). This psychological burden, combined with the uneven distribution of inflation's impacts, has strained social cohesion and public institutions. As Keynes prophetically stated, "There is no subtler, no surer means of overturning the existing basis of society than to debauch the currency" (Keynes, 1919). The Turkish experience thus validates historical observations about inflation's capacity to destabilize not only economic systems but also social structures, echoing similar patterns observed in historical episodes such as the Weimar Republic's hyperinflation and more recent Latin American crises (Bernholz, 2003).

⁵ <https://www.worldbank.org/en/country/Türkiye/overview>

⁶ <https://www.euronews.com/business/2024/01/03/Türkiye-inflation-soars-to-over-one-year-high-at-648>

⁷ [https://www.europarl.europa.eu/RegData/etudes/STUD/2023/741495/IPOL_STU\(2023\)741495_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2023/741495/IPOL_STU(2023)741495_EN.pdf)

2.2. The Impact of Economic Hardship on Societal Well-being

Economic stressors adversely influence individual and collective mental health outcomes through a range of material, infrastructural, and psychosocial mechanisms. Empirical evidence consistently demonstrates a strong relationship between rising living costs (Liddell & Morris, 2010). and psychological deterioration, mediated by housing instability (Bentley et al., 2011; Smith et al., 2024), energy insecurity (Hernández, 2016), nutritional deprivation (Gundersen & Ziliak, 2015), limited mobility due to inadequate transportation systems (Zhao et al., 2018), escalating healthcare expenditures (Himmelstein et al., 2019), growing educational financial burdens (Walsemann et al., 2015), labor market precariousness (Benach et al., 2014), employment fragility (Roelfs et al., 2011), and diminished access to childcare, eldercare, and other critical social services (Berkman et al., 2014).

Moreover, persistent inflationary pressures and exchange rate instability contribute to investment uncertainty and foster a bleak investment environment, further constraining and eroding household wealth accumulation and heightening future economic insecurity (Solarin & Gil-Alana, 2021). Therefore, these conditions function simultaneously as direct economic determinants and as structural social determinants of health, which produce persistent psychological outcomes. They intensify income volatility, constrain household consumption capacity, deepen material deprivation, weaken financial buffers, and destabilize long-term financial planning, impede access to capital accumulation pathways, and reinforce cumulative socioeconomic disadvantage, ultimately destabilizing psychological resilience and exacerbating disparities in mental health across differentiated income strata (Solarin & Gil-Alana, 2021).

Therefore, the relationship between economic instability and mental health outcomes shows consistency across economic cycles, national boundaries, and geographical contexts, which points to universal psychological responses to economic precarity. Janlert established a causal link between unemployment and deterioration in health status through longitudinal analysis (Janlert, 1997). Similarly, this study documented strong positive associations between unemployment and numerous adverse health outcomes using multivariate analytical frameworks (Jin et al., 1995).

Nevertheless, specific economic hardships produce distinct psychological effects through varied pathways. Liddell and Morris quantified fuel poverty through a multivariable calculation that incorporated household income, heating fuel costs, and residential energy efficiency (Liddell & Morris, 2010). Their results documented significant negative effects on both physical and mental health outcomes. These effects occur through both physiological stress responses to inadequate thermal comfort and psychological distress related to financial insecurity. Others documented direct correlations between reduced food affordability from price increases and elevated psychological distress indicators (Friel et al., 2014). The physiological and psychological interconnections between nutritional status and mental health serve as key mechanisms through which economic pressures affect psychological well-being.

Furthermore, economic recessions represent periods of intensified economic pressure with corresponding mental health consequences. The 2008 global financial crisis generated Compelling evidence about these relationships. For instance, this report shows international suicide rate increases that coincided with heightened price inflation during this period (Ibrahim et al., 2019). The World Health Organization attributed these outcomes to recession-induced negative transformations across income distributions, educational opportunities, healthcare accessibility, and housing and labor market conditions. A study by Jónsdóttir and others confirmed increased stress and diminished well-being that persisted after the immediate economic shock, which was linked to sustained unemployment and financial strain (Jónsdóttir et al., 2020). One study that conducted a systematic review identified 18 studies that reported increased suicide rates during economic recession periods, with 10 of 12 studies that examined unemployment-suicide correlations and found positive associations (Pratap et al., 2021).

Moreover, geographic variations in these patterns provide additional evidence for causal mechanisms. An empirical study conducted in Korea documented a positive association between unemployment rates and suicide (Chan et al., 2014). Similar phenomena have been reported in Spain (Colell et al., 2015), while financial and employment-related issues were found to have contributed to 13% of suicide deaths in the United Kingdom between 2010 and 2011 (Coope et al., 2015). Likewise, evidence from Australia further supports this pattern, with increased rates of suicide

and health problems observed among economically inactive and unemployed populations (Milner et al., 2014). Subsequent research identified both unemployment and underemployment as significant contributors to suicide mortality between 2004 and 2016 (Skinner et al., 2023). These consistent findings across diverse economic and cultural contexts strengthen evidence for causal relationships between economic conditions and mental health outcomes.

Subsequently, the COVID-19 pandemic created a distinct economic shock with specific mental health implications. Pandemic-induced unemployment worsened pre-existing behavioral health disorders and contributed to the onset of new disorders for previously unaffected individuals in the United States (Drake et al., 2021). Also, both unemployment and underemployment were found to have threatened mental health during this period, with varying impacts across different demographic groups (Lee et al., 2021). These findings thus indicate that economic shocks produce heterogeneous effects that depend on pre-existing vulnerabilities and social support systems.

Consequently, social institutions moderate relationships between economic pressures and mental health outcomes. Higher levels of school social capital correlate with improved mental health outcomes and indicate that educational institutions provide protective benefits against economic stressors (Li et al., 2020). Economic hardship intensifies social exclusion for individuals with mental health conditions and worsens educational inequality, and calls for interventions to promote social participation during economic crises (Evans-Lacko et al., 2013). Multiple pathways through which recession affects mental health have been identified, including prolonged unemployment, job insecurity, financial loss, bankruptcy, and home repossession (Haw et al., 2015). These factors result in depression and anxiety disorders. These social mechanisms constitute potential intervention points for the mitigation of economic effects on psychological well-being.

Hence, prevention strategies require specific economic interventions according to recent research. Another study found that economic hardship and unemployment increase suicide risk at both societal and individual levels (Mathieu et al., 2022). Their analysis indicates that unemployment benefits and minimum wage protections may reduce suicide rates, though evidence on targeted financial interventions

remains limited. They recommend financial sector interventions and literacy programs alongside traditional mental health approaches.

Thus, the empirical literature establishes multiple causal pathways that connect economic conditions to mental health outcomes through both direct stress mechanisms and indirect effects on social participation, housing stability, and access to essential goods and services. The evidence supports policy interventions that address both economic security and social support systems to reduce adverse mental health consequences during periods of economic hardship.

2.3. The Definition and Dimensions of Quality of Life

This section discusses the meaning and dimensional constructs of the term Quality of Life. More detailed explanations are provided in Chapter 4. The term "quality of life" lacks definitive etymological origins and resists universal definitional consensus despite its significant scholarly attraction across disciplines. At its fundamental level, this construct refers to "the more or less 'good' or 'satisfactory' character of people's life" (Szalai 1980, p. 8). This multifaceted concept possesses several distinctive characteristics worthy of analytical attention: it applies exclusively to human existence; it consistently appears in singular rather than plural form; it functions as an indivisible generic term whose semantic boundaries remain malleable yet comprehensible; and it defies straightforward categorization within conventional social science taxonomies (Szalai 1980). Notwithstanding definitional variations, substantial conceptual overlap exists among methodological approaches researchers employ when operationalizing and measuring this construct in empirical investigations.

Quality of life assessment necessitates consideration of two fundamental dimensions, which create a dialectical relationship between external realities and internal perceptions. The first dimension encompasses exogenous (objective) circumstances constituting an individual's lived environment, including material conditions, infrastructural access, and quantifiable resources. The second dimension comprises endogenous (subjective) interpretations through which individuals perceive, evaluate, and internalize these external conditions (Dobrowolska & Kopczewska, 2024; Khalil,

2012; Lo, 1997; Santos & Martins, 2007). This dichotomous framework represents the principal categorical distinction recognized throughout quality-of-life literature. Grayson and Young (1994, p. 2) articulate this dualism succinctly:

There appears to be a consensus that in defining quality of life there are two fundamental sets of components and processes operating: those that relate to an internal psychological mechanism producing a sense of satisfaction or gratification with life and those external conditions which trigger the internal mechanism.

The objective assessment methodology concentrates on environmental factors and quantifiable living conditions that exist independently of individual perception. This approach privileges empirical measurement of material circumstances that theoretically influence well-being. Conversely, the subjective assessment tradition prioritizes affective and cognitive evaluations, essentially how individuals feel about and interpret their circumstances (Das, 2008; Garau & Pavan, 2018; Lotfi & Koohsari, 2009). Objective indicators typically include employment status, income levels, housing conditions, accessibility to urban amenities, and various other quantifiable metrics; these variables generally derive from governmental statistical agencies, administrative databases, or open-source repositories (Garau & Pavan, 2018).

In methodological contrast, subjective measures emerge primarily through survey instruments wherein residents evaluate their happiness levels, report life satisfaction, or articulate perceptions regarding specific quality of life components (Tuan Seik, 2000). These approaches complement rather than contradict each other. Objective indicators provide standardized metrics facilitating longitudinal and cross-sectional comparisons, while subjective indicators capture experiential dimensions that statistical aggregates might obscure. The former represents external conditions amenable to frequency-based measurement and policy intervention; the latter represents individual appraisals through which external conditions transmute into lived experience (Das 2007). This integrative perspective acknowledges that identical objective circumstances might generate divergent subjective evaluations depending on cultural contexts, individual expectations, adaptation mechanisms, and comparative reference frames.

Thus, the dialectical relationship between objective conditions and subjective perceptions creates a complex evaluative matrix that transcends simplistic quantification. Urban environments might provide objectively superior amenities yet generate subjective dissatisfaction if these amenities fail to align with resident expectations or cultural values. Conversely, objectively modest environments might yield high subjective satisfaction when aligned with cultural preferences or when residents employ adaptive preference formation. This conceptual duality underscores the necessity for multidimensional assessment frameworks that incorporate both statistical indicators and experiential narratives when evaluating urban quality of life.

2.4. Urban Accessibility

Urban accessibility constitutes a dynamic, interdisciplinary nexus that delineates the capacity of individuals to effortlessly attain essential services, amenities, and socioeconomic prospects within an urban matrix. It reflects the intrinsic quality of locales, whether commercial, institutional, or civic, to optimize their reachability through equitable, efficient mobility frameworks (Geurs & van Wee, 2004; Neutens et al., 2010). In other words, urban accessibility encompasses two main dimensions: people's ability to reach services and opportunities (the user perspective) and how places and services make themselves reachable (the provider perspective). This construct is not only limited to proximity, but it also encapsulates the nexus between geospatial distributional patterns of populations and urban infrastructure elements (such as employment hubs, public infrastructure, and the structural and operational dynamics of transit systems).

There are two terms that are used throughout the chapter that need to be clarified: urban accessibility and accessibility. So, let's clarify urban accessibility from the colloquial use of the term accessibility.

Accessibility refers to the conditions and design practices that enable individuals, regardless of physical or cognitive ability, to engage meaningfully with their environments. In its more focused interpretation, often termed microaccessibility, the concept pertains to how well-designed spaces, buildings, and transport systems accommodate diverse users in their everyday interactions (Pereira & Herszenhut,

2024). This includes the architectural layout of facilities, the usability of transit vehicles, and the spatial arrangement of services, all of which determine how easily people can reach and benefit from various activities.

In contrast, urban accessibility or macroaccessibility encompasses a more systemic structural perspective of mobility within cities. Rather than emphasizing individual interaction with space, it considers how urban form, transportation infrastructure, and the spatial distribution of people and opportunities interact to shape access on a metropolitan scale. It reflects how transportation networks, their connectivity, and reach affect the extent to which people can participate in work, education, healthcare, and social life (Pereira & Herszenhut, 2024). Thus, macroaccessibility highlights the systemic link between urban planning decisions and equitable access to opportunities.

At its core, urban accessibility is modulated by two cardinal dimensions: the synchronicity of spatial arrangements (e.g., residential zones relative to workplaces, educational institutions, healthcare facilities) and the infrastructural efficacy of transportation networks (e.g., connectivity, modal diversity, travel-time reliability). These determinants govern the feasibility of mobility, which dictates the temporal, financial, and cognitive effort required to bridge socio-spatial disparities.

As a fundamental determinant of equitable urbanism, accessibility shapes individual agency in securing employment, education, and cultural engagement while simultaneously governing broader societal outcomes. These encompass economic productivity, environmental sustainability, social inclusion, and the less tangible yet vital dimensions of psychological well-being, emotional resilience, and mental health. Operating as both a metric of urban performance and a policy imperative, accessibility necessitates calibrated interventions in land-use planning, transit innovation, and resource allocation. Such measures aim to mitigate spatial inequities while dismantling systemic barriers that compromise holistic well-being.

The encapsulation of psychological, emotional, and mental dimensions within urban frameworks redefines accessibility and shifts its role from a logistical mechanism to

a cornerstone of societal well-being. It cultivates societal well-being by alleviating stressors like chronic anxiety, social fragmentation, and existential marginalization.

Dependable transit systems, for example, temper the corrosive effects of chronic anxiety by eradicating the volatility of unreliable commutes. Inclusive public spaces, parks, plazas, and community centers mend social fragmentation by nurturing shared identity and spontaneous interaction, while equitable proximity to services (healthcare, education, and cultural) resources dispels the existential dread of marginalization. This recalibrated approach to accessibility fosters communal vitality, which empowers individuals to thrive not only through material security but also via emotional stability and cognitive enrichment. Therefore, urban design that prioritizes these dimensions signals a city's resolve to align human-centric principles attuned to the complexities of societal needs with infrastructural efficacy. Such alignment anchors resilient and inclusive ecosystems where spatial equity and holistic well-being intersect, which transmutes cities into landscapes of cohesion, equity, and collective prosperity (Pereira & Herszenhut, 2024).

Thus, urban accessibility emerges as a barometer of a city's commitment to harmonizing human-centric design with systemic functionality, a pursuit vital for fostering resilient, inclusive metropolitan ecosystems.

Urban accessibility is shaped by three fundamental elements, namely, infrastructure, land use, and individual circumstances (Pereira & Herszenhut, 2024).

- **Infrastructure:** The presence and quality of physical networks and transit systems directly influence movement efficiency. Robust public transportation spanning buses, subways, and trains requires expansive geographic reach, seamless interconnections between routes, and reliable service frequencies. Equally critical are well-maintained pedestrian pathways, cycling lanes, and roads that collectively reduce travel friction. Without cohesive spatial and temporal linkages across these systems, accessibility diminishes.
- **Land Use:** Accessibility thrives when essential services, employment hubs, and recreational spaces align with residential zones. Clustering schools,

healthcare facilities, and retail centers near housing reduces dependency on long commutes. Conversely, sprawling urban layouts where homes and amenities are geographically fragmented introduce barriers. Distance inversely correlates with ease of access: proximity fosters convenience, while dispersion heightens effort and time investments.

- **Individual Circumstances:** Personal and socioeconomic factors profoundly affect mobility. Physical disabilities, cognitive challenges, age-related limitations, or financial constraints may restrict transport options or deter movement altogether. Sociocultural dynamics, including gender, ethnicity, and income disparities, further compound obstacles, as safety concerns or systemic biases can limit freedom of movement. Tailored solutions such as affordable transit passes, inclusive infrastructure design, or anti-discrimination policies become essential to bridge these gaps.

2.5. Urban Accessibility Assessment Methodologies

Urban accessibility evaluation constitutes an essential component of modern urban planning and transportation research. Academic literature has established numerous methodological frameworks for the quantification and analysis of accessibility within cities. These methodologies serve dual purposes: they guide policy formulation while simultaneously deepening our comprehension of human-environment interactions in urban contexts. Scholarly discourse identifies two principal methodological paradigms: place-based measures and person-based measures. The two approaches diverge fundamentally in their conceptualization of accessibility, their data requirements, and their applicability to various planning objectives.

Place-based measures are analytical approaches that define accessibility as a property of locations and calculate how many destinations (such as jobs, schools, or hospitals) can be reached from a specific place within a given travel time, distance, or cost threshold. They treat all potential users the same and do not account for individual differences among travelers. For example, a place-based measure might tell us that from a particular neighborhood, residents can reach 50,000 jobs within a 30-minute

bus ride. These measures do not consider who lives in that neighborhood or their specific needs.

In other words, place-based measures conceptualize accessibility as an attribute inherent to a particular geographical location. These approaches have gained substantial traction among transport agencies and academic researchers for quantifying urban accessibility due to two principal advantages. First, they offer computational simplicity, which means that the mathematical calculations and data processing requirements are relatively straightforward and can be performed with standard computing resources. Without this simplicity, researchers would need to employ advanced computational techniques and powerful computing systems. This requirement would potentially limit the widespread application of accessibility studies. Second, these measures provide a straightforward interpretative framework. This framework allows planners and policymakers to easily understand and communicate findings to stakeholders without extensive technical knowledge (Boisjoly & El-Geneidy, 2017; Papa et al., 2015).

Place-based accessibility assessments incorporate trip costs through two primary mechanisms. The first mechanism predominantly expresses costs through travel time parameters. These parameters quantify the duration required to travel between origins and destinations (El-Geneidy et al., 2016; Venter, 2016). This method treats time as a valuable resource that individuals seek to minimize when they make travel decisions. For example, locations are evaluated on a spectrum of accessibility: a neighborhood where residents can reach essential services (grocery stores, healthcare facilities, schools) within 10 minutes is considered highly accessible, while areas requiring 45+ minutes to reach these same services are deemed poorly accessible or isolated. The second mechanism considers alternative cost dimensions that are not limited to simple time measurements.

First, physical distance measures the actual spatial separation between locations in kilometers or miles; neighborhoods within 1-2 kilometers of urban centers typically offer high accessibility to services, whereas those located 20+ kilometers away face significant accessibility challenges due to the physical separation alone. Second, financial expenditure accounts for all monetary costs associated with a journey;

affordable transportation options (such as a €1.50 bus fare) promote accessibility, while expensive requirements (such as €15 daily parking fees or €50 taxi rides) create financial barriers that reduce accessibility for lower-income populations. Third, subjective comfort perception recognizes that travelers evaluate routes based on qualitative factors beyond time and money; well-lit, smooth pedestrian paths with shade trees create comfortable accessibility conditions, whereas routes requiring pedestrians to cross dangerous intersections or walk along highways without sidewalks severely diminish perceived accessibility despite potentially shorter distances (Arbex & Cunha, 2020; Herszenhut et al., 2022).

The widespread adoption of these measures stems from their practical utility in policy formulation and their capacity to generate spatially explicit representations of accessibility patterns across urban landscapes. Urban planners can create accessibility maps that visually demonstrate how access to essential services varies throughout a city. These maps thereby identify areas that require infrastructure improvements or additional service provision.

2.5.1. Minimum Travel Tost

Travel Cost Proximity Index: Theoretical Framework and Practical Applications. This foundational accessibility metric quantifies the minimum resource expenditure (typically time, distance, or monetary cost) required for an individual to reach their nearest opportunity from any given origin point. Urban planners and transportation analysts frequently deploy this methodology to establish baseline accessibility conditions across metropolitan regions. For example, municipal authorities might utilize this approach to map the temporal journey requirements for residents across different census tracts to access their nearest emergency medical facility, thereby identifying underserved areas requiring intervention.

The mathematical formulation of this index can be expressed as

$$A_j = \min(c_{\{1\}}, c_{\{2\}}, \dots, c_{\{ij\}}, \dots, c_{\{i(n-1)\}}, c_{\{in\}}) \leftrightarrow O_j \geq 1 \quad (2.1)$$

Where:

A_i represents the accessibility value at the origin point i

c_{ij} denotes the travel cost (time/distance/money) between origin i and destination j

O_j signifies the quantity of opportunities available at destination j

The minimum travel cost has both methodological strengths and conceptual Limitations. From an implementation perspective, Minimum travel cost provides three advantages for planning practitioners. First, it demands relatively modest data requirements as it necessitates only origin-destination travel costs and facility locations rather than comprehensive socioeconomic datasets. Second, its computational procedure involves straightforward optimization algorithms that can be executed efficiently even for large metropolitan areas. (3), the resultant accessibility values translate into intuitive metrics (e.g., "residents in neighborhood X must travel 12 minutes to reach their nearest grocery store") that resonate with non-technical stakeholders and policymakers.

Despite these practical benefits, the Minimum travel cost suffers from two fundamental theoretical limitations that restrict its analytical power. The limitations are (1), the index operates on a binary assessment of opportunities; it acknowledges only the nearest facility while disregarding all other potential destinations, regardless of their proximity or quality. This reductionist approach fails to capture the multidimensional nature of accessibility in urban environments where individuals often consider multiple options before selecting a destination. The (2) is, perhaps more importantly, this methodology entirely neglects the competition dynamics that characterize access to limited-capacity services. This oversight becomes problematic when evaluating essential services with capacity constraints. For instance, a residential neighborhood might be situated merely 500 meters from a primary healthcare center, which suggests excellent accessibility according to this metric. However, if this facility serves as the sole medical provider for a densely populated district with 50,000 residents, the actual accessibility experience may involve prolonged waiting times, appointment scarcity, and diminished service quality factors completely unaccounted for in the proximity calculation.

2.5.2. Cumulative Opportunity Measures

The cumulative opportunity measure is a widely employed method in accessibility analysis that quantifies the number of desirable destinations reachable from a specific origin within a defined travel cost or time threshold. Rather than evaluating the quality or attractiveness of each destination individually, this approach simply counts the total number of opportunities, such as jobs, schools, or healthcare facilities, that lie within a preset travel constraint. For instance, one might assess how many health centers or employment centers are reachable by public transportation within x-hours, or how many educational institutions can be accessed by walking within x-minutes.

Mathematically, the cumulative opportunity at a given origin is computed by summing the number of destinations that fall within the acceptable travel cost. A binary function is employed in this computation: it assigns a value of one to destinations that are reachable within the threshold and zero to those that are not. This formulation requires three core inputs: the set of all destination opportunities, the travel cost between each origin-destination pair, and the pre-established threshold, which determines the maximum allowable travel time or distance.

$$A_i = \sum_{j=1}^n O_j \times f(c_{ij}) \quad (2.2)$$

$$f(c_{ij}) = \begin{cases} 1 & \text{if } c_{ij} \leq C \\ 0 & \text{otherwise} \end{cases} \quad (2.3)$$

Where accessibility at origin is the number of opportunities at destination, is the total number of destinations in the study area, is a binary function that assumes the values 0 or 1, depending on the travel cost between origin and destination, and is the travel cost threshold.

Just like any other framework, cumulative opportunity measures have both comparative strengths and practical appeal. One of the principal strengths of this measure lies in its simplicity. The data requirements are minimal, and the

calculations involved are straightforward, which makes the method attractive to practitioners, policy analysts, and transport agencies. Its intuitive interpretation facilitates clear communication with stakeholders and the public, which partly explains its widespread application in transport planning and investment assessments (see Papa et al., 2015; Boisjoly & El-Geneidy, 2017).

Nevertheless, despite its practical appeal, the cumulative opportunity measure is not without limitations. A key shortcoming is its inability to account for competition effects. It assumes that all accessible opportunities are available to the individual at the origin point, disregarding the fact that others may also be seeking access to the same destinations. Also, this method requires the arbitrary selection of a single travel threshold, such as 20, 30, or 60 minutes or hours, without accounting for variations in user preferences or levels of mobility.

Moreover, the binary nature of the threshold function introduces a blunt conceptual cutoff: opportunities located just within the boundary are treated as fully accessible, while those marginally outside are excluded entirely, even if the difference in travel time is negligible. Furthermore, the model implicitly assumes homogeneity in the value or attractiveness of all accessible opportunities. For example, two jobs, one located 10 minutes away and the other 55 minutes away, are treated as equally accessible, even though individuals may place different values on proximity.

2.5.3. Gravity-Based Measures

Gravity-based accessibility is not a singular metric but rather a broad conceptual category encompassing a range of models that estimate the potential ease of reaching opportunities from a given location. These models differ from cumulative opportunity measures in a fundamental way. While both approaches involve aggregating accessible destinations, gravity-based measures introduce a mechanism that accounts for the diminishing value of opportunities as the travel cost to reach them increases. In this sense, destinations located nearer to the origin exert a greater influence on accessibility outcomes than those situated farther away.

At the core of this approach lies the use of a decay function, which quantifies the extent to which the value of each opportunity decreases with distance, time, or other measures of travel impedance. This decay is not uniform across all functions. For example, the linear decay function assigns a gradually decreasing weight to destinations as travel cost rises, until a predefined threshold is reached, beyond which opportunities are excluded from consideration. This function assumes that travel deterrence operates at a steady rate, creating a clear boundary for accessibility influence.

In contrast, the negative exponential function represents a more continuous and rapid form of decline. Under this formulation, each opportunity is assigned a weight that diminishes exponentially as travel cost increases. This produces a sharp initial drop in value even for relatively small increases in travel time, with the weight approaching zero asymptotically as costs rise further. The exponential function is frequently applied in empirical transportation studies due to its ability to capture the sharp fall-off in user willingness to travel as cost or time escalates.

Thus, the formal structure of gravity-based measures includes two main components: the absolute magnitude of opportunities available at each destination and a cost-sensitive weight derived from the decay function. The combination of these two components yields an accessibility score that reflects both the abundance of reachable destinations and the relative ease of accessing them. This dual emphasis allows gravity-based models to represent spatial accessibility with greater behavioral and analytical realism than binary-threshold approaches.

One of the principal advantages of this approach lies in its ability to approximate how individuals cognitively assess access to services and opportunities. In real-world decision-making, proximity often translates into higher perceived utility. Gravity-based models, by reducing the influence of destinations as travel cost escalates, approximate this behavioral pattern more effectively than binary threshold methods. As a result, they provide a more flexible and realistic representation of spatial interaction patterns in contexts where user preferences and travel constraints vary across populations and regions.

However, while the theoretical foundation of gravity-based models enhances their descriptive richness, their practical implementation introduces a number of complexities.

Its methodological sophistication comes at a cost. A major limitation is the interpretability of the resulting accessibility scores. Because the contribution of each destination is mathematically attenuated by a decay function, the final values do not directly represent a count of accessible opportunities, nor do they offer an intuitive summary measure without additional context. Analysts and stakeholders may therefore find it difficult to draw straightforward conclusions from gravity-based indices when comparing across locations or periods.

Another important challenge relates to the calibration of the decay function, which plays a central role in shaping the final output of the model. The sensitivity of accessibility scores to the specific form and parameters of the decay function, such as the impedance coefficient in the negative exponential formulation, prescribes and dictates the use of empirical data that captures actual travel behavior. Without such calibration, the model risks misrepresenting accessibility patterns, thereby weakening its relevance for policy or planning applications.

Consequently, gravity-based models must be informed by detailed travel behavior datasets to ensure accuracy and behavioral validity, often derived from household travel surveys, GPS traces, or mobile phone location data. These sources provide the empirical grounding necessary to estimate decay parameters that reflect the real-world choices and constraints faced by different user groups. However, the acquisition, processing, and integration of such data can be resource-intensive and cumbersome, both in terms of time and technical capacity.

2.5.4. Other Accessibility Metrics with Competitive Dynamics in: The Floating Catchment Area Framework

In contexts where opportunities are finite and subject to competitive demand, other accessibility measures that focus solely on spatial proximity and travel costs fail to capture important dimensions of real-world access. This limitation becomes salient in

domains such as healthcare, education, and employment, where resources, whether ICU beds, school placements, or job vacancies, are inherently limited and cannot be simultaneously allocated to multiple individuals. In such cases, the presence of other users or individuals competing for the same opportunity significantly shapes the actual accessibility experienced by any given individual.

To tackle this defect, a class of indicators known collectively as the Floating Catchment Area (FCA) measures has emerged as a methodologically robust approach for incorporating competitive pressures into accessibility estimation. FCA metrics differ from other measures and models by considering the bidirectional relationship between supply and demand: not only can a single individual potentially access multiple service points, but each service point may be targeted by numerous individuals. The accessibility of an opportunity is therefore determined not only by its location and travel cost but also by the degree of crowding or saturation associated with it.

Among the FCA family, the most widely implemented method is the Two-Step Floating Catchment Area (2SFCA) model, first introduced by Luo and Wang (2003). This model operates through a sequential process: in the first step, the service-to-population ratio is calculated within a defined catchment area around each service location; in the second step, these ratios are aggregated for each population location based on its surrounding service points. Although innovative in its ability to reflect spatial interaction under competition, the 2SFCA approach is not without methodological weaknesses.

Its limitation arises from what scholars have termed the demand and supply inflation problem (Paez, Higgins, and Vivona, 2019). The 2SFCA model implicitly assumes that individuals can simultaneously seek multiple opportunities and that a single service unit, such as a hospital bed or a school seat, can be allocated to several individuals at once. These assumptions are at odds with the indivisible and exclusive nature of many services, potentially leading to distorted or inflated estimates of accessibility. To remedy these conceptual inconsistencies, Paez, Higgins, and Vivona (2019) developed the Balanced Floating Catchment Area (BFCA) method. This refinement introduces adjustments that ensure the exclusivity of both demand and

supply, thereby yielding more behaviorally realistic and statistically accurate representations of accessibility under competitive conditions.

Nevertheless, similar to the other models and measures discussed above, these competition-based and Floating Catchment Area frameworks, despite their practical strengths, also face significant analytical and interpretive challenges.

One of the key strengths of Floating Catchment Area (FCA) methods is their ability to incorporate competitive embedding into the evaluation of spatial accessibility. These models take into consideration the finite nature of many public resources, such as hospital beds, school seats, or employment opportunities, and the fact that multiple individuals may simultaneously seek access to the same resource. As such, FCA approaches provide a more behaviorally realistic and context-sensitive framework for analyzing access, particularly in settings where service capacity is constrained. Their methodological flexibility has enabled their application across a wide spectrum of empirical domains, including urban health infrastructure, educational provision, and employment accessibility.

Nevertheless, despite these methodological contributions, FCA models are often accompanied by significant barriers to interpretation and communication. The inclusion of competition-based adjustments and floating spatial boundaries frequently produces accessibility values that are less transparent and more difficult to explain to a non-technical audience. This level of abstraction may reduce the practical utility of FCA outputs in decision-making environments, especially when compared to more straightforward indicators that, while less nuanced, are easier to present and interpret in policy discussions.

On the other hand, person-based measures are analytical approaches that define accessibility as a property of individuals and calculate accessibility based on specific personal factors such as a person's daily schedule (when they need to be at work or school), their physical abilities (whether they can walk long distances, are young or old, have children or not), and their access to transportation options (whether they own a car or can afford public transit). For example, a person-based measure would recognize that a single parent who must drop children at school before 8:00 AM and

be at work by 9:00 AM has different accessibility than a retiree with no fixed schedule living at the same address.

To express this differently, person-based accessibility measures respond to the influence of diverse variables through four distinct categories of factors. The first category encompasses land use configurations. These include the spatial distribution of residential areas where people live, commercial districts where they shop, industrial zones where they might work, and recreational facilities where they spend leisure time. The arrangement of these land uses fundamentally shapes travel patterns and accessibility needs.

The second category involves transportation modalities. This category recognizes that accessibility varies significantly depending on whether individuals travel by public transit, walking, or cycling infrastructure. Each mode offers different speeds, ranges, and levels of flexibility. These differences thereby create different accessibility profiles. The third category focuses on temporal constraints and acknowledges that accessibility is not static but varies throughout the day, week, and year based on service schedules, traffic conditions, and individual time budgets. The fourth category considers demographic characteristics. These include gender, age, physical capabilities, and other individual factors that influence how people experience and navigate urban environments.

These measures acknowledge the heterogeneity of urban populations and recognize that accessibility experiences vary significantly across different demographic groups and socioeconomic strata. For instance, a location that appears highly accessible when measured using aggregate data might be quite inaccessible to elderly residents or those with mobility impairments. Nevertheless, these measures necessitate more intensive computational resources for two reasons. First, they require extensive individual-level data that can be difficult and expensive to collect. Second, they employ complex algorithms that model individual movement possibilities within space-time constraints. Consequently, person-based measures are implemented less frequently than their place-based counterparts despite their greater theoretical sophistication (Neutens et al., 2010; Miller, 2018).

The main reason is that for accessibility metrics to demonstrate efficacy, they must fulfill three critical criteria. First, they should be readily communicable to stakeholders. This means that the results can be presented in a clear, intuitive manner that non-specialists can understand and apply to decision-making processes. Second, they must be methodologically rigorous. This criterion requires that the metrics are built upon sound theoretical foundations and can withstand academic scrutiny. Third, they need to be computationally feasible to facilitate the development of multiple measurement approaches. This feasibility allows researchers to investigate various dimensions of accessibility without prohibitive technical barriers (Páez, Scott, & Morency, 2012). Therefore, even though the conceptual sophistication of person-based measures provides a more detailed and individualized understanding of accessibility patterns and dynamics, this theoretical advantage comes at the cost of increased computational demands, analytical complexity, and more extensive data collection requirements.

Hence, this study opts for the place-based measure, using the cumulative opportunity measure that calculates the number of opportunities reachable within a 15-minute travel cost limit. Widely embraced by urban planners and transport agencies, the cumulative opportunity measure stands out for its ease of computation and communication compared to alternative cost measures such as minimum cost, gravity, and competition measures. We will assess the accessibility of health and education facilities (such as hospitals, pharmaceuticals, clinics, schools, colleges, and universities), public transport and mobility, green spaces and recreational facilities, safety and security centers, and economic and financial hubs.

2.6. Spatial Justice Models in Urban and Temporal Proximity as Urban Design Philosophy

Contemporary urban planning literature examines several frameworks through which amenities and services might be distributed throughout metropolitan areas. Three predominant models emerge from these discussions: temporal accessibility frameworks, demand-responsive distribution, and spatial equity approaches.

The temporal accessibility framework ("X-minute city") conceptualizes urban design around travel duration to essential services. This paradigm stipulates that residents should reach necessary facilities within specified time frames, whether 15, 20, or 30 minutes. Carlos Moreno introduced this concept in 2016, which subsequently garnered substantial scholarly attention (Dobrowolska & Kopczewska, 2024; Lotfi & Koohsari, 2009; Moreno et al., 2021; Zhang et al., 2023; Zhong et al., 2020). Numerous metropolitan areas have implemented variations of this approach in their planning policies, including Melbourne's "20-minute neighborhood" initiative, Paris's "15-minute policy," and Singapore's "45-minute" accessibility standard.

Alternatively, the demand-responsive distribution model ("needs-based city") advocates allocating urban amenities according to demographic requirements within specific neighborhoods. This approach might entail, for instance, concentrating educational facilities and recreational infrastructure in zones predominantly occupied by families with children (Brambilla et al., 2013). Nevertheless, critics argue that such targeted distribution potentially fosters homogeneous, specialized communities which may transform into segregated enclaves of limited socioeconomic mobility, ultimately undermining urban productivity (Benabou, 1993).

On the other hand, the spatial equity approach ("just city") emphasizes uniform distribution of facilities throughout urban territories. This framework prioritizes equal accessibility to public services for all residents, irrespective of socioeconomic status or ability to pay (Talen, 1998). Central to this model is its focus on equality of opportunity (Brambilla et al., 2013) and its commitment to reducing disparities in quality-of-life indicators. Urban economics research generally validates this equitable distribution approach (Berliant et al., 2006; Hussaini et al., 2023).

The 15-minute city construct encapsulates the doctrine of 'chrono-urbanism,' which postulates an inverse relationship between urban life quality and transportation duration requirements. This theoretical foundation asserts that excessive travel time diminishes residential satisfaction and overall metropolitan experience (Moreno et al., 2021). Such frameworks reject automobile-centric planning traditions in favor of anthropocentric urban design, operating primarily at neighborhood scale. This approach reconceptualizes local districts as nuclei for quotidian activities,

fundamentally inverting traditional centralized planning by relocating amenities toward residential concentrations rather than compelling inhabitants to traverse substantial distances for essential services (Allam et al., 2022; Pozoukidou & Chatziyiannaki, 2021).

The architectural foundation of the 15-minute city paradigm rests upon four cardinal principles: proximity (minimizing distances between residences and services), diversity (ensuring heterogeneous land use patterns), ubiquity (guaranteeing universal access regardless of socioeconomic status), and density (supporting sufficient population concentration to maintain service viability) (Allam et al., 2022; Noworól et al., 2022). These principles synergistically create neighborhoods where residents access daily necessities through non-motorized transportation modes within quarter-hour timeframes.

Our investigation adopts the 15-minute accessibility framework due to several compelling factors. First, this model provides quantifiable metrics for evaluating service distribution efficacy across metropolitan regions. Second, its emphasis on pedestrian accessibility aligns with contemporary sustainability objectives in urban planning. Third, the framework offers practical implementation guidelines that transcend theoretical constructs. Fourth, substantial empirical evidence suggests a correlation between proximity-based planning and enhanced quality-of-life indicators. Finally, this approach facilitates interdisciplinary analysis, incorporating transportation engineering, land use planning, and social equity considerations within a unified evaluative structure.

2.7. A Synoptic Overview and Contextual Background of Recent Macroeconomic Indicators in Türkiye

This section sheds light on the Turkish Lira depreciation and its macroeconomic and financial implications.

Over the past two decades, the Turkish economy experienced substantial growth, with an average annual GDP increase of 5.8% from 2002 to 2021. However, structural weaknesses within the economy became increasingly apparent and

contributed to macroeconomic instability. In 2013, the Turkish lira began a prolonged period of depreciation⁸, which accelerated over the following five years. The persistent decline in the currency's value led to rising import prices, higher production costs, the erosion of real wages, and inflation among the highest in Europe. The lira's diminished purchasing power disrupted various sectors and intensified socioeconomic hardships across the country.

On August 10, 2018, the situation escalated and reached a tipping point when the Turkish lira collapsed dramatically. A diplomatic conflict between Türkiye and the United States, centered around the detention of Evangelical pastor Andrew Brunson on terrorism charges, acted as the catalyst. In retaliation, the United States increased tariffs on Turkish steel and aluminum⁹ while Türkiye imposed higher tariffs on selected American goods. These tensions led to a sharp financial destabilization. The lira depreciated by 35% against the US dollar within just 47 days. The stock market fell by 17%, and government borrowing costs surged¹⁰ to 18%. The consequences affected not only currency markets but also policymakers, investors, and the general population. The figure below illustrates historical Turkish inflation.

In the following pages, we present Türkiye's main macroeconomic indicators over the past decade to provide a holistic background and understanding of the country's overall macroeconomic situation. These include inflation, GDP, employment, population change, and interest rates. For some indicators, historical data were unavailable, so we relied on the most complete data currently accessible.

⁸<https://www.euronews.com/2022/11/09/everything-is-overheating-why-is-Türkiye-s-economy-in-such-a-mess>

⁹ <https://www.aljazeera.com/economy/2018/8/17/Türkiye-lira-crisis-six-things-you-need-to-know>

¹⁰ <https://www.aljazeera.com/economy/2018/8/15/Türkiye-doubles-tariffs-on-some-us-goods-amid-rising-tensions>

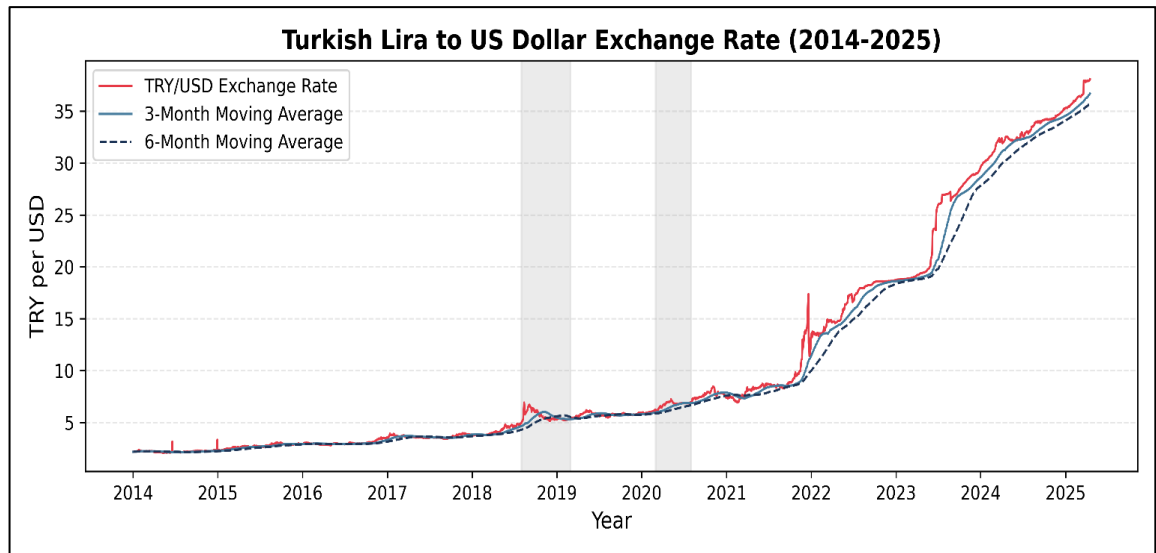


Figure 2.2. Turkish Lira Exchange Rates Movements Over Time

Reference: TUIK

As illustrated in the figure, just like the previous figures, the Turkish Lira maintained relative stability against the US Dollar between 2014 and 2016. However, between 2016 and 2018, it began a gradual depreciation, though it remained below 5 TRY per USD. Then, the exchange rate started to accelerate after 2018 and intensified drastically from 2021. Subsequently, the depreciation of the Lira became more acute and irreversible in late 2021 and continued through 2022-2025, reaching approximately 37 TRY per USD by 2025. As elaborated in the two previous figures, the problem mainly stemmed from multiple economic factors, such as the monetary policy decisions that diverged from conventional approaches, persistent current account deficits that increased external financing needs, and the global economic conditions that reduced risk appetite for investment.

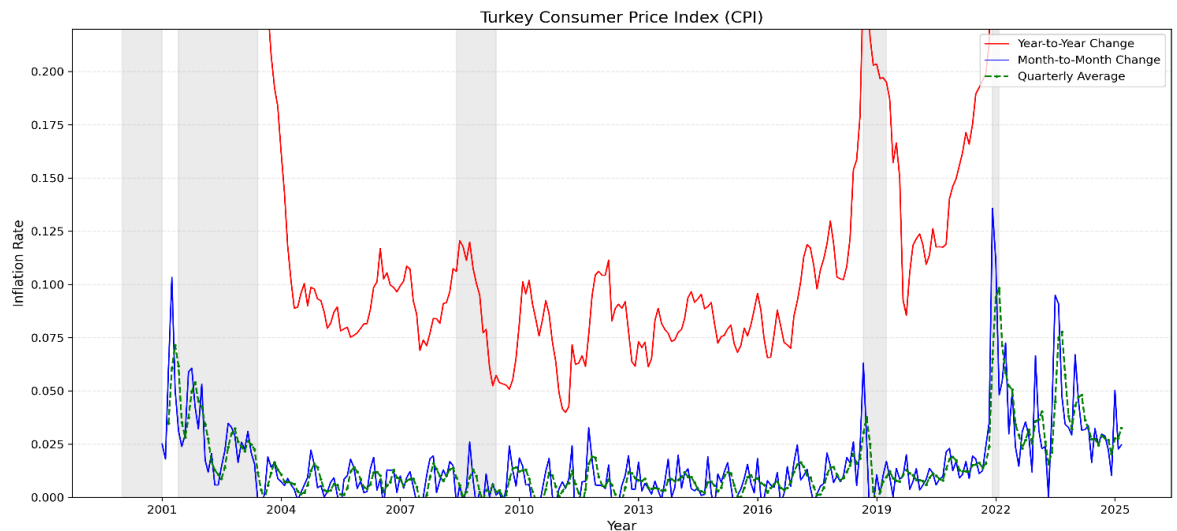


Figure 2.3. Turkish Consumer Price Index (CPI)

Reference: TUIK

The figure demonstrates how price instability became a persistent feature of Türkiye's economic landscape. As illustrated in the figure, Türkiye's Consumer Price Index (CPI) showed relatively moderate levels between 2004 and 2016. It remained within a consistent range, though with noticeable fluctuations. Then, inflation began an upward trajectory after 2016, and this trend intensified substantially from 2019 and reached its apex in 2022, when year-to-year inflation exceeded 20%.

Several factors contributed to this such as the currency depreciation that eroded purchasing power, unconventional monetary policy that decreased interest rates despite rising inflation, which further accelerated capital outflows and currency depreciation, expansionary fiscal policies that increased domestic demand due to COVID-19 stimulus measures, and the supply disruptions caused by global economic conditions that constrained production capabilities. The month-to-month inflation rates displayed greater volatility throughout the period, with significant spikes occurring in 2001 and 2022. The quarterly averages smoothed these short-term fluctuations while still capturing the fundamental inflationary trend.

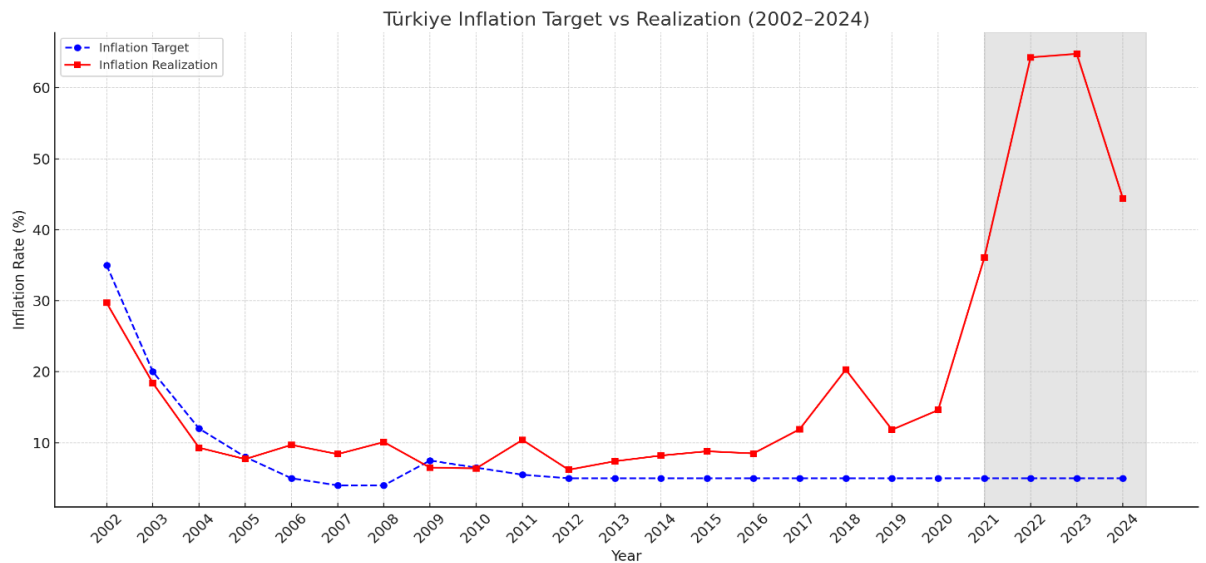


Figure 2.4. Turkish Inflation Target Versus Realization

Reference: TUIK

As illustrated in the figure, actual inflation remained below the official target before 2005. However, between 2006 and 2009, it slightly exceeded the target, though it stayed relatively stable. Then, inflation began to rise steadily after 2013, and this upward trend intensified from 2016.

This upward movement became more aggressive, severe, and evident from 2020 and showed no signs of reversal. This escalation reflected the combined effects and sequence of several disruptive events, with the key contributing episode being the 2016 coup attempt that severely undermined investor confidence, followed by subsequent geopolitical tensions, such as the tariff dispute between the United States and Türkiye, which deepened external fragility, and the economic and logistical disruptions triggered by the COVID-19 pandemic, which strained supply chains and caused demand shocks, while repeated election cycles introduced persistent political and economic uncertainty. Each of these events incrementally intensified inflationary pressures, and together they sustained the momentum behind rising inflation. As a result, Türkiye's price levels deviated further from the targeted path, with inflation becoming more entrenched and embedded in the economic landscape and expectations.

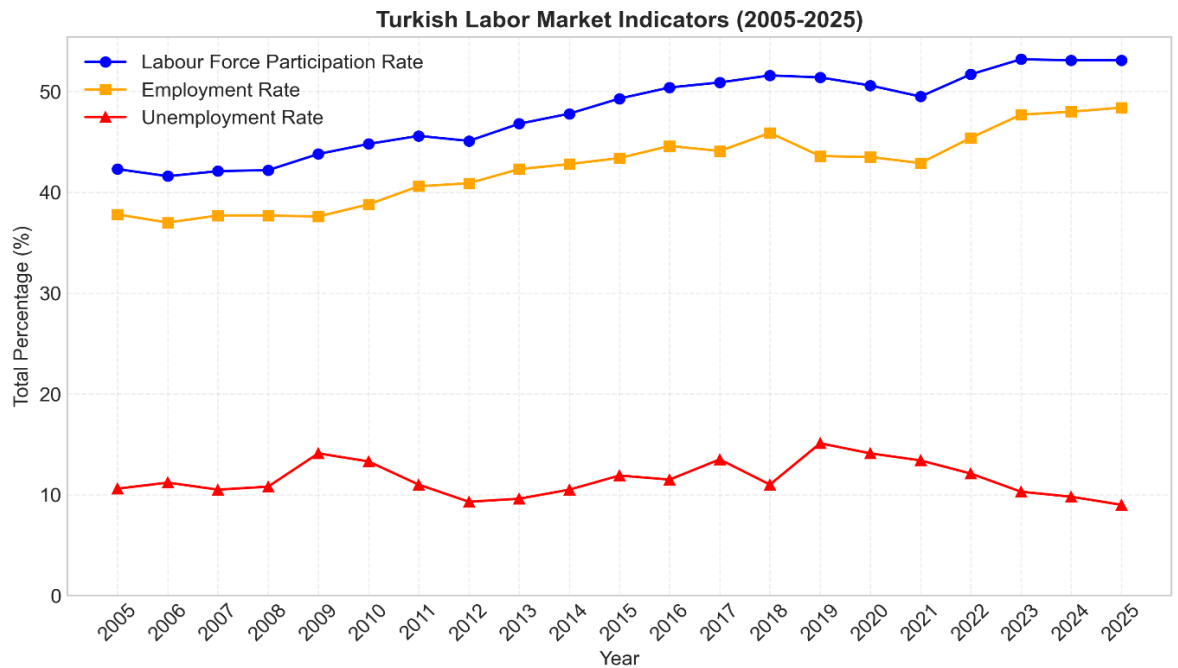


Figure 2.5. Turkish Labor Market Indicators

Reference: TUIK

Figures show Türkiye's labor market indicators. The figures demonstrate the dynamics of key labor market indicators in Türkiye over twenty years. As illustrated in the figure, Türkiye's Labor Force Participation Rate showed a steady upward trend between 2005 and 2016, increasing from approximately 42% to about 51%. It remained relatively stable until 2019, experienced a slight decline during 2020, and then recovered and stabilized around 52% through 2025.

The Employment Rate followed a similar but more modest trajectory, rising gradually from about 38% in 2005 to 43% by 2016, before experiencing fluctuations between 2017 and 2021. Subsequently, it resumed its upward trend to reach approximately 48% by early 2025. However, the Unemployment Rate exhibited more cyclical behavior throughout the period, with peaks in 2009 (approximately 14%), 2019 (about 15%), and moderate increases in 2017. These patterns might be influenced by the global financial crisis that reduced employment opportunities in 2009, structural economic transformations that gradually increased labor force participation, and the COVID-19 pandemic that temporarily disrupted labor markets in 2020 but had a surprisingly limited long-term impact on unemployment. The convergence of increasing labor force participation and employment rates after 2021

contributed to the decline in unemployment rates during the later period. As a result, Türkiye's labor market showed resilience despite periodic economic challenges, with long-term trends pointing toward higher workforce engagement and improved employment outcomes.

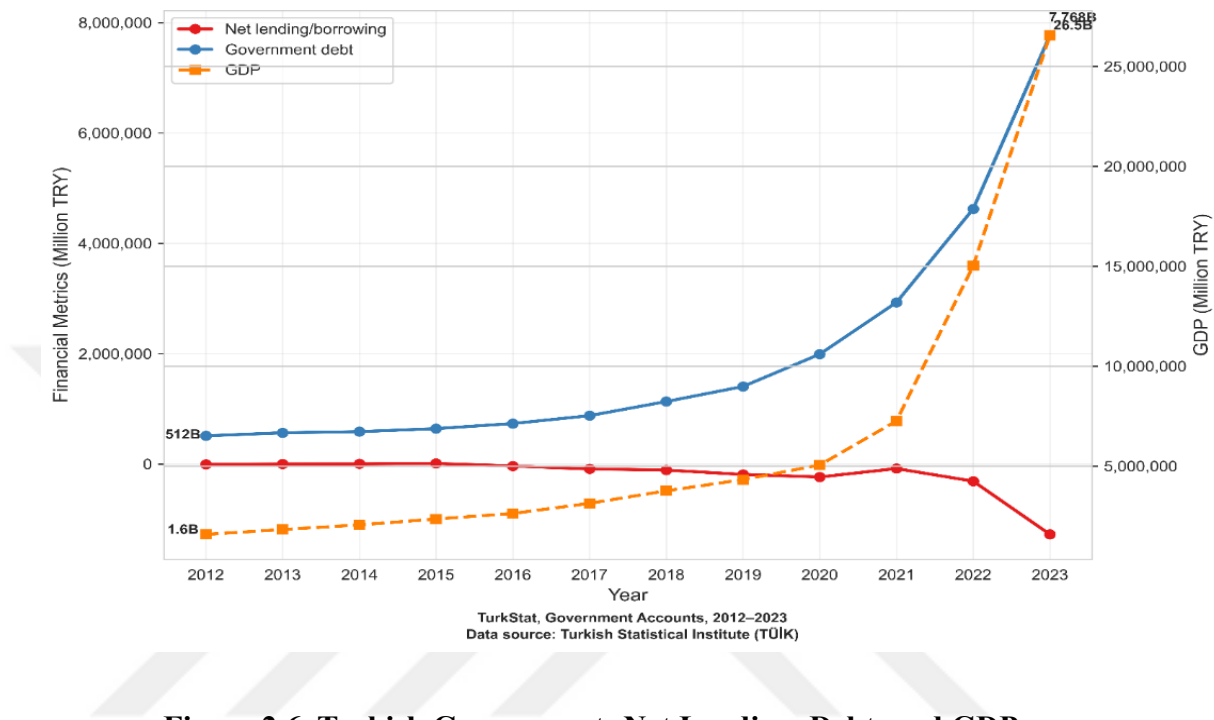


Figure 2.6. Turkish Government: Net Lending, Debt, and GDP
Reference: TUIK

Figure X depicts the government account. Government debt was significantly higher than GDP from the outset; however, a steady increase followed by a sharp acceleration occurred from 2020 onward, ultimately bringing the two figures to near parity.



Change in Unemployment Rate in Turkish Provinces (2022-2024)

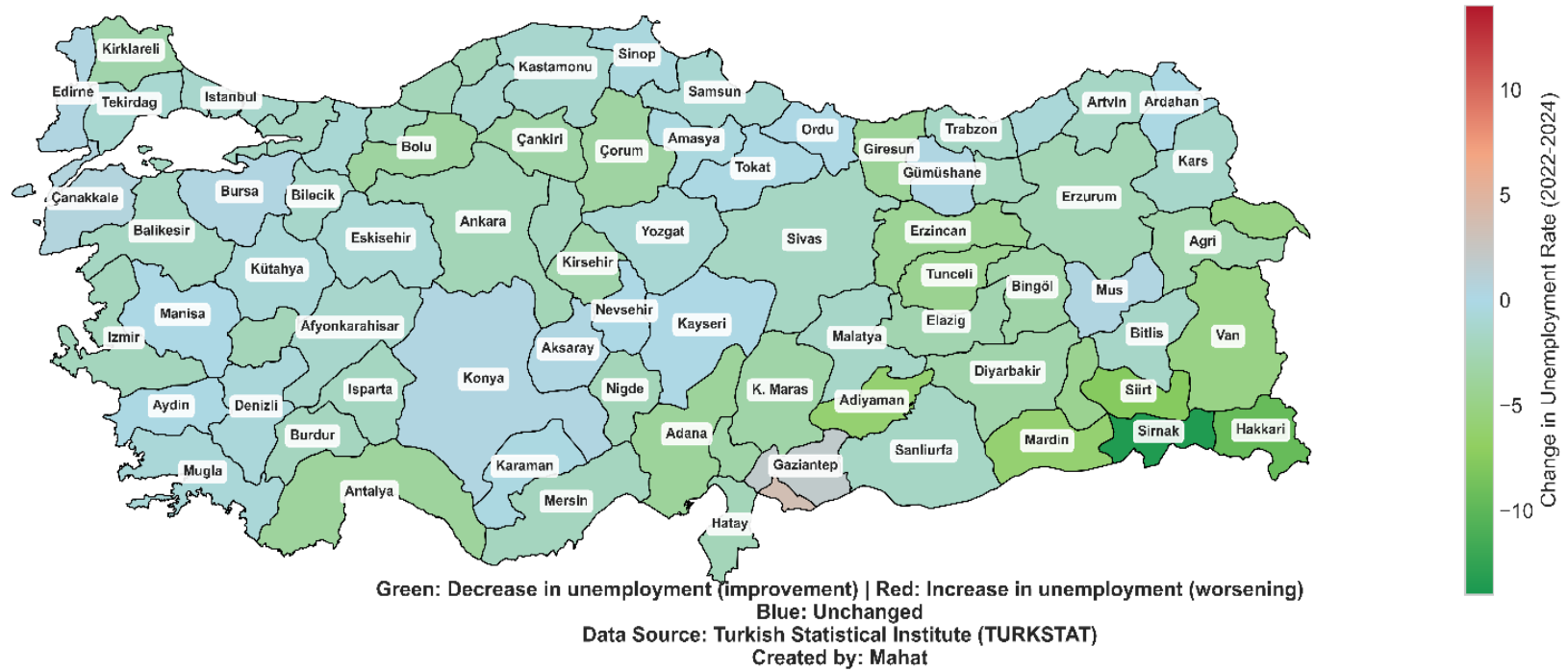


Figure 2.7. Unemployment Dynamics Per Province

Reference: TUIK

As illustrated in Figure X, the change in unemployment by province between 2022 and 2024 was moderately positive overall. There were no sharp increases or decreases, except in two or three provinces. In most provinces, unemployment remained relatively stable.

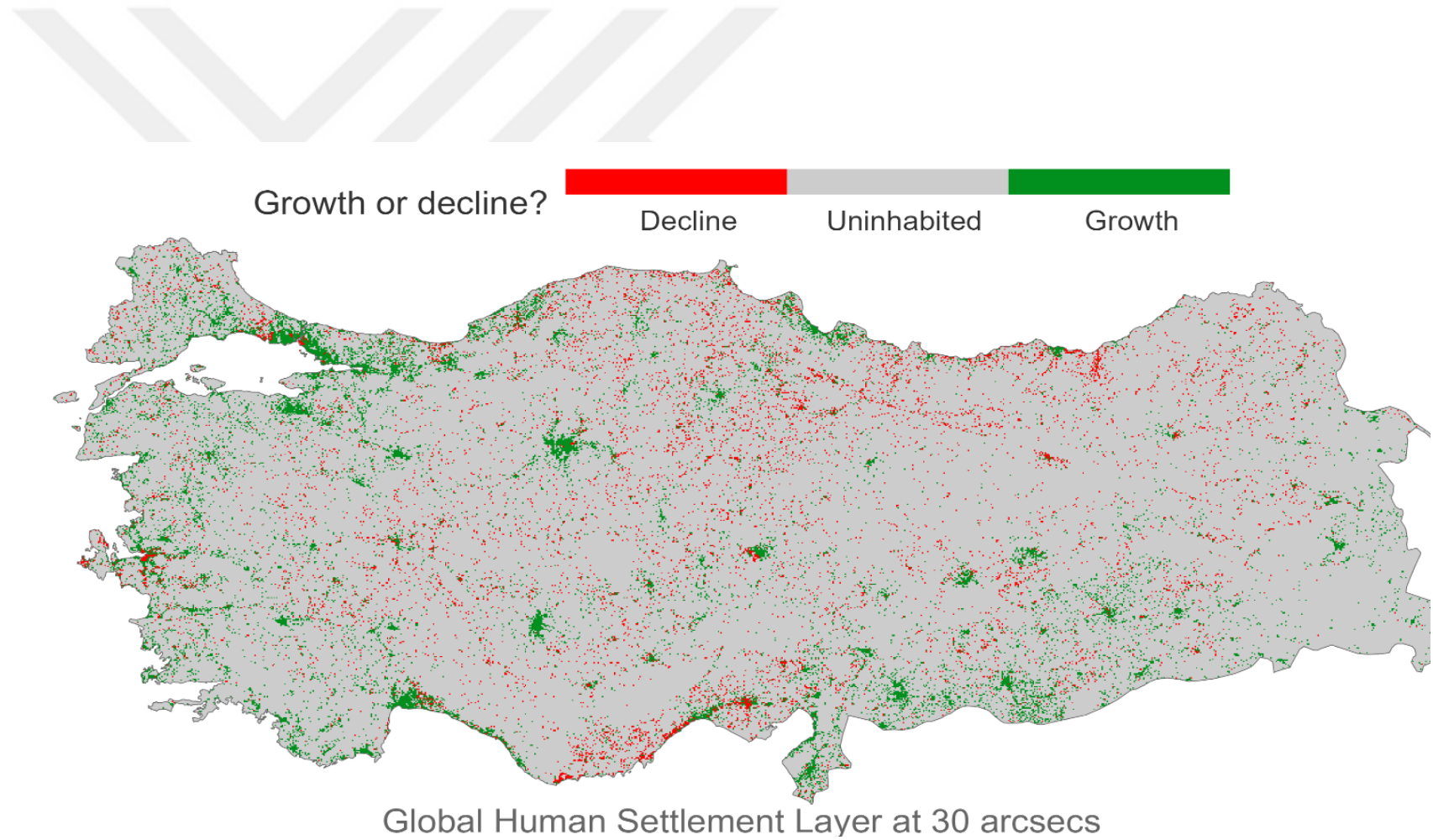


Figure 2.8. Turkish Dynamics from 2000-2025
Reference: GHSL-Global Human Settlement Layer

As illustrated in the map, population growth is increasingly concentrated in major urban centers such as Istanbul, Ankara, Bursa, and Izmir, while many other regions across the country have experienced a population decline.

The academic literature offers an in-depth analysis of the Turkish lira crisis and its subsequent repercussions on the broader economic landscape. For instance, Hadi (2023) used wavelet coherence analysis and quantile-on-quantile regression on data from April 2012 to December 2021 to analyze the effects of the lira collapse across various Turkish sectors. His study evidence an anti-phase relationship between the lira and the Turkish stock market. However, some stocks showed co-movement patterns, which opened opportunities for hedging, safe-haven investments, and diversification during times of currency volatility.

Others assessed the connection between geopolitical uncertainty and the devaluation of the lira from 2003 to 2021 (Kyriazis et al. 2021). They used the Caldara-Iacoviello geopolitical uncertainty index and GARCH methods. Their report that heightened geopolitical risks significantly pressured the lira, especially in comparison to the US dollar.

Similarly, the interaction between geopolitical risks and Türkiye's financial stability has been examined (Mansour-Ichrakieh & Zeaiter, 2019) through a Threshold VAR model applied to monthly data from 2006 to 2018. Drawing on IMF guidelines (Balakrishnan, 2014), a New Financial Stress Index was constructed to evaluate the dynamics of financial stress. The analysis revealed that declining consumer confidence was the predominant driver of financial instability in Türkiye. Moreover, the findings highlighted asymmetrical effects of regional geopolitical risks: instability in Russia appeared to bolster Türkiye's financial stability, whereas rising tensions with Saudi Arabia increased its economic vulnerability

Furthermore, other studies analyzed the volatility of 15 Turkish energy companies between 2018 and 2020 using multiple regression (Oran and Aydos, 2021). The findings showed no significant relationship between currency fluctuations and energy stock prices during the crisis. This indicates that the energy sector demonstrated resilience in the face of financial turmoil.

In the highly intertwined contemporary global financial and economic system, a crisis or depreciation of an emerging country's currency can have ripple effects on global markets and influence the stability of financial institutions in other regions. The international effects of lira volatility on 29 major European banks were also examined (Arbaa and Varon, 2019). The study found that banks with higher leverage, declining liquidity, or decreased profitability experienced substantial abnormal losses on the event day and shortly afterward. This illustrates how financial shocks from emerging economies can ripple through international banking systems and generate widespread instability.

Orhangazi and Yeldan (2021) offered a structural analysis of the crisis. They attributed the 2018 collapse to long-standing imbalances in Türkiye's growth model, which relied heavily on foreign capital inflows and debt-driven expansion, particularly in construction. The COVID-19 pandemic exacerbated these weaknesses and deepened Türkiye's economic fragility, which led to financial instability.

Finally, A structural analysis of the crisis was offered by Orhangazi and Yeldan (2021), who attributed the 2018 collapse to long-standing imbalances in Türkiye's growth model, which relied heavily on foreign capital inflows and debt-driven expansion, with construction being a leading sector. The COVID-19 pandemic exacerbated these weaknesses and deepened Türkiye's economic fragility, leading to financial instability. Therefore, there is a plethora of studies regarding the lira's volatility and its subsequent socio-economic and financial repercussions. However, to maintain focus and clarity, let us conclude this section here.

CHAPTER III

DECODING TURKISH LIRA VOLATILITY USING NATURAL LANGUAGE PROCESSING, NEWS & TWITTER SENTIMENT, AND EXPLAINABLE AI (XAI)

3.1. Introduction

Since time immemorial, humanity has been captivated by the unknowable future. From ancient oracles consulting entrails to modern data scientists wielding complex algorithms, our species has persistently sought to pierce the veil of tomorrow. This intellectual yearning permeates numerous disciplines, from meteorologists predicting weather patterns (Price et al., 2025; Tripathy et al., 2021), to epidemiologists forecasting disease spread and pandemic dynamics (Chowell & Skums, 2024; Roosa et al., 2020), to astronomers anticipating celestial movements (Ni et al., 2024; Shirafkan et al., 2025), to transportation experts planning traffic and population flow (Y. Chen et al., 2023; Hu & Xiong, 2023),—all employing time series forecasting to extract order from apparent chaos¹¹. Economics and finance stand firmly within this tradition, utilizing mathematical models and algorithms to anticipate market movements, inflation rates, economic growth, stock prices, and currency valuations. Among these variables, exchange rates present perhaps the most formidable challenge to predictive methodologies, combining technical complexity with real-world implications.

The foreign exchange market has ascended to unprecedented prominence as the world's dominant financial marketplace, now facilitating an extraordinary daily transaction volume of \$7.51trillion¹². This enormous expansion, however, has been accompanied by a proportional amplification of foreign exchange risk

¹¹ Time Series - an overview | ScienceDirect Topics

¹² Forex Daily Trading Volume Statistics in 2025

exposure(Windsor & Cao, 2022). Moreover, the significance of exchange rates is that these rates function as essential economic indicators, influencing everything from international trade flows to investment decisions. A country's exchange rate serves as both a barometer and determinant of its economic health, affecting import prices, export competitiveness, and capital flows. The foreign exchange market, where currencies are traded in staggering volumes exceeding trillions of dollars daily, responds sensitively to myriad macroeconomic variables: interest rate differentials, inflation expectations, fiscal stances, monetary policy decisions, and broader economic growth trajectories(He et al., 2021).

In the aftermath of the Bretton Woods system's dissolution in the early 1970s, central banking authorities across the globe have predominantly embraced more flexible and adaptive exchange rate policies. This fundamental shift in monetary governance has substantially contributed to the inherently volatile character of contemporary currency markets. These unpredictable monetary fluctuations pose multifaceted threats extending well beyond the immediate profit concerns of multinational corporations. Indeed, such volatility represents a potentially destabilizing force that may undermine the structural integrity and operational resilience of international financial systems, raising vital questions about sustainable economic governance in an increasingly interconnected global economy.

The evolution of exchange rate forecasting methodologies mirrors broader technological transformations within global financial institutions. As these entities have embraced increasingly sophisticated computational capabilities, forecasting techniques have undergone parallel advancements. Particularly, machine learning algorithms have emerged as preeminent tools for time series prediction. These algorithmic approaches have gained scholarly recognition for their capacity to identify subtle patterns within what appears to be chaotic data patterns that traditional econometric models and statistical techniques might overlook.

What renders exchange rate forecasting challenging is the fundamental obscurity of the data-generating process itself. Unlike physical phenomena governed by immutable natural laws, currency valuations result from the aggregated decisions of countless market participants, as in Figure 1, each responding to distinct incentives

and information sets (Windsor & Cao, 2022). This complexity can be attributed to three primary factors (Cao et al., 2020). First, exchange rates emerge from an intricate system of coupled relationships between diverse market indicators, including stock performance and macroeconomic policies, each with distinctive transmission mechanisms that interact across multiple national markets. Second, market participants' decisions extend beyond numerical indicators to include sentiment responses to new information (Kočenda & Moravcová, 2018). The resultant price movements exhibit properties that statisticians characterize as “non-stationary” and “non-linear,” mathematical terminology that essentially acknowledges the formidable complexity of these systems.

Two theoretical frameworks illuminate the role of sentiment in market dynamics. The Efficient Market Hypothesis (EMH) posits that markets rapidly incorporate new information (Fama, 1970; Jiao et al., 2020), a principle subsequently applied to currency markets (Shmilovici et al., 2009). Simultaneously, behavioral finance theory recognizes irrational elements in market behavior, including herding and risk aversion, which significantly influence price movements (Barberis & Thaler, 2005; Frank & Sanati, 2018). Third, profound bidirectional coupling exists between market indicators and investor sentiment, as illustrated in Figure 1.

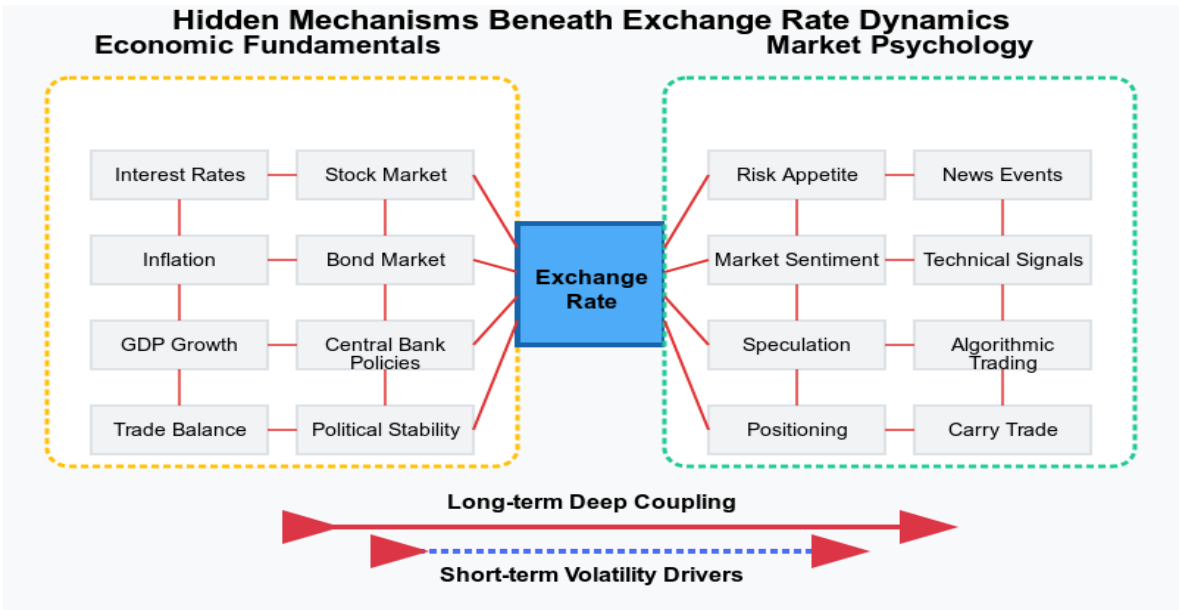


Figure 3.1. Hidden Mechanisms Beneath the Exchange Rate

The figure is constructed by the authors following (Windsor & Cao, 2022).

Given these multidimensional complexities, forecasting approaches limited to single information modalities, whether quantitative indicators or sentiment analysis, inevitably fall short. Effective forecasting methodologies must capture both the internal dynamics within each information type and the complex interrelationships between these distinct modalities. The resulting analytical challenge has spurred methodological innovation. Researchers have progressed from rudimentary time series models to sophisticated neural networks capable of discerning previously undetectable relationships within financial data. Each algorithmic advancement represents an incremental step toward unraveling the mystery that is the future trajectory of currency valuations.

The existing literature establishes both the methodological diversity and the persistent challenges in exchange rate forecasting. The Turkish Lira case presents a particularly compelling research context, given its significant volatility and profound macroeconomic implications. This study attempts to forecast the Turkish Lira/US Dollar exchange rate from January 2015 through February 2024. During this period, the Lira depreciated against the dollar, resulting in severe macroeconomic consequences. The currency devaluation contributed to heightened inflation rates, significant increases in import prices, and substantial erosion of purchasing power. The pass-through effect from exchange rate depreciation to domestic prices created persistent inflationary pressures while simultaneously reducing real wages and household wealth. Additionally, the currency crisis exacerbated external debt servicing costs for both public and private sectors, constrained monetary policy options, and increased financial market volatility.

While several studies have utilized Twitter sentiment for financial market predictions, to our knowledge, no research has combined local and international news sources for exchange rate forecasting. Therefore, our study aims to fill this gap in the literature two ways: First, by analyzing international news outlets (The Economist, The New York Times, and The Guardian) as well as local news (proxied with Yeni Şafak and local tweets) sentiment on Turkish Lira/Us dollar exchange rate volatility. Secondly, the study employs explainable AI techniques alongside the

conventional “black box” machine learning approaches to enhance interpretability and transparency.

In the remaining part of this chapter, section 2 reviews the concise literature on exchange volatility. Section 3 outlines the data and methodology employed in the study. Section 4 presents empirical findings along with discussions, while Section 5 concludes the chapter with key findings and policy implications.

3.2. Literature Review

The exploration of exchange rate dynamics has garnered significant scholarly attention, yielding a diverse array of methodological approaches. Numerous researchers have applied various forecasting techniques to capture the inherent volatility and complexity of currency valuations. This literature review synthesizes relevant studies, examining both general time series forecasting approaches and specific applications to the Turkish Lira/US Dollar exchange rate, thereby establishing the theoretical and methodological foundation for our current investigation.

Time series forecasting faces challenges due to temporal dependencies and nonlinearity. Some studies utilize neural networks, such as Radial Basis Function Networks with weighted moving averages, to improve predictions for volatile financial data. (Hota et al., 2017). Others highlight the limitations of linear models for economic data, advocating for hybrid deep learning and fuzzy logic approaches to better capture nonlinear patterns (Tealab et al., 2017).

In addition to neural network approaches, Ensemble methods, including model averaging, bagging, and boosting, have also enhanced forecasting robustness (Barrow et al., 2010). Similarly, neural networks have been widely applied for temporal data analysis, with studies detailing architectures, training methods, and their trade-offs (Vijh et al., 2020). Hybrid systems combining linear and nonlinear techniques often outperform single models, as demonstrated by data-driven approaches that integrate linear time series modeling with nonlinear error correction (de O. Santos Júnior et al., 2019). Comparative studies between traditional and deep

learning methods, such as ARIMA and LSTM with attention mechanisms, show that while deep learning slightly outperforms classical methods, both remain relevant (Zhou et al., 2020). Evolutionary optimization techniques, like hybrid differential evolution and artificial bee colony algorithms, have further improved ARIMA's accuracy in multi-step forecasting (Kumari et al., 2022).

For the TRY/USD rate, machine learning methods, including Multilayer Perceptron, Support Vector Machines, and Random Forest, have been employed for prediction and investment modeling (Dirik, 2021). During high-volatility periods, simple exponential smoothing has surprisingly outperformed complex models in short-horizon forecasts, despite the exchange rate's long-memory trends (Sarkandiz & Ghayekhloo, 2024). Hybrid approaches, such as combining univariate models with NARDL and neural networks, reveal the currency's dependence on recent observations and asymmetric responses to macroeconomic factors (Sabri et al., 2022). Additionally, sentiment analysis integrated with time series modeling, using deep learning for social media text processing, has improved prediction robustness (Yasar & Kilimci, 2020).

3.3. Hypothesis

The following hypotheses for Chapter 2 examine the relationship between news sentiment and exchange rate volatility. These hypotheses build on the Efficient Market Hypothesis (Fama, 1970), which argues that markets incorporate all available information into asset prices. They also draw from behavioral finance theories (Shiller, 2003; Kahneman & Tversky, 1979) that show how psychological factors affect financial decision-making. Additionally, Media Effects Theory (McCombs & Shaw, 1972) supports the premise that news content influences public perception and subsequent market behavior:

Hypothesis 1: News sentiment from international and local sources predicts Turkish Lira exchange rate volatility.

Null Hypothesis 1: News sentiment from international and local sources does not predict Turkish Lira exchange rate volatility.

Hypothesis 2: International news sources have stronger predictive power for exchange rate volatility than local news sources and social media.

Null Hypothesis 2: International news sources do not have stronger predictive power for exchange rate volatility than local news.

Hypothesis 3: News sources have stronger predictive power for exchange rate volatility than social media.

Null Hypothesis 3: News sources do not have stronger predictive power for exchange rate volatility than social media.

3.4. Methodology

3.4.1. Data Source

Our research employs a multifaceted approach to predict Turkish Lira/US Dollar exchange rates, combining international and local news sources with social media data. We selected three major international publication media outlets, The Economist, The New York Times, and The Guardian, due to their global influence and comprehensive financial coverage. To incorporate domestic perspectives, we included Yeni Şafak newspaper, which serves as a proxy for local media sentiment, and Turkish Twitter posts serve as local social media. To maintain relevance, we focused exclusively on economic, finance, and business sections across all sources.

The dataset spans January 1, 2015, to March 9, 2025, aligning with our financial market data that includes daily TRY/USD exchange rates, trading volumes, and price movements. All financial data was obtained from Yahoo Finance¹³.

3.4.2. Data Acquisition

We streamlined the extraction process using available APIs from The New York Times, The Guardian, and Yeni Şafak. For The Economist, we utilized university

¹³ Yahoo Finance - Stock Market Live, Quotes, Business & Finance News

database subscriptions and manual collection methods. Twitter's academic API facilitated the extraction of relevant social media posts. We supplemented API access with Python libraries, including Requests and BeautifulSoup, along with regular expressions for data refinement. The extraction captured publication dates, article titles, summaries, full text, and source URLs.

All collected data was consolidated into a single CSV file for subsequent preprocessing. Figure 2 illustrates our data extraction workflow.



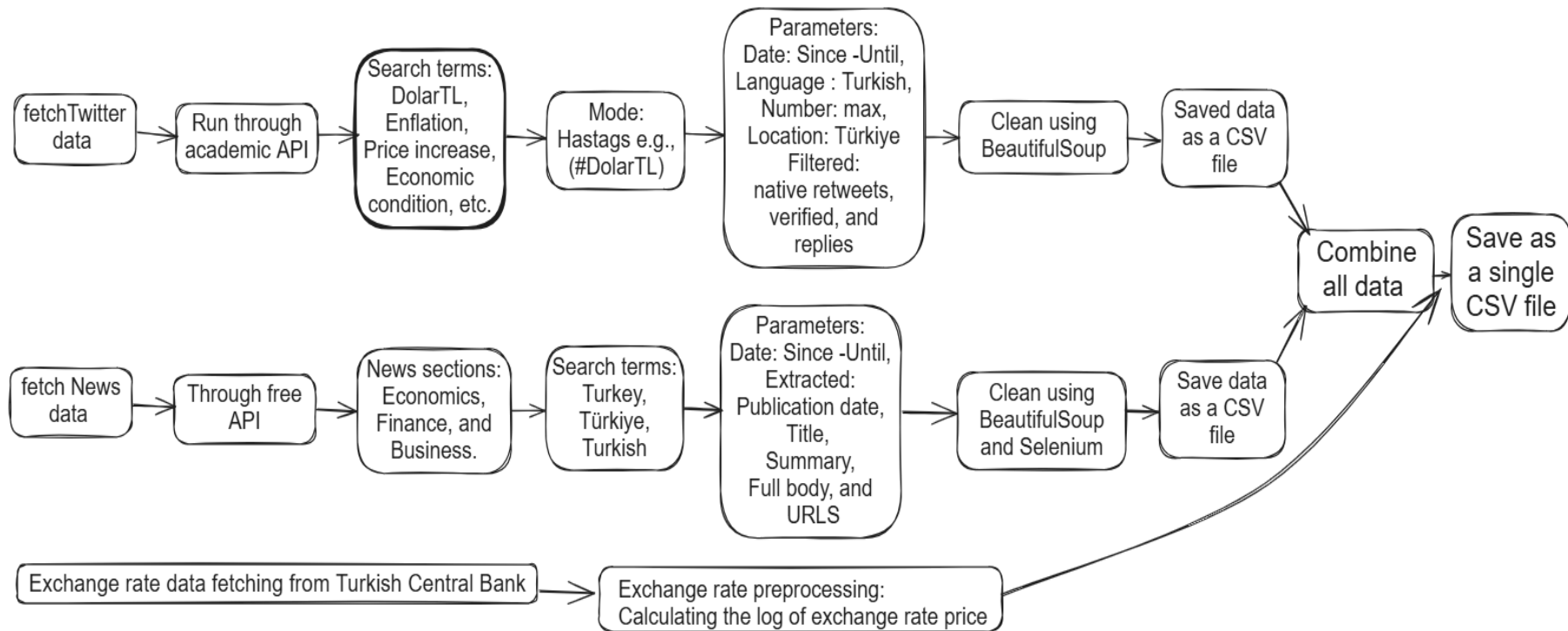


Figure 3.2. Data Extraction Workflow

3.4.3. Data Preprocessing

Raw text data required extensive cleaning to remove noise and irrelevant information. Using Pandas, SpaCy, and Neattext libraries, we implemented a systematic preprocessing pipeline that included:

1. Removal of URLs, HTML tags, excessive spaces, special characters, numbers, email addresses, hashtags, and improper quotations
2. Lemmatization to reduce words to base forms
3. Case conversion to lowercase
4. Punctuation and white space removal
5. Text normalization and spelling correction

After comparative analysis, we retained stop words as their inclusion improved model performance.

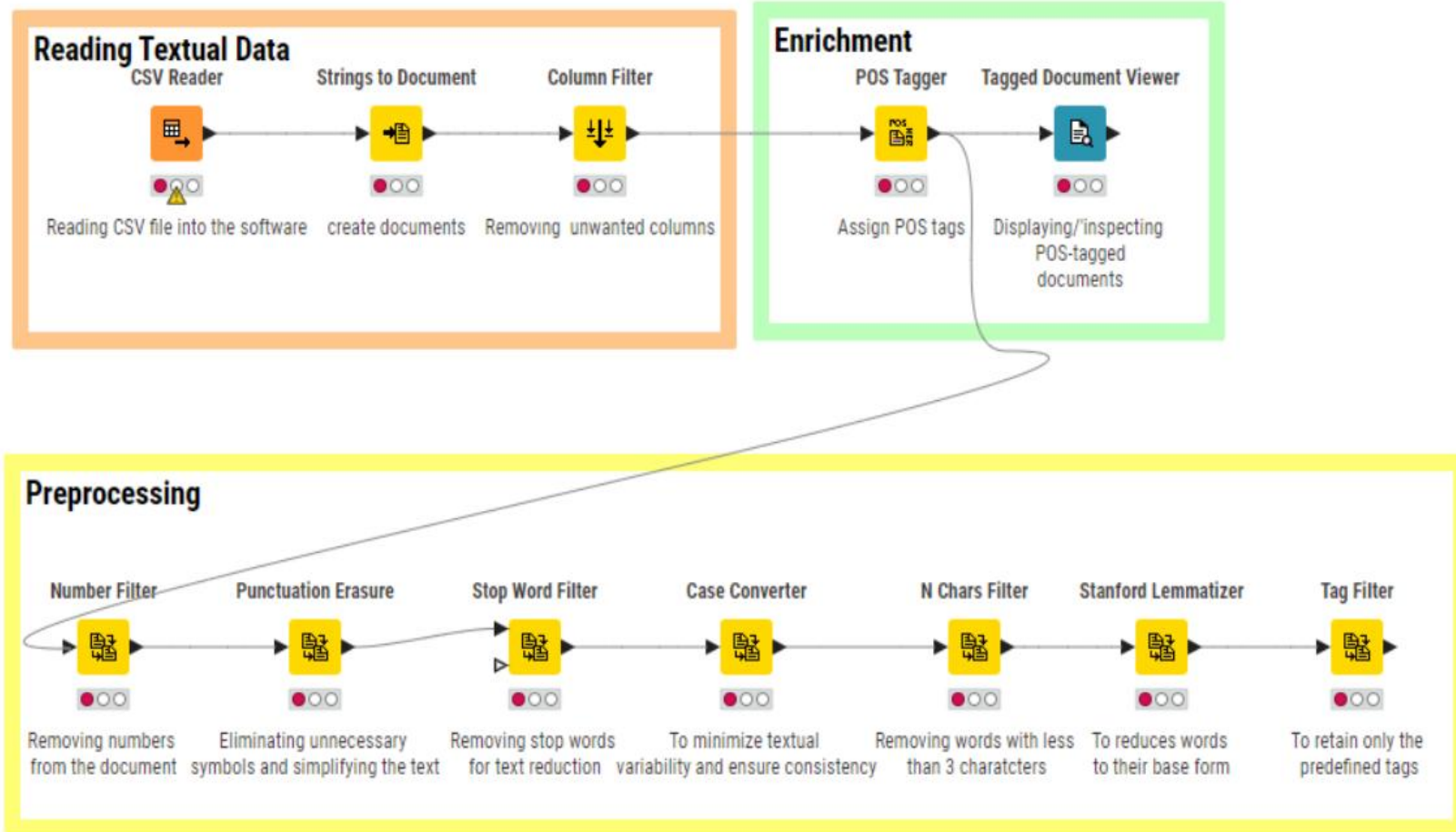


Figure 3.3. Data Preprocessing Flowchart

The cleaned data was then processed using the FinBERT transformer model for feature extraction, followed by topic modeling to identify key themes in financial news. We conducted sentiment analysis to measure market attitudes and named entity recognition to identify relevant economic actors and indicators. Additional features included volatility indicators, event markers, market trend signals, n-grams (unigrams, bigrams, and trigrams), and parts of speech classification with sentiment levels, all tailored specifically for exchange rate prediction. Please see chapter 4 section 3.4 (4.3.4) for a more detailed explanation of the FinBERT model.

In classification tasks where one class occurs much more frequently than the other, the resulting class imbalance can cause the learning algorithm to become biased toward the majority class. This typically leads to models that perform poorly in identifying minority class instances, which are often the cases of greatest interest in applied settings such as fraud detection, medical diagnosis, or rare event forecasting. To address this issue, data-level balancing techniques have been developed that modify the training distribution without altering the learning algorithm itself.

One of the most direct approaches is random undersampling, which involves reducing the size of the majority class by randomly removing instances (Drummond & Holte, 2003). This method can restore balance effectively, but it does so at the cost of discarding potentially informative data from the majority class. As a result, it may lead to models that generalize poorly due to the loss of important patterns.

An alternative is random oversampling, which duplicates instances from the minority class until a desired balance is achieved (Chawla et al., 2002). Unlike undersampling, this technique retains all available data. However, because it creates exact copies of existing instances, it can increase the risk of overfitting, especially in models that are sensitive to repeated examples.

To mitigate the drawbacks of naive oversampling, more sophisticated methods such as SMOTE (Synthetic Minority Over-sampling Technique) have been proposed. Instead of replicating existing data points, SMOTE generates new synthetic examples by interpolating between existing minority class instances and their nearest neighbors (Chawla et al., 2002). This results in more diverse and informative training data,

which improves the model's ability to generalize. Moreover, SMOTE reduces the risk of overfitting by introducing new patterns rather than duplicating existing ones, and it avoids the loss of information that occurs with undersampling. Variants of SMOTE, such as Borderline-SMOTE or ADASYN, further refine the generation process by focusing on samples near the decision boundary or by weighting difficult instances more heavily (Han et al., 2005; He et al., 2008), although these variants introduce additional complexity and assumptions.

In this study, SMOTE is used as the primary balancing technique. Its ability to synthesize new minority class examples makes it especially effective for improving classifier performance without discarding data or introducing excessive redundancy. The use of SMOTE ensures a more representative training set for both classes and facilitates the learning of more accurate and generalizable decision boundaries. Its adoption in this work is motivated by the need to preserve data richness while mitigating the bias associated with imbalanced class distributions.

3.4.4. Basic Bert Model

The attention mechanism is defined as:

$$\mathbf{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \mathbf{softmax}\left(\frac{\mathbf{QK}^\top}{\sqrt{d_k}}\right)\mathbf{V} \quad (3.1)$$

The output of the attention layer is then transformed as follows:

$$\mathbf{V}_l = \mathbf{linear}(\mathbf{W}_l \mathbf{Concat}(\mathbf{Attention}_1, \mathbf{Attention}_2, \mathbf{Attention}_3, \dots, \mathbf{Attention}_h) + \mathbf{b}_l)$$

Here, Q , K and V represent different transformations of the input vector X_a . The softmax function is applied to generate the attention output V_l .

Next, residual connections are introduced $V_a = X_a + V_l$

This output is then normalized and passed through a feed-forward neural network, leading to the final transformer output V_t : which is computed as follows:

$$\mathbf{V}_t = \mathbf{h}(\mathbf{W}_f \mathbf{V}_a + \mathbf{b}_f) + \mathbf{V}_a \quad (3.2)$$

Since BERT is composed of multiple bidirectional transformer layers, this process is repeated iteratively for any given input X_a , ultimately producing the BERT output representation V_b .

3.4.5. Machine Learning Models

In this study, we use GARCH (1,2) as a baseline and various machine learning techniques, including Decision Tree, Random Forest, Gradient Boosting, AdaBoost, XGBoost, and Neural Networks to predict Turkish Lira/US Dollar exchange rates. These forecasting techniques offer distinctive advantages for capturing the exchange rate dynamics.

Decision Tree Regression (Breiman et al., 1984; Quinlan, 1986) serves as the foundational building block for many ensemble methods. It partitions the feature space into regions and assigns constant values to each, offering interpretability but often suffering from high variance and overestimation. To overcome this inherent weakness, Random Forest Regression (Breiman, 2001) emerged as an ensemble methodology founded on the bagging paradigm, aggregating predictions from multiple decision trees to enhance forecasting precision while mitigating overfitting through dual mechanisms of bootstrap aggregation and feature randomization. Also, building upon the decision tree framework through a different approach, Gradient Boosting Regression (Friedman, 2001) employs sequential model construction to rectify predecessor errors through differentiable loss function optimization. Though powerful, it necessitates further parameter calibration to prevent variance amplification. Hence, further advancing the boosting paradigm, XGBoost Regression (T. Chen & Guestrin, 2016) operates within the gradient boosting framework yet distinguishes itself through advanced optimization techniques, regularization capabilities, and parallel processing architecture. Similarly, addressing the limitations of single decision trees, AdaBoost Regression (Freund & Schapire, 1997) implements adaptive instance weighting to prioritize problematic observations. On the contrary, Neural Network Regression models complex non-linear relationships through layered neuronal architectures (Rumelhart et al., 1986). Detailed formulations and explanations of these models are in Chapter 4, Section (4.3.4).

3.4.6. Explainability (XAI) in Machine Learning

Conventional machine learning techniques, while powerful in capturing patterns and delivering predictive accuracy, often suffer from a lack of transparency and interpretability (Hassija et al., 2024). These models typically operate as "black boxes," producing outputs that obscure the underlying mechanisms driving their predictions. This opacity undermines trust and limits the practical utility of such models in critical decision-making contexts. To address these limitations, the field of Explainable Artificial Intelligence (XAI) has emerged, aiming to enhance the interpretability of machine learning models. Among the various XAI techniques, SHapley Additive exPlanations (SHAP) has gained prominence as a robust framework for model interpretability (S. Lundberg & Lee, 2017).

SHAP is rooted in cooperative game theory, drawing on the concept of Shapley values (Shapley, 1953) to fairly allocate contributions among participants in a cooperative game. In machine learning, SHAP leverages this theoretical foundation to quantify the contribution of each feature to a model's predictions. Through the assignment of Shapley values to individual features, SHAP provides a unified and interpretable framework for explaining the output of any machine learning model (S. M. Lundberg et al., 2020). This approach enhances transparency and fosters trust in model predictions, enabling users to understand the key drivers behind specific outcomes.

The SHAP framework has demonstrated significant effectiveness in applications requiring high interpretability. Using SHAP analysis, researchers can identify and interpret the features within news content that most significantly influence model predictions. This capability is critical for ensuring that machine learning models are not only accurate but also accountable and understandable to end-users. The computation of Shapley values can be expressed as shown in equations 1-2 (S. Lundberg & Lee, 2017).

$$\phi_m(v) = \sum_{S \subseteq N \setminus \{m\}} \frac{|S|! (|N| - |S| - 1)!}{|N|!} (v(S \cup \{m\}) - v(S)) \quad (3.3)$$

Where, $\phi_m(v)$, represents the Shapley value for a feature m , quantifying its contribution by considering all possible subsets of features. The $\phi_m(v)$ is computed as a weighted average of the marginal contributions of the feature m across every possible subset S of the feature set N . The marginal contribution is given by $(v(S \cup \{m\}) - v(S))$, where $v(S)$ is the value function evaluating the prediction for the subset S . The weights are determined by the factorials of the subset sizes, ensuring a fair distribution of contributions. Thus, the Shapley value is essentially a weighted average of the marginal contributions of the feature m across all possible subsets of features.

$$g(x') = \phi_0 + \sum_{m=1}^M \phi_m z'_m \quad (3.4)$$

Where, $g(x')$, describes the model's prediction for an instance x' as the sum of a baseline prediction ϕ_0 and the weighted contributions of each feature, represented by their Shapley values ϕ_m and binary indicators z'_m .

3.5. Model Evaluation

We allocated 80% of the dataset for training the machine learning regression models (Decision Tree Regression, Random Forest, Gradient Boosting, AdaBoost, XGBoost, and Neural Networks) while employing Grid Search Optimization methodology to determine optimal hyperparameters for each algorithm. We selected the grid search hyperparameter tuning approach for two key reasons: its exhaustive examination of every potential hyperparameter combination, which guarantees optimal solution identification; and its methodological clarity, which facilitates straightforward implementation (Ogunsanya et al., 2023). Following the training phase, we validated all regression models using the reserved 20% of data, assessing their predictive capability through multiple statistical metrics: coefficient of determination (R^2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Feature importance. These metrics are computed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (3.5)$$

$$MSE = \frac{1}{N} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3.6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (3.7)$$

$$MAE = \frac{1}{N} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (3.8)$$

Whereby, y_i represents the actual value and $\hat{y}_i$ denotes the predicted value of the i th Observation and N stands for the total number of observations.

R^2 measures how well the model explains the variation in the data, while MSE calculates the average squared difference between predicted and actual values. RMSE is the square root of MSE and presents errors in the same units as the original data, whereas MAE measures the average absolute difference between predicted and actual values. On the other hand, feature importance analysis identified which news sources most influenced exchange rate predictions, extracting coefficient magnitudes from linear models and native importance scores from tree-based models.

3.6. Results and Discussion

This section offers the results of the regression analysis by discussing the relationship between different firm characteristics and the probability of perceiving access to finance as a major obstacle, and other obstacles as well. Lastly, we outline the findings from the estimation of the association between firm performance and the degree of financial restraint.

**Table 3.1. Coefficients of Exogenous Variables in the Mean Equation GARCH
(1, 2) Model**

Variables	Coefficients	p-value:	Impact on exchange rate returns	Statistical Outcome
The Economist	0.086365	0.0000	Positive impact on returns	Significant
The New-York Times	-0.020956	0.0000	Negative impact on returns	Significant
The Guardian	-0.016174	0.0000	Negative impact on returns	Significant
Yeni Şafak	-0.002532	0.0569	negative impact	Significant
Tweets	0.000802	0.1251	Positive impact	Not significant

The GARCH (1, 2) results in Table 3.1 indicate that international news sources, such as The Economist, The Guardian, and The New York Times, have a significant impact on the volatility of the Turkish Lira/US Dollar exchange rate. The Economist shows a positive effect, while The Guardian and The New York Times show negative impacts. On the other hand, local media sources, such as Yeni Şafak, and social media content, such as Tweets, exhibit weaker or insignificant effects on the exchange rate volatility. AS shown in Figures 4, 5, and 6, the news sentiment captures the exchange rate volatility quite well. This aligns with previous studies suggesting that text mining and AI models provide a promising approach for predicting trends in the foreign exchange market (Naderi Semiromi et al., 2020; Xueling et al., 2023).

Table 3.2. Evaluation Metrics of the Machine Learning Models

Model	R²	MSE	MAE	RMSE
Gradient Boosting	0.736	0.093	0.163	0.304
AdaBoost	0.228	0.270	0.465	0.520
Decision Tree	0.630	0.130	0.178	0.360
Random Forest	0.735	0.093	0.175	0.305
XGBoost	0.724	0.097	0.176	0.311
Neural Network	0.401	0.210	0.363	0.458

The evaluation metrics presented in Table 3.2 provide a comparison of various machine learning models in predicting exchange rates. Among the models evaluated, Gradient Boosting, Random Forest, and XGBoost emerge as the top performers, indicating that these models explain a significant proportion of the variance in exchange rates. Both models exhibit the lowest Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values, further indicating their predictive accuracy. In contrast, AdaBoost performs comparatively poorly, capturing less of the variance in exchange rate volatility, and showing the highest MSE and RMSE values, indicating substantial prediction errors. Decision Tree shows intermediate performance, providing reasonable predictive accuracy with moderate MSE and RMSE values. The Neural Network model also shows lower performance, suggesting that while it captures some variance in exchange rates, it is less effective than the ensemble methods like Gradient Boosting and Random Forest. Overall, Gradient Boosting, Random Forest, and XGBoost are the most effective models for predicting exchange rates based on the provided metrics. Their high explanatory power and low error metrics make them superior choices for this task. While Decision Tree and offer decent performance, AdaBoost and Neural Network are less suitable for this specific predictive challenge. Neural networks are data-hungry algorithms that require substantial amounts of data to achieve optimal performance. Consequently, ensemble methods often outperform neural networks in scenarios with limited data. However, no single technique holds a monopoly on predictive accuracy; model efficacy depends on the specific use case and constraints.

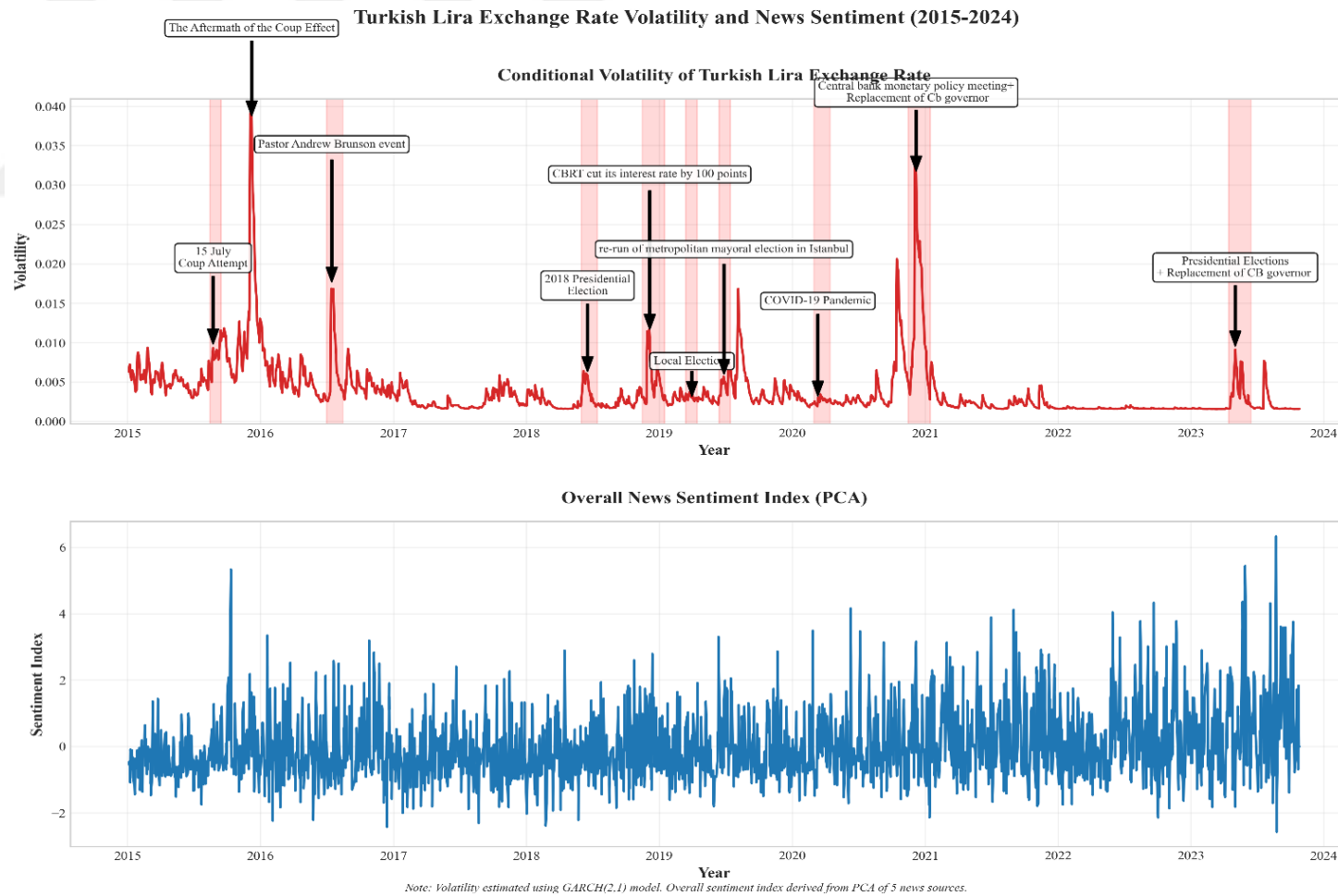
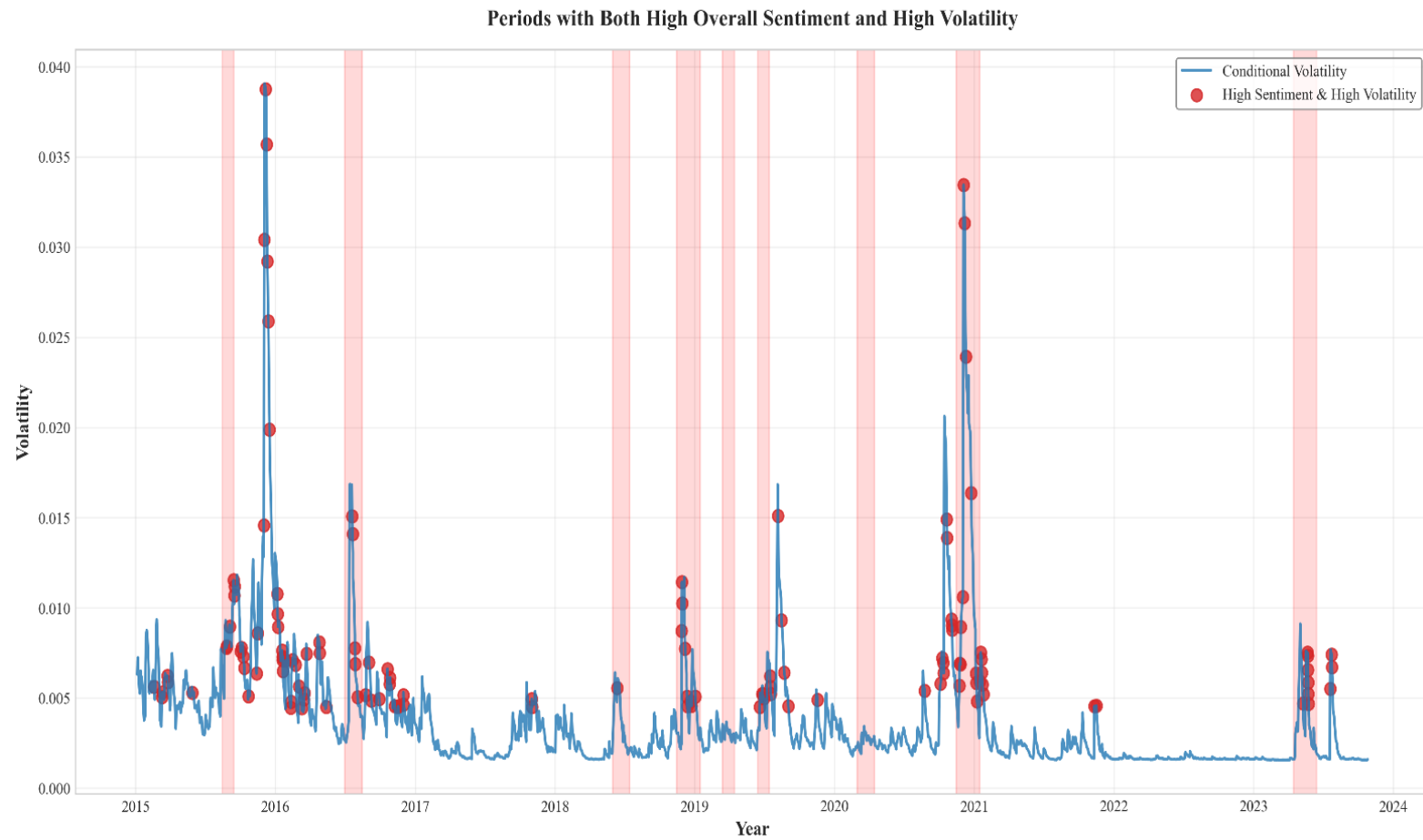


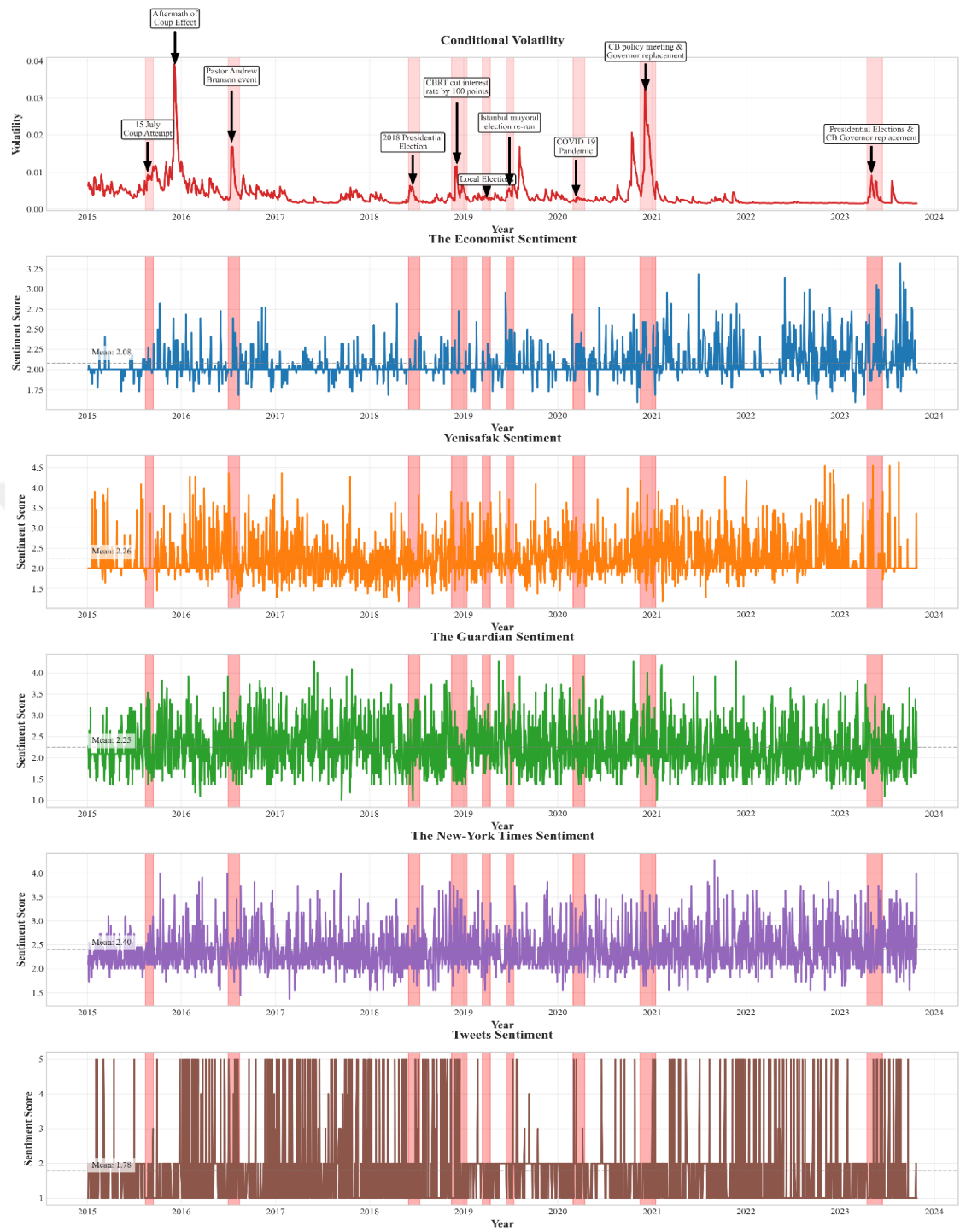
Figure 3.4. Overall News Sentiment



Note: High sentiment defined as top 25% of overall sentiment index. High volatility defined as top 25% of conditional volatility.

Figure 3.5. Periods with Both High Overall Sentiment and High Volatility

Turkish Lira Exchange Rate Volatility and News Source Sentiment (2015-2024)



Note: Volatility estimated using GARCH(2,1) model. Sentiment scores range from 1 (negative) to 5 (positive).

Figure 3.6. Individual News Outlet's Sentiments

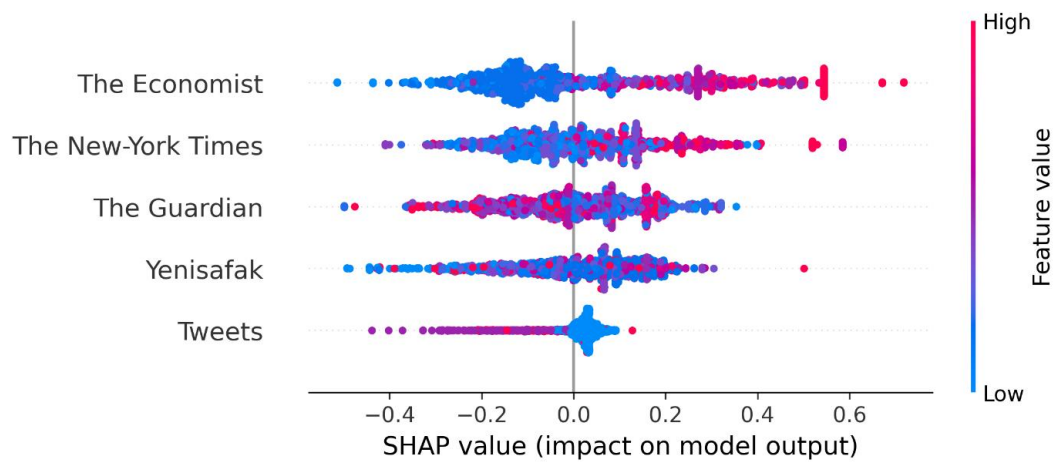


Figure 3.7. Gradient Boosting Beeswarm Plot

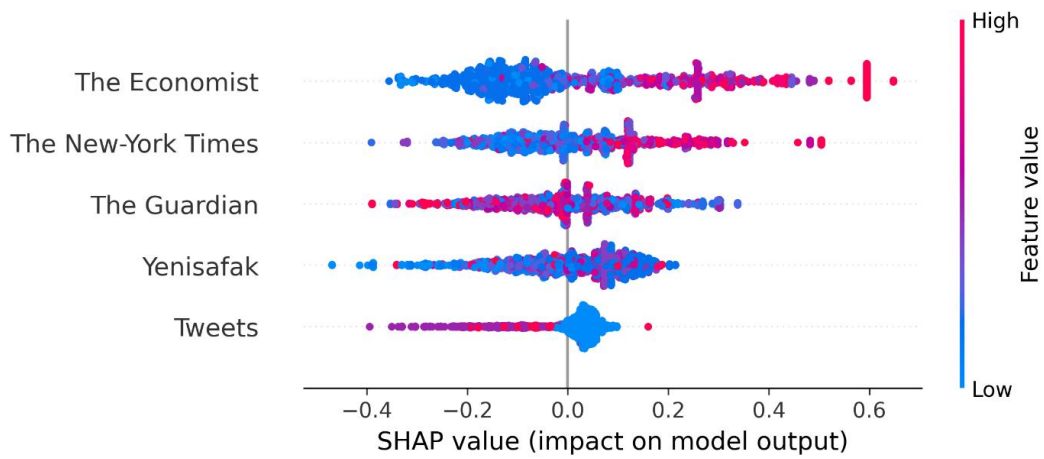


Figure 3.8. Random Forest Beeswarm Plot

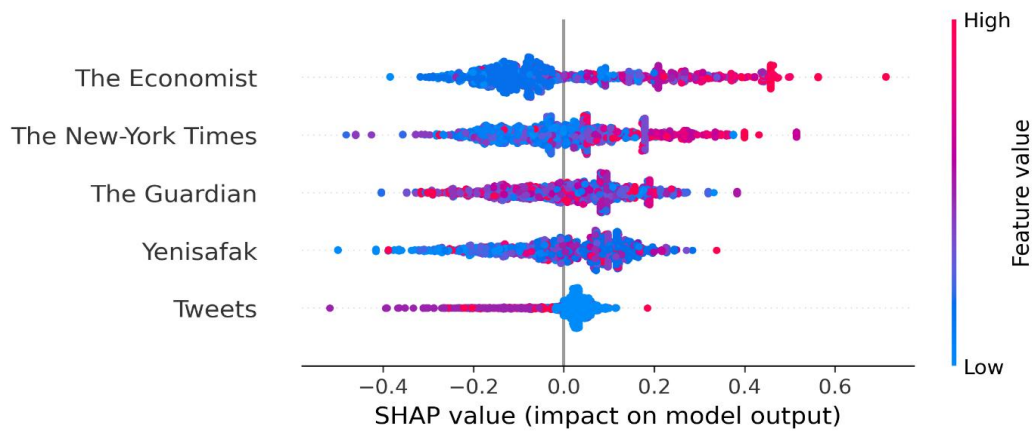


Figure 3.9. XGBoost Beeswarm Plot

The SHAP value visualizations in Figures 3.7–3.9 highlight the varying influence of different news sources on the model’s exchange rate predictions. Among them, The Economist emerges as the most influential, consistently exhibiting high SHAP values. This suggests that sentiment from this source plays a key role in driving positive changes in the exchange rate. The publication’s strong reputation for global economic analysis and its audience of policymakers, investors, and financial institutions likely amplifies its impact on market sentiment. Similarly, The New York Times also contributes positively to exchange rate movements, though to a lesser extent. Its influence, while still notable, appears to be more moderate compared to The Economist. The findings suggest that these two sources provide coverage that aligns with developments perceived as favorable for the Turkish lira, shaping expectations among market participants.

In contrast, The Guardian and Twitter exhibit a markedly different pattern, consistently displaying negative SHAP values. This suggests that sentiment from these sources exerts downward pressure on exchange rate predictions. The effect could stem from a more critical tone in reporting, particularly concerning economic and political risks. Given The Guardian’s emphasis on social and political issues, its influence may reflect broader concerns about governance, policy uncertainty, or external geopolitical risks that could weigh on the Turkish economy. Similarly, Twitter, being a platform where diverse opinions, including speculative and reactionary content, are widely shared, may amplify negative sentiment, particularly during periods of economic volatility or political uncertainty.

Yeni Şafak, a domestic news outlet, has a minimal effect on the model’s predictions, with SHAP values close to zero. Unlike international financial media, its sentiment does not appear to meaningfully shape expectations about the exchange rate. This suggests that global investors and currency traders place greater weight on international sources when assessing the Turkish lira, possibly due to differences in credibility, audience reach, and the perceived objectivity of reporting. While Yeni Şafak is influential within domestic discourse, its limited impact on exchange rate movements highlights the role of internationally recognized publications in shaping financial market expectations.

3.7. Conclusion

Predicting exchange rates is of paramount importance due to their significant role in shaping economic stability, trade, investment, and inflation. Exchange rates are influenced by a range of domestic and international factors, making their accurate prediction essential for policymakers, investors, and financial analysts. This study examined the Turkish Lira exchange rate's (in USD) volatility during a period of substantial depreciation, employing advanced methodologies to analyze the role of news sentiment in exchange rate movements.

The study implemented a range of methods, including natural language processing techniques, sentiment analysis, and machine learning models. News data was collected from international sources such as The Economist, The New York Times, and The Guardian, as well as domestic sources (Yeni Şafak) and social media (Twitter). The data was preprocessed using Python tools for feature extraction and cleaning, FinBERT was utilized for sentiment extraction, and machine learning models such as Gradient Boosting, Random Forest, and XGBoost were employed to forecast exchange rate movements. Additionally, explainable AI techniques (SHAP), were used to interpret the influence of individual features on model predictions using the Shap and Shapash Python libraries. The findings revealed that international news sources, especially The Economist and The New York Times, had the most significant impact on exchange rate predictions. In contrast, domestic sources like Yeni Şafak and Twitter had a comparatively weaker influence, reflecting the preference of global investors for internationally recognized media when assessing the Turkish Lira.

One of the key limitations of the study is the underrepresentation of local news sources, which stems from data unavailability of other domestic media outlets. While Yeni Şafak was included as a representative local source, its coverage, although highly active in policy-related areas, may not fully capture the economic and financial dimensions of the Turkish economy, even though the analysis focused exclusively on its economic and financial sections. This could limit the ability of the study to comprehensively assess the influence of domestic media on exchange rate movements.

Additionally, while Twitter was incorporated to reflect social media sentiment, its content is often speculative and reactionary, which may dilute its relevance in predicting exchange rates. These limitations suggest that future research could benefit from broader access to local media data and more refined methods for analyzing social media sentiment to enhance the robustness of the findings. The study also acknowledges the potential bias inherent in both international and domestic media, which may influence the tone and focus of their reporting, thereby affecting the sentiment analysis and its predictive power.



CHAPTER IV

FROM HEADLINES TO STOCK TRENDS: NATURAL LANGUAGE PROCESSING AND EXPLAINABLE ARTIFICIAL INTELLIGENCE APPROACH TO PREDICTING TÜRKİYE’S FINANCIAL PULSE

4.1. Introduction

Financial markets have been the subject of intense scrutiny and analysis for decades, with researchers and investors alike seeking to find clarity in the behavioral complexities of financial and economic systems and predict market movements (Zhang et al., 2019). Traditional approaches have focused mainly on time series analysis, fundamental economic indicators, and quantitative models to predict and decipher market trends, resulting in a lack of research regarding the impact of wider political, macroeconomic uncertainties on the stock market (Pal et al., 2020).

These methods, while valuable, often struggle to capture the patterns of the rapidly changing landscape of global finance, in an era of instantaneous information flow and highly interconnected market interrelations. Predictive models have become increasingly sophisticated as technology (Shen et al., 2022), has progressed, including larger datasets and efficient algorithms (Quinlan, 1986; Sako, Mpinda, & Rodrigues, 2022). The prevalence of Big Data, driven by advancements in information technology, has triggered a transformative shift revolutionizing data usage from traditional time series to encompassing diverse forms such as text data, thereby enhancing decision-making processes in financial markets (Rizkiana et al., 2019; Tian, Zhou, & Zhang, 2020; Xing, Cambria, & Welsch, 2018; Yuanyuan et al., 2023).

Investor decision-making is influenced by both current events and expectations about future developments. In this context, negative news¹⁴ sentiment plays a significant role in shaping investor behavior, especially among international investors¹⁵, who tend to be more sensitive to uncertainty and market volatility.

As a result, the financial sector is increasingly employing text data to gain deeper insight and understanding into market behavior, sentiment, and emerging trends (Balaneji et al., 2024). This shift toward integrating unstructured, noisy text data such as news articles (Chari et al., 2023; Chatchawan, 2021; Jin et al., 2024; Krinitz et al., 2017; Pröllochs et al., 2015, 2016), social media posts (Bollen, Mao, & Zeng, 2011; Botchway et al., 2020), and financial reports into predictive models represents a frontier in financial analysis, which enables context-rich assessments of market conditions.

However, the complexity of unstructured data deters many researchers, resulting in a nascent body of literature employing this methodology.

Similarly, sentiment analysis has gained significant momentum in various social science disciplines, including economics and finance. In one such study, Gonzalez et al. (2020) demonstrate how central banks can influence market expectations through the sentiment expressed in their press releases, underlining the vital role of clear communication in financial policy. The widespread use of central bank statements for sentiment analysis is further substantiated by a plethora of ongoing research efforts throughout the world. Studies by Kahvecia & Odabaş (2016), Omotosho (2019), Kumari & Pandey (2025), Lee et al. (2023), and Picault et al. (2023), all contribute to this increasing body of work.

These studies emphasize the role of central bank communication and its importance in sentiment analysis in deciphering economic dynamics and predicting financial market behavior. Similarly, researchers have used data from various news and social media sources. Djourellov et al. (2017) highlighted the evolving media landscape and the impact of online competition on local newspapers. Their research underlines the

¹⁴ Plunge in Lira, Türkiye 's Currency, Fuels Fears of Financial Contagion - The New York Times

¹⁵ Plunge in Lira, Türkiye 's Currency, Fuels Fears of Financial Contagion - The New York Times

potential consequences of media consolidation by indicating that decreased coverage of political news, a result of shrinking newsrooms, can have a substantial impact on investor information and behavior.

Furthermore, there is evidence from previous research regarding the connection between news sentiment and asset prices. Pyo & Kim (2012) demonstrated a positive correlation in Korea, with investor optimism leading to higher stock prices and lower volatility. Johnman et al. (2014) suggested similar findings for the FTSE 100 index, with positive sentiment reducing volatility even without impacting returns. Öztürk (2022) extended this concept to the cryptocurrency market, highlighting the predictive power of Twitter sentiment on Bitcoin returns and trade volume. Notably, the influence of overall sentiment seemed stronger than that of individual accounts.

Despite these advancements, a gap exists in research combining local and international news sentiment analysis to predict the Turkish stock market. Previous studies are based on either financial reports (Atak, 2023) or Twitter only (Gumus & Sakar, 2021). This study aims to bridge this gap by utilizing Natural Language Processing (NLP) techniques and sentiment analysis on international news sources, local news outlets, and Twitter. Sentiment from both global news media (The Economist, The New York Times, The Guardian) and domestic ones (Yeni Şafak and Local Tweets) is taken into account to analyze the Turkish stock market.

Moreover, to enhance the accuracy and interpretability of the predictions, the study employs advanced explainable AI (XAI) techniques alongside state-of-the-art natural language processing using Financial Bidirectional Encoder Representations from Transformers (FinBERT) transformer models. FinBERT, a variation of BERT specifically fine-tuned for financial text, offers superior performance in understanding and analyzing the nuances of financial language. Its high capacity to comprehend entire texts contextually and compute sentiment as continuous values, rather than binary classifications, supports our research objectives.

Transformers, including FinBERT, offer significant advantages over classical models by combining a self-attention mechanism, parallelization, and positional encoding. These features are particularly beneficial when working on projects that involve

semantic feature extraction from large datasets (Vaswani et al., 2017). Unlike traditional neural networks such as Long-Short Term Memory (LSTM) and Convolutional Neural Network (CNN) components, which rely on sequential analysis and can be limited in their effectiveness, transformer models excel at capturing complex relationships within text data (Heaton et al., 2017).

The remainder of the chapter is structured as follows: Section 2 presents a review of the related literature, providing context and background for the study. Section 3 describes the data sources and the methodology employed, detailing the analytical framework used in the research. Section 4 presents the results and discussion of classical supervised machine learning models, analyzing their performance and implications. Section 5 focuses on the application of explainable AI techniques, offering insights into the interpretability of the models. Finally, the paper concludes with Section 6, which summarizes the findings and suggests directions for future research.

4.2. Literature Review

Sentiment analysis has become a crucial tool in understanding market dynamics (Nabeen et al., 2022; Nyakurukwa & Seetharam, 2023). Case and Clements (2021) emphasize the importance of sentiment analysis in extracting subjective, speculative information from media, which can influence investment decisions and asset prices. They utilized contextual word representations from pre-trained BERT language models to analyze Wall Street Journal articles and found that financial news sentiment significantly predicts daily returns, while longer-term economic news sentiment is more relevant for monthly returns.

On the other hand, Gu et al. (2021) constructed a financial news sentiment lexicon and an auxiliary lexicon specific to the financial domain. They introduced a Comprehensive Sentiment Index (CSI) that incorporates both textual sentiment and structured stock market data. Their comparative analysis of GARCH and LSTM models revealed that LSTM models, augmented with these sentiment indices, outperform traditional approaches in predicting stock returns.

The scope of sentiment analysis in financial markets extends beyond general news to specific topics of global concern. Fedorova and Iasakova (2024) investigate the impact of climate change news on US stock indices, employing a pre-trained bidirectional FinBERT neural network for sentiment analysis. They examined the influence of five main news topics (finance and politics, natural disasters and consequences, industrial sector and innovations, activism and culture, and the coronavirus pandemic) on stock index dynamics. The study reveals that these topics significantly influence the financial market. Other studies focus on the predictive power of social media sentiment.

For instance, Jiang et al. (2021) explore the relationship between Twitter sentiment and stock returns using a deep learning framework that integrates both textual and visual information from tweets. The findings suggest that incorporating multimodal social media data can enhance stock return prediction accuracy. Similarly, Zhang et al. (2022) propose a hybrid model combining LSTM networks with attention mechanisms to capture both long-term dependencies and key information in financial news. Their approach demonstrates improved accuracy in stock price prediction compared to traditional methods.

Beyond text-based sentiment analysis, Chen et al. (2023) investigate the impact of audio sentiment in earnings conference calls on stock price movements. The study highlights the importance of considering multiple modalities of communication in assessing market sentiment.

On the other hand, the geographical scope of sentiment analysis in financial markets is also diverse. While many studies focus on the US markets, some studies explore other regions. For example, Li et al. (2020) examined the Chinese stock market, developing a sentiment-aware stock trend prediction model that incorporates both market data and news sentiment. Similarly, methodological innovations are evident across the literature. Sezer and Ozbayoglu (2021) employed capsule networks for financial sentiment analysis, demonstrating improved performance over traditional convolutional neural networks.

Similarly, Wang et al. (2023) propose a multi-task learning framework that predicts stock movement and classifies sentiment simultaneously. The impact of major global events on market sentiment is also a significant area of study. Several researchers examine the effects of the COVID-19 pandemic on stock market sentiment and returns, highlighting the importance of sentiment analysis during periods of high uncertainty (e.g., Liu et al., 2022).

Meanwhile, other studies explore approaches that are more expansive to sentiment analysis. For instance, Xu et al. (2023) proposed a multi-modal framework combining textual and visual information from social media. Additionally, Zhao et al. (2024) suggest an attention-based neural network for sentiment-aware stock prediction. Furthermore, other studies focused on specific sectors or events. Yang et al. (2023) analyzed the impact of sentiment on renewable energy stocks, while Johnson and Smith (2022) examined how geopolitical events influence market sentiment and returns.

The highlighted literature reveals a rapidly evolving field at the intersection of sentiment analysis, news media, and stock market prediction (Azimi and Agrawal, 2021). The integration of advanced machine learning techniques, particularly transformer-based models, represents a significant advancement.

4.3. Data and Methodology

4.3.1. Data Source

A multifaceted approach was utilized, incorporating news articles, both from international and local sources, alongside local social media data. Three prominent international publications were selected for news data: The Economist, The New York Times, and The Guardian. These newspapers were chosen due to their extensive global reach and reputation for in-depth coverage. Additionally, a local newspaper, Yeni Şafak, was included to offer a domestic perspective. To capture real-time sentiment surrounding Turkish markets, we further enriched the dataset with local Twitter posts. Due to limitations in accessing data from other local news outlets, Yeni Şafak and local Twitter posts were selected as proxies for the broader

local media landscape. To ensure data relevance and minimize noise from extraneous content, we focused on the economic, finance, and business sections for all news sources.

The obtained data provides a substantial dataset for analysis, spanning from January 1, 2015, to February 27, 2024. This timeframe aligns with our financial market data, which includes Turkish daily stock returns, opening prices, lows, highs, and trading volumes. All financial data is sourced from Yahoo Finance.

4.3.2. Data Acquisition

Extracting large datasets is often a cumbersome task. Fortunately, modern software infrastructure simplifies this process. Most of our chosen news sources possess sophisticated Application Programming Interfaces (APIs) that facilitate smooth and systematic data retrieval. The New York Times, The Guardian, and Yeni Şafak offer user-friendly and free APIs that streamline data extraction. For The Economist, we utilized the university's subscribed database as well as manual data collection to access the latest relevant articles. Similarly, Twitter's academic API was utilized to extract relevant tweets. In conjunction with APIs, we employed Python libraries such as Requests and BeautifulSoup, as well as regular expressions, to further refine the extracted data. These tools assisted in removing unnecessary characters and extra spaces, ensuring a clean and organized dataset. The extracted data encompassed the publication date, article title, summary, full body, and URLs for each news article and tweet.

Finally, we consolidated the data from all sources and saved it in a single CSV file, which was readily prepared for the subsequent preprocessing stage. Figure 4.1 illustrates the data extraction processes.

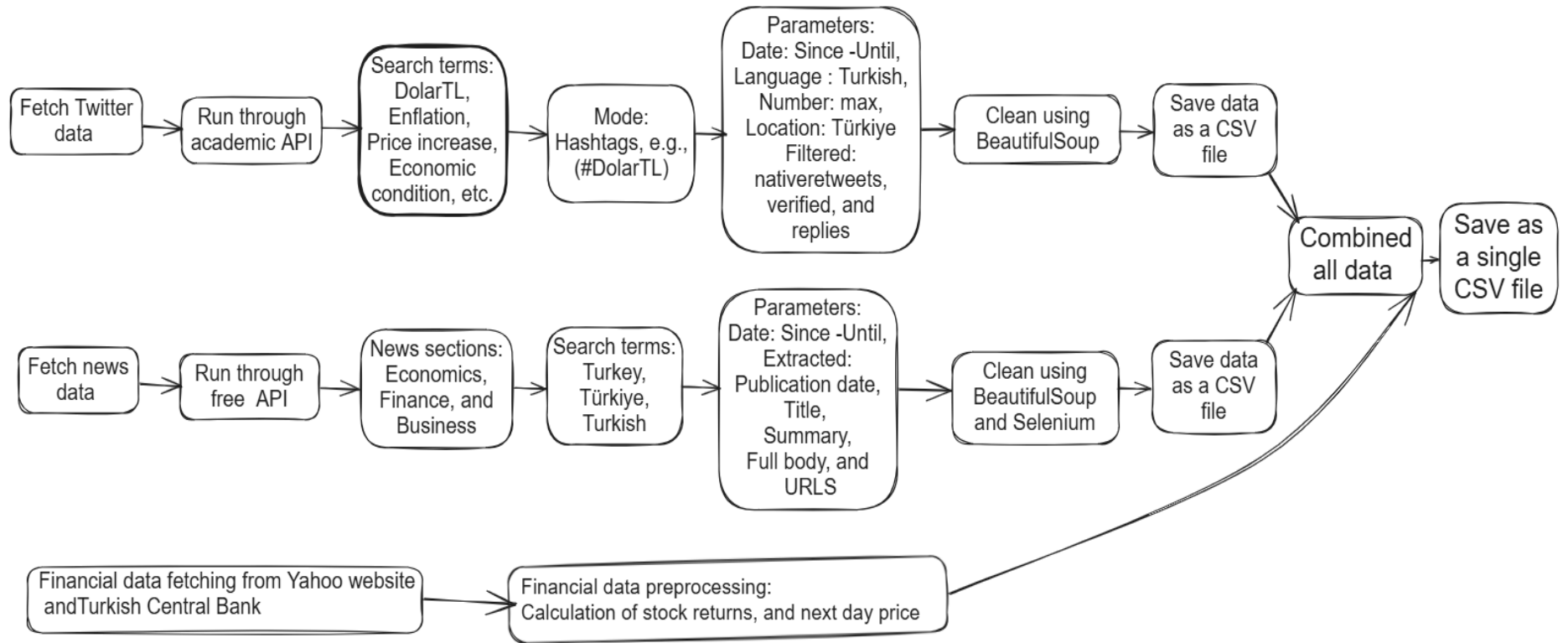


Figure 4.1. Data Extraction Workflow

4.3.3. Data Preprocessing

Raw text data obtained from various sources often presents challenges in the form of noise and irrelevant information. To address these issues, we implemented a series of data preprocessing and cleaning tasks using Pandas, SpaCy, and Neattext libraries. SpaCy and Neattext are powerful Natural Language Processing (NLP) tools specifically designed for text-cleaning and preprocessing tasks (Agbe, 2020; Honnibal & Montani, 2017).

The cleaning stage focused on removing extraneous elements such as URLs, HTML tags, excessive spaces, special characters, numbers, email addresses, hashtags, and improper quotations. The subsequent preprocessing stage involved several steps:

- i. Lemmatization: reducing words to their base dictionary form.
- ii. Case conversion: converting text to lowercase to minimize textual variability and enhance consistency.
- iii. Punctuation removal: eliminating unnecessary symbols to streamline the data.
- iv. White space removal: ensuring textual coherence.
- v. Normalization: standardizing the text format.
- vi. Spelling correction: improving the overall quality and readability of the text, minimizing potential confusion or misunderstanding.
- vii. After analyzing the removal and retention of stop-words, the decision was made to retain them as the analysis improved when the stop words were maintained.

Through this systematic preprocessing pipeline, we transformed the raw text data into a clean and structured format, ready for further analysis. Figure 4.2 depicts the data-preprocessing flowchart and techniques employed.

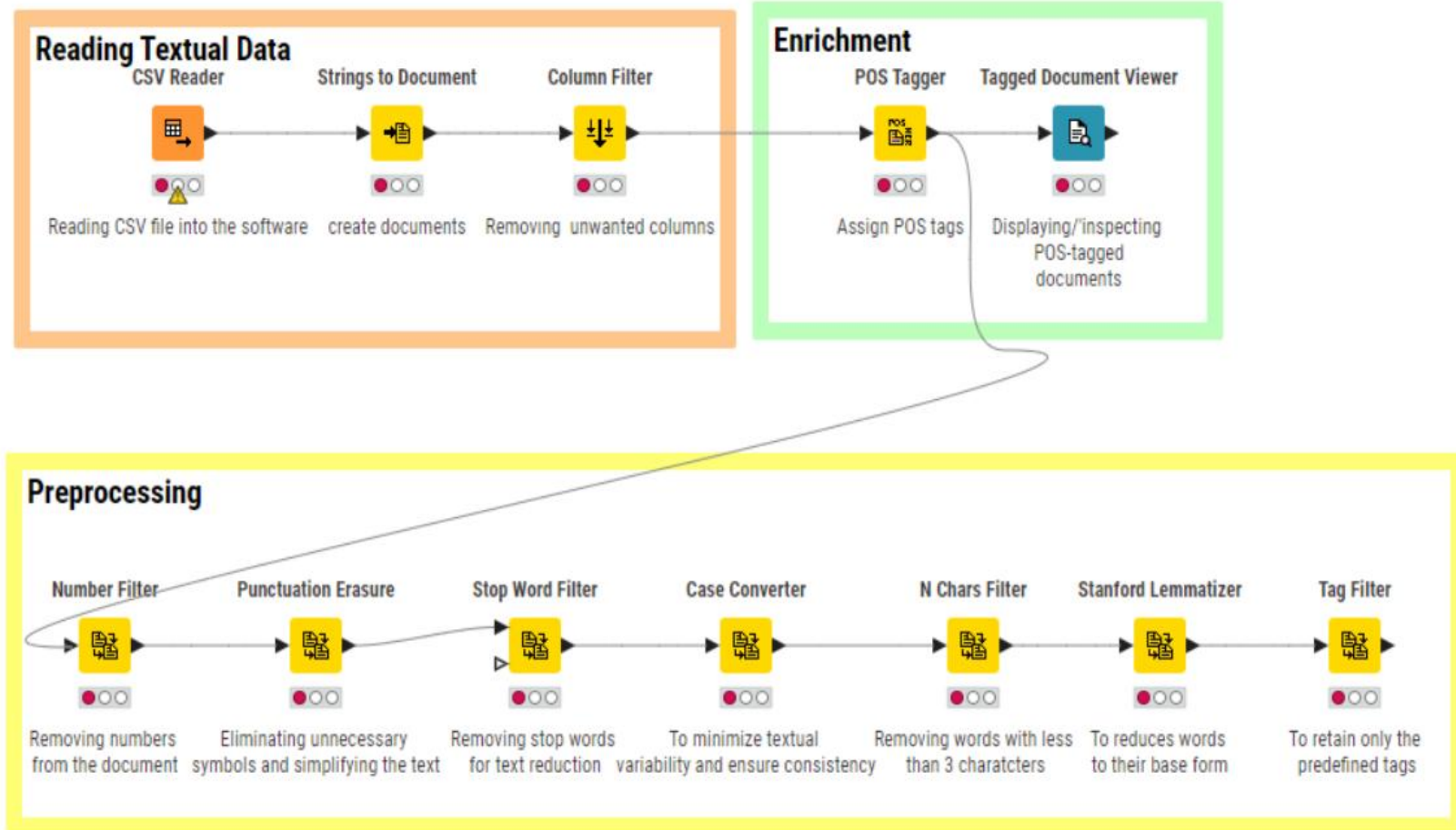


Figure 4.2. Data Preprocessing Flowchart

4.3.4. Methodology

After preprocessing the data, we carried out the following tasks: utilization of the FinBERT transformer model for advanced feature extraction, topic modeling to identify key themes and narratives in the news articles, sentiment analysis to gauge positive, negative, and neutral sentiment towards financial events, and named entity recognition to identify relevant entities such as companies, government policies, and economic indicators. Volatility and event indicators as well as market trends, capture potential signals from news content. N-grams (unigrams, bigrams, and trigrams) capture the frequency and co-occurrence of words or phrases that are related to the stock market. Parts of speech classify words based on their syntactic and semantic roles in a sentence, such as verbs, adverbs, and adjectives, and their sentiment levels.

Our selection of FinBERT was driven by five compelling methodological advantages. First, FinBERT's specialized training on financial corpora allows for precise interpretation of domain-specific terminology that general language models often misinterpret. Second, its transformer-based architecture captures contextual relationships between words when analyzing complex financial statements, where meaning depends heavily on surrounding text. Third, empirical comparisons demonstrate FinBERT's superior classification accuracy compared to traditional lexicon-based approaches like (Loughran & McDonald, 2016) when distinguishing sentiment variations. Fourth, FinBERT shows remarkable performance even with the limited Turkish financial dataset available to us, which can be seen as an advantage on account of the relatively smaller size of the Turkish market compared to major global exchanges.

Finally, its proven capability to identify informational content in financial texts that alternative models miss ensures more comprehensive coverage of market-moving news events in our analysis framework (Huang, Wang, & Yang, 2022). To attest to the robustness of our analysis, we also employed the Loughran-McDonald dictionary, which also offers five methodological strengths for financial text analysis. First, this lexicon was specifically developed to address misclassification issues found when general-purpose dictionaries are applied to financial contexts. Second, the dictionary categorizes financial terminology into distinct sentiment categories

that effectively capture the tone of corpora documents and financial news. Third, empirical validation demonstrates its effectiveness in measuring sentiment when examining market reactions, trading volumes, and volatility patterns. Fourth, the dictionary shows consistent performance across various financial contexts, including fraud detection, material weakness identification, and unexpected earnings analysis. Finally, its application requires minimal computational resources compared to transformer-based models, which makes it a practical complementary approach for verifying sentiment analysis results in financial market studies (Bodnaruk et al., 2015; Huang et al., 2022; Loughran & McDonald, 2011, 2016, 2024).

Sentiment Calculation Formula: Given a text input T , we calculated the sentiment score $S(T)$ as follows:

$$S(T) = f(M(E(T[:512])))$$

Where:

$T[:512]$ represents the first 512 characters of the input text T .

E is the encoding function that converts text to tokens

M is the BERT model function that processes the encoded tokens

f is a function that maps the model output to a sentiment score (1 to 5)

In our implementation:

$$f(x) = \text{argmax}(x) + 1$$

The sentiment scoring function processes text in chunks of 512 characters due to the FinBERT model's input size limitation. For texts longer than 512 characters, we iteratively applied the sentiment analysis to successive 512-character segments to ensure that the entire text was analyzed, regardless of its length. Thus, each text was split into consecutive 512-token chunks due to model input constraints. The system processed the first 512-token chunk completely before continuing to the next 512-token chunk, until the whole text was processed. Sentiment was then computed for each chunk, and the final sentiment score was obtained by combining or aggregating the scores across all chunks of each row.

Using a 1-5 scale for sentiment scores offers greater granularity compared to a 0-1 scale. This allows capturing subtle differences between slightly positive, neutral, and slightly negative sentiments better (Vaswani et al. 2017). The integer scores are also

more intuitive for human interpretation, between 1 (very negative) and 5 (very positive), facilitating easier analysis and reporting of results (Goldberg, Y. 2017).

Predicting stock market trends has been a formidable task in financial analysis, traditionally approached using statistical methods like ARIMA (Autoregressive Integrated Moving Average) and econometric models such as GARCH (Generalized Autoregressive Conditional Heteroskedasticity) (Tsay, 2005). While these methods have been instrumental in understanding and forecasting time series data, they are often constrained by assumptions of linearity and stationarity, making them less effective in capturing the complex and non-linear nature of financial markets (Atsalakis & Valavanis, 2009).

In response to the limitations of traditional methods, the development and application of Machine Learning (ML) models have emerged as powerful tools for stock market prediction (Hu et al., 2021). ML models have demonstrated superior performance by leveraging large datasets and identifying intricate patterns in data without the stringent assumptions required by classical methods (Cortes & Vapnik, 1995; Breiman, 2001). Given the potential of ML in financial forecasting, the selection of appropriate algorithms is crucial to ensure robust and reliable predictions. In this study, a diverse array of machine learning techniques, ranging from individual models to ensemble-based approaches have been employed, each offering distinct advantages in capturing the dynamics of the Turkish stock market (T.Chen & Guestrin, 2016; W. Chen, & Hong, 2020). A longside the machine learning models, GARCH model has been employed as the foundational framework for our analysis. The GARCH model did not reveal statistically significant relationships between stock market returns and sentiment indicators derived from various news sources. The result of the GARCH model mean equation is presented in Table 4.8.

The machine learning models utilized in this research include Logistic Regression, Decision Tree, K-Nearest Neighbors, Support Vector Machine, and Artificial Neural Network. These models are widely recognized for their ability to learn complex patterns from data and provide interpretable insights into the underlying relationships (Hastie et al., 2009; Goodfellow et al., 2016).

Logistic Regression, for instance, excels at modeling the probability of binary outcomes, making it well-suited for stock market classification tasks (Hosmer et al., 2013). Similarly, Decision Trees and their extensions have demonstrated remarkable performance in capturing non-linear interactions within the data, with the added benefit of easy interpretation (Breiman, 2001).

To further enhance predictive accuracy, ensemble-based algorithms have also been incorporated into the modeling framework. These methods, including Random Forest, XGBoost, Gradient Boosting, and AdaBoost, leverage the strengths of multiple individual models to produce more accurate, robust, and consistent predictions (Abbott, 2014; Rokach, 2010; Dietterich, 2000). Ensemble techniques have gained widespread popularity in finance and economics due to their ability to handle complex, non-linear relationships and their inherent robustness to outliers and noise in the data (Breiman, 2001; Chen & Guestrin, 2016). The utilization of this diverse array of algorithms serves for robustness checks and to enhance the predictive accuracy of stock market forecasts.

An essential component of model development in machine learning involves selecting appropriate hyperparameters, which are parameters that govern the training process but are not learned from data. The values of these hyperparameters can significantly affect model performance, yet there is no analytical solution to determine their optimal configuration. To solve this problem, several optimization frameworks have been proposed that automate the search over a predefined hyperparameter space.

One of the most widely used methods is Grid Search, which exhaustively evaluates every possible combination of hyperparameters defined within a fixed grid. This technique is deterministic and guarantees that the global optimum within the grid will be found, provided that it exists within the search space (Pedregosa et al., 2011). Its main advantage lies in simplicity and reproducibility. However, the computational cost increases exponentially with the number of hyperparameters and candidate values, which makes it inefficient when the search space is large or when many of the combinations are suboptimal.

To reduce this computational burden while retaining the potential to discover high-performing configurations, Randomized Search was introduced as an alternative. This method samples a fixed number of combinations from the hyperparameter space according to a specified probability distribution (Bergstra & Bengio, 2012). Because it explores more configurations when the budget is limited, it can often identify near-optimal solutions with fewer evaluations. It is especially useful when only a small subset of hyperparameters has a significant impact on model performance, since it does not waste resources on unimportant combinations as grid search tends to do.

More recently, probabilistic methods have been developed to guide the search using past evaluation results. Bayesian Optimization is one such approach that models the objective function using a surrogate model, commonly a Gaussian Process or Tree-structured Parzen Estimator (TPE), and uses an acquisition function to select the most promising hyperparameter configurations to evaluate next (Snoek et al., 2012). This allows the algorithm to focus evaluations on regions of the space that are more likely to yield better performance while minimizing redundant or uninformative trials. Bayesian methods have been shown to require fewer iterations than both grid and random search, and they perform well when model evaluations are expensive or when the objective landscape is irregular and non-convex.

In this study, a combination of Grid Search and Bayesian Optimization is employed to tune model hyperparameters. Grid Search is applied in preliminary stages where the number of candidate values is small and interpretability is important, as it enables the identification of stable parameter ranges that form a basis for further refinement. For the final tuning, Bayesian Optimization is used because it achieves better efficiency by incorporating performance feedback from previous evaluations, which accelerates convergence to optimal regions of the search space. The combined use of these methods allows for both robust initial exploration and efficient fine-tuning, which is essential given the computational complexity of the models considered in this work (Chen & Guestrin, 2016).

Moreover, in machine learning, optimization plays a central role in enabling models to learn from data by minimizing a predefined loss function. The underlying goal is to iteratively adjust model parameters in a manner that achieves convergence to a

local or global minimum of the objective function. However, the non-convexity and high dimensionality of modern models introduce challenges that include vanishing or exploding gradients, poor convergence rates, and instability in learning trajectories. To remedy these issues, various optimization algorithms have been developed, each designed to update parameters with different assumptions and computational strategies.

A foundational class of methods is based on first-order gradient information, where the optimization relies solely on the first derivative of the loss function. The most basic example is Stochastic Gradient Descent (SGD), which updates the model's parameters using a single data point or a small subset at each iteration (Bottou, 2010). This approach is computationally efficient and well-suited for large datasets, but the updates can be noisy and unstable due to the high variance introduced by small sample sizes.

To mitigate this instability while retaining computational efficiency, Mini-batch Gradient Descent was introduced. This method uses a fixed-size subset of data at each step rather than a single example. As a result, it reduces the variance in the gradient estimates while still being faster than computing gradients over the entire dataset. On the other hand, Batch Gradient Descent, which computes the gradient using the entire training dataset, offers the most stable updates but is often too slow and memory-intensive for large-scale learning problems. These three variants, stochastic, mini-batch, and batch, represent different trade-offs between accuracy and computational cost, but they all share the same fundamental mechanism of following the negative gradient direction to minimize loss.

To improve the efficiency of gradient-based learning, momentum-based algorithms incorporate historical gradient information. SGD with Momentum improves on vanilla SGD by including a fraction of the previous update in the current one (Polyak, 1964). This helps the optimizer maintain its direction across iterations, which reduces oscillations and allows it to traverse shallow regions of the loss surface more efficiently. Building on this idea, Nesterov Accelerated Gradient (NAG) introduces a more anticipatory update. Instead of computing the gradient at the current parameters, it evaluates the gradient at a look-ahead point based on the

momentum direction (Nesterov, 1983). This adjustment results in more informed updates and can lead to faster convergence in some scenarios. Both methods enhance basic gradient descent by adding a form of inertia that helps the optimizer move more consistently toward minima.

Another group of optimizers addresses the problem from a different angle by introducing adaptive learning rates. These methods adjust the size of each parameter's update based on the history of gradients. AdaGrad is one such method that increases the learning rate for parameters with infrequent updates and decreases it for those with frequent updates (Duchi et al., 2011). This feature makes it effective for problems with sparse features. However, a major limitation is that the learning rate can decay too quickly over time, causing the optimizer to stop prematurely. To rectify this, RMSProp was proposed. It modifies AdaGrad by maintaining a moving average of the squared gradients rather than summing them, which prevents the learning rate from shrinking excessively (Tieleman & Hinton, 2012). AdaDelta extends RMSProp by removing the need for a manually set global learning rate and instead uses a ratio of accumulated updates to gradients to determine the step size (Zeiler, 2012). All three methods share the goal of adapting the learning rate dynamically to improve convergence stability, though they differ in how they compute and apply the scaling factors.

A more advanced category of optimizers combines both momentum and adaptive learning rates to benefit from the strengths of each. Adam (Adaptive Moment Estimation) is the most prominent example in this group. It maintains exponentially weighted averages of both the first and second moments of the gradients, which allows it to adjust step sizes for each parameter individually while also retaining directional consistency (Kingma & Ba, 2015). AdamW modifies this structure by decoupling weight decay from the adaptive updates, which improves the model's generalization performance and corrects a regularization flaw in the original Adam implementation (Loshchilov & Hutter, 2019). Another variant, Nadam, introduces Nesterov momentum into the Adam framework to further enhance the optimizer's responsiveness to gradient curvature (Dozat, 2016). AMSGrad alters Adam's second-moment update rule to guarantee theoretical convergence in certain settings by preventing the learning rate from increasing unexpectedly (Reddi et al., 2018). These

extensions are closely related to Adam and offer targeted improvements that address specific empirical or theoretical concerns.

In addition to these mainstream methods, several recent optimizers explore different update rules and mechanisms. Yogi modifies the second-moment estimation in Adam to handle sparse updates more effectively (Zaheer et al., 2018). RAdam introduces a rectification mechanism to stabilize the variance of adaptive learning rates, especially in early training stages (Liu et al., 2020). Lookahead is a meta-algorithm that operates alongside other optimizers by maintaining two sets of weights, one updated frequently and one updated more conservatively, which helps smooth out erratic training behavior (Zhang et al., 2019). Lion is a newer method that simplifies the update rule by using the sign of the gradient rather than its magnitude and has been shown to perform competitively on some large-scale training tasks (Chen et al., 2023). These approaches differ significantly in formulation, yet they all aim to address instability, poor convergence, or inefficiency in large neural models.

Among the wide range of optimizers described above, Adam has become the default choice in deep learning research and practice due to its strong empirical performance across diverse architectures and datasets. It avoids the need for extensive hyperparameter tuning, converges efficiently, and performs robustly in settings where gradients are noisy or sparse. The combined use of momentum and adaptive learning rates enables Adam to handle complex and irregular loss landscapes more effectively than earlier methods. These characteristics make it especially suitable for high-dimensional problems and data with heterogeneous feature distributions. For these reasons, Adam is selected as the optimization method in this study. Table 4.1. contains concise comparative descriptions of optimization techniques.

Table 4.1. Comparative Summary of Different Optimizers

Optimizer	Adaptive Learning Rate	Momentum	Description
SGD	X	X	Baseline
SGD+Momentum	X	✓	Smooths updates
AdaGrad	✓	X	Good for sparse data
RMSProp	✓	X	Fixes AdaGrad decay
Adam	✓	✓	Most widely used
AdamW	✓	✓	Better regularization
Nadam	✓	✓	Adam + Nesterov
RAdam	✓	✓	Rectified variant
Lookahead	✓	✓	Works alongside other optimizers
Lion	✓	✓	Recently, strong in vision tasks

Following the initial supervised machine learning prediction phase, explainable AI (XAI) techniques were employed to shed light on the rationale behind the model's predictions. The Shapley Additive exPlanations (SHAP) library was used specifically for its user-friendliness and ability to provide human-interpretable explanations of the model's features (Lundberg & Lee, 2017). Understanding the local explanations and importance of these features allows for a deeper comprehension of how media discourse influences market movements. The Models are presented in the following pages.

- **Logistic Regression:** The Logit model is written as:

$$(Y = 1 | X) \frac{1}{(1 + e^{-(X'\beta)})} \quad (4.1)$$

$$P(Y = 1 | X) = \frac{1}{(1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 \dots + \beta_k x_{23})})} \quad (4.2)$$

- **Decision Tree:** Let the input vector be denoted by $x = \{x_1, x_2, \dots, x_5\} \in R^5$, where each x_i represents a sentiment score (scaled from 1 to 5) derived from a headline. The target variable $y \in R$ denotes the future stock return associated with the news context, either as a binary class (e.g., up/down) or a continuous value (e.g., percentage return).

Decision Trees split each node by minimizing an impurity function that quantifies the degree of class heterogeneity. A widely used measure for impurity is the Gini index (Breiman et al., 1984), which for a node t is defined as

$$G(t) = \sum_{k=1}^K p_k(1 - p_k) = 1 - \sum_{k=1}^K p_k^2 \quad (4.3)$$

where p_k represents the proportion of samples belonging to the class k Within the node, and K denotes the total number of classes. This measure reaches its minimum of zero when the node is pure (i.e., all samples belong to the same class).

An alternative measure is the Shannon entropy (Information Gain Criterion), defined

$$H(t) = - \sum_{k=1}^K p_k \log_2(p_k) \quad (4.4)$$

which captures the uncertainty in class distributions (Quinlan, 1986). When a node is split based on an attribute A that partitions the node t into the left and right child nodes t_L and t_R the reduction in entropy, termed Information Gain, is expressed as:

$$IG(t, A) = H(T) - \left(\frac{N_L}{N} H(t_L) + \frac{N_R}{N} H(t_R) \right) \quad (4.5)$$

Where N is the number of samples in the node t , A is the attribute used for the split, and N_L , and N_R are the numbers of samples in the child nodes, respectively.

The optimal splitting attribute A^* is determined by minimizing the weighted impurity of the resulting nodes, namely:

$$A^* = \underset{A}{\operatorname{argmin}} \left[\frac{N_L}{N} \cdot \operatorname{Impurity}(t_L) + \frac{N_R}{N} \cdot \operatorname{Impurity}(t_R) \right] \quad (4.6)$$

where the impurity metric can be either Gini or entropy.

- **Random Forest model (Ensemble of Decision Trees):** While Decision Trees offer interpretability and simplicity, they are highly prone to overfitting, especially when the tree grows deep and attempts to perfectly classify the training data. This overfitting limits their generalization performance on unseen data, making them less reliable in high-variance settings such as financial forecasting, where sentiment-driven features introduce substantial noise. To address these limitations, the Random Forest algorithm extends the basic Decision Tree model through an ensemble learning framework designed to enhance robustness and predictive accuracy (Breiman, 2001). A Random Forest is composed of B individual decision trees, denoted $\{(h_b(.))\}_{b=1}^B$, each trained on a bootstrap sample drawn from the original dataset. To further decorrelate the trees and increase the diversity of the ensemble, a random subset of features is considered at each node when determining the optimal split. For a given input vector x in this context, a vector of sentiment scores derived from five news headlines, the prediction in a classification task, such as determining whether a stock return is positive or negative, is obtained through majority voting across the ensemble:

$$\hat{y} = \operatorname{mode}\{(h_b(x))\}_{b=1}^B \quad (4.7)$$

This ensemble approach ensures more stable and generalizable predictions in the context of noisy, financial data.

In the case of regression, where the output is a continuous stock return, predictions from individual trees are averaged as:

$$\hat{y} = \frac{1}{B} \sum_{b=1}^B h_b(x) \quad (4.8)$$

The dual use of bootstrap sampling and randomized feature selection ensures both variance reduction and improved model robustness, which is important in time series forecasting tasks like financial data that are often characterized by high volatility and noise (Lemhadri et al., 2021). Hence, mitigates the overfitting issue observed in single trees.

- **Support Vector Machines (SVMs):** Support Vector Machines (SVMs) are founded on the principle of maximizing the margin between classes in the feature space (Cortes & Vapnik, 1995). For binary classification, such as predicting whether a stock return is positive or negative, the SVM aims to determine the hyperplane that separates classes with the widest possible margin. This is formalized through the convex optimization problem:

a vector $x_i \in R^D$, where each observation corresponds to a labeled return class $y_i \in \{0,1\}$, representing, for instance, negative or positive stock return directions. The foundational objective of the SVM is to find a decision boundary (hyperplane) defined by a normal vector $w \in R^d$ and a bias term $b \in R$, such that the separation between classes is maximized. The optimal separating hyperplane satisfies the condition:

$$y_i(w^\top x_i + b) \geq 1, \forall i = 1, \dots, n$$

To achieve maximal separation, SVM minimizes the Euclidean norm of the weight vector, which geometrically corresponds to maximizing the margin between the closest data points (support vectors) and the hyperplane. This leads to the following convex optimization problem:

$$\min_{w,b} \frac{1}{2} \|w\|^2 \text{ subject to } y_i(w^\top x_i + b) \geq 1$$

However, in practical settings such as ours, where the sentiment data derived from natural language processing is inherently noisy and possibly non-separable, a soft-margin SVM is employed. This introduces slack variables $\xi_i \geq 0$ to tolerate margin violations, leading to the relaxed formulation

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i, \quad \text{subject to } y_i(w^\top(x)_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$

The regularization parameter $C > 0$ controls the trade-off between maximizing the margin and penalizing misclassifications. A smaller value of C leads to a wider margin with more tolerance for error, while a larger C forces stricter separation, potentially at the cost of generalization.

To accommodate non-linear relationships between sentiment and returns, particularly important in financial text, we project the input space into a higher-dimensional feature space via a kernel function $K(x_i, x_j)$. The dual form of the optimization problem, which leverages this transformation, is expressed as: The dual form of the optimization problem, which leverages this transformation, is expressed as:

$$\max_{\alpha} \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j K(x_i, x_j) \quad \text{subject to } 0 \leq \alpha_i \leq C, \sum_{i=1}^n \alpha_i y_i = 0$$

Here, α denotes the vector of Lagrange multipliers. Common kernels include the linear, polynomial, and radial basis function (RBF) kernels; in our application, the RBF kernel is particularly effective in capturing latent nonlinear dependencies between sentiment signals and market movements.

The resulting decision function used for prediction is given by:

$$f(x) = \text{sign} \left(\sum_{i=1}^n \alpha_i y_i K(x_i, x) + b \right) \quad (4.9)$$

- **AdaBoost:** AdaBoost, short for Adaptive Boosting, was introduced by Freund and Schapire (1997) as one of the first practical boosting algorithms. The method combines multiple weak learners, typically decision stumps (i.e., one-level decision trees), into a single strong classifier. The key innovation of AdaBoost lies in its adaptive reweighting mechanism: after each round of training, the algorithm increases the weights of incorrectly classified instances so that subsequent learners focus more intensely on difficult examples.

Considering a binary classification problem with a training set $D = \{(y_i, x_i)\}_{i=1}^n$, where $x_i \in R^d$ as a d -dimensional feature vector and $y_i \in \{-1, +1\}$, is the corresponding class label (in our case, sentiment direction relating to stock returns). AdaBoost initializes weights $w_i^{(1)} = \frac{1}{n}$, for $i = 1, 2, \dots, n$. At each boosting iteration $m \in \{1, \dots, M\}$, a weak classifier $H_m(x)$ is trained to minimize the weighted classification error:

$$\alpha_m = \sum_{i=1}^n w_i^{(m)} \cdot \mathbb{I}[h_m(x_i) \neq y_i] \quad (4.10)$$

where $\mathbb{I}(\cdot)$ is the indicator function, returning 1 if its argument is true, and 0 otherwise.

The classifier's contribution to the final decision is weighted by:

The classifier's contribution to the final decision is weighted by:

$$\alpha_m = \frac{1}{2} \log \left(\frac{1 - \epsilon_m}{\epsilon_m} \right) \quad (4.11)$$

This weight α_m reflects the confidence in the classifier h_m : smaller errors lead to higher confidence. Subsequently, the sample weights are updated to emphasize misclassified instances:

$$w_i^{(m+1)} = \frac{w_i^{(m)} \cdot \exp(-\alpha_m y_i h_m(x_i))}{Z_m} \quad (4.12)$$

Here, Z_m is a normalization constant ensuring $\sum_{i=1}^n w_i^{(m+1)} = 1$. The final prediction $H(x)$ of the ensemble is then the sign of the weighted sum of individual predictions:

$$H(x) = \text{sign} \sum_{m=1}^M \alpha_m h_m(x) \quad (4.13)$$

AdaBoost demonstrates strong performance in predictive modeling tasks when the base models constitute weak learners, yet it is susceptible to overfitting when training data contains substantial noise or sparsity, a limitation mitigated by modern boosting frameworks that integrate regularization mechanisms or robust loss functions.

- **Gradient Boosting:** AdaBoost's reliance on the exponential loss function limits its flexibility to classification tasks and makes it sensitive to noisy or outlier-heavy data, as it disproportionately amplifies misclassified samples. Also, it lacks built-in regularization, increasing overfitting risks with noisy or sparse datasets.

Gradient Boosting introduced by Friedman, enhances these limitations by generalizing the framework to any differentiable loss function (e.g., squared error for regression), reducing noise sensitivity through gradient-driven updates (fitting residuals instead of reweighting samples), and incorporating regularization mechanisms like learning rate shrinkage, tree depth constraints, and stochastic subsampling to enhance robustness and control model complexity. The motivation behind Gradient Boosting is to iteratively construct a strong predictive function $H(x)$ that minimizes a specified loss over the training data.

Given a training set $\{(x_i, y_i)\}_{i=1}^n$ and a differentiable loss function $L(x, f(x))$, the model is initialized with a constant predictor:

$$f^0(x) = \underset{c}{\operatorname{argmin}} \sum_{i=1}^n L(y_i, c) \quad (4.14)$$

At each iteration m , the algorithm computes pseudo-residuals $r_i^{(m)}$, which are the negative gradients of the loss function evaluated at the current model estimate:

$$r_i^{(m)} = \frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \quad (4.15)$$

$$r_i^{(m)} = \left. \frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right|_{f=f^{m-1}} \quad (4.16)$$

These residuals indicate the direction and magnitude of error at each data point. A base learner $H(m_x)$ is then trained to fit these residuals. The model is updated using a shrinkage parameter $v \in (0,1)$, known as the learning rate:

$$f^m(x) = f^{(m-1)}(x) + v h_m(x) \quad (4.17)$$

The process is repeated for M iterations. The final prediction is $f^M(x)$, which can be interpreted as a functional approximation minimizing the empirical loss.

Here, $f^m(x)$ denotes the ensemble prediction after m iterations, the error signal or direction of steepest descent, $r_i^{(m)}$ is the error signal or direction of steepest descent, and v the rate at which new learners contribute to the ensemble. Therefore, Gradient Boosting allows the use of tailored loss functions such as Mean Squared Error (MSE) for regression or Log Loss for directional classification. Thus, it is suitable for both regression and classification paradigms. Its main limitation, however, is computational cost and sensitivity to hyperparameters.

- **XGBoost.** **XGBoost:** short for Extreme Gradient Boosting, enhances the gradient boosting framework by employing regularized additive tree models to enhance predictive performance while controlling overfitting (Chen & Guestrin, 2016). Given an input vector x_i , the prediction from an XGBoost model consisting of T trees are expressed as:

$$\hat{y}_i = \sum_{t=1}^T f_t(x_i), \quad f_t \in F \quad (4.18)$$

where each f_t is a decision tree from the functional space F . Model training is guided by the minimization of a regularized objective function:

$$L(\phi) = \sum_{i=1}^n \ell(y_i, \hat{y}_i) + \sum_{t=1}^T \Omega(f_t) \quad (4.19)$$

where L is a convex differentiable loss function, such as logistic loss for classification or squared error for regression, and $\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \|w\|^2$ serves as the regularization term to penalize model complexity. The optimization process incorporates second-order Taylor approximations of the loss function, which allows the model to identify optimal splits efficiently and scale to large datasets. This ability to capture nonlinear relationships among variables makes XGBoost suitable for analyzing financial time series prediction tasks.

- **Artificial Neural Networks (ANNs):** Artificial Neural Networks (ANNs) are a class of function approximators inspired by the architecture of biological neural systems. They are particularly well-suited for capturing nonlinear interactions among high-dimensional features. The core principle underlying ANNs is to learn a composite function that maps an input vector to an output, optimizing model parameters via backpropagation and gradient descent.

Consider a supervised learning task with a training dataset set $D = \{(x_i, y_i)\}_{i=1}^n$, where $x_i \in R^d$ is a feature vector composed of sentiment scores

from five news headlines and $y_i \in R$ is a stock return (in classification settings, (0,1)). An ANN with L layers define a function $f: R^d \rightarrow R$, represented as a composition of layer-wise transformations: represented as a composition of layer-wise transformations:

$$\mathbf{f}(\mathbf{x}) = \boldsymbol{\phi}^{(L)}(\mathbf{w}^{(L)}\boldsymbol{\phi}^{(L-1)}(\dots\boldsymbol{\phi}^{(1)}(\mathbf{w}^{(1)}\mathbf{x} + \mathbf{b}^{(1)})\dots) + \mathbf{b}^{(L)}) \quad (4.20)$$

Where each $\boldsymbol{\phi}^{(l)}$ is a nonlinear activation function applied element-wise, commonly chosen as the ReLU function $\phi(z) = \max(0, z)$ sigmoid $\phi(z) = \frac{1}{1+e^{-z}}$. The matrices $\mathbf{w}^{(l)} \in R^{d_l \times d_{l-1}}$ contain the weights connecting layer l to layer $l-1$, and $\mathbf{b}^{(l)} \in R^{d_l}$ are the bias vectors. The dimensionality function $d_0 = d$ corresponds to the input feature dimension, and $d_L = 1$ for a univariate stock return prediction. The output of each hidden layer is computed recursively as:

$$\mathbf{h}^{(l)} = \boldsymbol{\phi}^{(l)}(\mathbf{w}^{(l)}\mathbf{h}^{(l-1)} + \mathbf{b}^{(l)}) \text{ for } l = 1, \dots, L \quad (4.21)$$

With $\mathbf{h}^{(0)} = \mathbf{x}$. The final output $\hat{y}_i = f(x_i)$ is compared to the true return y_i , and the model parameters $\{\mathbf{w}^{(l)}, \mathbf{b}^{(l)}\}_{l=1}^L$ are optimized by minimizing a loss function, typically the Mean Squared Error (MSE) for regression tasks:

To minimize L , stochastic gradient descent (SGD) or one of its adaptive variants (e.g., Adam or RMSProp) is employed. The gradient of the loss with respect to each parameter is computed using the backpropagation algorithm, which efficiently applies the chain rule through the layers of the network.

Artificial Neural Networks (ANNs) differ from linear models in their ability to extract patterns at multiple levels. In sentiment analysis, early layers might detect simple positive or negative language, while deeper layers pick up on context or interactions between different headlines. This structure allows ANNs to identify nonlinear links between time series data, in our case (the market sentiment and asset returns), connections that standard econometric models often miss.

Nevertheless, ANNs can be sensitive to model specification and prone to overfitting when applied to limited or noisy sentiment data. Thus, despite their flexibility, ANNs require careful regularization (e.g., dropout, weight decay) and hyperparameter tuning (e.g., learning rate, number of layers/neurons) to prevent overfitting when working with limited or noisy data. Nonetheless, when properly calibrated, they represent a powerful tool for modeling return dynamics signals. Table 4.2. gives a concise and clear comparative summary of the machine learning techniques.

Table 4.2. Summary of the Advantages and Disadvantages of Machine Learning Models Employed

Model	Advantages	Disadvantages
Gradient Boosting	High predictive accuracy via sequential error correction; handles non-linear relationships.	Prone to overfitting without regularization; computationally intensive.
Random Forest	Reduces variance via ensemble learning; robust to high-dimensional data.	Lower interpretability; memory-intensive for large datasets.
XGBoost	Scalable with regularization; efficient handling of missing data.	Complex hyperparameter tuning; high computational cost.
K-Nearest Neighbours	Non-parametric flexibility; minimal assumptions about data distribution.	Sensitive to irrelevant features; poor scalability for high-dimensional data.
Decision Tree	Interpretable structure; handles non-linear relationships.	High variance; prone to overfitting without pruning.
Logistic Regression	Probabilistic interpretation; computationally efficient.	Assumes linear decision boundaries; struggles with non-separable data.
Support Vector Machine	Effective in high-dimensional spaces; kernel flexibility for non-linearity.	Computationally expensive for large datasets; sensitive to kernel choice.
AdaBoost	Adaptive boosting reduces bias; performs well with weak learners.	Sensitive to noisy data and outliers; risk of overfitting.
Artificial Neural Network	Models' complex non-linear patterns; parallel processing capabilities.	Requires large datasets; black-box nature limits interpretability.
Linear Regression	Simple interpretability; closed-form solution for coefficients.	Assumes linearity, homoscedasticity, and independence; sensitive to outliers.

4.4. Evaluation Metrics and Accuracy Assessment

The evaluation metrics include Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Accuracy, Precision, Recall, and F1 Score. The Receiver Operating Characteristic (ROC) has also been reported, as well as specificity and sensitivity. These are detailed as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (4.22)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (4.23)$$

$$MAE = \frac{1}{N} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4.24)$$

Where y_i is the actual value and $\hat{y}_i$ is the predicted value of the i^{th} observation, and N is the total number of observations.

When evaluating the accuracy of regression models, two key metrics emerge: Mean Absolute Error (MAE) and Mean Squared Error (MSE)¹⁶. Both metrics measure the discrepancies between predicted and actual values but do so in fundamentally different ways. MAE focuses on the average magnitude of errors, disregarding their direction. It calculates the absolute difference between each predicted and actual value, sums all these differences, and then divides by the total number of predictions. This approach gives equal weight to all errors, regardless of whether they are over- or underpredictions. MAE is robust to outliers, as a single large error cannot significantly skew the final value. However, it can be difficult to interpret because it lacks a natural scale comparable to the data itself. MSE, on the other hand, amplifies the influence of larger errors. It squares the difference between each predicted and actual value, essentially penalizing deviations more severely. This leads to a higher

¹⁶<https://towardsdatascience.com/20-popular-machine-learning-metrics-part-1-classification-regression-evaluation-metrics-1ca3e282a2ce>

overall error measure when large errors are present, highlighting their detrimental impact on model performance. While MSE allows for easier interpretation in the same units as the data, it is sensitive to outliers, potentially inflating the overall error due to a few extreme cases.

To address this sensitivity, Root Mean Squared Error (RMSE) emerges as a compromise. RMSE is the square root of MSE, bringing the metric back to the original scale of the data while retaining some emphasis on larger errors. This offers a more balanced interpretation compared to both MAE and MSE, making it a popular choice for evaluating regression models in several scenarios. RMSE exaggerates the importance of greater error values but still maintains a scale comparable to MAE, facilitating easier comparison between these two metrics and enhancing our understanding of model performance.

On the contrary, when evaluating the accuracy of classification models, the key metrics that emerge are Accuracy, Precision, Recall, F1 score, Sensitivity, Specificity, and Receiver Operating Characteristic (ROC) curve.

Accuracy

$$= \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{True Positives (TP)} + \text{True Negatives (TN)} + \text{Falsepositives (FP)} + \text{False Negatives (FN)}} \quad (4.25)$$

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}} \quad (2.26)$$

$$\text{Sensitivity (Recall)} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negative (FN)}} \quad (2.27) \quad \text{F1 Score} = 2 \times$$

$$\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2.28)$$

$$\text{Specificity (True Negative Rate)} = \frac{\text{True Negative (TN)}}{\text{True Negative (TN)} + \text{False Positive (FP)}} \quad (2.29)$$

Precision and recall are essential classification metrics, primarily defined using the following terms:

- TP (True Positive): Instances that are true and correctly classified as true.
- TN (True Negative): Instances that are false and correctly classified as false.
- FP (False Positive): Instances that are false but incorrectly classified as true.
- FN (False Negative): Instances that are true but incorrectly classified as false.

Accuracy, however, is one of the most widely employed metrics in machine learning evaluations (Rainio et al., 2024). Its popularity stems from its simplicity and ease of understanding, facilitating straightforward model comparisons. However, despite its user-friendly nature, it may not always be the most appropriate evaluation metric, as it oversimplifies complex scenarios. Therefore, in this study, accuracy has been complemented with additional metrics, such as precision, recall, and F1 score. These metrics are predominantly utilized in binary classifications but can also be applied to other classification tasks.

Precision represents the percentage of correctly labeled instances out of all positively labeled instances. In other words, it indicates the accuracy of positive class predictions among all instances labeled as positive or belonging to a specific class. On the other hand, Recall, also known as Sensitivity or True Positive Rate, denotes the percentage of correctly labeled positive instances out of all actual positive instances. It reveals how effectively the model captures instances belonging to a specific class, whether positive or negative. Precision and recall are often used together because they offer different perspectives on the same model, providing insights into its performance and highlighting areas for improvement.

The F1 score, a combination of precision and recall, is often preferred by researchers. It represents the harmonic mean of recall and precision, offering a balanced metric that considers both false positives and false negatives. In binary classification problems, the Receiver Operating Characteristic (ROC) curve serves as a graphical assessment tool. It plots the true positive rate (sensitivity) against the false positive rate (1 - specificity). The Area Under the Curve (AUC) offers a valuable metric for comparing the performance of different prediction models. As it is independent of scaling, AUC allows for objective ranking of various methods. One major advantage of AUC is its classification-threshold invariance¹⁷. It measures the inherent predictive power of a model irrespective of the chosen classification threshold, unlike metrics like F1 score or overall accuracy, which can be sensitive to threshold selection. AUC determines the overall unbiased predictive power of a classifier by accounting for potential biases. A perfect classifier achieves an AUC of 1, while a

¹⁷<https://towardsdatascience.com/20-popular-machine-learning-metrics-part-1-classification-regression-evaluation-metrics-1ca3e282a2ce>

model with no predictive power scores 0.5 (equivalent to random chance). Real-world scenarios typically present AUC values between these extremes. Table 4.3. summarizes the evaluation metrics.

Table 4.3. Summary of Evaluation Metrics and Accuracy Assessment of the Machine Learning Models

Name	Description	Equation	Justification
Accuracy	Ratio of correct predictions (TP + TN) to total instances. Misleading if classes are imbalanced.	$\frac{TP + TN}{TP + TN + FP + FN}$	Olofsson et al. (2014)
Precision	Measures avoidance of false positives. Critical for minimizing Type I errors.	$\frac{TP}{TP + FP}$	Waleed, Sajjad, Shazil, et al. (2023)
Sensitivity (Recall)	Measures ability to detect all true positives; critical for minimizing false negatives (Type II errors).	$\frac{TP}{TP + FN}$	Waleed, Sajjad, Shazil, et al. (2023)
F1 Score	The harmonic mean of precision and recall.	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	Waleed and Sajjad (2022)
Specificity (True Negative Rate)	Quantifies correct identification of true negatives; complements sensitivity in binary classification.	$\frac{TN}{TN + FP}$	Widely used.
Mean Square Error	Penalizes large prediction errors quadratically; sensitive to outliers.	$\frac{1}{N} \sum_{i=1}^n (y_i - \hat{y}_i)^2$	Waleed and Sajjad (2022)

Table 4.3. (cont.)

Mean Square Error	Penalizes large prediction errors quadratically; sensitive to outliers.	$\frac{1}{N} \sum_{i=1}^n (y_i - \hat{y}_i)^2$	Waleed and Sajjad (2022)
Root Mean Square Error	Square root of MSE; retains scaling to original data units but emphasizes large errors.	$\sqrt{\sum_{i=1}^n \left(\frac{y_i - \hat{y}_i}{n}\right)^2}$	Waleed and Sajjad (2022)
Mean Absolute Error	Average absolute deviation between predictions and true values; robust to outliers.	$\frac{1}{N} \sum_{i=1}^n y_i - \hat{y}_i $	Waleed and Sajjad (2022)

4.5. Empirical Findings and Discussions

Tables 4.4 and 4.5 provides the performance of various classification models in predicting stock returns, evaluating them across several key metrics: Accuracy, Precision, F1 Score, Specificity, Sensitivity (Recall), and ROC AUC (Receiver Operating Characteristic Area Under the Curve). The analysis of the various classification models reveals important insights into the relationship between model performance and investment behaviors of risk aversion and risk-taking. In addition, Figure 5 is a graphical illustration of the ROC AUC scores of the various algorithms used.

4.5.1. Ensemble Methods and Risk Management

The ensemble methods, including Random Forest, Gradient Boosting, and XGBoost, consistently demonstrate high performance across metrics such as accuracy, precision, and specificity. This is crucial for risk-averse investors who prioritize minimizing losses over potential gains. High specificity indicates the models' ability to correctly identify negative instances (i.e., when a stock will not perform well), which is essential in avoiding bad investments. This aligns with the risk management strategies of conservative investors who prefer to avoid losses even at the cost of missing out on some profitable opportunities.

The ensemble methods' robustness, particularly their strong ROC AUC scores, further underscores their suitability for investors who seek to minimize false positives (unwarranted investments) and false negatives (missed profitable investments). These models' ability to aggregate multiple decision trees helps mitigate overfitting, ensuring stronger and increasingly reliable predictions in diverse market conditions key factor for long-term, risk-averse strategies.

These algorithms have been the most widely used algorithms since 2000 for price competition. The Netflix¹⁸ Prize, one of the most well-known ensemble competitions, offered a \$1 million reward for improving the accuracy of its movie recommendation algorithm. Participants were tasked with reducing the Root Mean Square Error (RMSE) by at least 10% compared to the existing model. The top-ranking teams, including the winner and runner-up, predominantly relied on model ensembles, combining hundreds of predictive models to achieve superior results.

This competition underscored the power of ensemble methods in achieving significant predictive accuracy gains in complex tasks. Vorhies (2016) aptly highlighted the value of model ensembles in predictive analytics, particularly in competitive settings like Kaggle. To secure a top spot on the leaderboard or achieve a commendable ranking, it's essential to not only understand but also strategically apply ensemble methods.

4.5.2. Sensitivity, Risk-Taking, and Speculative Investments

Sensitivity (recall), on the other hand, is a critical metric for risk-taking investors who tend to identify and capitalize on all possible opportunities, even at the risk of incurring a few losses. Models like Neural Networks and Support Vector Machines, while not outperforming ensemble methods, show higher sensitivity, making them further suitable for aggressive investment strategies. These models' ability to detect true positives (successful investments) can be valuable in speculative markets, where missing out on a high-yield opportunity is more detrimental than making a poor investment.

¹⁸ <https://www.kaggle.com/datasets/netflix-inc/netflix-prize-data>

However, the relatively lower specificity of these models indicates a higher likelihood of false positives, which corresponds to a higher risk of poor investment decisions. This trade-off between sensitivity and specificity reflects the inherent risk-return trade-off in financial investments, where higher potential returns often come with higher risks.

4.5.3. F1 Score and Balanced Investment Strategies

The F1 score, which balances precision and recall, emerges as a crucial metric for investors seeking a balanced approach. The strong F1 scores of the ensemble methods and k-Nearest Neighbors suggest their ability to provide a balanced investment strategy that mitigates risks while still capturing opportunities. This suggests that investors with a moderate risk appetite might prefer these models as they offer a more reliable basis for decision-making without leaning heavily towards risk-averse or risk-taking behaviors.

4.5.4. Financial, Economic Implications and Model Selection

Economically, the superiority of ensemble methods in terms of F1 score and ROC AUC indicates their potential for application in algorithmic trading, where both risk management and opportunity capture are critical. The consistent performance across metrics suggests that these models are well-suited for dynamic financial environments, providing a reliable tool for forecasting in both bullish and bearish markets.

In contrast, the weaker performance of linear models like Logistic Regression highlights the challenges of employing simple linear approximations to the complex, non-linear nature of financial markets. The analysis emphasizes the importance of model selection in financial forecasting, considering both statistical performance and economic implications. Selecting models that align with investment strategies, whether focused on risk aversion, risk-taking, or a balanced approach, allows investors to navigate the complexities of financial markets more effectively, leading to further informed decision-making.

Table 4.4. Evaluation Metrics of Machine Learning Models with Control Variables

Model	Accuracy	Precision	F1 Score	Specificity	Sensitivity (Recall)	ROC
Decision Tree	0.90 ^A	0.88 ^B	0.88 ^B	0.91 ^A	0.88 ^B	0.90 ^A
Random Forest	0.88 ^B	0.87 ^B	0.86 ^B	0.90 ^A	0.85 ^B	0.97 ^A
Logistic regression	0.81 ^B	0.76 ^C	0.79 ^C	0.80 ^B	0.83 ^B	0.89 ^B
Neural Network	0.68 ^D	0.62 ^D	0.65 ^D	0.68 ^D	0.69 ^D	0.76 ^C
XGBoost	0.89 ^B	0.86 ^B	0.87 ^B	0.90 ^B	0.87 ^B	0.95 ^A
Support Vector Machine	0.84 ^B	0.80 ^B	0.82 ^B	0.85 ^B	0.83 ^B	0.87 ^B
k-Nearest Neighbors	0.86 ^B	0.83 ^B	0.84 ^B	0.87 ^B	0.84 ^B	0.94 ^A
AdaBoost	0.76 ^B	0.70 ^B	0.74 ^B	0.76 ^B	0.77 ^B	0.87 ^B
Gradient Boosting	0.91 ^A	0.90 ^A	0.89 ^B	0.93 ^A	0.88 ^B	0.97 ^A

Note: ^A: Greater than 90, ^B: Greater than 80, ^C: Greater than 70, ^D: Greater than 60

Table 4.5. Evaluation Metrics of Machine Learning Models without Control Variables

Model	Accuracy	Precision	F1 Score	Specificity	Sensitivity (Recall)	ROC
Decision Tree	0.86 ^B	0.83 ^B	0.83 ^B	0.88 ^B	0.83 ^B	0.86 ^B
Random Forest	0.86 ^B	0.84 ^B	0.84 ^B	0.88 ^B	0.84 ^B	0.95 ^A

Table 4.5. (cont.)

Logistic regression	0.57 ^E	0.49 ^F	0.57 ^E	0.49 ^F	0.67 ^D	0.55 ^E
Neural Network	0.66 ^D	0.58 ^E	0.66 ^D	0.60 ^D	0.75 ^C	0.73 ^C
XGBoost	0.81 ^B	0.76 ^C	0.78 ^C	0.82 ^B	0.79 ^C	0.90 ^A
Support Vector Machine	0.78 ^C	0.72 ^C	0.76 ^C	0.76 ^C	0.81 ^B	0.83 ^B
k-Nearest Neighbors	0.85 ^B	0.83 ^B	0.83 ^B	0.88 ^B	0.82 ^B	0.90 ^A
AdaBoost	0.67 ^D	0.60 ^D	0.64 ^D	0.66 ^D	0.69 ^D	0.73 ^C
Gradient Boosting	0.86 ^B	0.84 ^B	0.83 ^B	0.88 ^B	0.83 ^B	0.95 ^A

Note: ^A: Greater than 90, ^B: Greater than 80, ^C: Greater than 70, ^D: Greater than 60, ^E: Greater than 50

Figure 4.3 presents the combined ROC curves of all the models, arranged in descending order of performance, as indicated by the legend. Models with higher performance have curves that are positioned closer to the top-left corner of the plot, indicating better predictive accuracy. The higher the curve, the more effective the model is at distinguishing between classes.

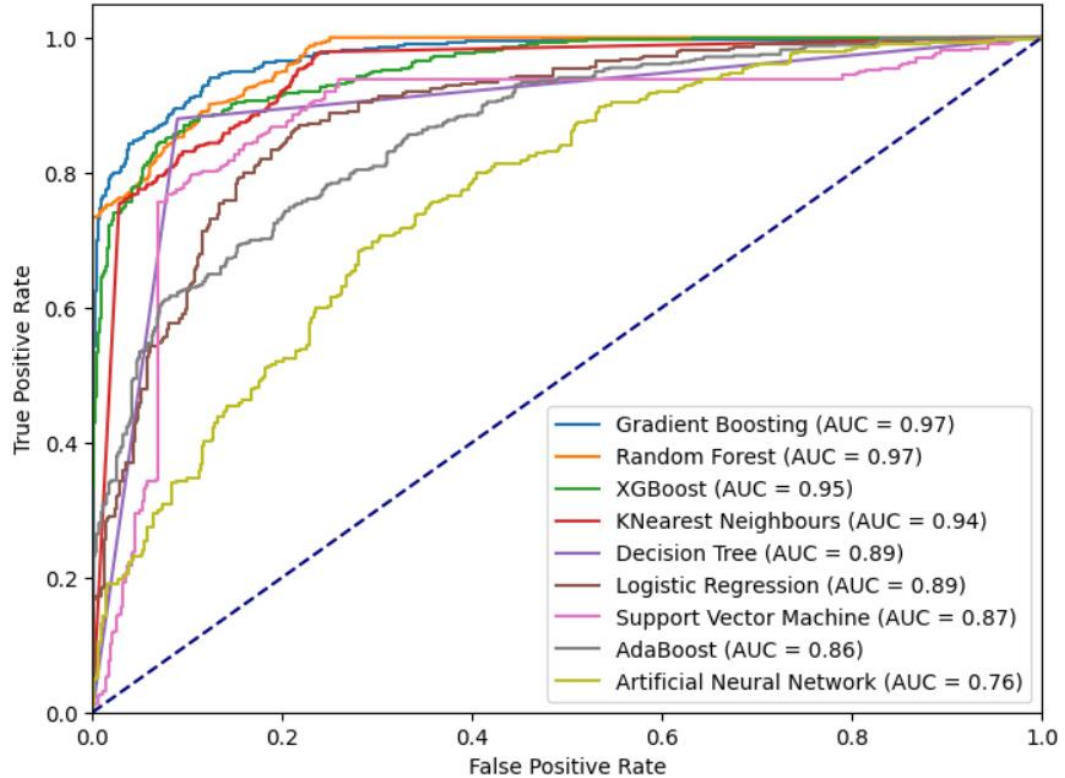


Figure 4.3. Combined ROC AUC Score

To ensure further robustness of the evaluation, we applied 10-fold cross-validation, a widely used technique that balances bias and variance by dividing the data into 10 equal parts, training on 9 and testing on 1 in rotation. This method provides a more reliable estimate of model generalizability. The cross-validation results closely align with the main test outcomes, confirming that the better-performing models are not only accurate but also consistent across different data subsets, while models with lower test performance also exhibited lower mean F1-scores and higher variability during validation. The result of the 10-fold cross-validation is presented in the Figure 4.4 below.

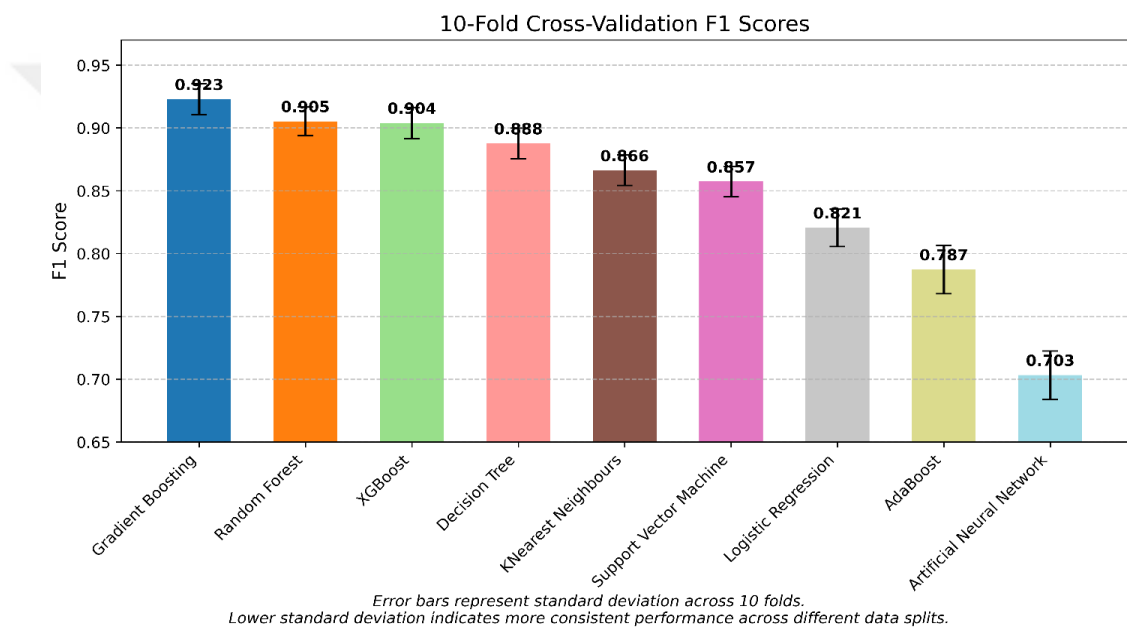


Figure 4.4. Cross Validation of the FinBERT Model-Based in Table 4.4. - 1

In addition to 10-fold cross-validation, we implemented walk-forward validation to evaluate how the models perform over time. The results show that models such as Gradient Boosting, XGBoost, and Random Forest perform well in both validation setups. Models such as Support Vector Machine and Artificial Neural Network perform worse in the walk-forward test. This pattern shows that some models can fit static data well but struggle with time-dependent data. Walk-forward validation gives a more realistic test of model stability in sequential prediction tasks. The comparative results of the 10-fold cross-validation and the walk-forward validation are shown in the Appendix (Figure A.3).

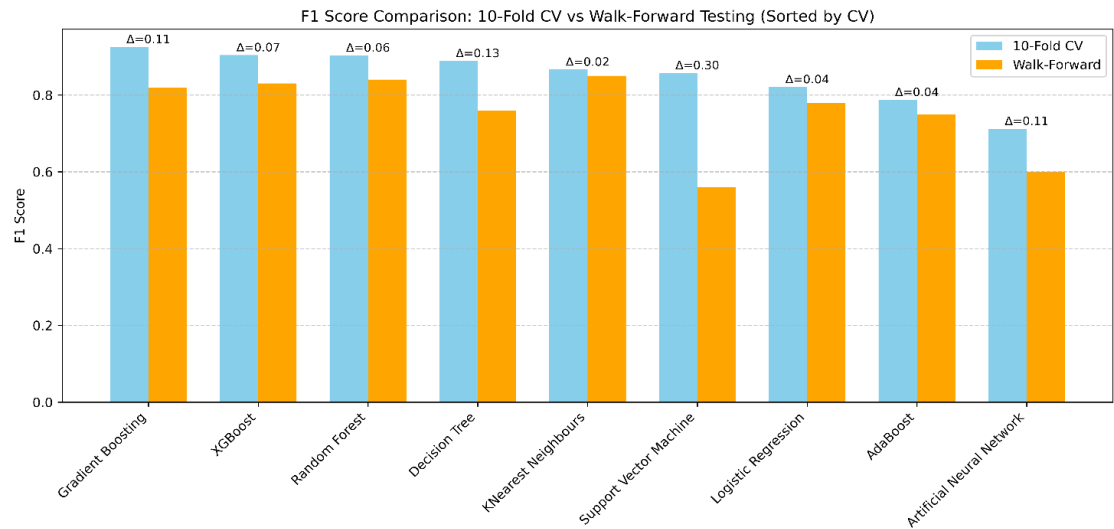


Figure 4.5. Cross Validation of the FinBERT Model-Based in Table 4.4. - 2

Table 4.6. Performance Metrics (Loughran-McDonald Sentiment Analyzer)

Model	Accuracy	Precision	Recall	F1 Score	Sensitivity (TPR)	Specificity (TNR)	ROC
Logistic Regression	0.64 ^D	0.56 ^E	0.78 ^C	0.65 ^C	0.78 ^C	0.54 ^E	0.76 ^C
Random Forest	0.88 ^B	0.86 ^B	0.88 ^B	0.87 ^B	0.88 ^B	0.89 ^B	0.93 ^A
Decision Tree	0.88 ^B	0.85 ^B	0.87 ^B	0.86 ^B	0.87 ^B	0.89 ^B	0.88 ^B
XGBoost	0.89 ^B	0.87 ^B	0.89 ^B	0.88 ^B	0.89 ^B	0.91 ^A	0.93 ^A
KNearest Neighbor	0.81 ^B	0.77 ^C	0.78 ^C	0.78 ^C	0.78 ^C	0.82 ^B	0.91 ^A
Support Vector Machine	0.66 ^C	0.59 ^E	0.72 ^C	0.65 ^D	0.72 ^C	0.62 ^D	0.72 ^C
Artificial Neural Network	0.66 ^C	0.58 ^E	0.80 ^C	0.67 ^C	0.80 ^C	0.56 ^D	0.75 ^C

Table 4.6. (cont.)

AdaBoost	0.70 ^D	0.63 ^D	0.70 ^D	0.66 ^D	0.70 ^D	0.70 ^D	0.7 ^C
Gradient Boosting	0.77 ^C	0.70 ^D	0.80 ^C	0.75 ^C	0.80 ^C	0.75 ^C	0.87 ^B

Note: ^A: Greater than 90, ^B: Greater than 80, ^C: Greater than 70, ^D: Greater than 60, ^E: Greater than 50.

As evidenced in Table 4.6, the ensemble-based algorithms (the Random Forest and XGBoost), along with Decision Tree, demonstrate superior performance metrics in the implementation of Loughran-McDonald sentiment analysis. Conversely, AdaBoost exhibited suboptimal efficacy in this analysis. Gradient Boosting and K-Nearest Neighbor algorithms achieved moderate performance outcomes. The models demonstrating the least favorable performance metrics include Artificial Neural Networks, Support Vector Machines, and Logistic Regression, which yielded relatively lower accuracy and predictive validity. The overall performance patterns of the Loughran-McDonald-based sentiment analysis are similar to those of the main FinBERT transformer-based model. However, it performs relatively worse than the FinBERT model in this analysis.

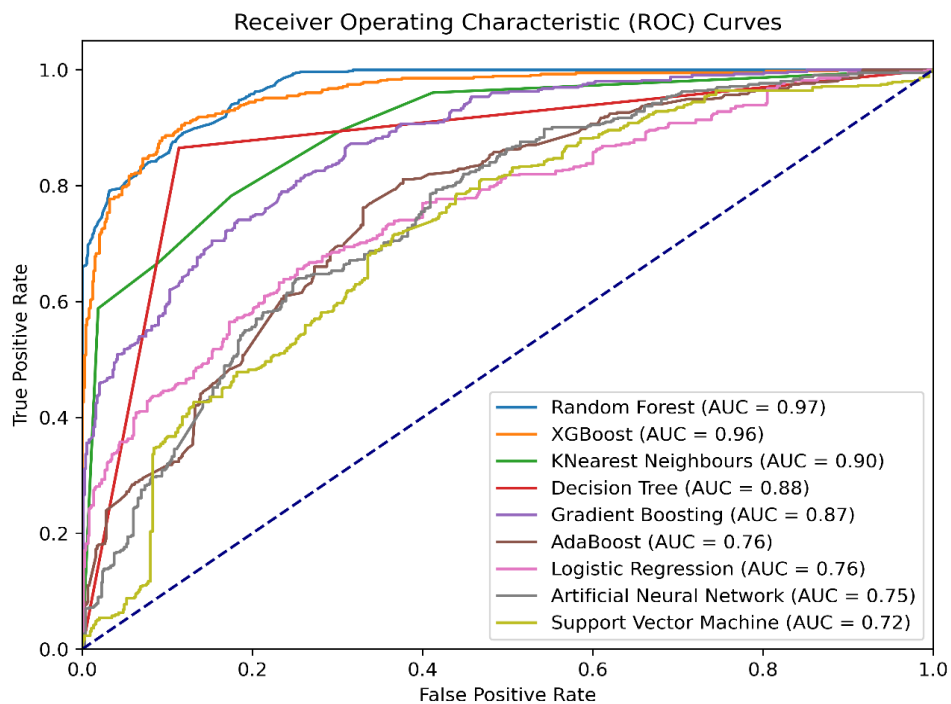
**Figure 4.6. ROC Curve from the Loughran-McDonald Sentiment-Based Result**

Table 4.7. Linear Machine Learning Models

Model	MAE	MSE	RMSE
Linear Regression	0.0112	0.0002	0.0155
Decision Tree	0.0168	0.0005	0.0226
Random Forest	0.0121	0.0003	0.0166
Neural Network	0.0151	0.0004	0.0198

Along with the classification models, linear machine learning models were applied to the log of the stock market price to evaluate their performance using metrics such as Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error, as shown in Table 4.7. Among the models, Linear Regression was observed to perform the best with the least errors, indicating that it makes relatively smaller errors and delivers more accurate predictions compared to the other models. On the other hand, the Decision Tree produced the highest errors, suggesting that it has larger discrepancies in its predictions. The Random Forest model performed slightly better than the Decision Tree but still falls short of Linear Regression in terms of accuracy. The Neural Network model falls in between, showing moderate accuracy.

Table 4.8. GARCH (2, 1) Mean Equation

Variable	Coefficient	Std. Error	t-Statistic	p-Value	Interpretation
Const (μ)	0.001352	0.000879	1.537	0.124	Intercept; not significant
Lagged Return	0.007746	0.02218	0.349	0.727	AR (1); not significant
The Economist	-0.000999	0.001514	-0.660	0.509	Neg. impact; not significant
Yeni Şafak	0.000505	0.000441	1.146	0.252	Pos. impact; not significant

Table 4.8. (cont.)

The Guardian	0.001335	0.001315	1.015	0.310	Pos. impact; not significant
The New York Times	0.000392	0.000525	0.748	0.454	Pos. impact; not significant
Tweets	0.000090	0.000204	0.443	0.658	Pos. impact; not significant

Table 4.8 from the GRACH model results shows that the majority of news outlets and Twitter are not significant predictors of the stock market. It also indicates a positive, though statistically insignificant, relationship between news sentiment and stock market movements.

4.6. Explainable Artificial Intelligence (XAI)

The rapid advancement of AI has given rise to increasingly complex and opaque models employed to address challenging real-world problems (Lundberg et al., 2020). Unlike their predecessors, such as time series ARIMA models, the complicated structures of these models often make them difficult to understand and operate. Decoding the source of their outputs, especially unexpected ones, becomes a monumental task, limiting our ability to effectively diagnose and remedy issues.

This is where Explainable AI (XAI) steps in as a critical ally in the evolving landscape of AI models. XAI shines a light on the inner workings of these intricate models, demystifying their decision-making processes. It empowers researchers to understand the performance of the model as well as the impact of individual features or variables. Shapley values, in particular, provide a clear understanding of the contribution of each feature to the model's predictions within the dataset.

Introduced by Lundberg and Lee (2017), Shapley Additive Explanations (SHAP) has become a widely adopted framework for model interpretability across various fields. Building upon the classic Shapley values from game theory and their extensions (Lundberg et al., 2020), SHAP effectively links optimal credit allocation with local explanations, fostering model transparency and trust.

This study employs SHAP values to interpret predictions and understand the key features in news articles that drive model predictions, thereby enhancing transparency and trust. SHAP is more appropriate for research production compared to its predecessors, such as LIME (Local Interpretable Model-agnostic Explanations) introduced by Ribeiro et al. (2016). While LIME was one of the earliest well-known methods in the explainability area and is more suitable for large data processing and industrial production, this project aims to employ SHAP methods due to their advantages in research contexts. We only ran the explainable models of the two best-performing supervised

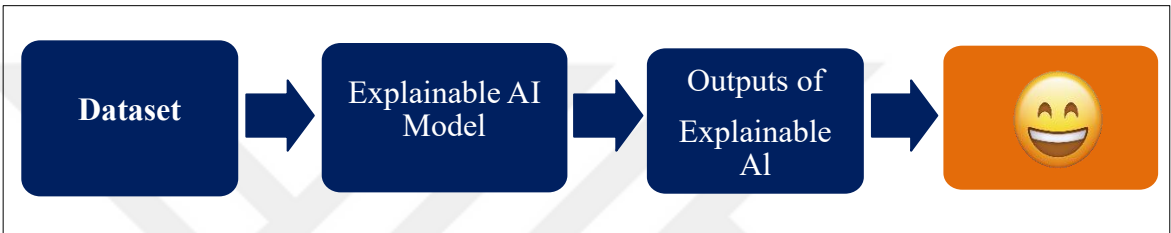


Figure 4.7. The Process of Artificial Intelligence Models without Explanation

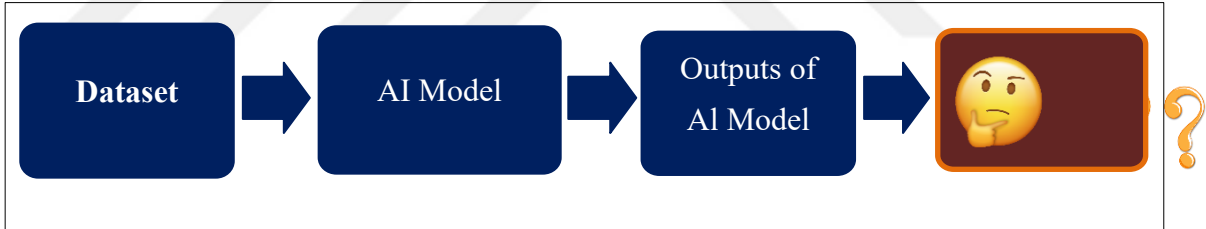


Figure 4.8. The Process of Artificial Intelligence Models with Explanation

Classification models, the Gradient Boost and XGBoost, are based on the ROC curve result portrayed in Figure 4.3. The Random Forest model provided results almost identical to the Gradient Boost, leading us to only report the Gradient Boost result to avoid repetitive tasks. Positive SHAP values indicate contributions pushing predictions higher, while negative values suggest a decreasing effect. This approach ensures an accurate and interpretable explanation of the outcome (Moustakidis et al., 2023).

The SHAP values, derived from cooperative game theory, represent the average marginal contribution of a feature across all possible feature combinations. This approach provides a unified method for interpreting model predictions, assigning each feature an importance value for a particular prediction. The integration of SHAP into our analytical framework represents a step towards increasingly transparent and accountable machine learning applications in financial prediction tasks, bridging the gap between model complexity and interpretability.

Figure 4.6 illustrates feature importance analyses for high-performing machine learning models, XGBoost (on the left), and Gradient Boosting (on the right). Across all models, historical price data and control features, such as "Low," "Open," and "High," consistently emerge as the most significant predictors. However, the relative importance of other features exhibits notable variation among the different models.

The XGBoost algorithm attributes greater importance to The Economist, Yeni Şafak, and The Guardian. On the other hand, Twitter data is seen as the least or weakest predictor of the stock returns. The Gradient Boost algorithm switches the relative importance of Yeni Şafak and The Economist, while other features largely remain the same as in the XGBoost algorithm.

The observed variations in feature importance across different machine learning models suggest that the choice of algorithm can influence the perceived relevance of input variables in predictive modeling. However, this comparative analysis between the two models indicates the interplay between algorithm selection and feature evaluation in the context of financial prediction tasks, which is crucial for interpretable outcomes in financial predictions.

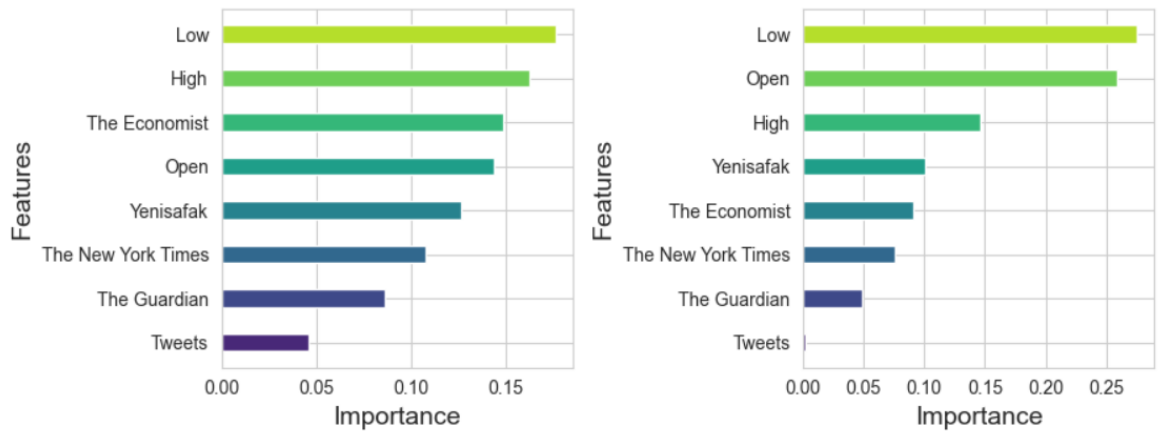


Figure 4.9. Feature Importance in XGBoost and Gradient Boosting Models

Nevertheless, feature importance only indicates the overall significance of each feature in the model's predictions but does not provide insights into how individual features influence the probability of a positive prediction. This limitation is addressed by using Beeswarm plots and SHAP mean values, which help visualize and quantify the impact of each feature on the model's output, highlighting how features drive predictions in specific directions.

4.6.1. Gradient Boosting and XGBoost Mean SHAP Analysis

Figure 4.7 presents the mean SHAP values across all observations for the Gradient Boosting and XGBoost models, respectively. These visualizations elucidate the most salient features for each model, based on the mean of the absolute SHAP values to prevent the offsetting effect of positive and negative contributions. The analysis employs a bar chart representation, with each bar corresponding to a distinct feature.

As depicted in Figure 8, the Gradient Boosting model reveals that The New York Times, The Economist, and Yeni Şafak exhibit the highest mean SHAP values of 0.27, 0.22, and 0.20, respectively.

This indicates that these news sources, on average, contribute positively to the prediction of stock market returns. The Guardian and Twitter data demonstrate comparatively lower influence, with mean SHAP values of approximately 0.18 and 0.01, respectively.

In contrast, the XGBoost model presents a different hierarchy of feature importance. In this model, The Guardian emerges as the most influential predictor, with a substantial mean SHAP value of 0.63. This is followed by The New York Times and The Economist, mirroring the pattern observed in the Gradient Boosting model. Yeni Şafak and Twitter maintain relatively lower positions in terms of predictive power, analogous to their status in the Gradient Boosting analysis in Figure 4.7.

The divergence in feature importance rankings between the two models underscores the complexity of the relationship between media sentiment and stock market dynamics. However, a consistent pattern emerges, with traditional news journals, particularly those with international reputations, demonstrating greater predictive power for stock returns compared to social media platforms like Twitter.

This suggests that these established media outlets play a more significant role in shaping investor sentiment, emotions, and decision-making processes than social media discourse.

These findings contribute to our understanding of the interplay between media sentiment and financial markets, highlighting the differential impact of various sources of information on stock market behavior. Future research could explore the temporal stability of these relationships and investigate potential causal mechanisms underlying the observed correlations.

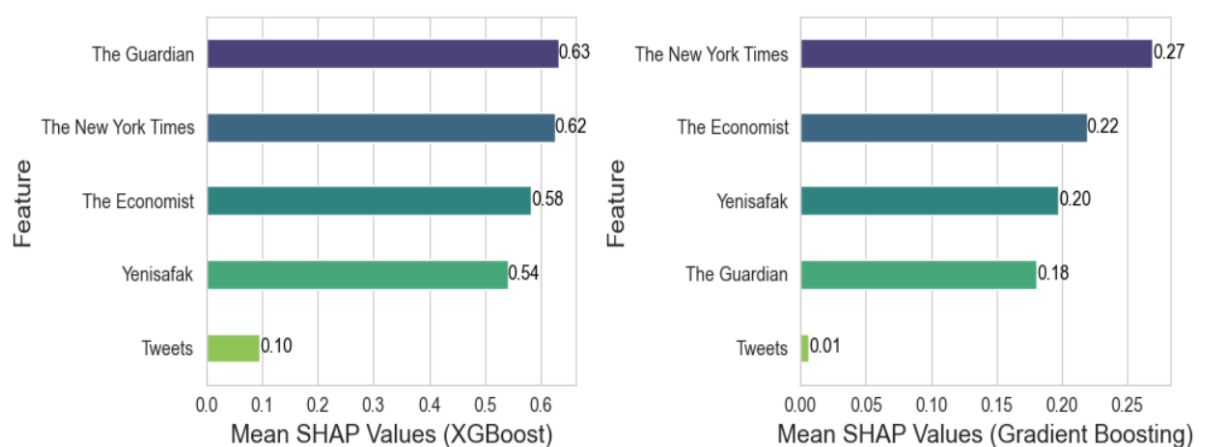


Figure 4.10. Mean SHAP Values of XGBoost and Gradient Boosting Models

Next, Figures 4.8 and 4.9 depict the Beeswarm visualization of all the SHAP values. On the y-axis, the values are grouped by features. For each group, the color of the points is determined by the feature value (higher feature values are redder, while the lower values are bluer). Just like mean SHAP, the Beeswarm highlights important relationships. The features in Figures 8 and 9 are ordered by mean SHAP.

The Beeswarm plot of the Gradient Boosting model in Figure 8 reveals the influence of the features on stock market predictions and investor sentiment. Traditional news outlets, The New York Times and The Economist, emerge as pivotal predictors with wide-ranging impacts (SHAP values ranging from approximately -1.0 to 1.2 for The New York Times).

Their broader distribution of SHAP values indicates that these sources can sway predictions towards both positive and negative stock returns, reflecting the complex nature of financial news interpretation. Yeni Şafak and The Guardian show a more moderate range of impact (mostly between -1.5 and 1.0).

The minimal influence of Tweets (SHAP values tightly clustered around 0) underscores that established journalism outweighs social media sentiment in predicting market movements in this model. The correlation between higher feature values and positive SHAP values for major news outlets suggests that positive sentiment tends to predict upward market movements, reflecting the intricate relationship between media sentiment and investor psychology. However, the presence of negative SHAP values, even for high-value features, highlights the sensitivity of the market to nuanced interpretations of news.

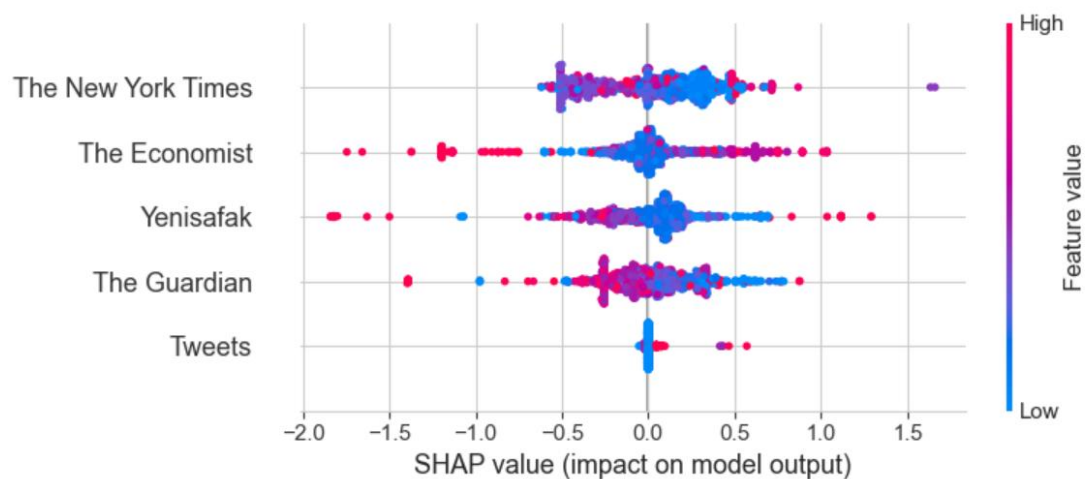


Figure 4.11. Beeswarm Plot of the Gradient Boosting Model 1

The XGBoost Beeswarm plot in Figure 4.9 reveals a subtle shift in the relative importance and impact of news sources compared to the Gradient Boosting model. The Guardian now exhibits the most substantial influence (SHAP values ranging from approximately -3.0 to 3.0), surpassing The New York Times (range of about -3.0 to 2.5).

This contrasts with the previous model, where The New York Times had the strongest impact. The Economist maintains a significant but more concentrated effect (mostly between -2.0 and 2.0), while Yeni Şafak shows a broader distribution than before (from about -4.0 to 2.0). Tweets continue to have the least variation, though with a slightly larger impact than in the Gradient Boosting model.

All major news sources in the XGBoost model demonstrate further extreme SHAP values, suggesting a higher sensitivity to media sentiment. The color distribution indicates a stronger correlation between high feature values (red points) and positive SHAP values across sources, implying that positive sentiment consistently predicts upward market movements in this model.

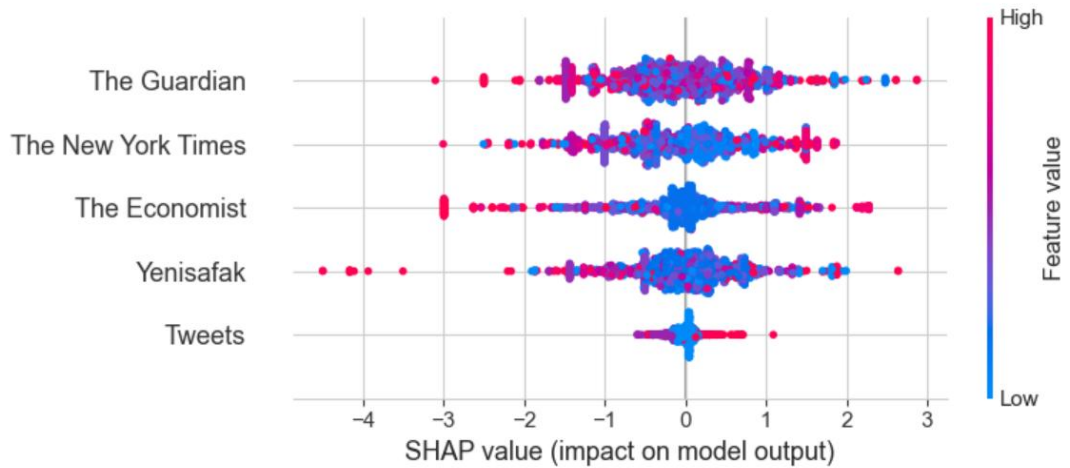


Figure 4.12. Beeswarm Plot of the Gradient Boosting Model 2

The Beeswarm visualizations for both the Gradient Boosting and XGBoost models illuminate the crucial role of news sentiment in stock market prediction and investor decision-making processes. These plots vividly demonstrate how different information sources are weighted in the collective judgment of market participants, with established news media consistently emerging as dominant predictors.

While both models emphasize the pronounced influence of reputable news outlets, the XGBoost model reveals a more nuanced picture. Its heightened impact and wider ranges of SHAP values suggest an enhanced sensitivity to subtle variations in media sentiment, potentially capturing more complex relationships between news coverage and market behavior. The comparison between these models not only reinforces the significance of media sentiment analysis in financial forecasting but also highlights the potential for machine learning algorithms to uncover increasingly sophisticated patterns in the interplay between information dissemination and market reactions.

4.7. Conclusion and Limitations

Reflecting on the findings, it is evident that the complex interplay of media discourse and investor sentiment on the Turkish stock market is best captured by sophisticated ensemble models. These models, such as Gradient Boosting, XGBoost, and Random Forest, excel in their ability to decode the emotional undercurrents that drive market

movements. The narratives woven through media reports often sway investor behavior. Stories of economic turmoil, financial risks, speculations, and optimism can stir emotions that ripple through trading floors. The highest predictive accuracy of these models suggests they are particularly attuned to these nuances, effectively translating the collective mood into market forecasts.

Linear models, like Linear Regression, also show a remarkable ability to predict market outcomes with precision, reflecting a more measured, perhaps rational, aspect of investor behavior. Yet, the superior performance of ensemble methods hints at the emotional complexity of the market, where sentiments, fear, and greed interplay, making simplistic approaches less effective. The Explainable AI methods reveal that the traditional international news media affects the Turkish stock market, while local news from (Yeni Şafak and Twitter) has lesser predictive power in comparison. These findings highlight the importance of the role of news investors' sentiment in understanding market dynamics, reminding us that beneath the cold numbers lies a very human market, swayed by emotions as much as by economic fundamentals.

- **Limitations:** The scope of this study was constrained by the use of a single local newspaper, Yeni Şafak, and Twitter, primarily due to the inaccessibility of historical data from other local news sources. This limitation restricts the generalizability of the findings, as the selected media outlets may not fully capture the broad spectrum of public sentiment and information flows that influence stock market dynamics. Future research should consider expanding the range of data sources by incorporating additional local newspapers and diverse social media platforms to provide a more comprehensive analysis of how various media channels impact different stock indices.

CHAPTER V

URBAN LIVABILITY DISPARITIES: 15-MINUTE WALKING ACCESSIBILITY IN ISTANBUL

5.1. Introduction

Consumer well-being and quality of life a multifaceted construct that extends far beyond mere transactional satisfaction, encapsulating a holistic array of emotional, cognitive, and behavioral dimensions that influence individuals' overall happiness and quality of life (Dobrowolska & Kopczewska, 2024). Central to this concept is the notion that consumption experiences transcend the mere acquisition of goods and services, instead encompassing the entirety of interactions, perceptions, and outcomes associated with the consumption process.

Similarly, international institutions such as the European Union, the World Health Organization (1998), and the OECD have increasingly prioritized systematic measurement and enhancement of citizens' quality of life. The European Union, in its 2016 directive, established annual monitoring of subjective life satisfaction across member states, reflecting its core mandate to advance citizen well-being. This initiative was further complemented by the OECD's comprehensive "How's Life?" framework (OECD Publishing, 2020), which deploys over 80 distinct indicators to evaluate quality of life and assess societal inequalities.

Thus, contemporary urban centers, regional authorities, and national governments engage in strategic competition to attract and retain both residents and businesses through enhanced urban livability (Dobrowolska & Kopczewska, 2024). This competitive dynamic has catalyzed increased attention to quality-of-life metrics as essential tools for urban policy formulation and evaluation.

As highlighted by Zhao and Wei (2019), consumer well-being embodies a profound sense of fulfillment, derived from the synergy of positive emotions, meaningful engagements, and subjective perceptions of value generated throughout the consumption journey. At its core, consumer well-being represents a linkage between subjective evaluations and objective circumstances, where individual preferences, aspirations, and socio-cultural contexts shape perceptions of satisfaction, happiness, and fulfillment (Dobrowolska & Kopczewska, 2024).

This allows us to recognize the susceptibility of well-being to various internal and external factors, ranging from personal beliefs and social comparisons to market dynamics and societal norms. Utilizing advanced geospatial analytics, this study evaluates urban accessibility and well-being in Istanbul through the lens of the 15-minute city framework.

The findings reveal that nearly half of Istanbul's residents lack adequate access to essential transport services, green spaces, and recreational facilities within a 15-minute journey from their homes. Additionally, the analysis identifies significant security hotspots throughout the city, further compromising neighborhood livability. These spatial disparities in access to vital urban amenities highlight substantial challenges in achieving equitable urban development across Istanbul's diverse districts.

The chapter is structured as follows: Section 1 provides the introduction; Section 2 discusses the background of the study; Section 3 reviews recent literature on accessibility; Section 4 outlines the data and methodology; Section 5 presents and analyzes the results; Section 6 discusses the findings and concludes; Section 7 explores policy implications; and Section 8 acknowledges the study's limitations and suggests directions for future research.

5.2. Background

The concept of consumer well-being emerged from a critical distinction made by economist Theodore Suranyi-Unger (1981). He argued that consumer behavior, traditionally studied in economics, focuses solely on the actions of acquiring and

using goods and services. In contrast, consumer well-being delves deeper, by examining the emotional and psychological outcomes of consumption experiences.

This distinction marked a turning point, establishing consumer well-being as a separate field of study within the economic paradigm (Suranyi-Unger, 1981). Following Suranyi-Unger's contribution, consumer well-being has been carved out as a distinct theoretical concept with its own research agenda. Located within the broader field of consumer research, it has evolved into a multifaceted concept beyond mere economic utility.

Studies have demonstrated well-being's link to improved physical and mental health (Huppert & So, 2013; Lee & Sirgy, 2012), fostering stronger consumer loyalty (Berg et al., 2015). However, despite a burgeoning consensus on the importance of consumer well-being in academic circles (Waterman et al., 2008; Venhoven, R, Veenhoven) significant challenges remain. The field grapples with a lack of uniformity in defining and measuring this complex construct despite attracting attention (Popescu, I. A., & Reis Mourão, P., 2025).

Moreover, research methods and contexts vary considerably, hindering generalizability and comparisons across studies. Moreover, the quest to quantify consumer well-being presents a significant challenge. Researchers employ a diverse array of methodologies. Fraser & Wu (2016) identified 58 measures of satisfaction and well-being based on research published between 2003 and 2013 alone. Other literature offers a rich tapestry of measurement frameworks. Zhao & Wei (2019) identify prominent approaches such as the Consumer Life Cycle Model (Lee et al., 2002), the Demand Satisfaction Model, the Asian Consumer Well-being Scale (Sirgy et al., 2010) and the Life Satisfaction Scale (Diener et al., 1985). Nonetheless, some approaches, like the Life Satisfaction Scale (Diener et al., 1985), while valuable in gauging overall happiness, may not capture the nuances of consumer well-being specific to consumption experiences.

5.2.1. Limitations of Existing Measures of Quality of Life

Current measurements of consumer well-being often emphasize traditional, market-oriented consumption scenarios. This overlooks the multidimensionality of the construct (Zhao & Wei, 2019). Firstly, these measurements struggle to capture the influence of factors beyond immediate consumption experiences. Secondly, cultural variations and diverse social behaviors necessitate frameworks that account for such nuances (Lee & Sirgy, 2012). One of the contemporary approaches to measuring societal well-being and quality of life involves assessing individuals' access to essential services and opportunities, coupled with their ability to navigate urban environments efficiently. This is an essential factor since modern cities grapple with a multitude of challenges, including inaccessible public spaces, limited opportunities, unattractive streetscapes (Cervero et al., 2017), crippling traffic congestion (Dobrowolska & Kopczewska, 2024), frequent road accidents (Ziakopoulos & Yannis, 2020), and urban sprawl contributing to noise pollution, air quality issues, and health risks (Bouguerra & Bhar Layeb, 2019).

However, it is important to note that, to the best of our knowledge, there is no comprehensive accessibility index for Istanbul. Therefore, this study aims to fill this gap by measuring city-wide accessibility and constructing a unified, district-level Livability index across Istanbul's districts.

5.2.2. Accessibility as a Measure of Urban Quality of Life

Modern urban societies grapple with the dual challenge of ensuring equitable access to mobility while adhering to the principles of environmental sustainability. Achieving a balance between these objectives remains central to urban development policies, as highlighted by recent studies (Ryghaug et al., 2023; Verlinghieri & Schwanen, 2020; Willberg et al., 2024).

Among the various approaches to addressing this challenge, spatial accessibility has emerged as a critical concept, underpinning both transport planning and urban equity. Indeed, accessibility is foundational to understanding the connections between people, transportation networks, and the opportunities available within urban environments (Hansen, 1959; Morris et al., 1979; Wachs & Kumagai, 1973).

More specifically, accessibility facilitates the measurement of how effectively individuals can reach essential destinations, including workplaces, schools, health services, green spaces, and economic centers.

Despite decades of study, accessibility remains a multifaceted concept that resists simple definition (Gutiérrez, 2001; Mościcka et al., 2019). Its measurement has evolved over time, incorporating methods that range from straightforward indices to sophisticated spatial analyses capable of capturing its economic, social, and environmental dimensions (S. Handy, 2020; Pereira, 2019; Wu & Levinson, 2020). Hansen (1959) first defined accessibility as the "potential for opportunities for interaction," a definition that has since served as the basis for a wide range of academic and practical applications.

Building on this foundation, (Ingram, 1971) defined it "accessibility is an inherent property of a place, associated with the ability to overcome spatial resistance (e.g., physical or temporal distance)." Likewise, Dalvi & Martin (1976) emphasized accessibility as the ease of accomplishing activities from any location, facilitated by specific transportation systems. Bertolini et al. (2005) furthered the discussion by framing accessibility as "what and how can be reached at a given point in space." Taking this concept forward, Handy's (2020) most recent work characterizes accessibility based on the available choices for diverse transportation modes. Historically, urban transportation planning prioritized efficiency and performance metrics (Banister, 2005).

However, a paradigm shift has emerged, with accessibility now recognized as a critical factor for achieving sustainable urban development and societal well-being (Saghapour et al., 2016; Tiznado-Aitken et al., 2018). Thus, the importance of accessibility is not confined to mobility; it also shapes land use patterns, impacts property values, informs public policy decisions, and serves as a measure of urban equity by highlighting disparities in the availability of essential resources and opportunities (Cervero et al., 2017; Wu & Levinson, 2020).

Furthermore, several studies revealed that poor accessibility continues to exacerbate social exclusion, disproportionately affecting those in disadvantaged communities

who are unable to fully participate in urban life due to barriers in reaching essential services (Lucas, 2012). Recently, scholars have argued that transport planning should prioritize accessibility rather than merely expanding mobility, as the former better aligns with the objectives of sustainability and equity in urban areas (Banister, 2011; Levine, 2020).

Ultimately, accessible transport systems are essential for enabling individuals to meet their basic needs, such as accessing employment, education, healthcare, and recreational spaces. Urban planners can create inclusive frameworks that address systemic inequities and improve societal well-being while reducing the environmental burden of excessive travel by focusing on accessibility (Lucas et al., 2018; Pereira, 2021; Raza et al., 2023).

5.2.3. Review of Recent Accessibility Literature

Contemporary analyses of mobility patterns in large modern cities underscore a significant prevalence of transportation dependency (Gamboa, 2017). Motivated by pressing concerns such as health issues, noise pollution, quality of life, and environmental factors, modern cities are actively working to mitigate reliance on cars. The emphasis lies in establishing multimodal mobility systems designed to facilitate individuals in reaching their desired destinations, opportunity centers, or points of interest through alternative and sustainable modes of transportation (European Commission, 2020). Among the alternative transportation modes being implemented, active transport, which encompasses walking and cycling, assumes particular importance.

Active transport emerges as a crucial component in formulating sustainable transportation strategies, given its potential to address various urban challenges (Vale et al., 2016). Consequently, contemporary urban sustainability policies assign heightened significance to the incorporation and promotion of active transport modes (Shashank & Schuurman, 2019; Da Silva et al., 2020). The imperative recognition of walking and cycling as key priorities in urban sustainability policies reflects a paradigm shift towards fostering more environmentally friendly and health-conscious transportation alternatives in modern cities.

The concept of the 15-minute city, as pioneered by Carlos Moreno in 2016 and has garnered considerable traction in both academic discourse (Zhong et al., 2020; Moreno et al., 2021; Allam et al., 2022; Zhang et al., 2023) and urban planning practices worldwide. This idea has been adapted into various models, such as Melbourne's 20-minute neighborhoods, Paris's 15-minute policy, and Singapore's 45-minute framework (Zhang et al., 2023).

A prominent illustration of its influence is the 2020 re-election campaign of Paris Mayor Anne Hidalgo. She effectively connected with the electorate, which played a key role in securing her victory by incorporating the 15-minute city concept into her policy campaign. The framework is anchored by four key metrics: proximity which focuses on minimizing distances between residents and essential facilities, green spaces, and other daily necessities; diversity which encompasses both multicultural communities and a variety of urban amenities that provide a broad range of goods and services; ubiquity, which ensures equitable access to public resources for all individuals, regardless of their socioeconomic status or background, and density which ensures neighborhoods have enough residents to sustain local businesses (Allam et al., 2022; Dobrowolska & Kopczewska, 2024).

These principles aim to create neighborhoods where all necessities and opportunities are within a 15-minute walk or bike ride, fostering convenience, inclusivity, and sustainability. Recent scholarship in urban accessibility reflects growing concerns about environmental sustainability, social equity, and digitalization. Willberg et al. (2024) establish a framework for analyzing accessibility within planetary boundaries, while Ryghaug et al. (2023) examine sustainable mobility transitions across European cities. In Finland, Pönkänen et al. (2025) investigate transport inequity, providing insights into accessibility challenges in Nordic urban contexts.

Several studies focus on spatial disparities in accessibility. In China, Du et al. (2024) analyze urban-rural differences in hospital accessibility within metropolitan areas, complementing Xu et al.'s (2022), broader examination of public facility inequalities between urban and rural regions. Yang et al. (2022) further explore these dynamics through analysis of production factor flows within urban agglomerations.

The relationship between transport infrastructure and social equity features prominently in recent research. (Pereira, 2018) examines how transport legacies influence urban accessibility in Rio de Janeiro. More recent studies by Pereira and his colleagues explore ride-hailing impacts on transit accessibility and the potential for enhanced transport accessibility to reduce social segregation in foreign-born areas (2024).

Their emphasis on accessibility is arguably justified, as transportation primarily serves the purpose of facilitating access to locations, opportunities, and centers of social activities, rather than solely aiming to enhance mobility itself (Lucas, 2012). Healthcare accessibility has emerged as a critical research focus, with Tomasiello et al. (2023) providing high-resolution analysis of social and racial inequalities in healthcare access. In urban quality of life research, Dobrowolska & Kopczewska (2024) develop comprehensive mapping methodologies for Warsaw.

Several studies used different methods and approaches to calculate the index for urban accessibility to measure urban well-being (Leung et al., 2020; Marozzi & Bolzan, 2018; Mitropoulos et al., 2023; Yenisetty & Bahadure, 2020). A recent study by Muñoz-Moreno et al. (2023) used risk measurement index for assessing social services at the municipal level.

5.3. Data and Methodology

This study utilizes data from OpenStreetMap (OSM), an open-access platform managed by the OpenStreetMap Foundation¹⁹ and Istanbul Metropolitan Municipality²⁰. OSM provides a robust repository of geospatial data that is excellent for urban research due to its detailed mapping of global infrastructure. Population data is derived from WorldPop²¹. The data were extracted programmatically using the Overpass API²² in Python. Following Janosov, (2024a; 2024b), the analysis focuses on five key dimensions of urban accessibility and livability:

¹⁹ <https://www.openstreetmap.org/#map=9/39.393/32.531>

²⁰ <https://data.ibb.gov.tr/en/>

²¹ <https://hub.worldpop.org/project/categories?id=3>

²² https://wiki.openstreetmap.org/wiki/Overpass_API

Transport accessibility and Mobility (1), Green Spaces and Recreational Facilities (2), Public Services Infrastructure (3), Safety and Urban Security (4), and Economic Opportunities (5). Each dimension is represented by specific OSM features selected to capture essential elements of urban life in the city.

The five dimensions were selected based on their comprehensive coverage of the foundational elements that constitute a livable 15-minute city as established in the urban planning literature. Transport and mobility form the backbone of urban accessibility; green spaces contribute significantly to physical and mental well-being; public services ensure residents' basic needs are met; safety addresses fundamental human security concerns; and economic opportunities capture the socioeconomic vitality necessary for sustainable urban living.

Together, these dimensions provide a holistic framework for evaluating urban environments against contemporary standards of livability, while remaining measurable through available geospatial data sources.

To represent the Transport and Mobility dimension, the study utilized all types of roads, pathways, and public transportation systems. Data on roads and pathways encompasses a range of urban routes, capturing the connectivity of the city. For public transportation, features such as bus stops, tramlines, and metro stations were used to assess the availability and reach of transit options, which are crucial for evaluating urban mobility.

For the Green Spaces and Recreational Facilities dimension, natural and recreational areas were chosen for their importance in enhancing residents' quality of life. This includes parks, gardens, nature reserves, and forests, as well as specific features like grasslands, wetlands, and meadows. Recreational facilities, such as sports centers, playgrounds, fitness stations, swimming pools, tracks, and stadiums, were included to capture spaces that support various physical activities and leisure pursuits.

Health and educational facilities were chosen to capture the Public Services Infrastructure dimension. We focused on these two essential services for their role in supporting social well-being. Healthcare facilities, including hospitals, clinics,

pharmacies, and doctors' offices, while educational institutions, such as schools, universities, libraries, kindergartens, and colleges, were selected to assess the distribution of educational resources within the city.

The Safety and Urban Security dimension is represented by features related to emergency services and safety infrastructure. Emergency services, such as police stations, fire stations, emergency clinics, ambulance stations, and shelters, are paramount for immediate response and public safety. Urban safety features, including street lighting, traffic signals, and surveillance systems, were included to evaluate the city's safety infrastructure.

For the Economic Opportunities dimension, features were chosen to reflect the spatial distribution of commercial activities, employment centers, and financial hubs. Retail and commercial establishments, such as supermarkets, clothing stores, electronics shops, and general retailers, indicate the availability of economic resources. Employment centers, including office buildings and industrial areas, highlight job opportunities across the city, while financial hubs are represented by banks, ATMs, cafes, restaurants, and marketplaces, which show the accessibility of essential financial services. Table 5.1 shows a detailed description of the variables used. We also used Household characteristics and housing price data to check their impact on the livability index. The results are in the Figures 5.19-5.21. Moreover, descriptive, summary statistics and correlation matrix are shown in Figures 5.22-5.24.

Table 5.1. Dimension and Feature Descriptions

Dimension	Main Features	Description
1. Accessibility and Mobility	a. Roads and Pathways	All the roads and pathways in Istanbul.
	b. Public Transport	All the public transport facilities, including bus stops, train stations, and other transit points.
2. Green Spaces and Recreational Facilities	c. Green Spaces	Includes parks, gardens, nature reserves, and other natural areas.
	d. Recreational Facilities	Information on sports centers, playgrounds, fitness stations, and other facilities for physical activity and mental well-being.
3. Public Services infrastructure	e. Healthcare Facilities	Includes hospitals, clinics, pharmacies, and doctors' offices.
	f. Educational Institutions	Data on schools, universities, libraries, kindergartens, and colleges.
4. Safety and Security	g. Emergency Services	Locations of police stations, fire stations, clinics, and shelters.
	h. Street Lighting	Data on street lamps, traffic signals, and surveillance cameras.
5. Economic Opportunities	i. Retail and Commerce	Information on various shops and markets.
	j. Financial Institutions	Includes data on banks, ATMs, cafes, restaurants, and marketplaces.
	k. Employment Centers	Locations of offices and industrial areas. Reflects the presence of employment opportunities and business activity in the area.

5.3.1. Study Area and Data

Istanbul is the largest city in Türkiye, covering an area of 5,343 km² and home to a population exceeding 16 million across its 39 districts, making it one of the most populous cities in the world. Historically, it served as the capital of both the Byzantine

Empire and the Ottoman Empire²³. With a rich history spanning over 2,500 years, Istanbul's urban landscape showcases a blend of historic neighborhoods and contemporary developments. Currently, Istanbul is the economic, cultural, and historical heart of Türkiye. While the old city is characterized by narrow winding streets, ancient monuments, and traditional architectural houses, suburban areas are characterized by residential complexes and green spaces. In this study, we utilized population and geographical data of Istanbul for the selected Points of Interest (POI). The data was acquired from various open sources: population data came from WorldPop²⁴, while other datasets were obtained from OpenStreetMap²⁵ and Istanbul Metropolitan Municipality (Istanbul Büyükşehir Belediyesi) via their open data portal²⁶.

5.3.2. Methodology

The study employed a multi-step approach to assess population distribution and administrative boundaries in Istanbul using various spatial analysis techniques and data visualization libraries. First, national-level population data of Türkiye was acquired from the WorldPop, which was then refined to focus specifically on Istanbul. Initially, the dataset was parsed and processed using rioxtarray to extract population information from a raster file.

The population data was filtered to retain only positive values, thereby eliminating null or erroneous entries. Subsequently, it was extended spatially constrained to the geographical area of Istanbul using a GeoJSON file containing the city's administrative boundaries. This GeoJSON file, which aggregated the individual boroughs into a unified urban entity, served as a precise spatial reference for the cropping operation. Population data points were transformed into a GeoDataFrame, enabling spatial overlay with Istanbul's boundaries to allow an accurate representation of population distribution within the city. The steps are shown in Figure 5.1.

²³ <https://www.britannica.com/place/Istanbul>

²⁴ <https://www.worldpop.org/>

²⁵ <https://www.openstreetmap.org/#map=6/39.03/35.25>

²⁶ <https://data.ibb.gov.tr/en/>

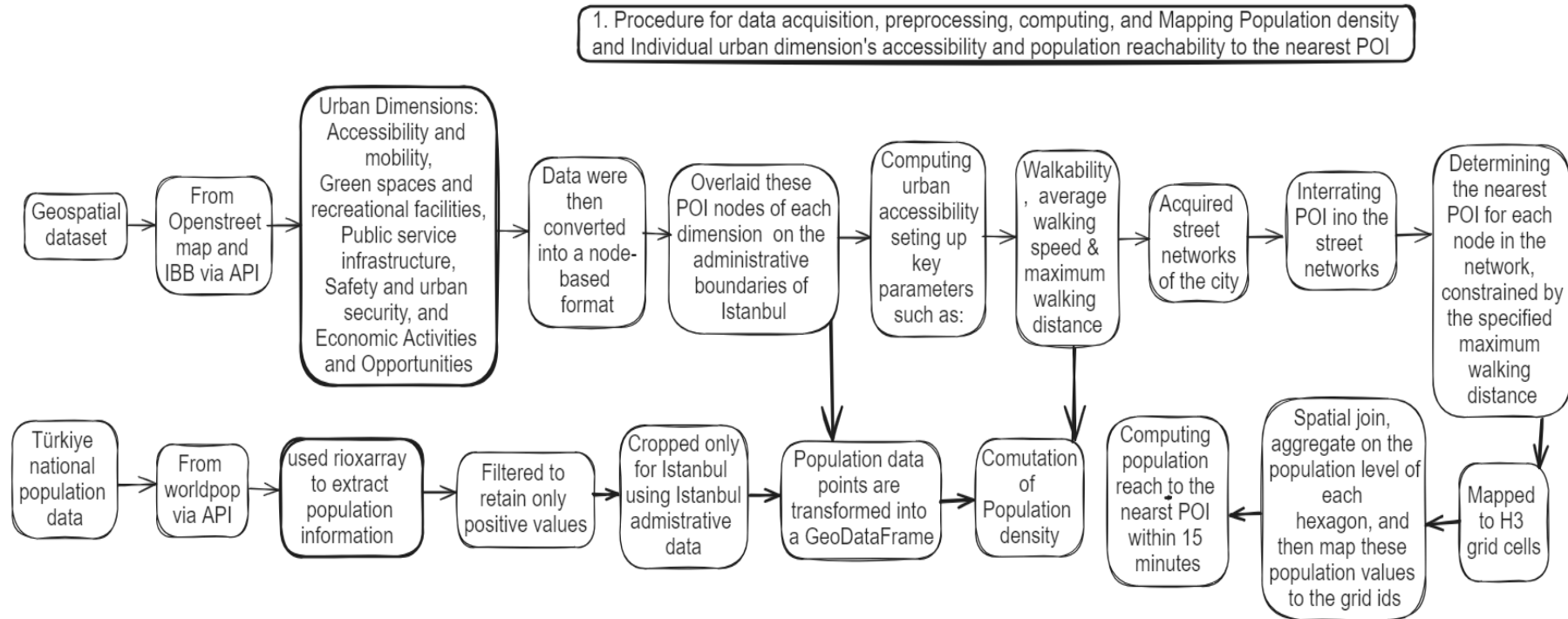


Figure 5.1. Flowchart of Data Preprocessing

Following the population data processing, we obtained five dimensions used to capture urban accessibility and well-being. These data were then converted into a node-based format to ensure more efficient integration with other geographical data structures. Nodes represent discrete points in space, enabling precise localization of each point of interest (POI) and facilitating subsequent spatial operations. Subsequently, we overlaid these POI nodes on the administrative boundaries of Istanbul.

We used hexagonal tessellation for spatial visualizations due to its advantages in harmonizing data within and across different districts. Hexagons lacking network nodes were excluded from the analysis. Hexagonal grids minimize sampling bias and edge effects compared to traditional square grids, providing a more accurate representation of spatial relationships (Birch et al., 2007; Willberg et al., 2024; Vale and Lopes, 2023). These hexagonal units maintain consistent distances between cell centers and offer superior connectivity with neighboring cells (Vale and Lopes, 2023). Furthermore, hexagonal tessellation reduces directional bias in distance calculations and better approximates circular catchment areas. Uber's Level 7 Hexagonal Hierarchical Spatial Index (H3) was opted to create the necessary hexagon grids due to its clarity, as shown in Figure 2 in the supplementary document.

- **Hexagon-Level Accessibility:** For each hexagonal unit h , accessibility is calculated by identifying the 20 closest points of interest (POIs) for a given dimension or category. This approach aligns with established methodologies in urban accessibility studies (Bruno et al., 2024; Cui & Levinson, 2020). The selection of 20 POIs balances computational efficiency with comprehensive coverage, providing robust estimates of service accessibility while maintaining practical implementation. Please see Figures 5.25-5.27 at the end of the chapter.

The average time required to reach these POIs, denoted as $T_{k,h}$ is computed as:

$$T_{k,h} = \frac{1}{n} \sum_{i=1}^n t_i^{k,h} \quad (5.1)$$

where n represents the total number of POIs, which is 20 in this case, and $t_i^{k,h}$ denotes the travel time to the i -th POI of the specified category within hexagon h . This value reflects the accessibility for a particular category within a hexagon and serves as a proxy for the ease of reaching nearby opportunities.

- **City-Level Accessibility:** The city-wide accessibility index for each hexagon is derived by averaging the accessibility measures across all POI categories. For a hexagon h , the proximity time index PT_h expressed as:

$$PT_h = \frac{1}{c} \sum_{i=1}^n T_{k,h} \quad (5.2)$$

Here, C is the total number of categories being considered. This calculation ensures that accessibility for different types of POIs is evenly represented in the final measure for each hexagon. The city-level accessibility measure provides a broad view of proximity to urban amenities by aggregating the results from individual hexagons.

- **Population Weighting:** To compute an overall measure of city accessibility, individual hexagon accessibility scores are weighted by the population residing within each hexagon. The weighted accessibility score for the city, PT_{city} , is given as:

$$PT_{city} = \frac{\sum_h^H PT_h P_h}{\sum_{h=1}^H P_h} \quad (5.3)$$

Here, H represents the total number of hexagons, PT_h is the proximity time index for hexagon h , and P_h is the population within hexagon h . This approach ensures that the measure reflects accessibility relative to where people live, emphasizing areas with higher populations.

- **15-Minute Accessibility:** This metric evaluates the proportion of the city's population that can reach urban amenities within a 15-minute travel time. The percentage of the population with access within this threshold, F_{15} is calculated as:

$$F_{15} = \frac{\sum_{h=1}^H PT_{h \leq 15} P_h}{\sum_{h=1}^H P_h} * 100 \quad (5.4)$$

- **Inequality Assessment:** is obtained as shown below.

$$G = 1 - \frac{2 \sum_{p=1}^{N_{pop}} \sum_{p' \leq p} PT_{p'}}{N_{pop} \sum_{p=1}^{N_{pop}} PT_p} * \quad (5.5)$$

Here, PT_p is the p-th proximity time measure of a single person in the city when sorted in non-decreasing order. This measures the unequal accessibility in the city.

Our hypothesis posits that significant disparities in accessibility exist across Istanbul, with central districts demonstrating higher levels of accessibility to essential services and amenities, while peripheral districts exhibit comparatively lower levels.

5.3.3. Accessibility of Individual Dimensions

We analyzed the individual urban accessibility. First, we defined key walkability parameters, such as average walking speed and maximum walking distance, to ensure the analysis reflects real-world conditions. These parameters help ensure the analysis reflects the real-world constraints residents face in their daily lives.

Next, we used the administrative boundaries of the cities to set the geographical scope, ensuring the analysis covers the entire urban area. Then, we created detailed street networks, which serve as the foundation for calculating accessibility metrics. These networks were combined with Points of Interest (POI) data, including public services, green spaces, and economic hubs, to integrate essential amenities into the analysis. After that, we calculated accessibility by identifying the nearest POI for

each node in the street network, using the predefined maximum walking distance as a constraint.

This produced metrics like distance and estimated walking time to the nearest amenities, giving us a detailed picture of accessibility patterns across the city. Finally, we overlaid the resulting accessibility data onto the cities' administrative boundaries to provide spatial context. Visual representations of these findings are included in the supplementary document figures 3-7.

5.3.4. Building Overall Livability Index

To construct an overall index, we calculated accessibility across the districts of Istanbul using data sourced from OpenStreetMap (OSM). We collected and processed the five urban features for each of the 38 districts in Istanbul separately. Following the extraction, the acquired data is saved in GeoJSON format, ensuring that it is organized and compatible with other datasets. Additionally, the administrative boundaries of Istanbul's districts are defined and stored in a similar manner.

5.3.5. Deriving Accessibility Metrics for Each District

Once the data acquisition phase is complete, all the retrieved files in GeoJSON format for each district are compiled. Accessibility and mobility metrics are derived by calculating the density of each urban feature, which involves dividing the number of occurrences of each feature by the total area of the district following (Janosov, 2024b), as shown in equations 6-18. The results for each district are then aggregated into a structured DataFrame to compare across districts.

$$L \text{ (total length of roads (in km))}_{di} = \frac{\sum \text{edge lengths}}{1000} \quad (5.6)$$

$$A \text{ (Total area by road network (in km}^2\text{))}_{di} = \frac{\text{convex hull of road network}}{1000^2 \text{ (km}^2\text{)}} \quad (5.7)$$

$$\text{Road density}_{di} (\text{km of road per km}^2) = \frac{A (\text{total area by road network (in km}^2)_{di})}{A (\text{km}^2)} \quad (5.8)$$

$$\text{Public transport density}_{di} = \frac{\text{number of public transport points}}{A (\text{km}^2)} \quad (5.9)$$

$$\text{Park coverage}_{di} (\%) = \frac{\text{total area of green spaces}}{A * 1000^2} * 100 \quad (5.10)$$

$$\text{Recreation density}_{di} (\text{POI/ km}^2) = \frac{\text{number of recreational facilities}}{A} \quad (5.11)$$

$$\text{Health density}_{di} (\text{POI/ km}^2) = \frac{\text{number of healthcare facilities}}{A} \quad (5.12)$$

$$\text{Education density}_{di} (\text{POI/ km}^2) = \frac{\text{number of educational institutions}}{A} \quad (5.13)$$

$$\text{Emergency density}_{di} (\text{POI/ km}^2) = \frac{\text{number of emergency service facilities}}{A} \quad (5.14)$$

$$\text{Street lighting density}_{di} (\text{POI/ km}^2) = \frac{\text{number of street lamps}}{A} \quad (5.15)$$

$$\text{Retail density}_{di} (\text{POI per km}^2) = \frac{\text{number of retail shops}}{A} \quad (5.16)$$

$$\text{Employ. centers density}_{di} (\text{POI/ km}^2) = \frac{\text{number of employment centers}}{A} \quad (5.17)$$

$$\text{Financial centers density}_{di} (\text{POI/ km}^2) = \frac{\text{number of financial centers}}{A} \quad (5.18)$$

5.3.6. Building Livability Index for the Whole City

Finally, we developed an Overall Livability Index (OLI) depicted in Figure 5.5 for each district in Istanbul from the aggregated densities of urban features of each district using equation 21. The development of an Overall Livability Index (OLI) involves the following steps:

- a. Normalization of Urban Features:** Each urban feature from the compiled DataFrame is standardized using the MinMaxScaler function from the scikit-learn library as in equation 19. This step ensures that different units and scales, such as road density, public transport access, and healthcare availability, are converted to a common range, facilitating a balanced evaluation across all features.

$$X_{id}^{norm} = \frac{X_i - X_{id,min}}{X_{id,max} - X_{id,min}} \times (10 - 1) \quad (5.19)$$

X_{id} is the original value of the feature i for a given district d , $X_{id,min}$ and $X_{id,max}$ are the minimum and maximum values of that features across all districts, respectively, X_{id}^{norm} is the normalized feature value, scaled between 1 and 10.

- b. Weighting of Urban Features:** Principal Component Analysis (PCA) was applied to the normalized dataset to determine the relative importance of each feature as shown in equation 20. The intuition behind the weighting is that for example, Public Transport Density is assumed to be important than Park Coverage due to its significant impact on daily routine accessibility. This approach ensures that the final index reflects the varied contributions of different features to the overall livability of each district.

$$X_{id}^{weighted} = W_{id} \times X_{id}^{norm} \quad (5.20)$$

W_{id} is the weight assigned to feature X_{id} (with $\sum W_{id} = 1$ to maintain scale), $X_{id}^{weighted}$ is the weighted feature value.

- c. Overall Index Construction:** The weighted values of all features are aggregated to form a unified score for each district in the previously compiled DataFrame. The calculation is performed using the Place column to accurately assign scores to the corresponding districts.

$$\text{Unified Livability Index} = \sum_{i=1}^n X_{id}^{\text{weighted}} \quad (5.21)$$

- d. Rescaling for Consistency:** The unified index is rescaled using the MinMaxScaler to a consistent range of 1 to 10. This rescaling ensures that the index values are easy to interpret and compare across different districts, highlighting areas with high or low livability scores.
- e. Integration with Administrative Data:** The final index values are merged with the geographical boundaries of Istanbul's districts using the Place column as a common key.
- f. Spatial Analysis and Visualization:** The resulting GeoDataFrame is used to map the Overall Livability Index, visually depicting the distribution of livability across Istanbul. Districts are represented with different color spectrums based on their index scores, providing a clear visual summary of urban accessibility and well-being across the city's diverse districts.

5.3.7. Software and Tools

We utilized several Python packages for spatial and network analysis.

- **For Data Manipulation and Geospatial Operations,** we employed pandas, Geopandas, and Numpy. OSMnx facilitated the extraction of points of interest from OpenStreetMap. Network analysis was conducted using Pandana for accessibility metrics and shortest path calculations. For spatial indexing and geometry operations, we used H3 and Shapely, while Rioxarray and Xarray were used to handle multi-dimensional geospatial data. Lastly, Matplotlib and Contextily were used for visualization.
- **Tabular Data Management and Numerical Computation:** We used Pandas for reading, organizing, and manipulating structured tabular datasets. It was applied for tasks such as merging different data sources, grouping values by category or region, filtering specific rows, and computing statistical summaries of accessibility measures. Its dataframe format allowed efficient integration of non-spatial data into the geospatial pipeline, especially when handling service attributes, area codes, or lookup tables.

For numerical operations involving arrays and matrix-like structures, we used NumPy. It was necessary for the efficient execution of mathematical operations, including element-wise computation of accessibility scores, transformation of distance arrays, and array-level masking. NumPy arrays were also used in intermediary steps before converting outputs back to geospatial formats.

- **Geospatial Vector Operations:** Spatial data operations involving vector geometries were carried out using GeoPandas. It extends the functionality of pandas to include geometric objects in dataframe structures. We used it to read shapefiles, perform spatial joins, calculate centroids, and store hexagonal grids along with associated accessibility results. It also supported projection transformations, which were essential for aligning spatial data from different sources into a common coordinate system.

We used Shapely for geometric operations that required precise spatial logic. These included computing intersections between polygons, checking point-within-polygon relationships, and applying geometric transformations such as buffering or simplifying edges. It operates at the object level and underlies the geometric functionality in GeoPandas.

To discretize space into regular, comparable units, we used the H3 spatial indexing library. H3 divides the surface of the Earth into hexagonal cells at varying resolutions. We selected a resolution appropriate for intra-urban analysis, and all accessibility scores were computed at the hexagonal cell level. This enabled consistent spatial aggregation and comparison between locations without depending on administrative boundaries.

- **Network Construction and Routing:** OSMnx was employed to download and process spatial data from OpenStreetMap. This included street networks and points of interest such as schools, clinics, or markets. The library was used to construct urban networks and extract node coordinates and edges in graph format. It also enabled spatial filtering of features based on geographic boundaries and tag attributes.

For calculating accessibility metrics using the street network, we used Pandana. This library builds a routing graph and computes shortest paths from origins to destinations across a given cost constraint. We applied it to calculate cumulative and distance-decay-based accessibility measures, using a pre-defined cost threshold or impedance function. The resulting accessibility values were stored by origin location and later joined to the hexagonal grid.

- **Raster and Multidimensional Spatial Data:** We utilized Xarray and Rioxarray to handle raster data that included multiple spatial and non-spatial dimensions. These tools were used to read GeoTIFFs, assign coordinate reference systems, clip rasters to city boundaries, and align raster cells with the hexagonal index. Xarray's support for labeled dimensions enabled consistent referencing across different data layers.
- **Visualization:** We used matplotlib to visualize accessibility scores by hexagonal unit. It provided fine control over color schemes, figure size, and spatial boundaries. Plots were generated directly from dataframes, and classification thresholds were set manually to ensure interpretability.

Finally, Contextily was used to add basemaps beneath our accessibility visualizations. It provided background tiles for contextual reference, such as roads and building footprints, using web mapping services compatible with our projected spatial data.

5.4. Findings and Discussion

This section presents the results and findings of Chapter Four. The analysis begins with an examination of population settlement patterns in Istanbul, which establishes the demographic context necessary for interpreting the geographical dispersion of locational reachability in the subsequent pages. Understanding where people reside allows a more accurate evaluation of whether access to services aligns with population needs.

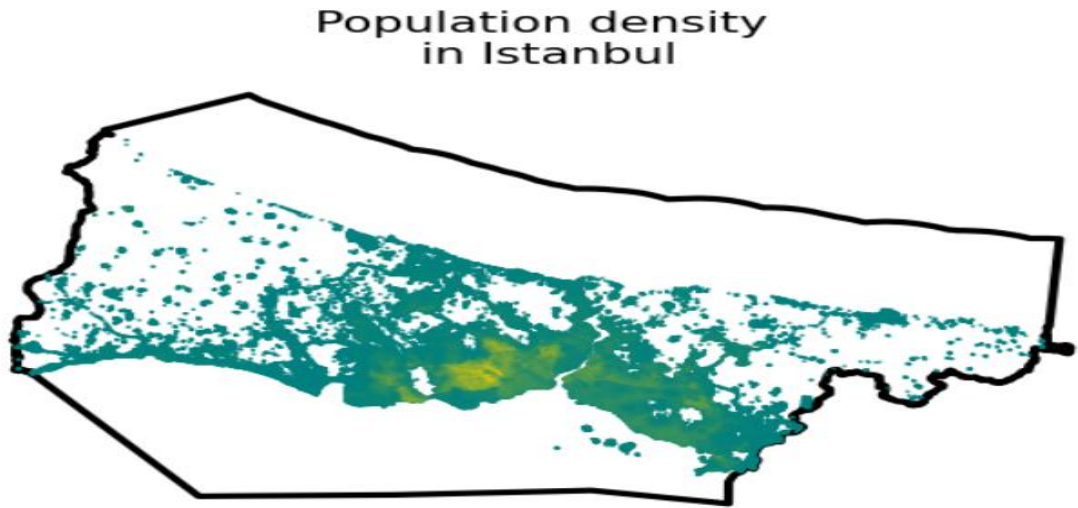


Figure 5.2. Population Density in Istanbul

Figure 5.2 shows the population density dispersion in Istanbul. Areas shaded in gold represent zones with a high number of inhabitants, whereas green and white colors correspond to areas with low population density or uninhabited land. As Figure 5.2 depicts, the most densely populated areas are located in the historical urban districts such as Fatih, Bayrampaşa, Beyoğlu, Kadıköy, and Beşiktaş. Population clusters are also visible in several peripheral districts. This visualization indicates that urban expansion has not remained confined to the historical center but has spread and expanded outward following modern development patterns.

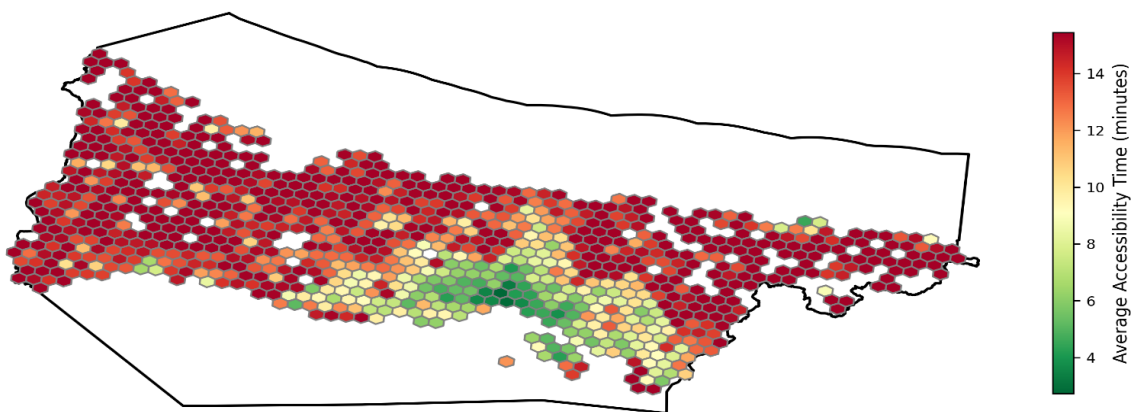


Figure 5.3. Accessibility Levels Across the Five Urban Dimensions

The geographic configuration is illustrated in Figure 5.3, which quantifies reachability levels across five urban dimensions throughout Istanbul's metropolitan area. The hexagonal grid representation employs a chromatic gradient wherein green cells signify optimal reachability with minimum travel times (3-4 minutes), while red cells indicate severely constrained accessibility requiring substantially longer travel times (14+ minutes). Thus, the accessibility index aggregated at the hexagonal grid level facilitates identification of underserved urban territories while simultaneously highlighting areas of service concentration.

This visualization reveals pronounced spatial heterogeneity in access to urban opportunities, manifesting as a strong core-periphery gradient. The historical urban centers Fatih, Üsküdar, Kadıköy, Beşiktaş, and Bakırköy exhibit higher connectivity scores due to their high concentration of services and amenities. These results correspond to the historical development trajectories of these districts as Istanbul's foundational urban nuclei.

Conversely, the peripheral districts, such as Silivri, Şile, and Arnavutköy, demonstrate ample diminished accessibility. The figure shows that these regions suffer from dual disadvantages: lower concentrations of urban opportunities and extended travel times to essential services. The observed spatial polarization suggests persistent, enduring inequalities in urban resource allocation that transcend mere geographic distance factors, potentially incorporating socioeconomic stratification elements.

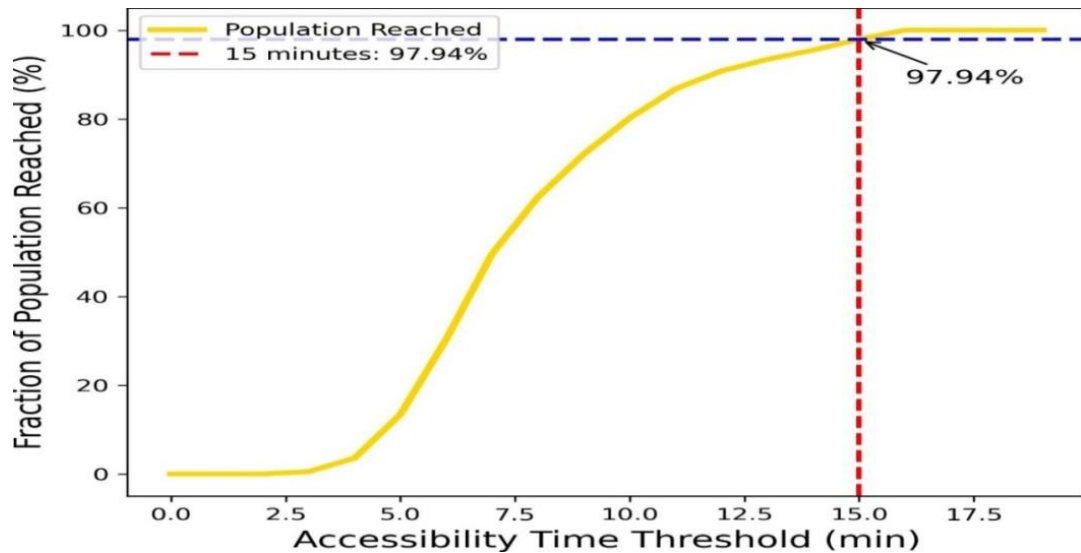


Figure 5.4. Fraction of Population V. Opportunity and Service Accessibility in Istanbul

Figure 5.4 presents the correlation between population distribution and opportunity accessibility in Istanbul. The graph illustrates the percentage of the population with access to urban services across the city's districts based on the 15-minute walkability thresholds. The horizontal axis represents reachability time thresholds in minutes, while the vertical axis shows the fraction of the population reached as a percentage.

The yellow continuous line traces the cumulative population percentage with access to at least one urban opportunity at each time threshold. It exhibits minimal growth until approximately 2.5 minutes, after which it increases rapidly between 5 and 10 minutes. The curve subsequently flattens as it approaches the 15-minute threshold.

The 15-minute walking threshold, marked by a vertical red dashed line, is our target point. At this threshold, the figure demonstrates that 97.94% of Istanbul's population can access at least one urban opportunity, as noted by the blue horizontal dashed line and the annotation at the upper right section of the graph.

This quantitative, visual assessment provides evidence for urban accessibility planning effectiveness throughout Istanbul. The steep gradient between 5 and 10 minutes suggests that heft improvements in accessibility occur within this interval,

which holds implications for targeted urban development strategies. The near-universal access (97.94%) at the 15-minute threshold constitutes a significant urban planning achievement, yet this figure warrants further investigation regarding the quality, variety, and distribution of opportunities available within this temporal constraint across different urban districts. That is done by examining each individual urban dimension separately. Since the aggregate measurement might obscure variations, each urban dimension is examined individually. Subsequently, the Disaggregation by urban dimension reveals greater variations in accessibility patterns, as illustrated in (7-18).

Transport infrastructure accessibility remains limited, with merely 52.39% of the population able to reach these facilities within the 15-minute threshold, followed by green spaces and recreational facilities, which demonstrate constrained accessibility, with only 52.48% of residents achieving access within this temporal parameter.

Economic opportunities, however, present markedly superior accessibility patterns. The data confirms that 92.40% of Istanbul's population can access commercial centers, financial zones, and related economic facilities within the 15-minute threshold.

Similarly, education and health services connectivity exhibit remarkable coverage, with roughly 94.46% of the population accessing educational and healthcare facilities within the 15-minute walking threshold. On the other hand, security and emergency services' approximate reachability falls between the extremes, available to 77.73% of residents within this temporal parameter. These differential patterns across service categories and urban features portray inconsistent efficacy in settlement structure strategies for various urban amenities.

The analysis produces paramount imperative urban planning implications that demand identification of priority intervention zones to enhance infrastructural and service accessibility. Particular attention must focus on transport and mobility infrastructure as well as green zones and recreational facilities, which demonstrate the most significant accessibility deficits. The stark, definitive contrast between economic, public service (education and health) coverage, and transport mobility

infrastructure accessibility metrics illustrates potential disconnections and distributional asymmetry between service locations and the infrastructure required to reach them efficiently. In other words, it indicates inequities in urban resource allocation across the city.

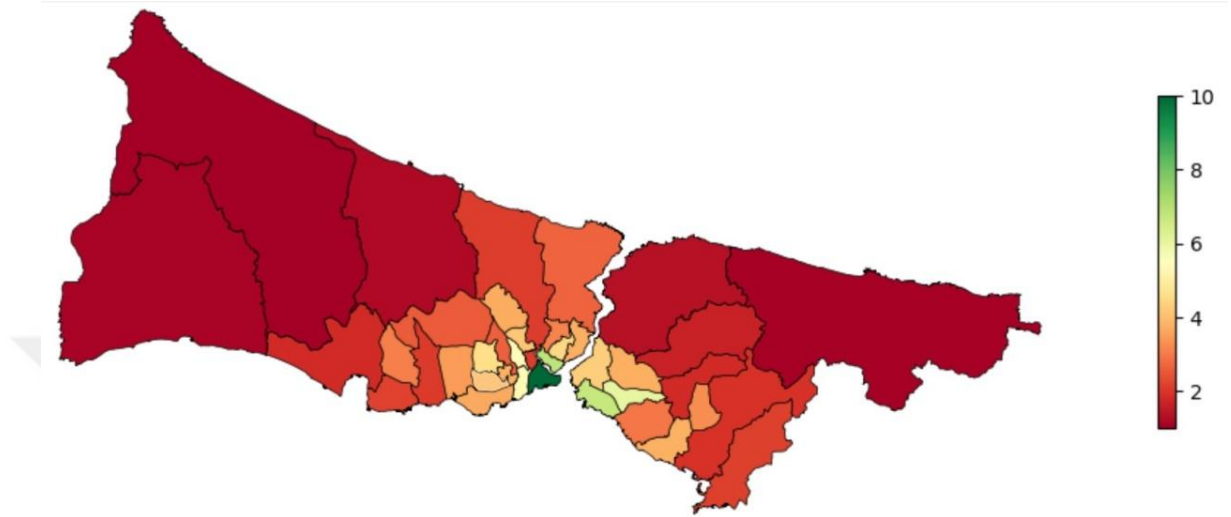


Figure 5.5. Unified Livability Index

Figure 5.5 displays a unified livability index across Istanbul's urban territory, encompassing 38 of the 39 administrative districts. Adalar district, which includes the Princes' Islands, remains excluded from this analysis due to data unavailability. The index aggregates the five primary urban dimensions into a composite livability metric, represented through a color gradient wherein green signifies optimal livability conditions and red indicates suboptimal livability areas.

The livability scores exhibit considerable asymmetry across Istanbul's urban landscape. Fatih district attains the highest livability score, characterized by superior accessibility to urban amenities and services. The findings correspond with Fatih's historical position and status as Istanbul's traditional urban nucleus and its continued function as a principal center of urban activity and infrastructural deployment. Fatih district's higher performance likely stems from its established urban infrastructure, abundant service availability, and central, strategic metropolitan location.

Moreover, the result reveals a clear core-periphery pattern, with central districts generally exhibiting higher livability scores compared to peripheral areas. Districts adjacent to Fatih, such as Beyoğlu and Kadıköy, also demonstrate relatively high livability scores, though not matching Fatih. This pattern reflects the concentric development of Istanbul's urban structure throughout its historical evolution, with service concentration diminishing as distance from the traditional center increases.

On the contrary, Peripheral districts at the western and eastern edges of the city display predominantly red coloration, which signifies much lower livability scores. These districts face challenges of limited service availability, reduced connectivity, and inadequate urban infrastructure. The stark contrast between central and peripheral districts confirms persistent locational inequity in Istanbul's urban development patterns. Figure 6 presents all districts ranked from lowest to highest livability scores.

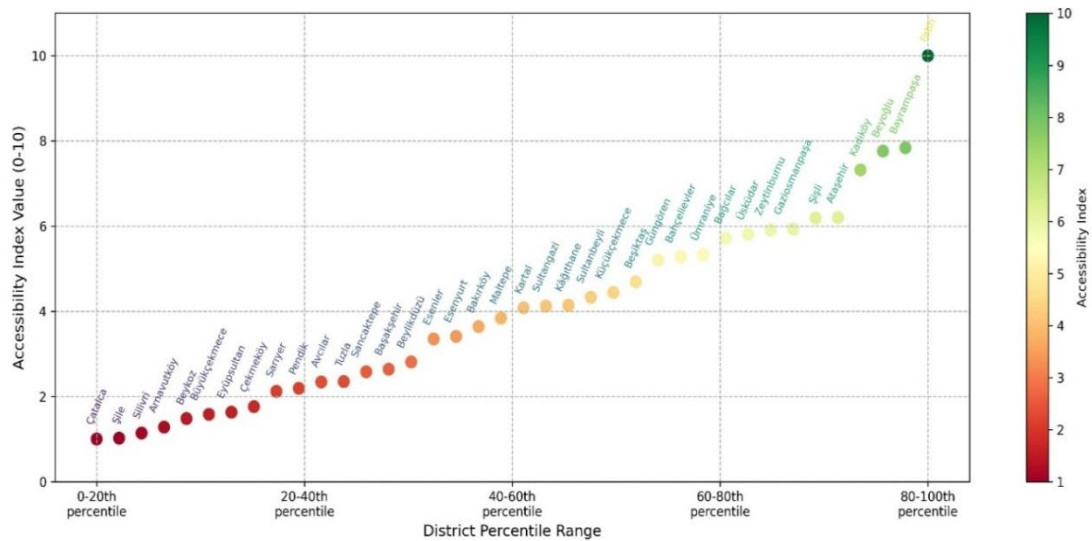


Figure 5.6. District's Percentile Range According to the Livability Index

Figure 5.6 presents the hierarchical distribution of Istanbul's districts based on their computed livability index. The graph illustrates clear patterns in urban quality of life across the city.

The districts occupy distinct percentile ranges according to their livability scores. Catalca, Sile, Silivri, Arnavutkoy, Beykoz, Bayrampasa, and Cekmekoy fall in the lowest percentile range (0-20th and 20-40th). These districts record livability index values between 1 and 2.5. These areas constitute peripheral zones with limited urban amenities.

The middle percentile range (40-60th) contains Tuzla, Sancaktepe, Beylikduzu, Esenler, and Esenyurt, with livability index values between 3 and 4.5. These districts form transitional zones between the urban periphery and core areas.

Districts in the 60-80th percentile include Kartal, Sultangazi, Kucukcekmece, Sultanbeyli, Besiktas, Gungoren, Bahcelievler, and Umraniye, with livability scores between 4.5 and 6.5. These areas exhibit improved urban conditions compared to lower-ranked districts.

The highest percentile range (80-100th) comprises Uskudar, Zeytinburnu, Gaziosmanpasa, Kadikoy, Beyoglu, Bayrampasa, and Fatih, with livability scores between 6.5 and 10. Fatih achieves the maximum score of 10, which confirms its status as Istanbul's most livable district. These top-ranked districts form the historical and functional core of Istanbul with ample services and amenity dissemination and ease of accessibility.

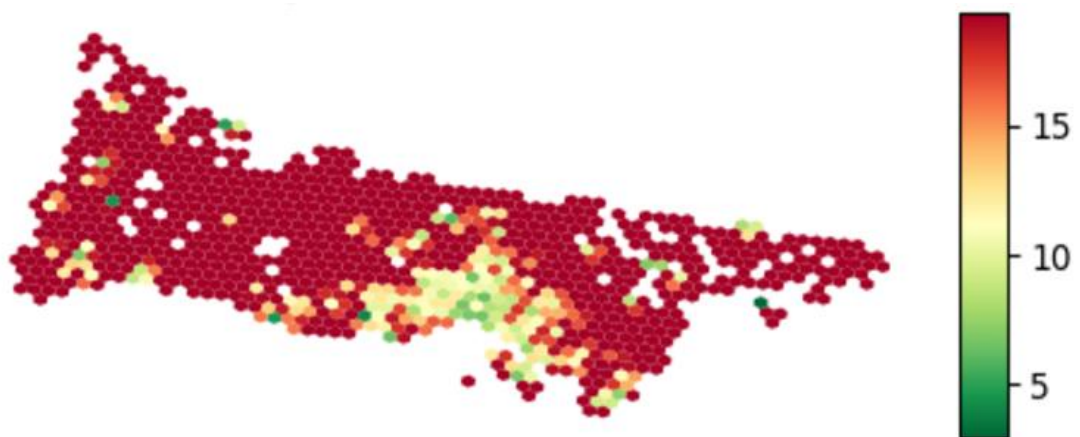


Figure 5.7. Public Transport and Mobility Accessibility

Figures 5.7 and 5.8 illustrate a disquieting reality of transport accessibility across Istanbul, a metropolis confronting persistent mobility challenges amid its burgeoning population of 16 million. The spatial dispersion map reveals the concentration of public transport access points within central districts. Extensive peripheral zones, characterized by dominant red areas, expose a marked deficit in urban permeability that undermines the principle of equitable urban connectivity.

The accessibility curve, shown in Figure 8, portrays a bleak scenario. Merely 52.39 % of Istanbul's residents can access transport facilities within a fifteen-minute walking radius. This deficiency becomes more striking when contrasted with other urban services. While 94.46% of residents benefit from proximity to education and health services (figures 5.15 and 5.16), 92.40% to economic hub (figures 5.9 and 5.10), 77% to security (figures 5.13 and 5.14), transport accessibility languishes at the same low level as green spaces, both occupying the base of the urban amenity hierarchy.

In a megacity defined by chronic traffic congestion, such a deficient distribution of public transport infrastructure engenders profound consequences. The prevalence of private vehicle usage during peak hours attests to the systemic failure to provide alternatives, thereby exacerbating the urban mobility crisis. This imbalance is most severe in peripheral districts, where the pace of urban expansion has consistently outpaced the development of transport systems.

What emerges from this pattern is not a random phenomenon but a manifestation of structural imbalances in urban growth management, whereby central districts, benefiting from historical investments in metro networks, bus corridors, and multimodal connections, continue to maintain relative connectivity. On the contrary, outer districts, which absorb much of the city's demographic pressure, remain trapped in conditions of transport fragmentation. this not only impedes daily commuting efficiency but also shapes long-term economic opportunity, social mobility, and the general quality of urban life and well-being of the residents.

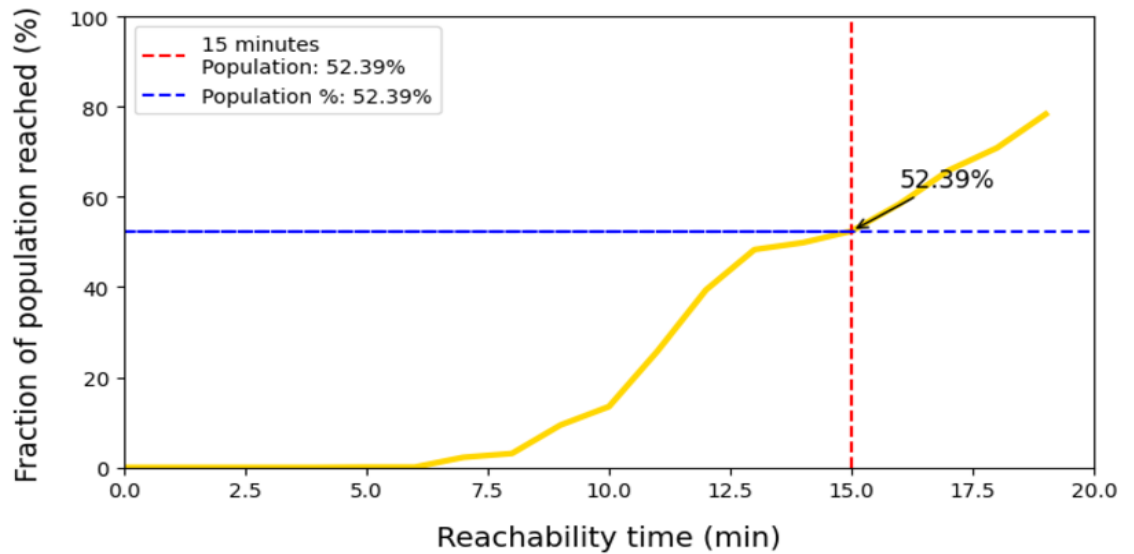


Figure 5.8. Fraction of the Population Versus Accessibility Time to Public Transport and Mobility

Figures 5.7 and 5.8 show the uneven state of transport accessibility and mobility in Istanbul, where mobility remains a persistent challenge for the city's 16 million residents. Figure 7 shows a sharp divide as public transport access is concentrated mainly in the central districts, represented by green color, while the outlying districts, shown largely in red, face accessibility mobility shortfalls.

Figure 8 paints an equally stark picture. Only 52.39% of Istanbul's population can reach a public transport point within a 15-minute walk. Compared to other essential services. While 94.46% of residents can access public services and 92.40% can reach economic hubs within the same timeframe, transport accessibility and mobility stand at 52.48%.

In a city where daily traffic congestion is already a major issue, this lack of convenient access to public transport and mobility has significant consequences. During peak hours, when nearly half of the population cannot easily reach a bus, metro, or tram station, many turn to private vehicles, worsening congestion across the city's already overburdened road network. This situation is severe in peripheral areas, where rapid urban growth has not been matched by corresponding investments in transport infrastructure.

The established metro lines and bus routes provide good coverage in the older, central parts of the city, but the newer suburban districts are poorly served. Limited access to public transport affects more than daily mobility. It reduces opportunities for employment, education, and social interaction. As a result, inequalities between central districts and peripheral areas of Istanbul become more severe over time.

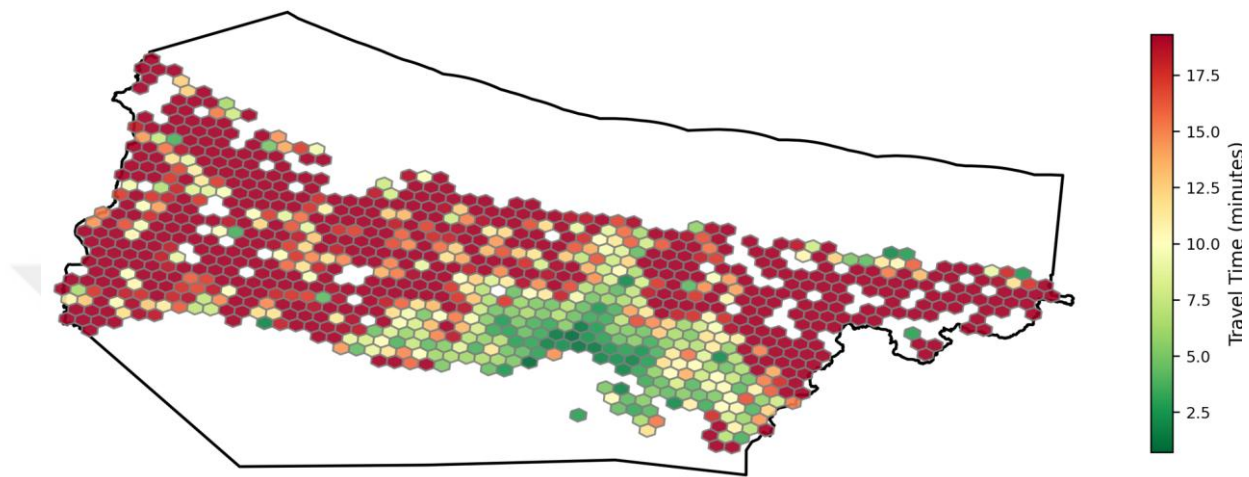


Figure 5.9. Economic Accessibility

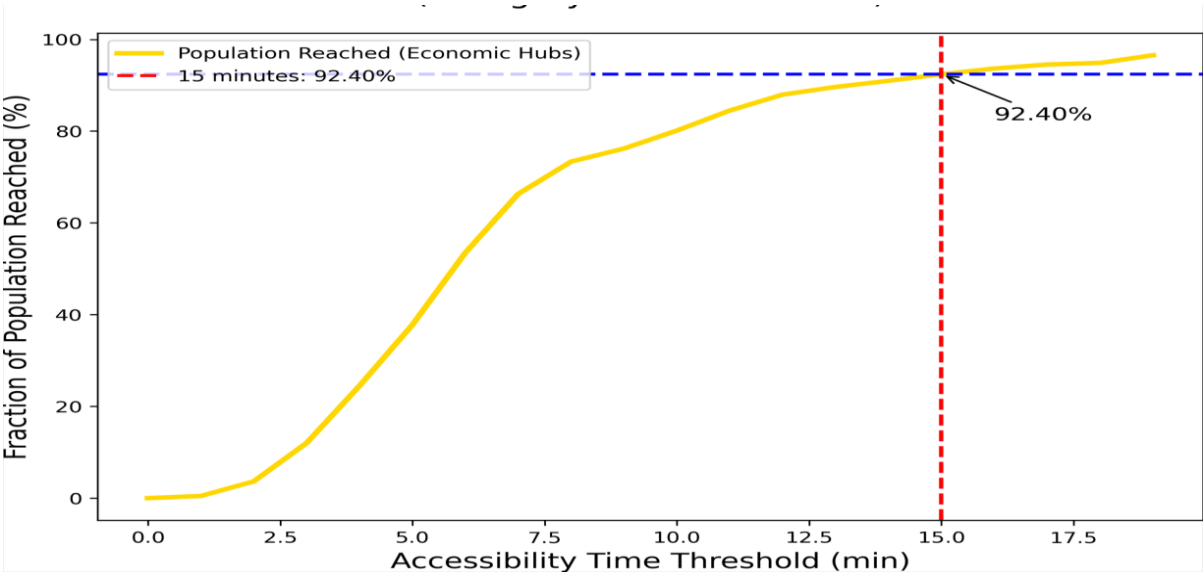


Figure 5.10. Fraction of the Population Versus Accessibility Time to Economic Hub

Figures 5.9 and 4.10 show the patterns of accessibility to economic hubs in Istanbul. Figure 5 displays the spatial distribution of travel times, where green hexagons represent areas with travel times under 7.5 minutes and red areas represent travel times over 15 minutes. Central districts have shorter travel times to economic hubs because of the historical concentration of commercial activities in these areas.

Figure 5.10 shows the cumulative opportunity curve for accessibility to economic hubs. The curve indicates that 92.40% of Istanbul's population can reach an economic hub (banks, shopping malls, grocery stores, restaurants) within 15 minutes. The steep increase between 2.5 and 7.5 minutes shows that a large share of the population is located close to economic centers.

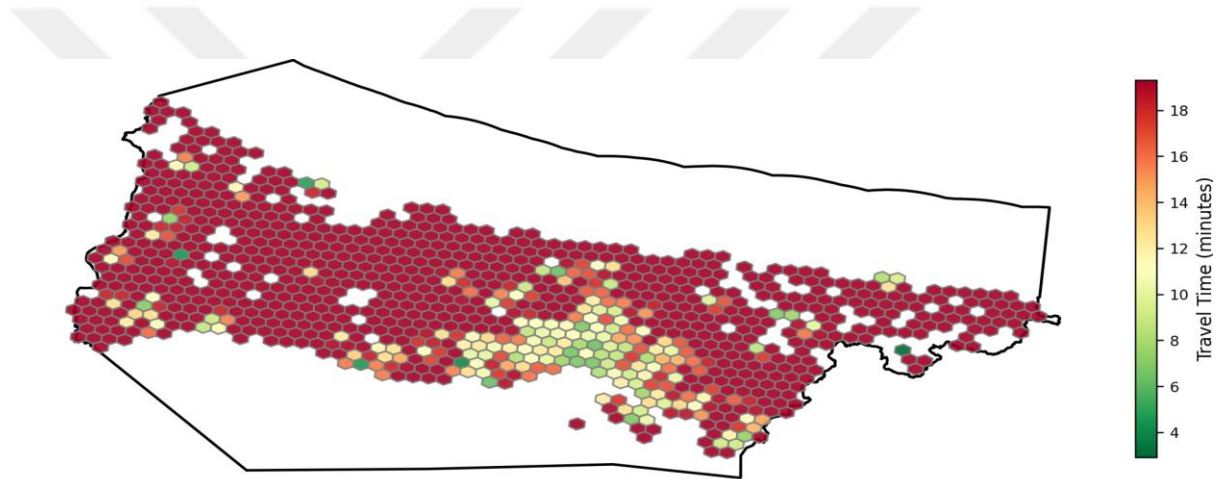


Figure 5.11. Public Green Space Recreational Facility Accessibility

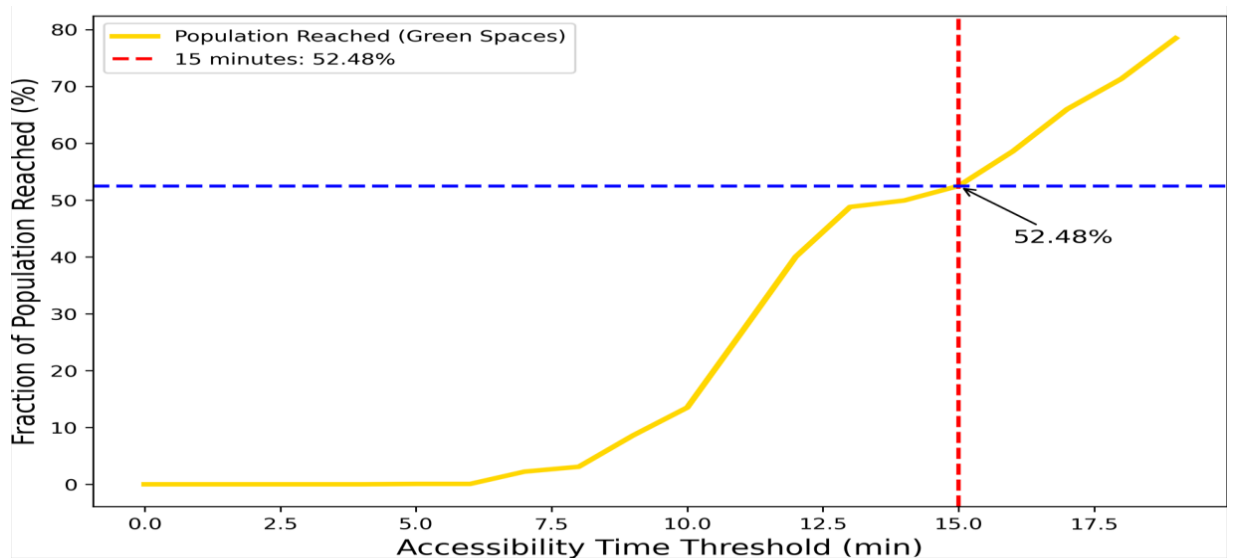


Figure 5.12. Fraction of the Population Versus Accessibility Time to Green Space Recreational Facility

Figures 5.11 and 5.12 examine the green space and the recreational facility's accessibility. Figure 11 presents the spatial arrangement of travel times to parks, gardens, and recreational facilities. Extensive areas of the city require travel times exceeding 15 minutes to reach the nearest green space or recreational facilities. Only limited and scattered areas, predominantly in the central zones, exhibit walkability times under 7.5 minutes.

Figure 5.12 is the cumulative opportunity curve for green space and recreational hubs' accessibility. As shown in the figure, 52.48 percent of the population can access a green space or recreational hotspot within 15 minutes. This is the second lowest urban dimension after public transport and mobility, which is 52.39, shown in Figure 5.8.

Accessibility remains low during the initial travel time intervals and only increases considerably between 10 and 15 minutes. The curve indicates a spatial concentration of green spaces rather than a widespread, uniform distribution across the city.

Parks and recreational areas constitute vital components of urban infrastructure that support physical activity, mental restoration, psychological relaxation, and

opportunities for social interaction. Hence, limited accessibility to these facilities and centers might negatively impact urban health and quality of life.

A well-distributed network of green spaces contributes to improved air quality, reduced stress levels, and broader public health outcomes. The current pattern suggests that swath segments of the population have insufficient access to these essential amenities.

Urban expansion processes often prioritize residential and commercial development at the expense of green infrastructure. Without strategic interventions, spatial inequalities in access to recreational and green spaces are likely to intensify. Therefore, ensuring a more equitable distribution of parks and recreational facilities is essential for the advancement of urban sustainability, the improvement of environmental quality, and the promotion of inclusive urban living conditions.

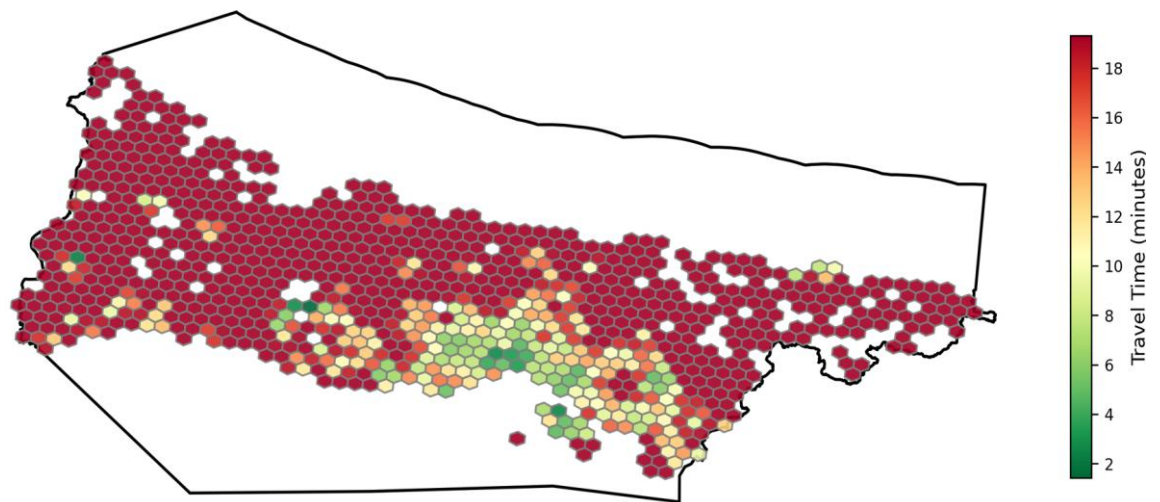


Figure 5.13. Security Centers' Accessibility

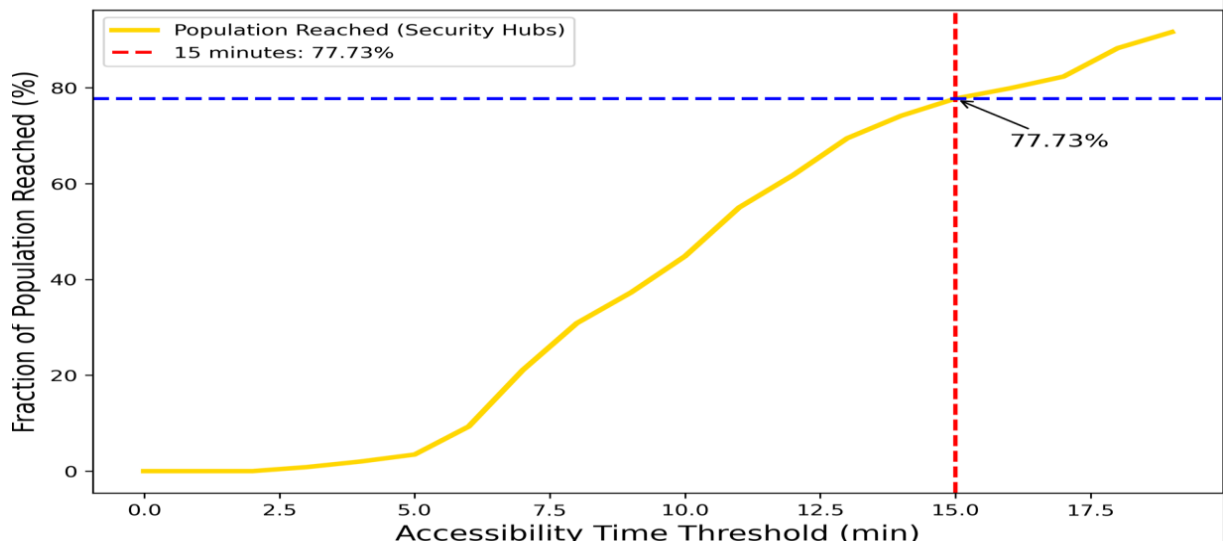


Figure 5.14. Fraction of the Population Versus Accessibility Time to Security Centers

Figures 5.13 and 5.14 present the security hub accessibility across Istanbul's districts. The results indicate a more favorable pattern than that observed for green spaces, and public transport and mobility, although the coverage remains less extensive compared to economic hubs. Similar to previous patterns, central districts, depicted with green and yellow hexagons, demonstrate satisfactory accessibility, whereas large areas along the city's periphery continue to experience extended travel times to reach security services.

Figure 5.14 shows that 77.73% of Istanbul's population can reach security centers on foot within 15 minutes. This proportion falls between the higher accessibility recorded for economic hubs (92.40%), as illustrated in Figure 10, and the lower accessibility for transport and green spaces (approximately 52%), as shown in Figure 9. The steady progression of the curve from the five-minute mark onward reflects a more gradual spatial distribution of security centers.

In a city of Istanbul's scale, timely access to police stations, fire stations, and emergency medical services has direct implications for safety outcomes. However, the fact that close to one-quarter of the population remains beyond a 15-minute threshold raises concerns regarding emergency responsiveness in newly developed or peripheral neighborhoods.

Security infrastructure forms a fundamental component of urban livability, although it often receives less visible attention compared to amenities such as parks or public transport. Deficiencies in green spaces or transit systems tend to be immediately apparent to residents, whereas the adequacy of security services typically becomes evident only in urgent circumstances.

The current accessibility rate suggests that Istanbul has allocated considerable resources toward security infrastructure. Nevertheless, the uneven distribution across peripheral areas reveals ongoing vulnerabilities that require further policy attention, as urban development continues to expand the city's physical footprint and economic capacity.

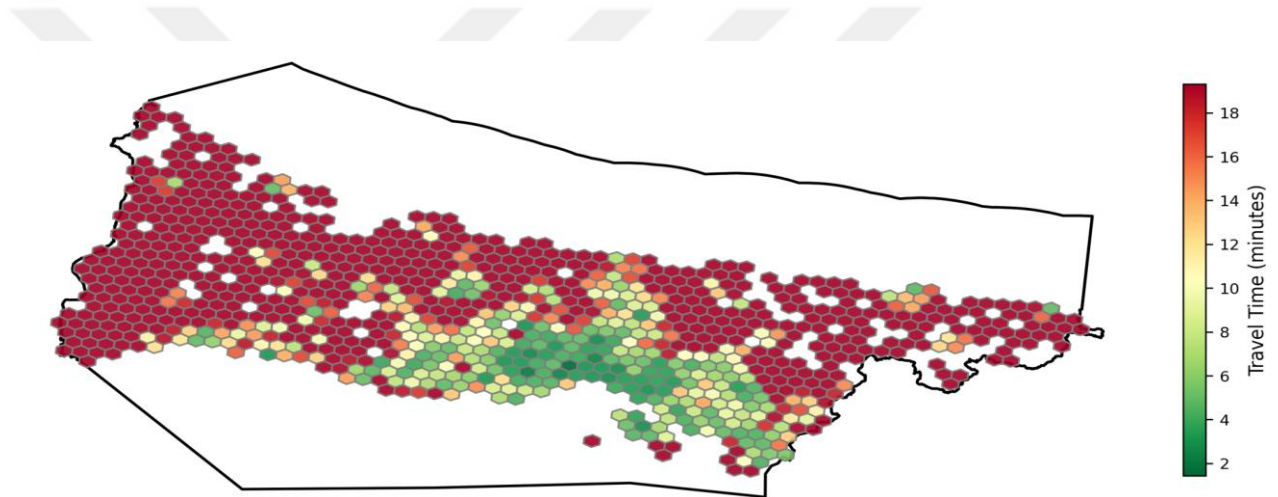


Figure 5.15. Public Services (Health and Education) Accessibility

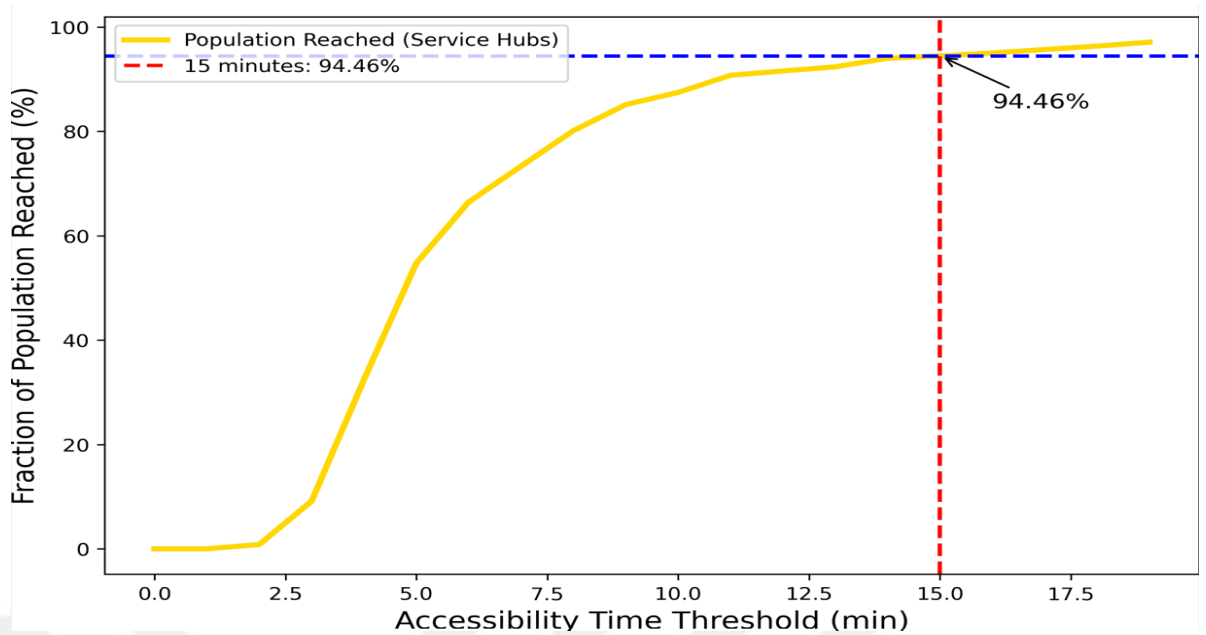


Figure 5.16. Fraction of the Population Versus Accessibility Time to Public Services (Health and Education)

Figures 5.15 and 5.16 present a largely positive picture of public service accessibility as compared to other urban features. Figure 5.15.4 portrays extensive green and yellow areas in the central districts, which correspond to high levels of access to healthcare and educational facilities.

Similarly, Figure .16 further confirms the extent of service provision. It shows that 94.46% of Istanbul's residents can access healthcare and education centers within 15 minutes on foot. This is the highest rate among the four other urban features analyzed.

This figure contrasts sharply with the lower accessibility rates for transport (52.39%), in Figure 5.7. and 4.8, green spaces and recreational facilities (52.48%), in Figures 5.11. and 4.12, and security centers (77.73%), in Figures 5.13. and 5.14. The curve rises steeply between 2.5 and 7.5 minutes, which shows the proximity of most residents to healthcare and educational facilities.

In most districts, residents have easy access to schools and health centers. This is essential for promoting public welfare, as it ensures that educational and medical services are available within a maximum walking time of 15 minutes. In this way,

residents can access at least one of the two types of service centers within this threshold.

Nevertheless, certain disparities remain. Although the majority of the population can reach basic services within 15 minutes, peripheral neighborhoods exhibit lower levels of access to larger hospitals and specialized educational institutions. These disparities expose an ongoing asymmetry in service provision that requires renewed policy attention to ensure both spatial proximity and equitable service quality across all districts.

In a comparative perspective, Istanbul demonstrates substantial public service accessibility relative to its urban scale and population density. However, future urban development strategies must prioritize the reduction of quality differentials to establish uniform access to healthcare and educational infrastructure across the metropolitan region.

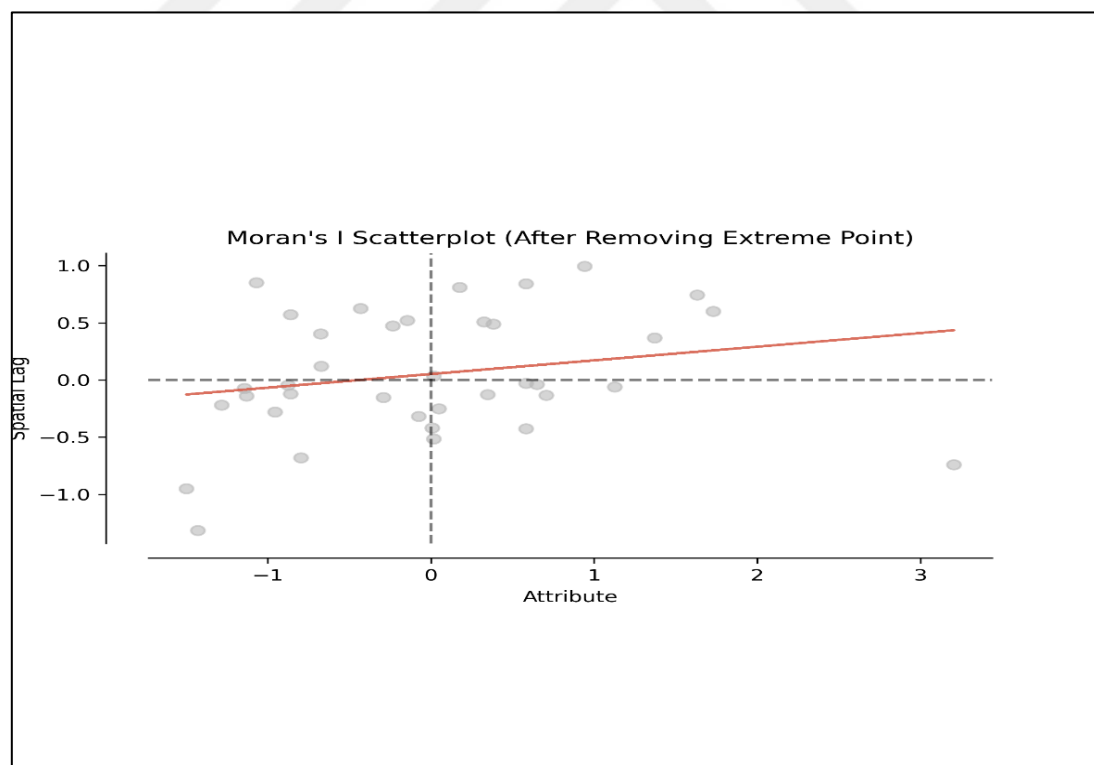


Figure 5.17. Moran's I Scatterplots of Rental Price Spatial Autocorrelation in All Istanbul's Districts

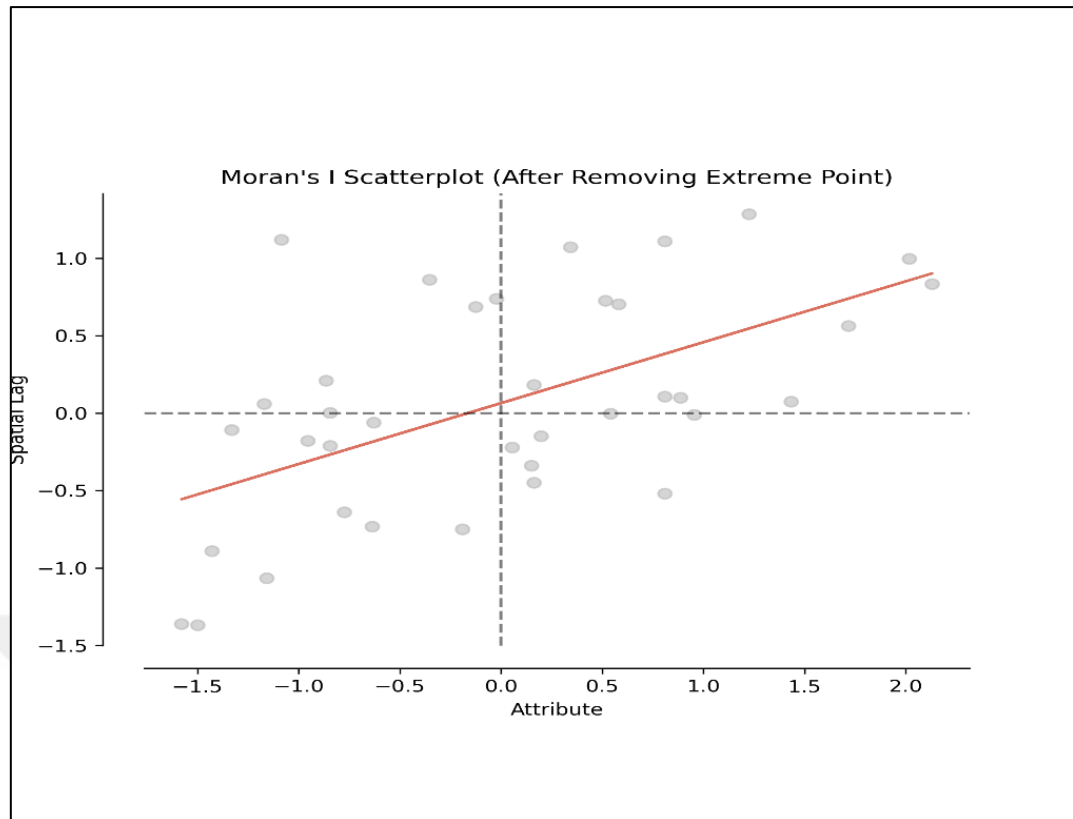


Figure 5.18. Moran's I Scatterplots of Rental Price Spatial Autocorrelation in Istanbul's Outlier District Excluded

Figures 5.17 and 4.18 display the Moran's I scatterplots from rental prices. Moran's I measures spatial autocorrelation, which identifies whether similar values are clustered or dispersed in neighboring locations. A positive value suggests clustering, while a negative value indicates dispersion. In our case, this means examining whether areas with high rental prices are surrounded by districts with similarly high rental prices.

Figure 5.14, which incorporates all districts, exhibits a weak positive spatial autocorrelation, as demonstrated by the modest upward slope of the regression line. In contrast, the removal of a major outlier in Figure 4.15. results in a steeper positive slope. This change demonstrates a stronger spatial dependence among Istanbul's districts.

The amplification of spatial clustering is consistent with the earlier findings from the livability maps. Central districts such as Fatih, Beyoğlu, and Kadıköy exhibit high scores, while peripheral districts show weaker outcomes. This configuration reflects the historical and infrastructural processes that have shaped the urban form. Areas with high livability tend to be surrounded by similarly advantaged districts, largely because infrastructure systems and public services expand across boundaries rather than remaining confined within them.

The difference between the two scatterplots illustrates the structural vulnerability of Istanbul's spatial order. The presence of a strong outlier suggests deviations where localized development exceeds or lags behind the surrounding context. Such anomalies often arise either from accelerated investment in isolated districts or from persistent differentials in resource allocation.

The spatial configuration of livability across Istanbul reflects not incidental improvements but the long-term institutionalization of interconnected urban processes. Infrastructure development, the diffusion of important amenities, and the consolidation of residential environments have collectively shaped the emergence of territorially cohesive districts.

These demonstrate that urban quality is not distributed randomly but follows pathways forged through sustained investment and infrastructural continuity. Mitigating and resolving the residual differentials across the city landscape requires strategic planning that prioritizes the reinforcement of integrated urban systems and guarantees that improvements in accessibility and welfare reach all areas, rather than being confined to concentrated zones.

After constructing and developing the overall livability index, we examined the factors that affect livability by using household characteristics and machine learning techniques. We found that being a tenant, higher rental prices, greater average household size, longer average years of residency, existence of disabled person in the household, and increased traffic negatively affect livability. In contrast, a smaller number of disabled persons in a household, higher sales prices, urban transformation, greater population density, and holidays tend to have a positive impact. However,

only the number of disabled persons and tenant status are statistically significant in explaining variations in livability. The results are shown in Figures 5.19-5.21 below.

Variable	Coeff	p-Value	0.025	0.975	Sig
No_disabled_person	0.057364	0.0229	7.3772	88.0957	**
Tenant	-0.028781	0.0414	-48.6756	-1.0805	**
rental_price	-10.7739	0.0584	-21.9725	0.4247	*
sales_price	0.086739	0.1034	-1.9391	19.2870	*
No_holiday	-0.036477	0.3323	-11.3211	4.0258	*
Pop_density	0.019529	0.3414	-1.0911	2.9970	
Urban_transformation	0.08332	0.4838	-3.2747	1.6084	
Avg. years	-0.1743	0.5241	-0.7366	0.3879	
Average_Hsize	-0.07666	0.5545	-3.4332	1.9000	
Holiday	0.02622	0.6272	-0.8496	1.3741	
Traffic	-0.1131	0.6592	-0.4151	0.6413	*
No_urban_transformation	-0.01929	0.9698	-10.7084	10.3225	
const	13.3709	0.6141	-411.1865	677.9283	

Figure 5.19. Regression Result

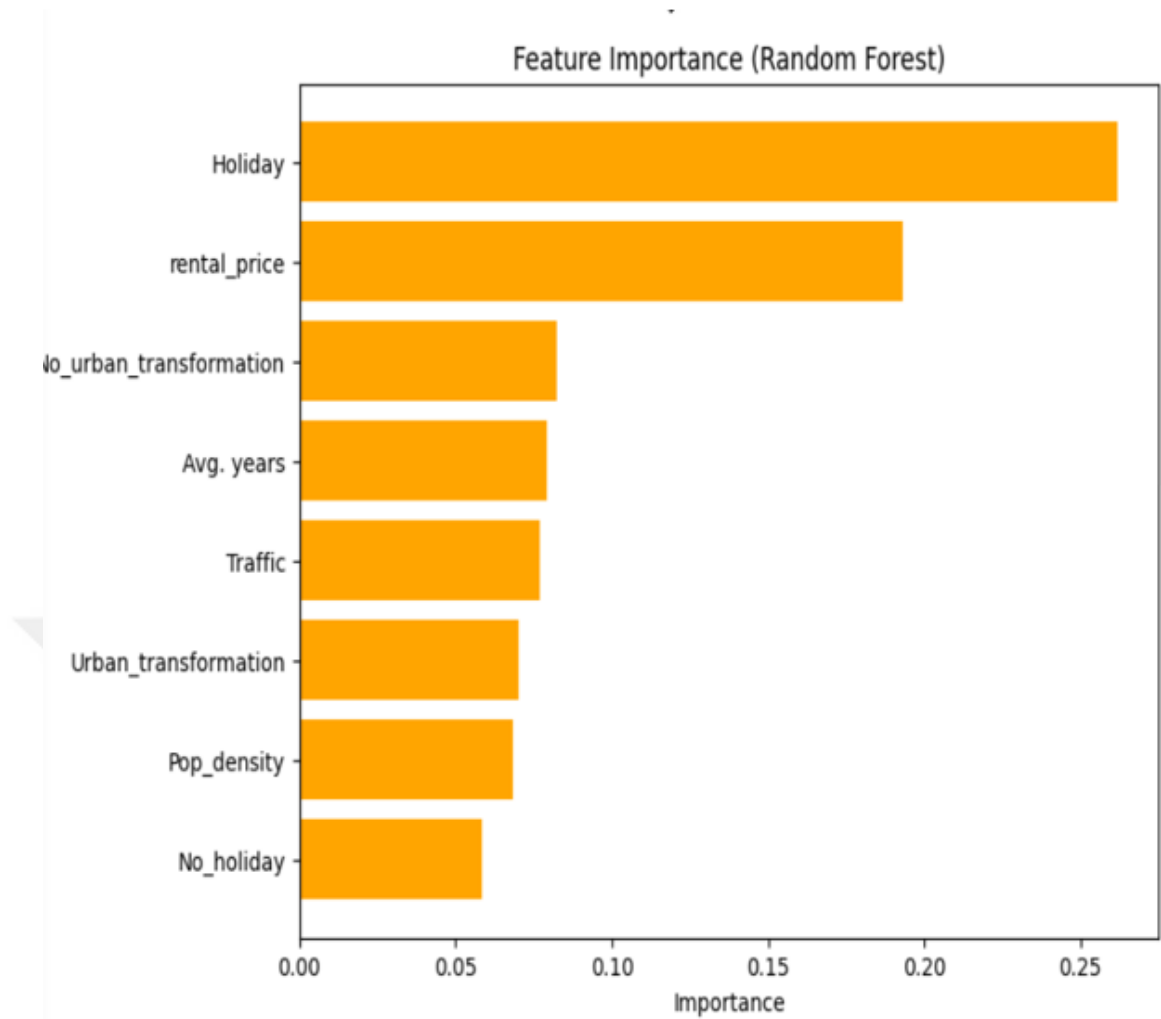


Figure 5.20. Feature Importance of the Determinants of Livability Index

Model Comparison Results

Model	MSE	MAE	RMSE
Ridge Regression	8.3013	2.32257	2.8813
Lasso Regression	6.3248	2.0496	2.5149
Random Forest Regression	3.9877	1.6245	1.9969
OLS Regression	11.7050	2.8463	3.4212
Decision Tree Regression	5.6223	1.9775	2.3711

Figure 5.21. Evaluation Metrics of Machine Learning Models

Amenities	Total Amenities
Public Transport	12854
Parks	7330
Recreation	9739
Healthcare	4464
Education	3081
Emergency Services	781
Street Lighting	758
Commerce	25020
Employment Centers	3625
Financial Centers	11749

Figure 5.22. Summary of the Total Features

	Road Density	Public Transport Density	Park Coverage	Recreation Density	Healthcare Accessibility	Education Accessibility	Emergency Services Density	Street Lighting Coverage	Retail Density
count	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000
mean	26.916399	7.715961	0.097379	4.228017	3.942100	2.315789	0.517467	0.294769	24.788234
std	13.169463	6.211716	0.130128	3.266044	4.524587	2.177336	0.967176	0.565738	51.602821
min	3.598253	0.031100	0.008492	0.065031	0.009510	0.010727	0.000000	0.000000	0.050721
25%	14.424994	2.698666	0.025527	1.942390	0.563944	0.611445	0.000000	0.000000	1.801705
50%	31.173795	6.912145	0.047899	3.451964	2.579320	1.818003	0.060466	0.035043	6.392641
75%	38.586212	10.323474	0.096304	5.718451	6.091427	3.696256	0.511494	0.260101	19.576603
max	47.838770	25.847187	0.551801	14.059509	20.513259	10.450151	4.983174	2.056599	279.251249

Figure 5.23. Summary Statistics

	Road Density	Public Transport Density	Park Coverage	Recreation Density	Healthcare Accessibility	Education Accessibility	Emergency Services Density	Street Lighting Coverage	Retail Density
count	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000
mean	26.916399	7.715961	0.097379	4.228017	3.942100	2.315789	0.517467	0.294769	24.788234
std	13.169463	6.211716	0.130128	3.266044	4.524587	2.177336	0.967176	0.565738	51.602821
min	3.598253	0.031100	0.008492	0.065031	0.009510	0.010727	0.000000	0.000000	0.050721
25%	14.424994	2.698666	0.025527	1.942390	0.563944	0.611445	0.000000	0.000000	1.801705
50%	31.173795	6.912145	0.047899	3.451964	2.579320	1.818003	0.060466	0.035043	6.392641
75%	38.586212	10.323474	0.096304	5.718451	6.091427	3.696256	0.511494	0.260101	19.576603
max	47.838770	25.847187	0.551801	14.059509	20.513259	10.450151	4.983174	2.056599	279.251249

Figure 5.24. Correlation Metrics

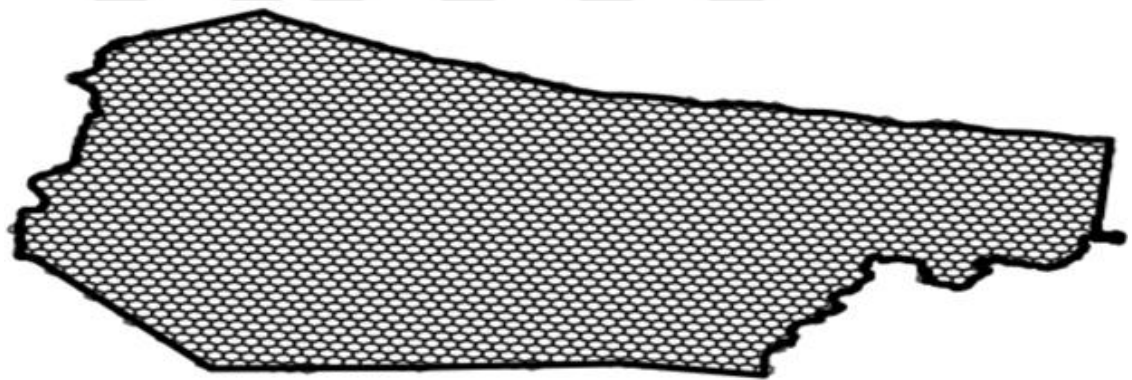


Figure 5.25. Uber's H3 Resolution 7

We used the resolution 7, due to its clarity and computational manageability as compared to resolutions 8 and 9 depicted in the figures A.10 and A.11, which are too detailed, opaque, and computationally intensive.



Figure 5.26. Uber's H3 Resolution 8

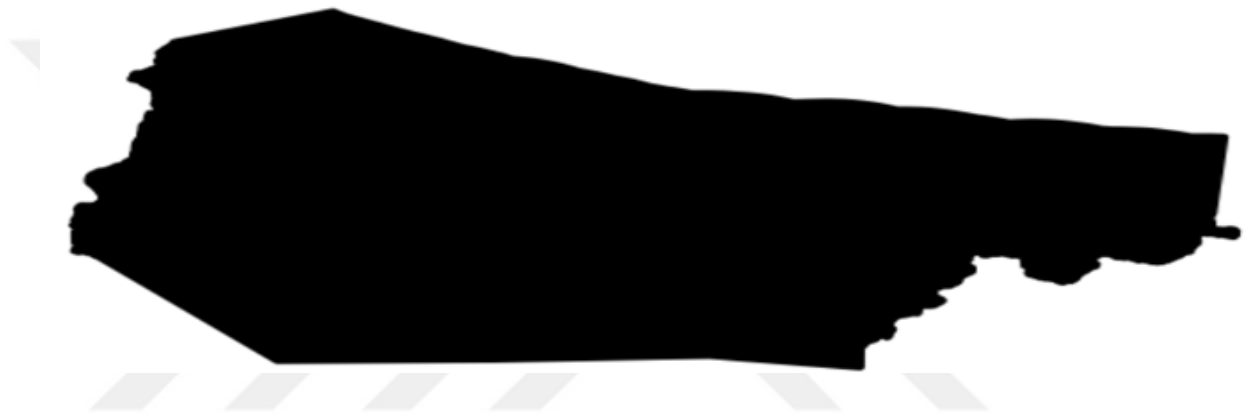


Figure 5.27. Uber's H3 Resolution 9

5.5. Conclusion

This study utilized advanced geospatial analytics to evaluate urban accessibility and well-being in Istanbul through the lens of the 15-minute city framework. The 15-minute city concept is rooted in the principle of ‘chrono-urbanism,’ which posits that the quality of urban life diminishes as travel times increase (Moreno et al., 2021). At its core, the concept advocates for people-centered urban design, focusing on micro-level interventions that transform neighborhoods into hubs of daily activity. Rather than requiring residents to travel to access essential services, the 15-minute city model prioritizes bringing these services closer to where people live (Pouzoukidou & Chatziyiannaki, 2021).

The findings of this study reveal that nearly half of Istanbul's residents lack adequate access to essential transport services, indicating considerable gaps in livability under the 15-minute city framework. Our hypothesis regarding the existence of disparities in accessibility across Istanbul, where central districts have higher levels of accessibility to essential services and amenities, while peripheral districts exhibit comparatively lower levels, could not be rejected.

As a critical concern for policymakers worldwide, urban livability tackles urban challenges such as urban sprawl, traffic congestion, environmental degradation, public health concerns, housing affordability, and security issues. Cities increasingly compete to enhance resident well-being through improved urban planning and service delivery. The 15-minute city concept has gained prominence as a metric for urban livability assessment, evaluating residents' ability to access essential services, transportation nodes, and opportunity centers within a 15-minute walking radius.

The Economist's 2024 Global Livability Report indicates marginal improvements in average city livability despite persistent challenges from housing market pressures and geopolitical tensions. Their assessment framework encompasses five dimensions: health, education, culture and environment, infrastructure, and stability. Vienna, Austria, maintained its position as the world's most livable city for the third consecutive year, achieving exceptional scores across all evaluation dimensions. Cities affected by conflicts, notably Tel Aviv and Kyiv, experienced significant declines in their rankings. While North American and European cities dominate the upper rankings, their scores showed decline amid social unrest. Conversely, Hong Kong demonstrated remarkable improvement, particularly in stability and health metrics.

Our analysis of Istanbul's accessibility patterns reveals substantial variations across urban service dimensions. In the transportation sector, only 52.39% of the population can reach public transport points within a 15-minute walk, indicating significant limitations in mobility infrastructure. Similarly, recreational accessibility remains constrained, with just 52.48% of residents able to access green spaces and leisure facilities within the same timeframe. These low percentages suggest critical gaps in

Istanbul's transportation network and recreational planning that require targeted policy interventions.

Security and emergency services demonstrate moderately better coverage, with 77.73% of residents able to reach these facilities within 15 minutes. While this represents improved accessibility compared to transportation and recreation, it still leaves nearly a quarter of the population beyond the desired access threshold. Public service infrastructure shows markedly higher accessibility rates, with 94.46% of the population having 15-minute access to healthcare and educational facilities.

This high percentage reflects successful planning in the distribution of essential public services across the urban landscape. Economic centers maintain strong accessibility at 92.40%, suggesting effective placement of commercial and business districts throughout the city. However, the stark contrast between economic hub access and transportation infrastructure indicates potential misalignment in urban development priorities.

These findings align with broader urban accessibility research, though with notable distinctions. Studies across multiple cities consistently identify central urban areas as accessibility focal points (Dobrowolska & Kopczewska, 2024; Zhong et al., 2020; Vale and Lopes, 2023; Ye et al., 2020; Gaglione, 2021; Moura et al., 2017; M. F. Pereira et al., 2024; Wang et al., 2021). The study of Vale and Lopes (2023) examining European cities with populations exceeding 100,000 people reveals that even well-developed urban centers have not achieved a comprehensive 15-minute accessibility. Their research documents significant internal disparities in service access, a pattern that mirrors our findings for Istanbul.

However, Istanbul's particularly low accessibility rates for transportation and green spaces suggest unique challenges in these sectors compared to its European counterparts.

The disparity between various service types in Istanbul, from the high accessibility of economic and public service facilities to the limited reach of transportation and recreational amenities, points to specific areas in need of policy attention. These

findings provide crucial guidance for urban planners and policymakers in prioritizing infrastructure development and service distribution to achieve more balanced urban accessibility.

- **Policy Implications:** The findings of this study carry significant policy implications for urban planning in Istanbul. First, the results highlight critical gaps in accessibility and mobility, with only 52.39% of the population able to reach essential facilities within a 15-minute timeframe. Similarly, access to green spaces and recreational facilities stands at 52.48%, underscoring a pressing need for improvement. These two factors—transportation and green infrastructure—are fundamental for modern cities like Istanbul, which face challenges such as severe traffic congestion, high population density, and air pollution.

To address these issues, policymakers should prioritize enhancing transportation networks, particularly in peripheral areas, to improve mobility and ensure equitable access to facilities. This would not only reduce time costs, stress, and physical fatigue associated with long commutes but also mitigate pollution levels.

Furthermore, expanding green spaces and recreational destinations is essential to promote residents' mental well-being, physical health, and environmental sustainability. Istanbul can foster a more livable, resilient, and inclusive urban environment by investing in these areas, aligning with the principles of the 15-minute city model.

Although redesigning the entire city to align with the 15-minute city concept may not be entirely feasible or practical due to constraints posed by its existing urban design, significant improvements can still be achieved. Significant improvements can still be achieved, even though redesigning the entire city to fully align with the 15-minute city concept may not be entirely feasible or practical due to constraints posed by its existing urban design. Through targeted interventions and strategic upgrades, Istanbul can move closer to the ideals of accessibility, sustainability, and livability envisioned by the 15-minute city framework.

- **Methodological Limitations and Future Research Directions:** First, it ought to be noted that data availability and comprehensiveness present notable constraints in this study. While OpenStreetMap and Istanbul Municipality Council databases provide substantial information, the absence of potential datasets from ministerial sources may affect result reliability. This limitation suggests our findings represent a partial, albeit significant, perspective on accessibility to urban opportunities in Istanbul.

Second, the study's adherence to the 15-minute walkability threshold, while aligned with current urban planning paradigms, may overlook variations in accessibility patterns that could emerge under different temporal parameters. This constraint reflects the classic Modifiable Area Unit Problem (MAUP) in spatial analysis, where results may vary with different spatial or temporal units of measurement.

Third, and perhaps most importantly, our accessibility calculations may not fully capture real-world pedestrian conditions. The analysis cannot account for microscale infrastructure elements such as sidewalk quality, pedestrian crossings, or overhead bridges. Therefore, the findings should be interpreted as measurements of potential accessibility, rather than actual accessibility.

Future research should address these limitations through specific approaches. For instance, integrating additional data sources, such as air pollution, could enhance the comprehensiveness of accessibility measurements. Studies incorporating variable time thresholds would provide more detailed deciphering of accessibility patterns. Furthermore, the development of methodologies to incorporate microscale pedestrian infrastructure features would strengthen the practical applicability of accessibility assessments. Such advances would move urban accessibility research closer to reflecting actual lived experiences in the urban environment.

CHAPTER VI

CONCLUSION

Well-being stands as a foundational concept in contemporary economic thought, transcending traditional measures of prosperity such as GDP and income levels. Nobel laureate Amartya Sen (1999) framed this shift: "Economic growth cannot be sensibly treated as an end in itself. Development must be more concerned with enhancing the lives we lead..." Similarly, Joseph Stiglitz, another Nobel Prize-winning economist, noted that GDP is not a good measure of economic performance; it is not a good measure of well-being. "GDP is not a satisfactory measure of well-being ... the time is ripe for our measurement system to shift emphasis from measuring economic production to measuring people's well-being (Joseph Stiglitz, 2009)." These perspectives reflect an evolution in economic thinking, one that recognizes human flourishing as the ultimate aim of economic systems rather than mere production or consumption metrics.

This thesis contributes to this evolving discourse through three chapters that deal with emotions and urban accessibility to examine different facets of well-being in Türkiye. Each investigation employs advanced methodological approaches to examine how economic, informational, and spatial factors shape collective welfare.

The first and second chapters introduces the conceptual framework, clarifies key concepts, and presents the background of the study.

The third chapter examined Turkish Lira volatility against the US Dollar during a period of substantial depreciation, 2015-2024. Through the application of natural language processing techniques, sentiment analysis, and machine learning models, the research assesses how news sentiment influences exchange rate movements. Data from international sources such as The Economist and The New York Times, as well

as domestic sources like Yeni Şafak and Twitter, underwent preprocessing and feature extraction.

The implementation of FinBERT for sentiment extraction and advanced machine learning models (Gradient Boosting, Random Forest, and XGBoost) enabled forecasting of exchange rate movements. The application of explainable AI techniques through SHAP and Shapash libraries allowed the interpretation of individual features' influence on model predictions.

The results demonstrated that international news sources, principally The Economist and The New York Times, exerted the strongest influence on exchange rate predictions. Domestic sources showed comparatively weaker influence, indicating that global investors predominantly rely on international media outlets when assessing the Turkish Lira. This finding carries economic implications currency stability affects inflation rates, purchasing power, and overall economic security for citizens. When currency values fluctuate based primarily on international rather than domestic narratives, this creates an economic vulnerability that directly impacts material well-being across society.

The fourth study expanded this analytical framework to examine stock market dynamics in Türkiye. The research assessed how media discourse and sentiment affect investor behavior and market outcomes. The methodological approach compared various modeling techniques, finding that ensemble models (Gradient Boosting, XGBoost, and Random Forest) achieved the highest predictive accuracy. This superior performance of ensemble methods suggests that market movements respond to complex emotional factors rather than purely rational calculations. Economic narratives presented through media reports, whether describing turmoil, risks, speculations, or optimism, generate emotional responses that manifest in trading patterns.

The application of Explainable AI methods further substantiated the finding that international news media exerts a stronger influence on the Turkish stock market than local news sources such as Yeni Şafak and Twitter. This pattern mirrors the results from the exchange rate study, establishing a consistent theme across financial

markets: international information flows disproportionately shape domestic economic conditions. The stock market's responsiveness to sentiment factors adds another dimension to our understanding of well-being. market volatility driven by emotional responses to news affects investment returns, retirement savings, and economic stability that form the foundation of financial security.

The fifth study shifted focus from financial markets to urban infrastructure, applying geospatial analytics to assess accessibility in Istanbul through the 15-minute city framework. This research tested the hypothesis that central districts provide higher accessibility to essential services while peripheral areas experience reduced access. The findings validated this hypothesis, with accessibility varying substantially across service categories. Transportation infrastructure showed particularly low accessibility (52.39% of residents), as did recreational facilities (52.48%). In contrast, public services (94.46%) and economic centers (92.40%) demonstrated substantially stronger coverage.

This spatial analysis connects directly to well-being through the material conditions of daily life. Transportation limitations restrict mobility and access to employment opportunities. Recreational facility gaps reduce options for physical activity and social interaction. The stark disparity between central and peripheral districts creates a geography of inequality that shapes life chances and daily experiences across the urban landscape.

Collectively, the study presents an integrated picture of how well-being forms through the interaction of multiple systems. Currency stability, stock market performance, and urban infrastructure each contribute distinct elements to the overall welfare of society. The common thread across all three investigations lies in their attention to distribution and access to reliable information in financial markets or to essential services in urban spaces.

The methodological approaches employed across these studies emphasize the value of computational techniques in economic analysis. Natural language processing, sentiment analysis, machine learning, and geospatial analytics allowed examination of phenomena that traditional economic methods might struggle to capture fully. The

consistent finding that complex modeling approaches outperform simpler alternatives suggests that the determinants of well-being involve multiple interacting variables rather than straightforward relationships.

Economic theory typically emphasizes efficiency and optimization. These studies add nuance to that framework by highlighting how information asymmetries in financial markets and spatial disparities in urban environments create uneven distributions of well-being. When international news sources dominate currency and stock valuations, this creates potential distortions based on external perspectives rather than domestic economic fundamentals. When urban services concentrate in central districts, this generates well-being imbalances based on residential location rather than need.

The connection between sentiment and economic outcomes emerges as particularly significant across the financial market studies. Traditional economic models often assume rational actors making decisions based on fundamental valuations. The finding that sentiment factors strongly influence both currency and stock movements suggests that emotional responses play a more substantial role in economic behavior than purely rational models would predict. This affects well-being not only through the direct economic consequences of market movements but also through the psychological impact of volatility and uncertainty.

The urban accessibility findings similarly challenge simplistic economic models by demonstrating how physical infrastructure creates or restricts opportunities in ways that market mechanisms alone cannot address. The substantial gaps in transportation access (with only 52.39% of residents able to reach public transport within 15 minutes) represent a market failure that requires deliberate planning interventions. The well-being implications extend beyond mere convenience to encompass economic opportunity, social connection, and environmental impact.

These findings contribute to the evolving understanding of well-being as a multidimensional concept that spans economic, emotional, and physical domains. Financial stability provides material security. Information flows shape expectations and confidence. Physical infrastructure determines access to opportunities and

services. Together, these elements create the conditions within which individuals and communities can flourish.

The economic significance of these findings lies in their challenge to traditional measures of prosperity. GDP growth, stock market indices, and aggregate economic statistics may mask substantial variations in lived experience across populations. The granular analysis presented in these studies examining sentiment patterns in specific news sources and accessibility metrics in particular neighborhoods provides a more textured view of economic conditions as they affect daily life.

- **Limitations, Policy Recommendations, and Future Research Directions:**

This thesis, while making substantial contributions to understanding economic phenomena and urban well-being in Türkiye, must acknowledge several methodological and empirical constraints that qualify its findings. These limitations simultaneously suggest promising avenues for subsequent scholarly inquiry and inform policy considerations.

First, data representativeness in the financial market studies presents a significant constraint. The reliance on a single local newspaper (Yeni Şafak) as representative of domestic media coverage stems from historical data accessibility issues with other Turkish news sources. While Yeni Şafak actively reports on policy matters, its economics and financial coverage may not fully capture the breadth of domestic economic discourse that influences market perceptions. This limitation affects both the exchange rate and stock market analyses, potentially understating the role of local media in shaping financial outcomes.

Second, the incorporation of Twitter as a social media sentiment source introduces measurement challenges across financial studies. Twitter content often exhibits speculative and reactionary characteristics that may diminish its predictive validity for systematic financial market movements. The platform's tendency toward extreme expressions and its self-selecting user base further complicate efforts to extract representative sentiment signals that accurately reflect broader market participant attitudes.

Third, inherent media bias affects sentiment measurement quality in both international and domestic sources. Editorial positions, reporting emphases, and linguistic framing vary systematically across publications, potentially distorting sentiment scores in ways that do not reflect genuine economic fundamentals. This bias may influence the comparative analysis of international versus domestic news impact on financial markets, though the consistency of findings across different modeling approaches suggests this effect did not fundamentally alter the main conclusions.

Fourth, the urban accessibility study faces substantial geographic data limitations. While OpenStreetMap and Istanbul Municipality Council databases provide extensive spatial information, the absence of certain ministerial datasets restricts analysis comprehensiveness. This limitation means the accessibility findings represent an important but incomplete assessment of Istanbul's urban infrastructure distribution, particularly for specialized service categories that might rely on non-public data sources.

Fifth, the 15-minute walkability threshold employed in the urban analysis, while theoretically justified, embodies the classic Modifiable Area Unit Problem in spatial research. Different temporal thresholds might yield varying accessibility patterns, suggesting a parameter sensitivity that warrants consideration when interpreting results. This methodological choice balances practical measurement considerations against theoretical urban planning standards but necessarily simplifies the continuous nature of accessibility experiences.

Sixth, and perhaps most consequentially, the urban accessibility calculations cannot account for microscale pedestrian infrastructure quality. Sidewalk conditions, crossing facilities, pedestrian bridges, lighting, and safety factors all influence actual walkability in ways that geographic distance metrics cannot capture. The findings thus measure potential rather than realized accessibility, with real-world impediments likely reducing effective access below the levels reported in the analysis.

These limitations suggest several policy directions that connect the financial market and urban planning domains. The finding that international news sources exert disproportionate influence on Turkish financial markets implies domestic information asymmetries that policymakers might address through enhanced financial journalism capacity and greater transparency in economic data dissemination.

Similarly, the identification of substantial urban accessibility gaps, particularly in transportation (47.61% without adequate access) and recreational facilities (47.52% without adequate access), points to specific infrastructure investment priorities that would improve both physical accessibility and overall well-being.

Istanbul faces particular challenges in transportation infrastructure that affect both economic function and quality of life. The severe traffic congestion, high population density, and resultant air pollution create a nexus of problems that strategic transportation planning must address. Enhanced public transit networks, particularly in peripheral districts, would not only improve facility access but also reduce commute-related stress, physical fatigue, and environmental degradation that adversely affect well-being across multiple dimensions.

The expansion of green spaces similarly serves both environmental and psychological functions that connect to economic well-being. Access to recreational areas promotes mental health, encourages physical activity, and provides environmental services that reduce urban heat island effects and improve air quality. These factors contribute to worker productivity and reduce healthcare costs that burden economic development.

While transforming Istanbul entirely into a 15-minute city presents practical challenges given its existing urban form, targeted interventions in underserved districts could substantially improve accessibility equity. Strategic placement of essential services in accessibility "deserts" would yield disproportionate well-being benefits while requiring relatively modest investment compared to comprehensive redesign.

Future research should address these limitations through methodological and empirical expansions. Studies incorporating a broader array of domestic news sources would provide a more comprehensive assessment of local media influence on financial markets. More sophisticated social media sentiment extraction techniques might better distinguish between informed market commentary and noise in platforms like Twitter, potentially uncovering domestic sentiment signals obscured by current methods.

For urban accessibility research, integration of traffic data, air quality measurements, and microscale pedestrian infrastructure assessments would move analysis closer to measuring actual rather than potential accessibility. Studies employing variable time thresholds and different transportation modes would provide a more nuanced understanding of how residents experience urban spaces across demographic groups and geographic areas.

The complementary nature of the financial market and urban accessibility findings suggests valuable integrated research approaches. How do accessibility patterns affect local economic development and property valuations? Do neighborhoods with better accessibility demonstrate greater resilience to economic shocks? These questions connect the financial and spatial dimensions of well-being in ways that merit further empirical investigation.

In sum, while acknowledging substantive limitations, this thesis provides empirically grounded insights that can inform both policy formulation and scholarly inquiry. The financial market studies identify important information asymmetries that affect economic stability. The urban accessibility analysis pinpoints specific infrastructure gaps that constrain quality of life. Together, they suggest an integrated approach to economic development that considers both information flows and physical infrastructure as essential components of societal well-being.

In a nutshell, while acknowledging substantive limitations, this thesis provides empirically grounded insights that can inform both policy formulation and scholarly inquiry. The financial market studies identify important information asymmetries that affect economic stability. The urban accessibility analysis pinpoints specific infrastructure gaps that constrain quality of life. Together, they suggest an integrated approach to economic development that considers both information flows and physical infrastructure as essential components of societal well-being.



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