IDEOLOGIES, EMOTIONS, AND ANTI-IMMIGRANT STANCE IN THE CONTEXT OF TÜRKİYE:

A SOCIAL MEDIA ANALYSIS THROUGH NATURAL LANGUAGE PROCESSING (NLP) TECHNIQUES

by

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I would like to express my heartfelt gratitude to my family.

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ABSTRACT

Ideologies, Emotions, and Anti-Immigrant Stance in the Context of Turkiye: A Social Media Analysis Through Natural Language Processing (NLP) Techniques

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In recent years, global migration has been on the rise, leading to intensified debates and growing anti-immigrant sentiment in many parts of the world. Türkiye, as one of the leading host countries for immigrants and refugees, has become a focal point in these discussions. Despite extensive research in Western Europe and the U.S., where right-wing ideologies are often linked with anti-immigrant views, the dynamics in non-Western countries like Türkiye are less explored. This study aims to investigate whether there is an interaction between ideological positions and emotional responses in shaping public stances toward immigration in Türkiye, incorporating Affective Intelligence Theory (AIT), which emphasizes the role of emotions—particularly fear, anxiety, and anger—in shaping political judgment and behavior. The research utilizes social media data sourced from Twitter to analyze the interaction between ideologies and emotions in shaping anti-immigrant sentiment. Natural Language Processing (NLP) techniques, including fine-tuned pre-trained BERT-based models like BERTurk and TurkishBERTweet, are employed to classify immigration-related tweets and detect pro- and anti-immigrant stances. The findings challenge the conventional association between right-wing ideologies and anti-immigrant sentiment commonly observed in Western Europe and the U.S., revealing a more complex range of views across both right- and left-wing ideologies in Türkiye. The study further highlights how emotions, as explained by Affective Intelligence Theory, can either reinforce or shift ideological stances on immigration. This interaction between emotions and ideologies provides deeper insights into the complex dynamics shaping immigration discourse in Türkiye, offering a nuanced understanding of public sentiment.

Keywords: international migration, anti-immigrant sentiment, migration studies, affective intelligence theory, social media analysis, BERT-based deep learning models, natural language processing, stance detection, automated text classification

ÖZETÇE

Türkiye Bağlamında İdeolojiler, Duygular ve Göçmen Karşıtlığı: Doğal Dil İşleme (NLP) Yöntemleri ile Sosyal Medya Analizi

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Son yıllarda, dünya genelinde artan göç hareketleri, birçok bölgede göçmen karşıtı söylemlerin ve tartışmaların yoğunlaşmasına neden olmuştur. Türkiye, göçmenler ve mülteciler için en fazla göç alan ülkelerden biri olarak bu tartışmaların merkezinde yer almaktadır. Batı Avrupa ve ABD'de yapılan araştırmalarda, sağ ideolojilerin genellikle göçmen karşıtlığı ile ilişkilendirildiği bilinse de, Türkiye gibi Batılı olmauyan ülkelerdeki dinamikler yeterince incelenmemiştir. Bu çalışma, Türkiye'de ideolojik pozisyonlar ile duygusal tepkilerin göç konusundaki kamuoyu tutumlarını nasıl etkilediğini araştırmayı amaçlamakta ve Duygusal Zeka Teorisi (AIT)'ni temel almaktadır. Bu teori, özellikle korku, kaygı ve öfke gibi duyguların siyasi yargı ve davranışları şekillendirmedeki rolünü vurgular. Çalışma, Twitter'dan elde edilen sosyal medya verilerini kullanarak ideolojiler ve duygular arasındaki etkileşimin Türkiye'deki göçmen karşıtı tutumları nasıl şekillendirdiğini analiz etmektedir. Göçle ilgili tweetleri sınıflandırmak ve göçmen yanlısı ya da karşıtı tutumları tespit etmek için, BERTurk ve TurkishBERTweet gibi önceden eğitilmiş BERT tabanlı modellerin ince ayar yapıldığı Doğal Dil İşleme (NLP) teknikleri kullanılmıştır. Bulgular, Batı Avrupa ve ABD'de yaygın olarak gözlemlenen sağ ideolojiler ile göçmen karşıtlığı arasındaki geleneksel ilişkiyi sorgulamakta ve Türkiye'deki sağ ve sol ideolojiler arasında daha karmaşık görüşlerin var olduğunu ortaya koymaktadır. Çalışma ayrıca, AIT''nin açıkladığı gibi, öfke, kaygı ve korku gibi duyguların ideolojik tutumları pekiştirebileceğini ya da değiştirebileceğini vurgulamaktadır. Bu duygular ile ideolojiler arasındaki etkileşim, Türkiye'nin benzersiz siyasi ve sosyal bağlamında göç söyleminin nasıl şekillendiğine dair derinlemesine bir bakış sunarak, kamuoyunun daha iyi anlaşılmasını sağlamaktadır.

Anahtar kelimeler: uluslararası göç, göçmen karşıtlığı, göç çalışmaları, duygusal zeka teorisi, sosyal medya analizi, doğal di işleme, BERT tabanlı derin öğrenme modelleri, duruş tespiti, metin sınıflandırma

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ABBREVIATIONS

AKP	Justice and Development Party
AIT	Affective Intelligence Theory
BOW	Bag-of-words
BERT	Bidirectional Encoder Representations from Transformers
CHP	Republican People’s Party
IOM	International Organization of Migration
ITT	Intergroup Threat Theory/Integrated Threat Theory
LFIP	Law on Foreigners and International Protection
NLP	Natural Language Processing
NUTS	Nomenclature of Territorial Units for Statistics
TF-IDF	Term Frequency-Inverse Document Frequency
UN	United Nations
UNDESA	United Nations Department of Economic and Social Affairs
UNHCR	United Nations High Commision of Refugees

Chapter 1:
INTRODUCTION

In recent decades, the global trend of migration has continued to rise, with nearly 4 percent of the world's population now consisting of international migrants (UN DESA, 2021). Factors such as economic and social conditions, as well as internal and international conflicts—like the Syrian Civil War, the Taliban takeover of Afghanistan, and the Russian invasion of Ukraine—have led developed countries to face a massive influx of immigrants, most of them being refugees, within a short period. International migration significantly impacts the economic, social, and political landscapes of both sending and receiving countries. One notable effect of this migration flow is the increase in anti-immigrant sentiment in receiving countries, driven by perceived cultural and economic threats posed by immigrants.

Existing literature has revealed the relationship between ideological dispositions and anti-immigrant stances, suggesting that right-wing individuals are more likely to oppose immigration due to heightened perceived cultural and economic threats (Callens & Meuleman, 2016; Gorodzeisky, 2011; Gorodzeisky & Semyonov, 2009; Halikiopoulou & Vlandas, 2020; Pichler, 2010). Additionally, psychological factors play a role in shaping attitudes towards immigrants (Stephan et al., 2009). Perceived threats from immigration trigger different emotions in individuals, which in turn affect their sentiments towards immigrants (Cottrell & Neuberg, 2005; Davis & Stephan, 2011). These emotions vary based on factors such as the type of threat (realistic or symbolic), whether the threat is to a group or an individual, and the characteristics of the immigrant groups. Consequently, the emotions arising from perceived threats significantly influence individuals' stances against immigrants.

1.1 Problem Statement

Despite extensive research into the relationship between ideological dispositions and anti-immigrant sentiment, much of the literature is Euro-centric or focused on the North American region. The applicability of these findings to non-Western contexts, particularly Türkiye, remains underexplored. In Türkiye, a unique situation arises where the incumbent right-wing populist party adopts a pro-immigrant stance, while the leftist main opposition party exhibits a more anti-immigrant position. This divergence challenges the conventional understanding of the ideological underpinnings of anti-immigrant sentiment, highlighting the need for a more nuanced approach to analyzing the interaction between ideology and emotions in this context. Moreover, there is a gap in the literature regarding how emotions triggered by perceived threats influence individuals' stances toward immigrants, particularly within the framework of ideological dispositions.

1.2 *Research Objective*

The objective of this study is to explore the interplay between ideological dispositions and emotional responses in shaping anti-immigrant sentiment in Türkiye, utilizing natural language processing (NLP) techniques on social media data. By focusing on a non-European context, this research aims to provide new insights into how specific ideologies, particularly in Türkiye, interact with emotional triggers to influence public attitudes towards immigrants. The study seeks to fill the existing gap in the literature by employing a novel approach that combines automated text classification and stance detection to analyze social media discourse. This study employs BERT-based deep learning models on Twitter data for both tasks. After text classification based on relevance to immigration in Türkiye, stance detection against immigrants or immigration is applied. The pre-labeled Twitter data in terms of emotions and ideologies is sourced from the Politus Project. For the analysis, a multinomial logistic regression is applied to see whether there is an interaction effect of ideologies and emotions on anti-immigrant stance controlling demographic variables with an economic indicator.[1]

1.3 *Contribution to the Literature*

While the link between ideologies and anti-immigrant sentiment has been extensively studied, much of this research is Euro-centric or focused on the North American region (Callens & Meuleman, 2016; Gorodzeisky, 2011; Gorodzeisky & Semyonov, 2009; Halikiopoulou & Vlandas, 2020; Rustenbach, 2010). A study by Leykin & Gorodzeisky (2024) suggests that the well-established relationship between right-wing ideologies and

[1] All the code used for this study, including data preprocessing, text classification, and stance detection, is available in the following GitHub repository: https://github.com/AlkanCan/ideology-emotion-interaction-effect-on-anti-immigrant-stance

increasing anti-immigrant sentiment cannot be generalized to other regions, such as post-socialist countries. In their study, they found out that in most of the post-socialist countries, there is no consistent pattern between the ideology and anti-immigrant sentiment. Instead, in some of them, the right-leaning citizens adopt a more positive attitude toward immigrants than leftists. Since they have different political histories and social and political dynamics the link between conservative values and right-wing does not necessarily exist within countries outside of the West. In the same study, they revealed that in these countries supporters of right-wing ideologies are not characterized by conservative values in terms of economic, social, and cultural. This study focuses on Türkiye, a non-European country, where the incumbent Justice and Development Party (AKP), despite being a right-wing populist party, adopts a pro-immigrant attitude, while the leftist main opposition party, the Republican People's Party (CHP), takes a more anti-immigrant stance (Saylan & Aknur, 2023).

Supporting the argument that the values of right-wing ideologies may differ in non-European countries, the traditional self-reported right-left political spectrum may not adequately explain the ideological nuances within the right and left divisions in such countries (Leykin & Gorodzeisky, 2024). This study adopts a more nuanced approach, considering specific ideologies such as Nationalism, Islamism, and Kemalism, rather than relying solely on traditional left-right spectrum positions. This provides a more reliable analysis of ideologies and anti-immigrant sentiment. Furthermore, the pre-labeled ideologies in the Twitter data provided by the Politus Project are extracted based on the tweets of the users rather than their self-reported positions, offering a novel approach to the detection of individual ideologies.

Until the recent study by Rico (2024), the interaction between emotions and ideologies in shaping anti-immigrant stances had largely been overlooked. That study, conducted in a European country (e.g., Spain) using a survey methodology, focused on analyzing the mediating effect of emotions on the relationship between ideologies and anti-immigrant sentiment. While groundbreaking in its approach, the study remained confined to a European context and relied on traditional data collection methods, potentially limiting its generalizability beyond specific cultural and political environments.

In contrast, this study adopts a novel methodology by utilizing social media data to examine the influence of emotions and ideologies on anti-immigrant sentiment in a non-European context. By shifting from conventional survey-based approaches to the analysis of big data derived from social media, this research not only expands the geographical scope but also enhances the robustness of the findings. Social media data allows for real-time analysis of instantaneous, natural responses, which provides a more dynamic and realistic understanding of public sentiment than surveys can capture.

Moreover, this study distinguishes itself from Rico's work by considering a more nuanced spectrum of ideologies, rather than focusing solely on the traditional left-right political axis. By accounting for diverse ideological perspectives, both within and beyond the left and right, this research uncovers a more complex interaction between ideologies and emotions in shaping anti-immigrant stances. This broader ideological lens enriches the analysis by including ideologies like Socialism, Islamism, Secularism, and Conservatism, which may have distinct relationships with both emotions and immigration sentiment.

Ultimately, by employing computational methodologies to analyze large-scale datasets from social media, this study is expected to make a significant contribution to the existing literature. Not only does it introduce a more inclusive and diversified framework of ideologies, but it also demonstrates the value of applying big data analytics to explore socio-political phenomena in a way that transcends the limitations of traditional survey methods.[2]

[2] This thesis complies with GDPR Article 9 and Turkey's Law on the Protection of Personal Data (KVKK). Special categories of personal data have been anonymized or pseudonymized, with processing conducted in accordance with GDPR Article 9(2). Only necessary personal data has been processed in line with KVKK principles, ensuring data minimization, confidentiality and respecting data subjects' rights such as access, rectification, and erasure.

Chapter 2:
MIGRATION OVERVIEW

Migration is a global phenomenon that has shaped human societies throughout history (Leykin & Gorodzeisky, 2024). The term 'migration' refers to the movement of people from one place to another, crossing a "spatial unit" with the intention of permanently or temporarily changing their place of residence to a new location (Kok, 1999). The spatial unit may be a political region such as a country, province, or local government area or an administrative division like a magisterial district or a census enumerator area (Kok, 1999). There are two types of migration: internal migration and international migration. International migration is the movement of individuals crossing international borders into a country where they do not hold nationality (IOM, 2019). When the movement occurs within the boundaries of a single country, it is referred to as internal migration (IOM, 2019).

There is no definition for the term "migrant" under international law. The International Organization (2019) defines "migrant" as an umbrella term encompassing individuals moving away from their usual residence, both temporarily or permanently, across domestic or international borders, for various reasons. The IOM adopts an inclusive approach that involves refugees. The term 'refugee' refers to individuals who flee their country due to war, violence, or persecution, as defined by the 1951 UN Convention Relating to the Status of Refugees.

2.1 Causes of Migration

According to Everett Lee's theory of migration (1966), the cause of migration can be considered under the categories of push and pull factors. Lee defines pull factors as attracting factors related to the receiving countries and push factors that are associated with home countries that force people to move outside of its borders.

Pull factors include economic elements such as higher wages, improved working conditions, and overall economic stability, which attract individuals seeking better employment opportunities and financial security (Lowell & Findlay, 2001). The choice of migration of highly educated motivated by these factors is considered a brain drain (Arslan et al., 2015). Social factors that draw migrants include higher public health and education standards, and cultural and religious tolerance (Urbański, 2022). Additionally, political factors such as political stability, democratic governance, and respect for human rights are significant pull factors (Urbański, 2022). Family reunification is also considered another pull factor for migration (Martin & Zürcher, 2008).

Push factors include economic, social, and political elements (Parkins, 2010). Economic push factors, such as low wages, unemployment, and poor living standards, drive individuals to migrate to developed countries and fuel brain drain (Martin & Zürcher, 2008; Urbański, 2022). Additionally, people often migrate to mitigate the impacts of natural disasters, which can lead to shortages of food and shelter, as well as damage to livelihoods (Mbaye, 2023; Urbański, 2022). Social factors such as lack of education opportunities, poor healthcare services, and lack of cultural and religious tolerance cause people to migrate to other countries (Parkins, 2010; Urbański, 2022). Political push factors that drive migration can be considered human rights abuses, social displacement, war and terrorism, and political crises in the host countries (Martin & Zürcher, 2008; Nurse, 2004).

2.2 *Effects of Migration*

Migration has effects on origin and destination countries which should be analyzed distinctly. The effects on sending and receiving countries can be categorized as political, social, and economic (Kapur, 2014; Katseli et al., 2006).

2.2.1 Economic Effects

International migration may yield positive economic impacts for host countries, enhancing the labor market, and contributing to the public treasury (OECD, 2014). Immigrants entering the labor market can boost the workforce in the receiving countries. Between 2000 and 2010, migrants accounted for a large portion of the increase in the workforce in Europe and the United States (OECD, 2012). In terms of contribution to the public treasury, although the effect of labor migrants on GPD is minimal studies suggest they tend to contribute in taxes more than they receive benefits (OECD, 2013) Migration primarily involving young and economically active individuals can also alter the demographic structure of host countries by increasing the proportion of a less dependent population. This shift depends on the receiving country's ability to align migrants' skills with labor market demands (OECD & European Union, 2014). Tabellini

(2020) indicates that the complementary skills of migrants provide natives with better job prospects and opportunities for upward mobility in their occupations. In the same study, he noted that migrants contribute to firms growth boosting production. In some cases, migrant entrepreneurship can contribute to employment and the introduction of new technologies within the host country (OECD, 2010). Besides the positive impacts claimed by these studies, some argue that immigration reduces the wages of native workers through competition (Borjas, 2003).

The refugees are a different case in terms of economic effects on host countries. Since they increase the supply in the labor market and are mostly willing to work with lower wages local people may suffer from depressing wages in the regions with a high number of refugees (Koca, 2016; Whitaker, 2002). The increasing number of refugees not only affects wages in the labor market but also causes an increase in the prices of local goods, services, and housing in the regions they settled (Salehyan & Gleditsch, 2006). Analyzing Tanzania's experience with refugees, studies by Alix-Garcia & Saah (2010) and Whitaker (2002) suggest that one of the economic effects of refugees is on food prices. They found that an increase in demand, driven by the number of refugees, causes food prices to rise in the affected regions.

Focusing on the economic impacts of migration on sending countries, Katseli et al. (2006) argue that these nations may benefit economically through the creation of job opportunities, the development of diaspora networks, remittances, and the accumulation and eventual return of human capital. According to their study, the remittances from migrants boost local economies by increasing disposable income and demand for goods and services. Furthermore, they discuss how the development of diaspora networks fosters economic development through capital flows, technology transfer, and improved access to global markets. They also note that returning migrants contribute to the local economy by bringing back valuable skills and knowledge, potentially leading to innovation and business creation. However, on the downside, uncontrolled large-scale emigration, especially of highly skilled workers (i.e. brain drain), can adversely affect service delivery, exacerbate labor shortages in key sectors, and lead to regional disparities in access to services (Koczan et al., 2021).

2.2.2 Social Effects

Immigration also has social impacts on receiving countries. When migrants integrate into their new host societies, they often bring and establish their existing cultural, religious, and social networks (Joly, 1995) . These networks, which include family ties, religious institutions, and political organizations, help them recreate a sense of community and support within the new context. This reconstitution of communities can significantly affect their integration process and the social dynamics of the host society. These networks encompass kinship ties, religious organizations, and even political entities. The integration of refugees can be different since they are forced migrants. Especially, when they are of different ethnicities from the host countries, cultural background and language differences can lead to communication challenges, making integration into the host country more difficult (Barman, 2020). In the regions where there is an imbalance between the number of refugees and local citizens, it may escalate local conflicts (Salehyan & Gleditsch, 2006).

Governments may adopt different approaches to accommodate migrants within society resulting in different social outcomes. One way is the assimilation of these communities into the country. Assimilative policies aim to have a homogenous society sharing the same cultural values by making minorities give up their own values that bound them to their country of origin (Lechuga & Fernandez, 2011). The second way is to adopt policies that eventually integrate them into society without preventing them from keeping their racial or ethnic identities and cultural values to some extent (Sam & Berry, 2010). Alternatively, governments can encourage multiculturalism meaning accepting and allowing the coexistence of different cultures within society (Johansson, 2022) as in the case of Mexican immigrants and the United States (Huntington, 2004).

One of the significant social effects of migration on sending countries is the transformation of gender roles within families. When one parent, either the father or the mother, migrates for work or other reasons, the parent who remains must assume the responsibilities of both, leading to a shift in traditional gender roles. This adaptation may affect the dynamics of the family structure, where roles that were once distinctly defined by gender become more fluid, as the staying parent navigates the dual tasks of caregiving and providing (Katseli et al., 2006). Another social effect is on children within the sending country. Migration can enhance household income through remittances—potentially reducing child labor and improving educational attainment—but it also disrupts family structures and roles, which can negatively affect educational outcomes (Katseli et al., 2006).

2.2.3 Political Effects

Immigration trends and policies in the host country can affect the political preferences and voting of the native citizens and increase support for right-wing parties (Alesina & Tabellini, 2024). A study by Halla et al. (2017) indicates that the skill of immigrants affects the support for the far-right in neighborhoods. Their study reveals that the flow of low-medium skilled rather than high-skilled immigrants causes Austrian citizens to turn their support to far-right parties. Another study, (Steinmayr, 2021) studying the effect of refugee inflow in Austria on voting behavior, indicated that long-term refugees do not have such an impact on voting because of consistent contact. However, in the regions where refugees settle for only a temporary period in which citizens do not get the chance to contact them, the support for far-right parties increased. In a study by Tabellini (2020), it is noted that immigration, particularly from ethnically diverse backgrounds, not only increases support for conservative parties but also influences native preferences toward reducing redistribution and advocating for policies that limit it.

Refugees, in particular, use their transnational connections to influence political dynamics in their home and host countries. This often involves international mobilization efforts to address the conflicts that caused their displacement (Joly, 1996) . Salehyan & Gleditsch (2006) from a security perspective, suggests that refugees can bring conflicts from their home countries to host countries. Refugee inflows can introduce combatants, arms, and conflict ideologies into host countries, extending conflict networks and challenging local authorities. Established refugee groups may form political organizations and engage in cross-border militancy, which can challenge the host government and regional stability. They also suggest that refugee populations, especially when they share similar goals, may cooperate with and support domestic opposition in host countries by sharing resources and ideas to challenge the host government.

Migration can have political effects on sending countries. While migrants may lose direct involvement in their home country's politics due to their absence, their remittances and other forms of engagement can enhance public accountability and stimulate community involvement back home. These contributions can serve as a form of political participation, impacting governance and policy-making indirectly (Fox & Bada, 2008). International migration also profoundly influences the political, economic, and social institutions of sending countries by transferring modern ideologies and practices through migrants who have studied or worked abroad (Kapur, 2014).

2.3 Global Trends in Migration

The number and proportion of international migrants in the world's population have shown an increasing trend from 1995 to 2020. By 2020, the number of migrants reached approximately 280 million globally, constituting 3.6 percent of the world's population (UN DESA, 2021). In 2024, the largest international migration corridor remains between Mexico and the United States, involving approximately 11 million migrants. The Syrian-Türkiye migration corridor is the next largest, with around 4 million migrants, primarily displaced individuals due to the Syrian civil war that began in 2011 (UN DESA,2021; UNHCR,2023a).

Unlike in low and lower-middle-income countries, international migration is a significant driver of population dynamics in high-income countries, where it has become the principal component of population growth, surpassing the natural increase from births over deaths (IOM, 2024; UN DESA, 2022).

In terms of refugees, according to the Global Migration Report by IOM (2024), by the end of 2022, the global refugee population reached approximately 35 million, marking the highest number recorded since the advent of modern statistical methods. From 2021 to 2022, the number of refugees surged dramatically, primarily due to the Russian invasion of Ukraine. Alongside the growing number of refugees, approximately 5.5 million asylum seekers globally were awaiting refugee status, with 2022 witnessing a record-breaking 3 million individual asylum applications (IOM, 2024). This spike in numbers has largely been driven by both internal and international conflicts in recent years. By 2022, the leading countries of origin for refugees were Syria, Afghanistan, and Ukraine, with the Syrian refugee count continuing to rise since the 2011 civil war, a significant uptick in Afghan refugees following the Taliban's 2021 takeover, and 5.7 million Ukrainian refugees due to the ongoing conflict initiated by Russia (IOM, 2024).

These figures underscore the persistent global impact of geopolitical instability on forced migration.

The findings from the Global Migration Report by the International Organization for Migration (2024) indicate a significant, unrelenting increase in international migration in recent years. The migration rates are now surpassing the natural increase from births over deaths in high-income countries, hinting at a potential shift in demographic trends in the future. By 2022, the number of refugees reached a record high, exacerbated by escalating conflicts, particularly in the Middle East and Eastern Europe. This surge has presented significant challenges for receiving countries including Türkiye as the leading host country, particularly in managing and accommodating the increasing numbers of displaced individuals.

2.4 Migration Trends in Türkiye

Before explaining the migration trends in Türkiye, it is important to understand the terminology regarding immigrants in the country. Türkiye grants three different statuses to international protection seekers: “refugee” “conditional refugee” or “subsidiary protection” status. Türkiye, although a party to the 1951 UNHCR Convention of Refugees, the country ratified it with a geographical limitation. According to this limitation, the country grants “refugee” status only to those coming from European countries (Kirişçi, 1996). According to article 62 of the local Law on Foreigners and International Protection (LFIP) adopted in 2013, Türkiye grants “conditional refugee” status to those who meet conditions stated in the 1951 Convention but come from non-European countries. According to article 63 of LFIP, for those who seek international protection due to the death penalty, torture, or threat of violence arising from national or international armed conflict but do not meet the conditions of “refugee” or “conditional refugee” status, Türkiye applies “subsidiary protection” status. Based on article 91 of LFIP, Türkiye grants “temporary protection” status on the condition of individuals who are forced to leave their countries in masses, as in the case of Syrians.

The refugee influx into Türkiye has escalated since the onset of the Syrian Civil War in 2011 as a result of the “Open Door Policy” started in 2011 (Karakoç Dora, 2020). The policy refers to the allowance of Syrian refugees into the country without the requirement of legal documents such as passports or visas (Tolay, 2016). Consequently, with the increasing number over the years, Türkiye emerged as a primary host country for refugees by September 2022 (UNHCR, 2022). Türkiye was not only a destination country for Syrians but also for forced migrants from countries involved in internal and international conflicts such as Afghanistan and Ukraine. By 2022, the country sheltered over 4 million individuals under temporary and international protection. The largest portion is Syrians with 3.8 million people under temporary protection, according to the UNHCR (2022). Additionally, significant populations of Afghans and Iraqis are under temporary and international protection in Türkiye each group numbering around 150,000 individuals (UNHCR, 2022). With the Russian invasion of Ukraine starting at the beginning of 2022, the country also hosts around 150,000 Ukrainian refugees by 2022 (UNHCR, 2022).

Alongside hosting a substantial number of refugees, Türkiye has become a prominent destination for labor migrants from regions such as Central Asia and Africa (IOM, 2023). According to the IOM’s Migrant Presence Monitoring Report (2023), which utilizes Turkish Presidency Migration Management (PMM) data, 2019 marked the peak year for irregular migrants entering Türkiye or overstaying visas. After a period of stability during the COVID-19 pandemic, the country recorded the second-highest number of irregular migrants in its history.

The distribution of immigrants in Türkiye is highly concentrated in a few major urban areas. According to the Turkish Statistical Institute (2024), in 2023, Istanbul hosted the largest share of immigrants, amounting to 36.4% of the total immigrant population in the country. This was followed by Antalya, 10%, and Ankara, 7.1%. Such a concentration presents additional challenges for Türkiye in managing migration, particularly in terms of resource allocation and integration efforts in these cities.

Türkiye is not only a destination country for immigrants. Its strategic geographical location on the migration routes from Central Asia, the Middle East, and Africa to Europe makes it also a transit country (IOM, 2023). This dual role underscores the complex challenges and responsibilities Türkiye faces in managing diverse migration dynamics.

Chapter 3:
ANTI-IMMIGRANT SENTIMENT

In the simplest terms, anti-immigrant sentiment can be defined as a negative opinion towards immigrants within a country (Muis & Reeskens, 2022). This sentiment can manifest as opposition to the immigrant population itself or broader disapproval of immigration policies and practices (Brug et al., 2005).

3.1 Drivers of Anti-Immigrant Sentiment

Integrated Threat Theory (ITT) (Stephan & Stephan, 2000) explains how perceived threats from an out-group can lead to prejudice and negative attitudes within an in-group. Two key components of this theory are realistic threats and symbolic threats. Realistic threats refer to tangible dangers that an out-group poses to the physical well-being, economic resources, or security of the in-group. On the other hand, symbolic threats arise from perceived differences in values, beliefs, and cultural practices between groups. These threats do not involve material competition but rather the fear that the out-group's presence will undermine the moral or cultural integrity of the in-group. This could manifest in concerns over changes in social norms, religious practices, or national identity. Both types of threats fuel intergroup anxiety, leading to prejudice and discrimination as the in-group reacts defensively to protect its resources and cultural dominance.

The additional factors that contribute to anti-immigrant sentiments can be categorized into individual-level factors, contextual influences such as the scale of immigration, and the specific attributes of immigrants (Dražanová & Gonnot, 2023).

Individual-level factors shaping anti-immigrant sentiment are influenced by perceived economic and cultural threats (Dražanová et al., 2022). A primary economic concern is labor market competition, where individuals oppose immigration perceiving newcomers as job competitors, especially when migrants possess similar skill sets (Gerber et al., 2017). This may result in low-skilled workers opposing low-skilled immigrants, and high-skilled workers opposing their high-skilled counterparts, viewing them as direct competition (Gerber et al., 2017). Similarly, a study by Gorodzeisky (2011) conducted in Europe, showed that in economically advanced regions, there is less resistance to migrants from poorer countries compared to immigrants from wealthier nations. Conversely, in less developed areas, the situation is reversed. This may be attributed to the perception that, in prosperous regions, immigrants from poorer countries are not viewed as direct competitors and are typically considered suitable only for low-skilled labor. Meanwhile, in poorer regions, immigrants from affluent countries are often seen as competitors, fueling local opposition (Gorodzeisky, 2011).

Another economic concern is the perceived fiscal burden, where natives may view immigrants as a potential strain on the welfare system supported by their taxes (Gorodzeisky & Semyonov, 2009), leading to a preference for high-skilled over low-skilled migrants due to the belief that the former are less likely to rely on public assistance (Gerber et al., 2017; Valentino et al., 2019).

The perceived economic threats may depend also both on the individual's economic conditions and the overall economic state of the country. The research by Dražanová et al. (2022) demonstrates that individuals' economic conditions are positively correlated with pro-immigrant attitudes, suggesting that better economic standing may lead to more favorable views toward immigration. A study by Heizmann & Huth (2021) shows that the perception of the economic condition of the host country affects the attitudes toward immigrants, the unemployment rate being the most effective factor. They also found that short-term economic developments are more influential in anti-immigrant attitudes than long-term. Their individual-level analysis indicates that individuals who are in worse economic conditions are more likely to see migrants as economic threats.

Individuals may prioritize cultural factors over economic ones and oppose immigration due to perceived threats to national and cultural homogeneity (Card et al., 2012; Tabellini, 2020). Tabellini (2020) focusing on the anti-immigrant attitudes in the U.S., suggests that although immigrants' effects on the economy are positive natives can still be against them which can be explained by cultural factors. One of the individual factors that affect perceived cultural threats is age. The studies revealed that older people can be against immigration more due to cultural concerns (Dražanová et al., 2022; Gorodzeisky & Semyonov, 2009). However, research shows that this relationship between age and anti-immigrant attitudes is not a linear one as attitudes established at a younger age regarding immigrants tend to persist into older ages (Hooghe & Wilkenfeld, 2008; Kustov et al., 2021). This perspective suggests that the influence of age on anti-immigrant sentiment primarily reflects a cohort or generational effect (Jeannet & Dražanová, 2019).

The research identifies educational attainment also as a significant factor; higher levels of education correlate with more positive attitudes toward migrants (Dražanová et al., 2022; Raijman & Semyonov, 2004; Rustenbach, 2010). This can be explained as poorly educated individuals lacking liberal values that promote diversity and opposition to discrimination against others (Hainmueller & Hiscox, 2007; Raijman & Semyonov, 2004).

Regarding the relationship between gender and anti-immigrant attitudes, while earlier research often linked anti-immigrant sentiments more strongly with men due to higher levels of authoritarianism (Adorno et al., 1950), more recent studies, such as Ponce (2017), challenge this view. Ponce's research, which focused on gender as a central theoretical variable, found no significant difference between men and women in terms of anti-immigrant sentiment. The study noted that women might exhibit less tolerance towards migrant groups they perceive as threatening gender equality, such as Muslims. In another study that focused on perceived threats, it was found that women expressed greater concern over crime-related threats posed by migrants compared to men, while no significant gender differences were observed in concerns related to job competition or welfare use by immigrants (Valentova & Alieva, 2014).

Geographical factors such as living in urban or rural areas significantly influence attitudes towards immigrants. According to Maxwell (2019), individuals in urban areas tend to have more positive attitudes toward immigrants due to the compositional effect. This effect stems from urban residents typically being more highly educated, engaged in high-skilled jobs, earning higher incomes, and choosing to live in multicultural environments, which collectively foster more positive perceptions of immigrants compared to those in rural areas (Valentova & Alieva, 2014).

The migration background also has a significant effect on the attitude towards migrants. Research indicates that individuals with a migration background are generally more favorable towards new immigrants compared to the native population (Becker, 2019; Just & Anderson, 2015; Šedovič & Dražanová, 2023). Research suggests that first-generation migrants tend to have a more favorable attitude toward new immigrants compared to later generations. This favorability decreases with each subsequent generation, indicating that the longer immigrant families reside in a country, the less favorable their attitudes become toward new arrivals (Becker, 2019). According to Just and Anderson (2015), even first-generation migrants become more skeptical and less supportive of immigration upon obtaining citizenship, particularly when influenced by the economic conditions of the host country.

The characteristics of immigrants are also a factor in attitudes toward immigrants. The research by Bridges & Mateut (2014) explores how the characteristics of immigrants influence native attitudes toward them. It finds that natives are more likely to oppose immigrants of the same race, perceiving them as direct competitors in the labor market. Conversely, opposition to immigrants of different races tends to be driven by cultural and social welfare concerns, highlighting different dimensions of threat perception among natives. Hale Williams and Chasapopoulos (2019), in a study conducted in the European Region, identified that immigrants from non-European countries are seen as cultural threats by natives, unlike those from EU countries. This sentiment is further intensified by cultural differences such as divergent ideologies or religious backgrounds, particularly from Muslim-majority regions like the Middle East, which contribute to the strength of anti-immigrant attitudes. Women in receiving countries could also oppose migrants from Muslim countries perceiving them as threats to gender inequality (Ponce, 2019).

In terms of the effect of the proportion of immigrants within the country, Weber (2015) found that at the national level, a higher proportion of immigrants is associated with less anti-immigrant sentiment among natives. However, this effect reverses in smaller regions, with increased contact and cohabitation with immigrants leading to more positive attitudes.

3.2 Ideologies and Anti-Immigrant Sentiment

Not just perceived threats but ideological beliefs also influence anti-immigrant attitudes. A political ideology is a set of ideas, beliefs, and values that offer a framework for understanding how society should operate and how power and resources should be organized and distributed (Heywood, 2013). Ideologies help shape political actions and policies by providing a guide to what is desirable and what needs to be changed in society. They also offer justifications for specific political structures and actions, influencing both individual and collective behavior (Heywood, 2013). Right-wing ideology includes conservative values, which prioritize tradition, social stability, and the preservation of established institutions like family, religion, and national identity. Conservatives resist rapid or radical change, believing in gradual, organic development, and they emphasize the importance of authority and order to maintain societal cohesion (Heywood, 2017). On the other hand, left-wing ideologies welcome political and social change based on a belief in progress. Left-wing views favor state intervention, collectivism, and policies that aim to reduce inequality. While advocating for liberty in personal freedoms and civil rights, left-wing ideology endorses authority to ensure social justice and equality (Bobbio,1996; Heywood, 2017).

In situations where economic competition or social vulnerability is not a primary concern, individuals are more likely to act on their ideological leanings toward immigrants (Pardos-Prado, 2011). In the existence of perceived economic and cultural threats, political disposition plays a more indirect role. The studies suggest that right-wing individuals who value national and cultural homogeneity may express stronger anti-immigrant sentiments than those with left-wing ideologies, particularly when they perceive immigrants as a cultural threat (Callens & Meuleman, 2016; Pichler, 2010).

The opposition of right-wing individuals against immigrants is also driven more by perceived economic threats than left-wing natives (Gorodzeisky, 2011; Gorodzeisky & Semyonov, 2009; Halikiopoulou & Vlandas, 2020). A study by Gorodzeisky (2011) in Europe reveals that right-wing older individuals also consider the economic conditions of immigrants' country of origin whereas left-wing younger individuals do not. Especially in prosperous regions right-wing individuals oppose the immigration of people from poor countries.

The perceived economic threat together with cultural concerns is a strong contribution to the voting for far-right political parties. Research shows that anti-immigrant attitudes cause increasing support for far-right parties (Erisen & Vasilopoulou, 2022; Halikiopoulou & Vlandas, 2020; Hooghe & Dassonneville, 2018). This relationship is a bilateral one in which far-right political parties also fuel anti-immigrant attitudes with strict policies and discourse regarding immigrants' potential threat to both the economy and national and cultural stability of the country (Rustenbach, 2010; Wimmer, 1997).

The anti-immigrant views held by right-wing individuals are closely linked to their socio-economic conditions. Lower-income and less-educated right-wing individuals are more likely to support restrictive policies against immigrants compared to their more prosperous or educated counterparts (Citrin & Sides, 2008; Raijman & Semyonov, 2004; Rustenbach, 2010).

The studies in the literature present a strong link between ideology and anti-immigrant sentiment emphasizing that right-wing citizens are more like to adopt an anti-immigrant attitude than left-wing individuals. However, a recent study (Leykin & Gorodzeisky, 2024) suggests that this is only valid for North American and Western European countries. Claiming that the link between conservatism and right-wing political orientation does not necessarily exist in post-socialist Central and Eastern European countries, the established relationship between political right and anti-immigrant attitude does not apply to these regions. Since different social and political dynamics in than that of the West, a left-right political scale would also fail to capture people's political stance in post-socialist countries (Leykin & Gorodzeisky, 2024).

3.3 Emotions and Anti-Immigrant Sentiment

The Intergroup Threat Theory (Stephan et al., 2009) explains how perceived threats from outgroups such as immigrants, evoke strong emotional responses such as fear, anxiety, and anger, which fuel anti-immigrant sentiments. These emotional reactions are influenced by both realistic threats, like competition for resources, and symbolic threats, such as clashes in values and beliefs. For instance, individual threats such as physical safety typically trigger fear, whereas group threats such as threats to economic resources or social coordination provoke anger (Cottrell & Neuberg, 2005; Davis & Stephan, 2011). Threats perceived as contamination, like opposing values or diseases, can lead to feelings of disgust. Additionally, when a group is seen as unable to reciprocate due to inability rather than choice, this may elicit pity (Cottrell & Neuberg, 2005).

The characteristics, beliefs, and cultural values of outgroups also affect the emotional responses. The study by Cottrell & Neuberg (2005) indicates that European Americans associate African Americans with threats to safety and resources so they mostly express fear and anger towards them. Activists feminists and fundamentalist Christians are seen as threats to cultural and moral norms triggering anger and disgust. Gay men, on the other hand, are associated with health issues (e.g. HIV) inducing emotions of disgust.

From a different perspective, a study by Aarøe et al. (2017) reveals that the behavioral immune system, which evolved to protect against pathogens, activates the emotion of disgust in response to perceived disease threats from immigrants. This system operates outside of conscious awareness, influencing political attitudes toward immigration by triggering feelings of disgust toward individuals perceived as potential carriers of infection. The behavioral immune system perceives foreigners as potential disease threats for several reasons. The appearance of foreigners might trigger instinctive health protection mechanisms if assumed anomalous. Foreigners may also be perceived carriers of pathogens unfamiliar and potentially more harmful to local populations. Moreover, local people can think foreigners disregard local cultural norms that historically reduced pathogen transmission, further escalating perceived infection risks (Schaller & Duncan, 2007). Consequently, individuals with high behavioral immune system sensitivity, regardless of other factors, driven by emotion of disgust avoid intergroup contact resulting in stronger opposition to immigration and supporting more restrictive immigration policies. In a similar direction, (Clifford et al. (2023) found a significant relationship between disgust sensitivity and anti-immigrant attitude in their study conducted across 5 countries including Türkiye.

The emotions resulting from perceived threats by immigrants also have political outcomes. A study (Erisen & Vasilopoulou, 2022) conducted in Europe indicates that "anger" rather than "fear" against immigrants increased the support for far-right political parties. This is mostly valid among citizens who have lower political trust in institutions. They also revealed that the emotion of anger is mostly driven by the overestimation of the size of the immigrants within the country.

Overall, the studies suggest that emotions regarding immigrants are associated with the perceived threats arising from immigration to the country. The emotions are also influenced by the physical, cultural, and ideological characteristics of the immigrant groups. Regardless of other factors, the behavioral immune system can also trigger anti-immigrant attitudes with the perceived threat of disease triggering the emotion of disgust. The emotions regarding immigrants can also affect political behavior. Anger against immigrants may increase the support for far-right political parties.

3.4 Anti-Immigrant Sentiment in Türkiye

Since Syrians are the most populated group, studies regarding anti-immigrant sentiment in Türkiye are mostly centered around Syrians. A 2022 study using data from the 2004

European Social Survey revealed that negative sentiments towards Syrian immigrants were already present in Türkiye before the substantial influx of refugees that began in 2011 (Karapınar Kocağ & Longhi, 2022). The negative attitudes towards immigrants during that period predominantly stemmed from non-economic factors and were most persistent in regions with a higher proportion of immigrants. However, starting in 2011 with the increasing numbers, economic factors also became prominent in attitudes towards refugees. One of the sources of anti-refugee attitudes regarding Syrians is natives seeing them as threats in the labor market (Koca, 2016). Since refugees are employed more in informal jobs with lower wages (Ceritoglu et al., 2017), locals see them as unfair competitors depressing wages in the market which fuels anti-refugee attitudes against Syrians (Erdogan & Semerci, 2020; Koca, 2016). Additionally, there is a perception that refugees disproportionately utilize public health and education services without equivalent contributions, further fueling anti-refugee sentiments (Koca, 2016). The reasons behind the anti-refugee attitude toward Syrians do not only include economic concerns but also security concerns. The criminalization of refugees seeing them as a security threat is also a part of the perception in Türkiye regarding Syrian immigrants (Cirakoglu et al., 2021; Erdoğan & Semerci, 2020; Gökçe & Hatipoglu, 2021; Koca, 2016). The tendency to blame Syrians for the increasing crime rate is prevalent both in public media and among locals (Erdoğan & Semerci, 2020; Koca, 2016). A study by Gokce & Hatipoglu (2024) revealed that among the topics discussed regarding refugees in Türkiye on social media, the most discussed one is "domestic security".

The perceived cultural threat also contributes significantly to the anti-refugee sentiment in Türkiye (Cirakoglu, 2021; Erdoğan & Semerci, 2020). The perception that Syrians will disrupt the cultural and moral structure due to their perceived lower moral standards and differing cultural values is among the drivers of anti-refugee attitudes in Türkiye (Cirakoglu, 2021; Erdoğan & Semerci, 2020). Ozduzen et al. (2021) indicated that the perceived cultural threat regarding Syrians is also part of the anti-refugee sentiment on social media in Türkiye. The study reveals that racial discrimination against Syrians is a strong element of the anti-refugee sentiment present within the Turkish public on social media. Syrian refugees are not the only ones targeted negatively on social media but also Afghan refugees during the major flow of refugees following the Taliban takeover in 2021 (Ulug et al., 2023). The findings of these studies align with the UNHCR (2023b) report on the refugee situation in Türkiye. The report suggests that the host community has been experiencing fatigue due to the existence of refugees within the country. The worsening economic conditions in recent years, such as the high inflation rate, increased the perception of Syrians exploiting the social services, taking jobs, and potentially leading to undesirable social behaviors.

The resistance to immigration in Türkiye is not only a widespread societal issue but also a highly politicized topic among political parties. The main opposition parties in Türkiye, namely the left-wing Republican People's Party (Cumhuriyet Halk Partisi) and Good Party (İyi Parti) have been noted for utilizing anti-refugee rhetoric centered around securitization and repatriation (Saylan & Aknur, 2023). In addition to those parties, Victory Party (VP) established in 2021, as a far-right single-issue political party with an anti-immigrant political agenda has been an influential party shaping public discourse regarding immigrants and refugees in Türkiye. The discourses by parties, although on varying degrees, are shaped on a common basis which sees the refugees in Türkiye as economic, cultural, and security threats. Within their discourses, they claim refugees as an economic burden, cultural threat as concerns with demographic changes, and also a security issue emphasizing the concerns related to uncontrolled irregular movements of refugees across the state's border (Saylan & Aknur, 2023). Conversely, the incumbent right-wing Justice and Development Party (AKP) which is responsible for the"open-door policy" follows a more pro-immigrant attitude emphasizing religious and humanitarian values and also historical bounds (Saylan & Aknur, 2023). Türkiye's politics regarding the immigration of refugees constitutes a distinct example in which the leftist opposition party RPP is strongly opposed to the accumulation of refugees within the country, whereas the right-wing incumbent party adopts a positive stance toward immigrants and refugees.

Overall it can be said that In Türkiye, anti-immigrant sentiment operates on both societal and political levels, influenced by perceived threats to economic stability, cultural identity, and national security (Cirakoglu et al., 2021; Saylan & Aknur, 2023).

Chapter 4:
IDEOLOGIES AND EMOTIONS

4.1 Theoretical Framework

Cognitive appraisal theory from the field of psychology aims to explain the process of different emotional responses. (Lazarus & Folkman,1984) According to this theory, prior to emotional response, there is a process of appraisal. This process consists of two phases which are 'primary appraisal' and 'secondary appraisal'. There are three kinds of primary appraisal: a) irrelevant, b)benign positive, and c)stressful. If the situation has no potential effect on the individual's well-being, it's considered irrelevant and no emotional response is triggered. The benign positive appraisal is associated with encounters having potentially positive and beneficial outcomes for the individual. Accordingly, it is about positive emotions like joy, happiness, etc. Stress appraisal is about harm/loss, threat, and challenge. In a situation in which the damage has already been done to an individual like injury, it falls within the first category. Threat and challenge are defined similarly to each other. Both activate the coping mechanism of the individual. In the situation referred to as a challenge, the focus is on the potential benefits of the situation, so it is associated with emotions like eagerness, excitement, etc. On the other hand, threat refers to an encounter in which the focus is more on the potential harms. Therefore, it is associated with negative emotions such as fear, anxiety, and anger. Then, during the "secondary appraisal" process, the individual checks whether it is possible to deal with the situation with available resources (Lazarus, 1991). This appraisal process is experienced unconsciously, and, in the end, an emotional response is triggered. If the situation is a threat and one is not able to deal with it, as in the case of cultural or economic threats by immigration, fear or anxiety is triggered.

Two main theories in the literature aim to explain the effects of emotions on an individual's political behavior or political judgment. The first one is rational choice theory. The rational choice theory claims that under any circumstances, individuals make their decisions based on their rational calculations of advantages, disadvantages, and risks of possible outcomes (Scott, 2000). It emphasizes the rational side of human beings and underestimates the role of emotions in decision-making.

The second theory, Affective Intelligence Theory (Marcus et al., 2000), emphasizes the role of emotions in the decision-making process. AIT posits that people operate with two emotional systems: the disposition system and the surveillance system. The disposition system is activated when individuals encounter familiar or routine situations, allowing them to rely on habits or previously learned behaviors. In contrast, the surveillance system is engaged in response to unusual or threatening conditions that cannot be managed by habitual responses.

In such situations, individuals experience emotions like anxiety or fear, signaling the need to abandon routine behaviors and seek new approaches. This emotional trigger initiates a process of gathering new information, making individuals more open to persuasion and learning. When extraordinary events, such as terrorist attacks or pandemics, arise, individuals are more likely to leave their "comfort zone" and become receptive to new behaviors or ideas.

In addition to fear and anxiety, anger plays a significant role in AIT. Unlike fear, which motivates individuals to seek new information and reconsider their positions, anger typically reinforces existing beliefs and encourages defensive behavior. Anger arises when individuals perceive a threat or challenge to their values or beliefs, motivating them to take action in defense of these positions rather than seeking alternative perspectives. Therefore, while fear and anxiety make people more open to change, anger strengthens commitment to existing viewpoints and increases political engagement or activism.

4.2 Related Work

Vasilopoulos, Marcus, and Foucault (2017) relying on a survey methodology studied the role of the anger and fear caused by the terrorist attacks in France on the shift to authoritarianism in the following period. They also found that there is a significant relationship between ideology, emotions, and the interaction of two and authoritarian preferences. Their results suggest that anger causes right-wing citizens to strengthen their opinions. On the other hand, angry left-wingers are less willing to support authoritarian policies. Fear, which causes left-wing citizens to change toward an authoritarian attitude, does not have such an effect on right-wing citizens.

Pliskin et al. (2014) aimed to explore the interactive influence of ideology and emotions on support for policies in the context of intergroup conflicts in Israel, involving

Jewish-Israeli and Palestinian citizens. Utilizing a combination of experimental and field study methodologies, the research investigated how induced emotions like empathy and fear affected policy support differently across ideological lines. The findings revealed that emotional responses had a greater impact on the policy support of leftists compared to rightists, suggesting ideology significantly moderates the influence of emotions on policy positions in conflict situations.

Aarøe et al. (2017) in their study focusing on the effect of the behavioral immune system of anti-immigrant attitude, found that there is an interaction effect of ideology and disgust sensitivity on the stance against immigrants. They revealed that liberals with high disgust sensitivity oppose immigration and support restrictive policies they would normally oppose. They suggest that the emotion of disgust causes ideological inconsistencies in the behaviors against immigration.

In the study by Sabucedo et al. (2011), ideological orientations moderated the influence of emotions on the intention to participate in political demonstrations. Specifically, the results indicated that enthusiasm significantly predicted the intention to participate in demonstrations supporting the Spanish Government's negotiation with ETA, particularly among individuals with left-leaning ideologies. Conversely, anger was a strong predictor for the intention to participate in protests against the negotiation, predominantly among those with right-leaning ideologies. This suggests that people's political ideologies influenced how specific emotions (like enthusiasm for supporters and anger for opposers) motivated them to engage in different forms of collective action.

A recent study (Rico, 2024) explores the emotional background of populist support, differentiating between nativism and populism. It argues that fear and anger relate differently to nativist and populist attitudes based on individuals' political predispositions and the type of perceived threats. The empirical analysis, conducted using data from a nationally representative survey in Spain, reveals that the relationship between anger and anti-immigrant attitudes changes based on the individuals' ideological orientation. Anger is more strongly associated with anti-immigrant attitudes among right-leaning individuals, while fear is linked to increased outgroup intolerance, especially among those on the center and the left. The study also finds that perceived cultural threats, significantly enhance the association between anger and anti-immigrant attitudes. This underscores that the specific nature of the threat plays a crucial role in influencing emotional reactions and subsequent political attitudes toward immigration. Populist attitudes, on the other hand, are mainly associated with anger, regardless of ideological leanings or the type of threat, pointing to a general effect of anger in populist contexts.

Chapter 5:
DATA COLLECTION & PREPARATION

Unlike the relevant studies mentioned above, this study is conducted using social media data, which offers several distinct advantages.

First, social media allows for the possibility of conducting a retrospective study, enabling researchers to gather and analyze historical data that reflects public opinion and behavior over time. This historical perspective is crucial for understanding how attitudes toward issues such as immigration evolve, and it offers a continuous, time-sensitive dataset that is often unavailable through traditional survey methods.

Second, social media data provides an opportunity to capture people's instant and natural reactions to events and issues as they unfold in real time. Unlike surveys or interviews, which often involve a delay between the occurrence of an event and the data collection process, social media captures immediate responses. This immediacy helps reveal genuine emotional reactions and public sentiment that might fade or change with time, giving researchers access to a raw and unfiltered representation of opinions.

Additionally, social media offers a platform for anonymous expression, which can reduce the effects of social desirability bias—the tendency of individuals to alter their responses to align with socially accepted views. Since many users operate under pseudonyms or without disclosing their identity, they may feel more comfortable expressing opinions that might otherwise be suppressed in face-to-face surveys or interviews. This anonymity can lead to more honest and diverse viewpoints, especially on sensitive issues like immigration.

Third, the integration of computational methods allows for the collection and processing of large-scale datasets in a relatively short time. Traditional surveys and interviews are often limited by sample size and time constraints, but social media data is abundant and can be analyzed using advanced algorithms and machine learning techniques. This scalability not only enhances the robustness of the study but also provides a more comprehensive picture of public opinion across various demographics, regions, and time periods.

Overall, social media data offers a unique combination of historical depth, real-time insights, anonymity, and scalability, making it an invaluable resource for studying complex societal issues such as immigration. This methodology provides a more dynamic, representative, and large-scale understanding of public opinion compared to conventional approaches.

Twitter as one of the most dominant and open social media platforms is used for this study. As a platform in which people express their opinions and emotions basically through short text and emojis, it is a suitable platform to conduct such a study.

5.1 Politus Project

The Twitter data to be used within the scope of this project is provided by the Politus Project. The Politus Project is an innovative initiative funded by the European Research Council, aimed at developing new methods for measuring public opinion in Türkiye using data from social media platforms like Twitter. By analyzing Twitter data, the project employs advanced techniques like natural language processing (NLP) and artificial intelligence (AI) to gauge public opinion and behaviors. The Politus Project's database is constructed from tweets collected randomly using the Twitter API, which targets user IDs identified through a snowball sampling technique. This process began with 100 prominent Turkish Twitter accounts, and expanded by sampling their followers and so forth. This method has compiled a substantial collection of approximately 6.6 million user IDs, from which tweets are gathered. Additionally, the number of users coming from replies, retweets, quotes, and follows is around 26.9 million. In total, they have 718 million tweets in their database. The user IDs include information such as user names, names, surnames, descriptions, and locations provided by Twitter API. Demographic information such as age and gender are assigned to users using M3inference. M3inference is a deep learning model trained on a large amount of Twitter data set to predict age and gender using profile pictures, screen names, names, and biographies.

The Politus Project has a gold-standard corpus of human-annotated tweets based on a pre-defined guideline to be used for training deep-learning models which can predict topics, ideologies, and emotions within tweets. The annotation process is done by two annotators who are graduate students from political and social sciences and finally adjudicated by a domain expert. The classification of tweets includes categorizing political and policy-related topics within randomly selected tweet text. The topics are grouped under four categories: “welfare”, “democracy”, “big 5”, and “municipal”. Under the welfare category, there are topics such as Social Policy, Labour and Employment, Education, Health and Public Health, Disability, and Housing. The democracy category includes Elections and Voting, the Justice System, Human Rights, Regime and Constitution, and the Kurdish Question. The big 5 refers to main political topics such as Internal Affairs, National Defense, Corruption, Foreign Affairs, and Economy. Finally, topics related to municipal issues are Public Infrastructure, Social Services, Environment and Public Health, Animal Welfare, Local Politics, and Culture. These topics are not mutually exclusive meaning a tweet can be related to more than one topic.

The annotation process also includes the classification of ideologies, beliefs, and values expressed within the tweets. The ideologies taken into consideration are Turkish Nationalism, Conservatism, Islamism, Liberalism, Kemalism, Social Democracy, Socialism, Feminism, Environmentalism, the Kurdish National Movement, and Secularism. These ideologies are not mutually exclusive meaning the users can support more than one ideology.

In addition to topics and ideologies, tweets are classified based on the emotions expressed. These emotions are neutral, happiness, love, hope, despair, confusion, gratitude, sadness, anxiety, fear, shame, regret, anger, disgust, desire, approval, and disapproval. The emotions within the tweets are not mutually exclusive.

5.1.1 Ideologies

According to the annotation manual of Politus Project (see Appendix A) which is prepared based on the work by Tanıl Bora (2016) titled: “Cereyanlar: Türkiye’de Siyasi İdeolojiler” (Currents: Political Ideologies in Türkiye), tweet ideologies are annotated using the descriptions below.

Turkish Nationalism: Turkish nationalism focuses on building and maintaining a strong national identity based on shared cultural, historical, and linguistic attributes. This ideology has played a central role in the formation and development of the Turkish nation-state, making it a core component of the country's official ideology. Turkish nationalism is not monolithic; it can be interpreted and expressed in various forms, such as Turkist, Islamist, conservative, or Westernist nationalism. These different variants reflect the ongoing ideological struggles to define or redefine Turkish national identity.

Conservatism: Conservatism is an ideology characterized by skepticism toward rapid and extensive social change, especially when driven by political agendas. Rooted in a desire to preserve long-standing traditions, conservatism emerged as a reaction to modern revolutionary movements. In Turkish politics, conservatism has influenced right-wing parties, particularly in response to the modernization efforts of the early Republic. It emphasizes gradual, society-driven change rather than top-down government imposition. Today, the Justice and Development Party (AKP) defines Turkish conservatism, advocating for social stability through traditional institutions like family and community.

Islamism: Islamism is a political ideology that seeks to structure state-society relations and legal frameworks based on Islamic principles as outlined in the Quran. In Türkiye, Islamism has influenced movements such as the National View (Milli Görüş) and various political parties like the Welfare Party and Justice and Development Party (AKP). Islamism emerged in opposition to the secular, Western-oriented ideology of the Turkish Republic (Kemalism), advocating for a Muslim identity over Turkish nationalism. Today, Islamist views focus on issues like gender roles, education, and public morality.

Liberalism: Liberalism is a political ideology focused on limiting state power to protect individual rights and liberties. It emphasizes that the government's role should be minimal, restricted to maintaining peace, ensuring a neutral legal framework, and providing public goods. Liberals view state power as a necessary evil, essential only for enabling individuals to exercise their freedoms. Liberalism advocates for government based on the consent of the governed, free elections, checks and balances, and political rights to ensure meaningful opposition, which are foundational to modern democracies.

Kemalism: Kemalism is the founding ideology of the Turkish Republic, emphasizing the preservation of state institutions over participatory politics. Rooted in reformist movements from the late Ottoman period, it has shaped Türkiye's national identity, prioritizing the state as a guardian of national interests. Kemalism also includes a distinct version of Turkish nationalism, which focuses on the nation as a community of citizens while often dismissing ethnic minority claims.

Social Democracy: Social democracy focuses on addressing economic inequality, improving living standards, and ensuring robust social policies like social insurance and assistance. It advocates for opposing the privatization of public goods and services and supports better working conditions, wages, and employment opportunities. Unlike socialism, social democracy doesn't emphasize social class or class antagonism; instead, it focuses on economic equality and social justice without framing issues in terms of class struggle.

Socialism: Socialism in Türkiye emphasizes collective or governmental control over production and equitable distribution of resources to address the inequalities of capitalist systems. It advocates for the oppressed classes to challenge their socio-economic conditions through collective action, seeking a transformation that replaces capitalist structures with socialist governance. This ideology underscores the importance of societal change and class struggle to achieve fairness and equality in the distribution of resources and opportunities.

Feminism: Feminism challenges patriarchal structures and advocates for gender equality in all spheres of life. It is a diverse movement that seeks to address gender-based disparities and promote societal understanding and inclusion. Feminism in Türkiye covers a wide range of issues, including reproductive rights, economic inequality, and cultural representation, with the aim of achieving equality and justice for all genders through transformative societal change.

Environmentalism: Environmentalism responds to ecological threats caused by human activities by advocating for sustainable interactions with the natural environment. It emphasizes the need for a cultural shift to recognize and respect nature's intrinsic value, supporting policies that promote practices like renewable energy adoption, conservation of natural habitats, and responsible land use. This movement plays a critical role in advancing both global and local initiatives aimed at mitigating environmental degradation and ensuring ecological health.

Secularism: Secularism in Türkiye is a foundational principle established during the early Republican period under Mustafa Kemal Atatürk. It emphasizes the separation of religion and state affairs, aiming to create a modern, secular national identity. Secularism in Türkiye has been a defining feature of its legal and political systems, influencing education, law, and governance by ensuring that religious institutions do not interfere with state policies.

Kurdish National Movement: This ideology focuses on the recognition and promotion of Kurdish identity and advocates for the end of discrimination against all minority ethnicities. Key demands include the right to education in one's mother tongue, increased local government power, and greater regional autonomy. The movement seeks to ensure that Kurdish cultural and political rights are acknowledged and protected within a broader framework of equality and self-determination.

In the analysis of ideologies and their connection to anti-immigrant sentiment, these ideologies are positioned on the left-right spectrum, allowing for a comparison with findings from existing literature. Turkish nationalism is considered on the right due to its emphasis on preserving a strong national identity rooted in tradition and cultural continuity, aligning with conservative values. Similarly, conservatism is positioned on the right as it prioritizes tradition, gradual change, and social stability through long-standing institutions like family and religion, resisting radical change. Islamism also aligns with right-wing ideology, emphasizing the preservation of religious traditions and social order.

On the other hand, liberalism is considered on the center-left, advocating for individual rights, personal freedoms, and equality, with limited state intervention to ensure liberty and fair opportunities for all. Kemalism is positioned on the left due to its focus on secularism, modernization, and progressive reforms aimed at societal transformation and equality, reflecting left-wing values. Social democracy and socialism clearly belong on the left, as both advocate for reducing inequality through state intervention, promoting social justice and economic equality. Feminism, challenging patriarchal structures and advocating for gender equality, and environmentalism, promoting sustainable practices and systemic change, are also placed on the left for their focus on social justice and progressive change. Finally, the Kurdish National Movement aligns with left-wing ideology as it advocates for minority rights, equality, and self-determination, consistent with leftist values of social justice for marginalized groups.

5.2 Data Collection and Preparation

The initial dataset provided by the Politus Project is the “user dataset”. This dataset includes information on user IDs, names, screen names, age, gender, location, total tweet count, and number of tweets of each user that can be associated with specific ideologies. Each ideology column indicates the number of tweets that is related to that ideology.

The exact number of users within the database provided by the Politus Project is 6,682,284. As mentioned above, the project does not collect tweets randomly, instead, tweets are collected based on user IDs. Related to this, there are users with demographic information but do not have any tweets within the database. As the first step, these users with zero tweets are excluded from the dataset. As a result, the number of users is reduced to 4,211,914.

This study focuses on understanding the effect of ideologies on the stance against immigrants. To achieve this, all users in the dataset must be associated with specific ideologies. This association is determined by identifying users who have tweeted in support of any ideology. Users without at least one such tweet are excluded, resulting in a filtered dataset of 1,687,527 users.

As the initial approach users are planned to assign an ideology based on the most frequently expressed ideological support in their tweets. However, this approach could lead to inaccuracies if a user expressed support for an ideology in only a single or a few numbers of tweets. To address this, the minimum threshold of five tweets supporting a specific ideology is determined before that ideology is assigned to a user. This threshold ensures that the assignment reflects a more consistent and reliable ideological alignment, rather than a potentially anomalous or insignificant expression of support. As a result, only users who have sent at least five tweets indicating support for a particular ideology are classified under that ideology, thereby improving the dataset's overall validity and accuracy. Regarding this approach, users who do not post at least 5 tweets related to any ideology are removed from the dataset. Based on this condition, the number of users is reduced to 474,416.

Additionally, the accounts that belong to organizations instead of individuals have to be removed from the dataset. Users who include words that can indicate an organization in their screen name are removed from the data set. These words specifically are *"müdürlüğü", "başkanlığı", "merkezi", "kaymakamlığı", "gazetesi", "haber", "partisi", "belediyesi", "bakanlığı", "kurumu", "bankası", "enstitüsü", "üniversitesi", "okulları", "dershane", "kurulu", "birimi", "teşkilatı", "ocakları", "gönüllüleri", "derneği", "topluluğu", "vakfi", "lisesi", "akademisi", "muhtarlığı", "ilkokulu"*. After the removal of the organization account based on this approach, the number of users is 464,670.

As the final filtration, since demographic information such as age and gender is a significant part of the analysis, the users who do not include such information are excluded from the dataset. The final version of the dataset consists of 460,140 users with 215,284,115 tweets.

However, because of the computational and time limitations, the number of users filtered further with random sampling. Approximately 25% of the users are selected randomly from the dataset. As a result, there are **115,000 users** with **53,459,427 tweets** in the final dataset.

5.2.1 Ideology Assignment

To assign ideologies to users effectively, a threshold is established requiring at least five tweets associated with a particular ideology. The ideologies are not mutually exclusive meaning that one user can be supportive of multiple ideologies. For this reason, rather than assigning a single ideology with a maximum number of tweet counts, the ideologies are sorted in descending order of their corresponding tweet count for each user, creating columns showing the first ideology up to the 11^{th} ideology. After analyzing the distribution of users across different numbers of ideologies, it was observed that the number of users decreased significantly after the number of users with a third ideology. For representativeness, therefore, the top three ideologies are assigned to each user, ensuring that only the most relevant ideologies are considered.

Chapter 6:
METHODOLOGY: TOPIC CLASSIFICATION

Social researchers have recently been interested in studying anti-immigrant attitudes using social media data with Natural Language Processing (NLP) techniques. NLP is a field of artificial intelligence that focuses on the interaction between computers and humans through natural language. It involves the ability of computers to understand, interpret, and generate human language in a way that is both meaningful and useful. NLP combines computational linguistics with machine learning and deep learning models to process and analyze large amounts of natural language data (Manning & Schutze, 1999).

Menshikova & van Tubergen (2022) used Twitter data to understand factors that drive anti-immigrant sentiment expressed on social media. To detect the tweets that include negative opinions about the immigrants they adopted a lexicon-based approach. In this approach, the tweets are labeled based on a pre-defined dictionary that includes polarity scores for specific words determined by domain experts. In another study Ahmed et al. (2021) linked their results from the survey regarding anti-immigrant attitudes to Facebook data. Using the survey respondents' Facebook accounts, they analyzed the posts sent regarding immigrants adopting a lexicon-based approach. The findings from the analysis of the Facebook data are consistent with that of the surveys they conducted which is an indicator of the reliability of social media data for such studies.

Besides the lexicon-based, a supervised machine-learning-based approach is also widespread in studies for social media analysis. Machine learning-based text classification predicts labels using human-labeled training data. A systematic literature review by Skoric et al. (2020) analyses and compares different studies that use different approaches to predict elections and public opinions based on social media data. Focusing on the sentiment analysis compare two approaches: lexicon-based and machine learning-based. After a comparative analysis, Skoric and his colleagues found that machine learning-based sentiment analysis provides better performance in terms of accuracy while predicting elections or public opinion based on sentiment.

A recent work (González-Carvajal & Garrido-Merchán, 2023)compared the BERT-based language models with machine learning algorithms for automated text classification. In 4 different languages and contexts with different text characteristics (e.g.

tweets, news, reviews) BERT-based approach outperformed the traditional supervised machine learning algorithms with TF-IDF feature extraction.

The methodology in this study consists of two parts, automated topic classification and stance detection. Within the scope of this study, a model that can automatically detect tweets related to immigration in Türkiye is developed through fine-tuning a pre-trained BERT-based deep-learning language model. In the second part, stance detection is applied to the tweets related to immigration. For the stance detection again a BERT-based model is fine-tuned to automatically analyze whether the tweet is pro-immigration, anti-immigration, or expresses a neutral stance toward immigration in Türkiye. All the processes are conducted in a Python environment. The packages used are numpy, pandas, and scikit-learn

6.1 Annotation

Since this study aims to understand the interplay between ideologies and emotions in the anti-immigrant stance, tweets related to the topic of "immigration" are required from the Politus Project database. However, the project did not have a model capable of predicting tweets related to "immigration." The project already had approximately 14,000 tweets annotated by human annotators, but these had not been adjudicated by a domain expert.

The definition of migration topic by Politus encompasses both immigration to Türkiye and emigration from Türkiye to another country. Therefore annotation by Politus has been made accordingly. However, this study solely is interested in immigration to Türkiye, not emigration from the country or Turkish emigrants abroad. Therefore, while adjudicating the annotated set, tweets related to emigration or Turkish emigrants abroad had to be excluded.

Consequently, the previously annotated relevant set was re-inspected and after adjudication of the tweets in a way that aligns with the purpose of this study, the set contained **13,516** irrelevant tweets and **91** relevant tweets on the topic of "immigration." The immigration topic includes tweets about the immigration of foreigners to Türkiye, the immigrant and refugee groups already present within the country, and tweets related to policies of immigration by the incumbent government. The sample tweets are shown below in Table 6.1.

Table 6.1. Sample Tweets Related to Immigration.

Tweet ID	Tweet (Original)	Tweet (English)
1414637730290622467	Ülkeden beyin göçü devam ediyor ve mültecilerle de Türkiye'nin demografik yapısı tamir edilmez boyutta bozuluyor. Göçü engelleyememek kötü ama sınırların yol geçen hanına dönmesi çok ama çok daha kötü. #SınırlarıKapat	*The brain drain from the country continues, and the demographic structure of Turkey is being irreparably damaged by refugees. Failing to prevent migration is bad, but turning the borders into a free-for-all is much, much worse. #CloseTheBorders*
1425580916781486099	Yaralanan çocukların fotoğraflarını gördüm korkunç! Mülteci politikasına karşı öfkesini siyasi iktidara değil de mültecilere yöneltenler, gücü yettiğini sopalayanlar siz bu ülkenin çaresizliğisiniz…	*I saw the photos of the injured children, it's horrifying! Those who direct their anger against the refugee policy not at the political power but at the refugees, and those who beat those who they can overpower, you are the desperation of this country…*
1420434276647120898	Biz batının göçmen deposu değiliz, Biz batının çöp deposu değiliz, Biz batının taşeronu değiliz, Biz dünyanın en güçlü ekonomisinden biriyiz. Bende Zeki Mürenim zaten..😂	*We are not the immigrant depot of the West, We are not the garbage dump of the West, We are not the subcontractor of the West, We are one of the world's strongest economies. And I am already Zeki Müren...* 😂
1170983804158271488	AKP’nin Açtığı Fabrikalar: 1 - Bankamatik memur fabrikası 2 - Mülteci besleme fabrikası 3 - Cengiz inş. Fabrikası..!	*The Factories Opened by AKP:* *1 - ATM civil servant factory* *2 - Refugee feeding factory* *3 - Cengiz construction factory..!*
1425787510614118405	Kuzey'de sel, güneyde yangın. Batısında Suriyeli nefreti Türkiye büyük bir imtihandan geçiyor. İçimizdeki beyinsizler yüzünden bizi de helak etme Allah'ım.	*Flood in the north, fire in the south. Syrian hatred in the west Turkey is going through a great ordeal. Do not destroy us because of the brainless among us, oh Allah.*

6.2 *Evaluation of the Models*

The first part of this study is to develop a predictive model to predict and classify the tweets that are related to the topic “immigration”. For this purpose, two BERT-based pre-trained models for the Turkish language, BERTurk, and TurkishBERTweet, are fine-tuned using the annotated data at hand.

BERT is a transformative model introduced by Google in 2018 that changed the landscape of how text data is handled in natural language processing (NLP). BERT models are designed to pre-train deep bidirectional representations by conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as text classification, and sentiment analysis without substantial task-specific architecture modifications (Devlin et al., 2019).

BerTURK[3] (128k-cased) is a BERT-based model specifically tailored for the Turkish language. It has been pre-trained on a diverse dataset that includes a Wikipedia dump and various other corpora, enabling it to handle a wide range of text inputs effectively. The model utilizes a large vocabulary size of 128,000, ensuring it can capture the nuances of the Turkish language.

TurkishBERTweet [4] is another BERT-based model specifically designed for the Turkish language, trained on a massive dataset of 894 million Turkish tweets. This model is uncased, meaning it does not distinguish between uppercase and lowercase letters, which is typical for processing social media text where case usage can be inconsistent. This extensive training on tweets makes it highly effective for applications involving social media data.

Different scenarios for the two models are used and the performances of the models are evaluated based on the evaluation metrics. **Accuracy** measures the proportion of all predictions—both positive and negative—that the model correctly identified(Jeni et al., 2013). It is a direct metric that indicates the overall effectiveness of the model across all classes. However, the metric accuracy can not be suitable for an imbalanced dataset since in that case its value is mostly determined by the success of detecting the dominant class (He & Garcia, 2009; Saito & Rehmsmeier, 2015). **Precision** quantifies the proportion of

[3] https://huggingface.co/dbmdz/bert-base-turkish-128k-cased
[4] https://huggingface.co/VRLLab/TurkishBERTweet

positive identifications that were indeed correct, serving as a measure of the reliability of the model's positive predictions. **Recall** assesses the proportion of actual positives that were accurately identified by the model, reflecting its capacity to capture all true positive cases effectively . The **f1-Score** is the harmonic mean of precision and recall, offering a balanced measure between the two. This metric is exceptionally useful for comparing models in cases where one demonstrates high precision and the other exhibits high recall. F1-score is particularly useful in scenarios involving imbalanced datasets where accuracy can be misleading (He & Garcia, 2009; Wegier & Ksieniewicz, 2020).

Finally, for consistent comparison, all the variable parameters of the models are fixed with a random seed in each run.

6.2.1 An Attempt to Expand the Dataset

Before evaluating the two models, since our dataset is pretty imbalanced in terms of relevant and irrelevant tweets, the first approach is to expand the number of relevant tweets including a set of tweets from another dataset. The separate dataset consists of tweets collected using the keywords "suriyeliler" (Syrians), "afganlar" (Afghans), and "ukraynalılar" (Ukrainians) referring to the mostly populated migrant groups in Türkiye. These tweets after annotation in terms of relevance, are included in the main dataset. As a result, there are 2048 relevant tweets. To provide balance, the same number of irrelevant tweets are randomly selected and 5096 tweets in total are used to fine-tune the BertTURK model. Before going into the model, all the tweets are preprocessed and normalized. As the next step, the tweet set is divided into train, test, and validation sets. The model is fine-tuned using training and test sets and its final performance is evaluated on the validation set.

The model provided a 99% f-1 score which can be considered a highly suspicious score. This is probably because the tweets collected with keywords created a bias that the model predicts all of them as relevant, thus increasing the score, which is quite misleading. Therefore rather than using tweets collected with keywords, improving the model's performance using only the relevant tweets from the main dataset which includes only randomly collected tweets would be a better approach.

6.2.2 Handling the Imbalance: Undersampling

Since expanding the dataset with the tweets collected with keywords does not work, alternative approaches to deal with imbalanced data would be oversampling or undersampling (He & Garcia, 2009). Oversampling refers to increasing the number of instances in the minority class while adding replicated samples to the dataset. On the other hand, undersampling refers to removing the sample from the majority class to rebalance the dataset for training the models (He & Garcia, 2009). The downside of the oversampling is that the model can overfit since the replicated instances and perform poorly on the unseen data (Mease et al., 2007). The problem associated with undersampling is the probability of removing the important information from the dataset and training the model with inadequate information (He & Garcia, 2009). In this study, because of the risk of overfitting a random under-sampling is preferred to be applied to handle data imbalance.

6.2.3 Evaluation of BERTurk (128k-cased)

At this step, using only the randomly collected tweets a pre-trained BertTURK model is fine-tuned. The dataset is split into train, test, and validation sets. 60% of the data is taken as a training set, 20% as a test set, and 20% as a validation set. In the first step, since there are only 91 relevant tweets, the same number of irrelevant tweets are randomly selected to provide balance before going into the model. Half of the relevant tweets that is 45 are put into the training set. The other half (i.e. 46 tweets) is split into the test and validation sets equally. Without applying any preprocessing to the data, a baseline model is developed for which the metrics are shown below in Table 6.2.

Table 6.2: Evaluation Metrics for the BERTurk Model without Preprocessing.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.60	0.67	0.63		91
Relevant	0.71	0.65	0.68		91
macro avg	0.66	0.66	0.66		
accuracy				0.66	

The baseline BERTurk model shows slightly better performance in classifying "Relevant" tweets related to immigration compared to "Irrelevant" tweets. The metrics indicate that the model is more effective at identifying relevant content, as seen in its higher precision, recall, and f1 score for the "Relevant" category. However, the differences between the scores for the two categories are not very large. Overall, the scores indicate a need for further optimization, either through better data balancing or enhanced training. As the next step, different experiments with various preprocessing steps are applied to the data to provide improvement, and the model is evaluated in each experiment.

Experiments

The experiments vary based on the preprocessing steps applied to the dataset.

- **Experiment 1**: All text has been converted to lowercase, and all punctuation, emojis, and irrelevant symbols (e.g. '@', 'http', '/n') are removed from the dataset.
- **Experiment 2:** Whether to keep stop words or not is another decision. In BERT models stopwords can provide meaningful information for some cases. Therefore, models should be tested for both scenarios to see if keeping stop words offers improvement. In this experiment in addition to steps in the first experiment, stop words are removed. The stopwords are Turkish stop words from nltk.corpus packages
- **Experiment 3:** Additionally to the preprocessing steps in the first two experiments, all the text in the dataset is normalized. Normalization is a process of converting words to their standard formats if they are spelled differently. For this purpose, the Zemberek library is used. Zemberek is a library that provides tools for natural language processing tools for the Turkish language.

In each experiment, the model is fine-tuned and its performance is evaluated. In Experiment 1 the model performed better than the baseline with 0.78 accuracy and 0.75 macro average f1 score.

In Experiment 2, stop words are removed and the model is evaluated to see whether there is a further improvement. With stop words removed from the dataset, the model's performance significantly improved with 0.90 accuracy and 0.89 macro average f1-score. The evaluation metrics are shown below in Table 6.3.

Table 6.3: Evaluation Metrics for the BERTurk with Preprocessing and Stop Words Removed.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.89	0.89	0.89		91
Relevant	0.91	0.91	0.91		91
macro avg	0.90	0.90	0.90		
accuracy				0.90	

In the final experiment, the normalization of text in the dataset did not offer further improvement with 0.80 accuracy and 0.80 macro average f1-score. The tools used for normalization in Turkish tweets did not provide consistent results. Applying normalization before and after stop words removed yielded different results. Even repeating the normalization on the same text data, when the tweets are checked randomly it is revealed that in each run, words are normalized differently. Overall, removing the noise in the data including removing emojis, punctuations, symbols, and stop words improved the BERT model's performance. On the other hand, the normalization of Turkish tweets did not provide improvement and consistent results across different runs.

Optimal Relevant-Irrelevant Ratio

After determining the optimal case, various ratios for the number of irrelevant to relevant tweets were used for better balancing. Given that the number of relevant tweets is fixed at 91, the number of irrelevant tweets was incrementally increased from a 1:1 ratio up to a 1:10 ratio, not exceeding a total of 1000 irrelevant tweets. In all, ten different scenarios concerning the ratios between relevant and irrelevant tweets were executed and evaluated, including the scenario with 1000 irrelevant tweets. The aim is to test the consistency of the model across different cases and to see if there is a better alternative to a 91-91 balance of tweets. As a result 1:6 ratio, (91 relevant – 637 irrelevant tweets) provided the best result which is shown in Table 6.4 below. Further increases in the number of irrelevant tweets did not provide any improvement and worsened the model's performance.

Table 6.4: Evaluation Metrics for the BerTURK Model with the Best Relevant-Irrelevant Ratio.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.97	1.00	0.98		637
Relevant	1.00	0.83	0.90		91
macro avg	0.98	0.91	0.94		
accuracy				0.97	

With this relevant-irrelevant ratio, the dataset can be considered as imbalanced. Therefore, rather than accuracy, the f-1 score should be taken into account. The best model provided a 0.94 macro average f-1 score. The f-1 score for relevant tweets is 0.90 with considerably high precision. The recall for relevant tweets is 0.83 meaning that the model can detect 83% of the relevant tweets.

6.2.4 Evaluation of TurkishBERTweet

The same processes are applied to the TurkishBERTweet and evaluation metrics are compared with those of the BERTurk model. The evaluation metrics for the baseline model with no preprocessing applied are shown below in Table 6.5.

Table 6.5: Evaluation Metrics for TurkishBERTweet without Preprocessing.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.72	0.72	0.72		91
Relevant	0.78	0.78	0.78		91
macro avg	0.75	0.75	0.75		
accuracy				0.76	

The baseline model of TurkishBERTweet yielded better results in all categories than that of the BerTURK model.

Experiments

All the experiments mentioned above for BERTurk are applied to this model, and its performance is evaluated to measure further improvements. As in the case with BERTurk, the best result is achieved in Experiment 2 which includes converting all the text to lowercase, removing emojis, punctuations, numbers, and irrelevant symbols, together with removing the stop words. The results are shown in Table 6.6.

Table 6.6: Evaluation Metrics for the TurkishBERTweet with Preprocessing and Stop Words Removed.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.82	0.78	0.80		91
Relevant	0.83	0.87	0.85		91
macro avg	0.83	0.82	0.83		
accuracy				0.83	

Although they provided the best performance in the same case, the metrics by BerTURK were far better at this point.

Optimal Relevant-Irrelevant Ratio

In the final stage of the model evaluation, various ratios between irrelevant and relevant tweets were tested, starting from a 1:1 ratio up to a 1:10 ratio, with the upper limit being 1000 irrelevant tweets. After evaluating ten different ratio scenarios, the best metrics were achieved with a 1:5 ratio, consisting of 91 relevant tweets and 546 irrelevant tweets, as shown in Table 6.7.

Table 6.7: Evaluation Metrics for the TurkishBERTweet with the Best Relevant-Irrelevant Ratio.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.98	0.99	0.99		546
Relevant	0.95	0.91	0.93		91
macro avg	0.97	0.95	0.96		
accuracy				0.98	

6.2.5 Selection of the Best Model

With 546 irrelevant tweets, the results suggest that TurkishBERTTweet provided better performance in macro average and both irrelevant and relevant f-1 scores compared to BERTurk. Although there is a reduction in the precision for relevant tweets, the recall is significantly higher with the model detecting 91% of the relevant tweets. Unlike BERTurk, although increasing the number of irrelevant tweets further did not provide improvements, it did not worsen the model's performance significantly either meaning that it provides more consistent performance across different ratios.

However, these scores should still be approached cautiously because of the very limited number of relevant tweets at hand. For a meaningful comparison, the tweets which are split into training, test, and validation sets are fixed to a number at the beginning. Regarding this, evaluating the models based on these specific sets can be misleading. Therefore, the model's performance should be validated with cross-validation.

5-Fold Stratified Cross-Validation

Cross-validation is a widely used technique in machine learning and statistics to assess the performance of a model by dividing the dataset into several folds and evaluating the model on each fold. It helps in understanding how well the model generalizes to an independent dataset (Kohavi, 1995; Sammut & Webb, 2011).

To validate the model with the best performance, a stratified 5-fold cross-validation is applied to TurkishBERTweet. Stratified cross-validation is used to keep the distribution of the categories in the training and test sets in each fold proportionate to the distribution in the actual dataset for representativeness especially in the case of imbalanced sets (Kohavi, 1995; Sammut & Webb, 2011). For cross-validation, the dataset is split into 80% training and 20% test sets in each fold. The results are shown below in Table 6.8.

Table 6.8: Results of 5-fold Stratified Cross-Validation for the Best TurkishBERTweet Model.

Folds	**Category**	**Precision**	**Recall**	**f-1**
	Irrelevant	0.99	0.98	0.99
1	Relevant	0.90	0.95	0.92
	macro avg	0.95	0.96	0.95
	Irrelevant	0.97	0.95	0.96
2	Relevant	0.75	0.83	0.79
	macro avg	0.86	0.89	0.88
	Irrelevant	0.95	0.99	0.97
3	Relevant	0.92	0.67	0.77
	macro avg	0.94	0.83	0.87
	Irrelevant	0.96	0.98	0.97
4	Relevant	0.88	0.78	0.82
	macro avg	0.92	0.88	0.90
	Irrelevant	0.99	0.97	0.98
5	Relevant	0.85	0.94	0.89
	macro avg	0.92	0.96	0.94
Average	**macro score**	0.92	0.90	0.91

Based on the results, the average f-1 macro score of 5 folds is 91%. On the other hand, the average f-1 score for the relevant class which is the main concern is reduced to 84%. Moreover, unlike the "irrelevant" category, the variation of metrics for the "relevant" category across the 5 folds is high which signals that the model's performance strictly depends on how the tweets are distributed into the train, test, and validation sets. In one of the folds, the f-1 score is 92% whereas in the other it is reduced to 77%. The results of cross-validation indicate a problem of generalizability for the model.

Evaluating Model Performance on an Independent Dataset

To evaluate the model further it is applied to an independent dataset of 15,000 randomly collected tweets from the Politus project and the predicted tweets are checked. The 301 tweets labeled as relevant by the model are read manually. As a result, only 43 tweets among the 301 were actually relevant which indicates the model's poor performance in terms of precision at least. When investigating the tweets that are incorrectly labeled "relevant" by the model, it is observed that it labeled the tweets regarding international conflicts between other countries. Additionally, the tweets regarding minority groups in Türkiye such as Kurds are labeled as relevant by the model. This indicates that our limited set of annotated tweets was not diverse enough and inadequate to provide a reliable context for the model. Therefore, the next step is to expand the annotated set.

6.3 Expanding the Annotated Set

To expand the annotated set to improve the model's performance, two approaches are adopted. The first approach is to predict more tweets in the independent random dataset using the model with the best performance again and manually annotating the tweets that are labeled "relevant" by the model. The second approach is to use an LLM model which is ChatGPT on the random set for annotation of tweets related to immigration.

6.3.1 Prediction with TurkishBERTweet

In addition to the first 15,000 tweets that are used to see how the model performs in real-world data, 45,000 more tweets are predicted using the model reaching a total of 60,000 tweets. These tweets are preprocessed and stopwords are removed but not normalized as it does not provide improvements.

Among 60,000 tweets, the model labeled 1263 tweets as “relevant”. These 1263 tweets are read manually and adjudicated by a single annotator. After this process, there are only 185 tweets that are actually related to immigration in Türkiye. The rest of the relevant tweets are labeled incorrectly by the model which indicates poor performance of precision which is around 15% for the relevant category (Table 6.9). As previously mentioned, this poor performance on the real-world data is probably due to the limited training set used in the fine-tuning process which fails to provide a diverse sample of tweets to represent the broad topic of migration.

Table 6.9: Random Tweets Classified by TurkishBERTweet.

Predicted Tweets	Irrelevant Tweets	Relevant Tweets	Relevant Tweets (True Positives)	Relevant Tweets (False Positives)	Precision (Relevant Category)
60,000	58,737	1263	185	1078	0.15

Since the aim is to increase the tweets related to immigration, the irrelevant tweets are not inspected. As a result, manually read 1078 irrelevant and 185 relevant tweets are included in the main dataset that is used to fine-tune the models.

6.3.2 Annotation with ChatGPT 3.5 Turbo

Annotation for text classification is among one of the wide range of use cases of LLMs. Therefore it became an area of interest for computational social science researchers. A study by Gilardi et al. (2023) showed that annotation with ChatGPT outperforms the crowdsourcing for annotation tasks although still behind the trained annotators.

In this part, only the tweets with the golden standard from the main dataset are used. The tweets gathered from the model prediction are only used as example tweets in the prompt but are not included in the evaluation of ChatGPT annotation. As a starting point, since Open AI costs API usage based on tokens a small set of tweets are used. 15 relevant and 15 irrelevant tweets with a simple prompt are used for ChatGPT annotation. The engine used for annotation is “GPT 3.5 turbo instruct”.

Initial Prompt

The first prompt specifically is *"Is the following tweet about immigration in Türkiye? “It can also be considered about immigration if it includes comments about the government's* *policies regarding immigration."* The first attempt resulted in around 76% accuracy for correctly annotated tweets.

Updated Prompt

After, inspecting the tweets that are incorrectly annotated, the prompt is updated with background information and example tweets in the second attempt, and annotation is repeated for the same set of tweets. This time the prompt specifically is "*Is the following tweet about immigration in Türkiye? It can also be considered about immigration if it includes comments about government's policies regarding immigration. In Türkiye, the most populated refugee groups are Syrians, Afghans, and Ukrainians. Do not consider tweets regarding emigration from Türkiye about immigration."Provide a simple 'Yes' or 'No' based on the content. Here are some example tweets: Relevant: 'bursada kafa keseceğim diyen onun bunun evladı suriyeli şerefsiz gözaltına alınmış onu gönderin kelle koltukta yaşasın birazda'. Irrelevant: 'ülkeri kuran yahudilerdir üller ailesi görüntüdür'.*" In the second attempt, the accuracy is improved to 87%.

Final Prompt

In the third attempt, the incorrectly labeled tweets are inspected again and the prompt is updated again. The new prompt is "*Classify the following tweet as 'relevant' or 'irrelevant' to discussions on immigration in Türkiye. Consider a tweet relevant if it directly mentions immigrant groups such as Syrians, Afghans, or Ukrainians, discusses the impacts of immigration policies, debates societal attitudes towards immigrants, or refers to Türkiye's international relations affecting immigration. Here are some example tweets: Relevant: 'bursada kafa keseceğim diyen onun bunun evladı suriyeli şerefsiz gözaltına alınmış onu gönderin kelle koltukta yaşasın birazda'. Irrelevant: 'ülkeri kuran yahudilerdir üller ailesi görüntüdür'. Pay special attention to keywords such as 'mülteci,' 'göçmen,' 'suriyeli,' 'afgan,' 'arap,' which are strong indicators of relevance to immigration. Based on the description and examples provided, classify the following tweet as either 'relevant' or 'irrelevant' to the topic of immigration in Türkiye:*". With the updated prompt the accuracy of the annotation reached 93% with only 2 relevant tweets annotated incorrectly.

As the next step, the number of tweets is increased incrementally and the performance of ChatGPT is evaluated in each step to balance the cost. The purpose is to detect if there is any significant reduction in accuracy in each step before working with a larger set, inspect the incorrect labels, and update the prompt accordingly. Since in these scenarios, a balanced set is used the accuracy is considered to evaluate the performance of the annotation. The model provided a consistent performance across different attempts which are shown below in Table 6.10.

Table 6.10 Accuracy Scores of ChatGPT Annotation on Balanced Sets of Tweets.

Relevant-Irrelevant number of tweets	**15-15**	**30-30**	**60-60**	**91-91**
accuracy	0.93	0.96	0.91	0.92

After the first process, the number of irrelevant tweets is increased incrementally to validate the annotation further with a more diverse set of tweets. At this stage, f-1 scores are used to evaluate the performance instead of accuracy, since the dataset is not balanced anymore. At first, the number of irrelevant tweets increased to 182 which provided an f-1 macro average score of 0.92. Then it is increased to the number of 273 irrelevant tweets that provided 0.94 f-1 macro average. The results are shown below in Table 6.11.

Table 6.11: Evaluation Metrics for ChatGPT Annotation.

category	**precision**	**recall**	**f-1**	**accuracy**	**number of tweets**
Irrelevant	0.96	0.98	0.97		273
Relevant	0.93	0.88	0.90		91
macro avg	0.95	0.93	**0.94**		
accuracy				0.95	

The scores provided by ChatGPT annotation are reliable enough to use in an independent random set of tweets. As the next step, with the same engine and prompt ChatGPT is used to annotate 20,000 randomly collected tweets. As in the predicted tweets with TurkishBERTweet, all the labeled "relevant" tweets by ChatGPT are read manually and adjudicated. Among the 20,000 tweets, ChatGPT labeled 448 tweets as "relevant". When these tweets are manually annotated, the number of tweets that are actually relevant is 68. As it was in the TurkishBERTTweet the precision for ChatGPT annotation is around 15% (Table 6.12).

Table 6.12: Random Tweets Annotated by ChatGPT 3.5 Turbo

Number of Predicted Tweets	Irrelevant Tweets	Relevant Tweets	Relevant Tweets (True Positives)	Relevant Tweets (False Positives)	Precision (Relevant Category)
20,000	19,552	448	68	380	0.15

Since the aim is to expand the relevant tweets in the main annotated set, the tweets labeled "irrelevant" by ChatGPT are not adjudicated and are not included in the main dataset. Only the irrelevant ones that are incorrectly labeled relevant by the model are included in the main dataset since they are manually read. In total 380 irrelevant and 68 relevant tweets are added to the dataset that is used to train the models in the first place.

The application of both ChatGPT and TurkishBERTweet on a real-world, randomly selected set of tweets did not match their performance on the original training sets. This reason is most likely the lack of diversity in the training set, which may not fully capture the broad topic of immigration. While both models performed similarly, ChatGPT was faster at processing and labeling tweets, making it more time-efficient. However, due to its token-based pricing, annotating a large volume of tweets with ChatGPT could be cost-prohibitive. In summary, ChatGPT offers a time advantage but at a potentially higher cost compared to using a BERT-based model.

As a result of the two approaches, the new data set consists of 345 relevant tweets in total which can be expected to provide a more diverse set of tweets related to immigration in Türkiye. The number of irrelevant tweets increased to 13,516 in total.

6.4 *Evaluation of the Models with the New Dataset*

6.4.1 TurkishBERTweet

Since it is the model with the better performance, at first the expanded annotated set is used to evaluate TurkishBERTweet to see if it performs better. Additionally, since it is the best scenario, all the tweets used are preprocessed and stopwords removed. The dataset is still imbalanced, therefore, together with 345 relevant tweets, 345 irrelevant tweets are included in the model as the starting point. 690 tweets in total are split into training, test, and validation sets based on a 60%-20%-20% split respectively. Since there are a considerably fair amount of relevant tweets, rather than putting a fixed count into the training, test, and validation set, the relevant tweets are distributed proportionately to each set using the "stratify" parameter of the train-test split method of the scikit learn library. The macro average f-1 score for the first run is 89% which indicates a better performance with the expanded annotated set (Table 6.13).

Table 6.13: Evaluation metrics for TurkishBERTweet with the Expanded Dataset with Balanced Categories.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.95	0.83	0.88		345
Relevant	0.85	0.96	0.90		345
macro avg	0.90	0.89	**0.89**		
accuracy				0.89	

As the next step, irrelevant tweets are incrementally increased, with different relevant-irrelevant ratios up to the 1:5 ratio each run is evaluated based on f-1 scores. The best score is yielded by the model with 345 relevant and 1035 irrelevant tweets (Table 6.14).

Table 6.14: Evaluation Metrics for TurkishBERTweet with the Best Relevant-Irrelevant Ratio.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.97	0.98	0.97		1035
Relevant	0.93	0.90	0.91		345
macro avg	0.95	0.94	**0.94**		
accuracy				0.96	

6.4.2 BERTurk (128k-cased)

With the new dataset, BERTurk is also evaluated. Although the model performs poorly with the balanced relevant-irrelevant set (Table 6.15), increasing the number of irrelevant tweets provided a significant improvement. With 1035 irrelevant and 345 relevant tweets, BERTurk outperformed the TurkishBERTweet (Table 6.16).

Table 6.15: Evaluation Metrics for BERTurk with the Expanded Data Set with Balanced Categories.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	1.00	0.03	0.06		345
Relevant	0.51	1.00	0.67		345
macro avg	0.75	0.51	**0.36**		
accuracy				0.51	

Table 6.16: Evaluation Metrics for BERTurk with Best Relevant-Irrelevant Ratio.

category	precision	recall	f-1	accuracy	number of tweets
Irrelevant	0.98	0.98	0.98		1035
Relevant	0.94	0.94	0.93		345
macro avg	0.96	0.95	**0.96**		
accuracy				0.97	

6.4.3 5-fold Stratified Cross-Validation

To validate the performance of BERTurk and TurkishBERTweet, stratified 5-fold cross-validation is applied to both models. The results are shown in Table 6.17 below.

Table 6.17: The Results of Stratified 5-Fold Cross-Validation for the Best Model.

5-Fold Cross Validation		**BERTweet Best Model**			**BERTurk Best Model**		
		Precision	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**
1	Irrelevant	0.98	0.98	0.98	0.97	0.97	0.97
	Relevant	0.93	0.94	0.94	0.91	0.90	0.91
	macro avg.	0.95	0.96	0.96	0.94	0.93	0.94
2	Irrelevant	0.98	0.97	0.97	0.98	0.96	0.97
	Relevant	0.91	0.93	0.92	0.88	0.93	0.90
	macro avg.	0.95	0.95	0.95	0.93	0.94	0.93
3	Irrelevant	0.99	0.97	0.97	0.98	0.99	0.98
	Relevant	0.88	0.97	0.92	0.96	0.94	0.95
	macro avg.	0.94	0.96	0.95	0.97	0.96	0.97
4	Irrelevant	0.95	0.98	0.96	0.97	0.99	0.98
	Relevant	0.94	0.84	0.89	0.97	0.91	0.94
	macro avg.	0.94	0.91	0.92	0.97	0.95	0.96
5	Irrelevant	0.98	0.98	0.98	0.99	0.98	0.98
	Relevant	0.93	0.94	0.94	0.94	0.96	0.95
	macro avg.	0.95	0.96	0.96	0.96	0.97	0.97
Average	**macro score**	**0.95**	**0.95**	**0.95**	**0.95**	**0.95**	**0.95**

The results of the cross-validation for both BERTurk and TurkishBERTweet are close to each other. The average f-1 macro scores of the 5 folds for both models are around 95% which suggests a reliable performance. Unlike before, the variation of metrics for the “relevant” and “irrelevant” categories across 5-folds is quite low which indicates a consistent performance

The results indicate that expanding relevant tweets provides improvement, consistency, and a more reliable evaluation of the models. With the lower number of relevant tweets at the beginning, the model’s performance may be strongly manipulated by how the tweets are distributed to training and test sets. Additionally, the low diversity among tweets may be misleading so the model can perform worse on an independent set. With the expanded dataset, both models are improved considerably. As the final decision, based on the metrics and the results of 5-fold cross-validation, since slightly better performance, the fine-tuned BERTurk with the best relevant-irrelevant ratio is used for the classification of tweets related to immigration on the whole dataset.

6.5 *Model Application*

The fine-tuned BERTurk model[5] with the best metrics is applied to the dataset consisting of 115,000 users with 53,459,427 tweets. The model labeled, **1,284,467** tweets from **89,827 users** as relevant to the topic "immigration". The next step is to apply stance detection to this relevant set of tweets.

[5] https://huggingface.co/AlkanCan/BERTurk-128k-cased-immigration

Chapter 7:
METHODOLOGY: STANCE DETECTION

Distribution of tweets based on stance towards immigration Stance detection is an NLP task that identifies the position expressed in a text towards a specific topic, distinguishing whether the stance is supportive, opposing, or neutral. Unlike sentiment analysis, which categorizes text based on emotional tone (positive, negative, neutral) regardless of the context, stance detection is topic-focused and context-specific (Augenstein et al., 2016; Mohammad et al., 2017). For instance, sentiment analysis might classify a tweet as having a negative sentiment, but stance detection would identify whether that negative sentiment is directed at a specific political policy, a public figure, or another topic. This distinction is crucial in tasks where understanding the viewpoint relative to a topic is essential, such as in political discourse or social media monitoring.

The target of the stance detection in this study is immigration in Türkiye together with immigrant groups present within the country and government policies that affect immigration.

7.1 Stance Annotation

All the relevant tweets at hand are annotated in terms of stance toward immigration. Tweets that include negative stances toward immigration, immigrant groups within Türkiye, and policies of the government that affect immigration are labeled as negative. The tweets that express support or positive thoughts such as empathy and mercy toward immigrants, are labeled positive. Tweets including criticism against the individuals who oppose immigration or immigrant groups are also labeled as positive. If a tweet does not indicate a clear stance toward immigration or immigrant groups, it is labeled as neutral. Irrelevant tweets are also included within the neutral category. The sample tweets are shown below in Table 7.1.

Table 7.1 Example Tweets for Stance Categories.

Tweet (Original)	English	Stance
kusura bakmada bundan yıl önce çocukken bende aynısını diyordum ben mülteci ülkeye gelen çocuklar büyüdü şimdi ülkede huzur bırakmadılar artık kadınına çocuğuna üzülmüyorum	Sorry, but a few years ago, used to say the same thing. The children who came to the country as refugees have grown up and now they have left no peace in the country. I no longer feel sorry for their women and children.	Negative
o kadar gocmen geldiki dogal artik siginmacilar seviyemizi düşurdü malum sahis yuzunden	So many immigrants have come that it's natural now. Refugees have lowered our standards because of that certain person.	Negative
hocam milyon afgan gelirse işçilik ucuzlar ülkeye bereket gelir	"If millions of Afghans come, labor will become cheaper, and the country will prosper."	Positive
suriyeden ülkemize gelmek zorunda kalmış insanlara karşı ırkçıayrımcı yabancı düşmanlarının bizi yönlendirmesine izin vermeyelim	Let's not allow racist, discriminatory xenophobes to influence us against people who have been forced to come to our country from Syria."	Positive
tam bir trolsün tam senin siyasi hayatında politikanda öyle ülkenin başına gelsen tane bile suriyeliyi gönderemeyecğini bile bile trollük yaparak oy toplamaya çalışıyorsun he utanma arlanma sende zaten kalmamış orası ayrı	You are a complete troll, just like your political career. You are trying to gather votes by trolling, even though you know you wouldn't be able to send a single Syrian if you were in charge of the country. Shame and decency are already long gone for you, that's a given."	Neutral
adamın sadece suriyeli problemi yok tamamen türk olmayan herşeyle problemi var	"He has a problem not only with Syrians but with everything that is not Turkish."	Neutral
ysk suriyeliler oy kullanamaz bakan soylu bin suriyeli oy kullanıcak kimin dediği belli değil	YSK says Syrians cannot vote. Minister Soylu claims a thousand Syrians will vote. It's unclear who is telling the truth.	Neutral

There are 224 negative, 87 neutral, and 34 positive tweets in the dataset after the annotation. The data is imbalanced and dominated by the majority of tweets including negative stances (Figure 7.1).

:

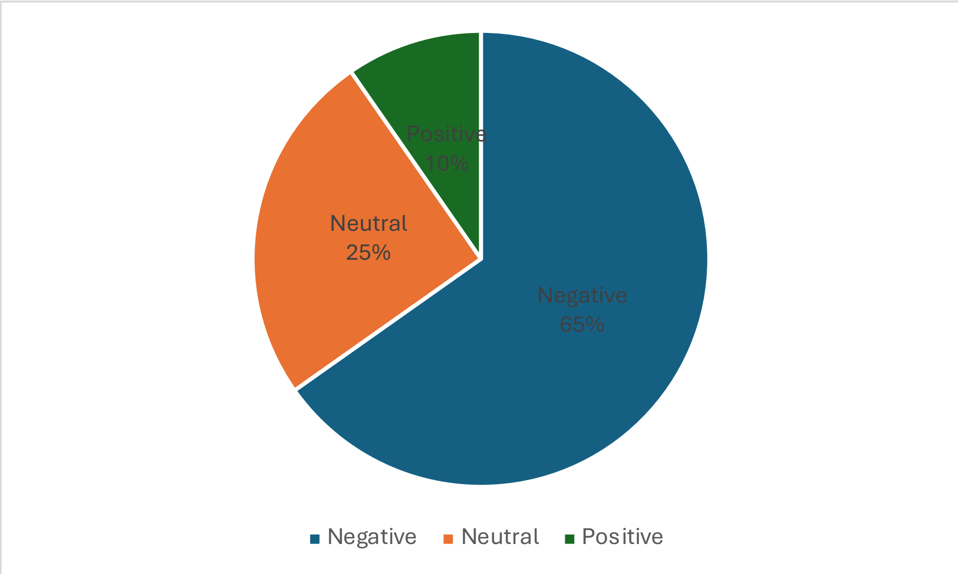


Figure 7.1: Distribution of Tweets Based by Stance Towards Immigration.

7.2 Evaluation of the Models for Stance Detection

With these numbers of negative, positive, and neutral tweets BERTurk and TurkishBERTweet are fine-tuned. Since the imbalanced set and the limited number of tweets belong to categories of neutral and positive the models performed poorly. Since the set is imbalanced, the number of tweets for each category is limited to the fewest which is 33. Fine-tuning the models with the balanced sets yielded poor results, as shown in Table 7.2 and Table 7.3.

Table 7.2 Evaluation Metrics of BERTurk For Stance Categories with a Balanced Set.

category	**precision**	**recall**	**f-1**	**accuracy**	**number of tweets**
Neutral	0.55	0.86	0.67		33
Positive	0.67	0.29.	0.40		33
Negative	0.33	0.33	0.33		33
macro avg	0.52	0.49	**0.52**		
Accuracy				0.50	

Table 7.3 Evaluation Metrics of TurkishBERTweet for Stance Categories with a Balanced Set.

category	precision	recall	f-1	accuracy	number of tweets
Neutral	0.54	1.00	0.7		33
Positive	0.57	0.57	0.57		33
Negative	0	0	0		33
macro avg	0.37	0.52	**0.42**		
Accuracy				0.55	

Although BERTurk provided a slightly better performance, both models yielded poor results. As the next step, the number of neutral and negative tweets is increased to 66. Increasing the number provided improvement in the negative category however, it worsened the metrics for the positive category since the imbalance which is shown in Table 7.4 and Table 7.5 below.

Table 7.4: Evaluation Metrics of BERTurk with the Increased Number of Neutral and Negative Categories.

category	precision	recall	f-1	accuracy	number of tweets
Neutral	0.78	0.50	0.61		66
Positive	0	0	0		33
Negative	0.44	0.85	0.58		66
macro avg	0.41	0.45	**0.40**		
Accuracy				0.53	

Table 7.5: Evaluation Metrics of Turkishbertweet with the Increased Number of Neutral and Negative Categories.

category	precision	recall	f-1	accuracy	number of tweets
Neutral	0.57	0.57	0.57		66
Positive	0	0	0		33
Negative	0.50	0.77	0.61		66
macro avg	0.36	0.45	**0.39**		
Accuracy				0.53	

The metrics for each category need to be improved. There is a considerably adequate number of negative tweets. Therefore, to expand the positive and neutral sets, ChatGPT is used for stance annotation as in the topic classification.

7.3 Expanding the Annotated Set with ChatGPT Stance Annotation

7.3.1 Model Selection

In this part, different ChatGPT models, GPT 3.5 Turbo, GPT 4o-mini, and GPT 4o, are used for stance annotation and their performances are compared to decide the most suitable model for this task

Initial Prompt

As the first approach, a simple prompt is used with the model " GPT 3.5 turbo instruct". The prompt specifically is "*Classify the stance of the following tweet related to immigration in Türkiye into one of three categories: positive, negative, or neutral.*
A tweet should be classified as:

- Positive if it shows empathy or sympathy towards immigrant or refugee groups in Türkiye, opposes racism and discrimination within the context of immigration, or discusses the advantages of immigrants and refugees or support the immigrants."

- Negative if it expresses opposition to immigration, criticizes immigrant or refugee groups, or criticizes the government's policies that lead to immigration, suggesting that these policies are problematic or harmful."

- Neutral if the tweet does not clearly express a negative or positive stance towards immigration, is merely informative, or unrelated to immigration issues in Türkiye."

Based on the descriptions provided, classify the following tweet as either 'positive,' 'negative,' or 'neutral' related to immigration in Türkiye:

With this prompt, 33 tweets from each category is annotated with GPT 3.5 turbo. The evaluation metrics for the three categories are shown below in Table 7.6.

Table 7.6: Evaluation Metrics of GPT 3.5 Turbo for Stance Categories with the First Prompt.

category	precision	recall	f-1	accuracy	number of tweets
Neutral	0.51	0.55	0.53		33
Positive	0.88	0.21	0.34		33
Negative	0.45	0.76	0.51		33
macro avg	0.61	0.51	**0.48**		
Accuracy				0.51	

Final Prompt

To improve the performance of the annotation, the prompt is updated with example tweets from the dataset. Providing an example tweet for each category did not improve the evaluation metrics for any category. After examining the tweets that ChatGPT annotated incorrectly, it is seen that it labels based on sentiments, not stance. If a tweet includes a negative sentiment but a positive stance, the model tends to label it as “negative” instead of “positive”. Therefore, the prompt is updated again explicitly stating the distinction between sentiment and stance, especially for positive and neutral categories. The final updated prompt is: “*Classify the stance of the following tweet related to immigration in Türkiye into one of three categories: positive, negative, or neutral. The tweets may include negative sentiment but express a positive stance toward immigrants. Label those as positive. Similarly can include negative or positive sentiment but does not express a clear stance toward immigration or immigrants, label those as neutral.A tweet should be classified as:*

- Positive if it shows empathy or sympathy towards immigrant or refugee groups in Türkiye, opposes racism and discrimination within the context of immigration, or discusses the advantages of immigrants and refugees or supports them.

Example: 'suriyeden ülkemize gelmek zorunda kalmış insanlara karşı ırkçı ayrımcı yabancı düşmanlarının bizi yönlendirmesine izin vermeyelim.'

Example: 'Hocam milyon Afgan gelirse işçilik ucuzlar ülkeye bereket gelir.’

- Negative if it expresses opposition to immigration, criticizes immigrant or refugee groups, or criticizes the government's policies that lead to immigration, suggesting that these policies are problematic or harmful.

Example: 'kusura bakmada bundan yıl önce çocukken bende aynısını diyordum ben mülteci ülkeye gelen çocuklar büyüdü şimdi ülkede huzur bırakmadılar artık kadınına çocuğuna üzülmüyorum.'

Example: 'O kadar göçmen geldi ki doğal artık sığınmacılar seviyemizi düşürdü malum şahıs yüzünden.'

- Neutral if the tweet does not clearly express a negative or positive stance towards immigration, is merely informative, or unrelated to immigration issues in Türkiye.

Example: 'ysk suriyeliler oy kullanamaz bakan soylu bin suriyeli oy kullanıcak kimin dediği belli değil.'

Example: 'Adamın sadece Suriyeli problemi yok tamamen Türk olmayan herşeyle problemi var.'

Based on the descriptions and examples provided, classify the following tweet as either 'positive,' 'negative,' or 'neutral' related to immigration in Türkiye:"

With the final prompt with expanded example tweets GPT 3.5 Turbo performed better. However, since it is a more complicated task than annotating tweets that are related to migration, alternatively, models GPT-4o-mini and GPT-4o are utilized and results are compared.

Table 7.7: Evaluation Metrics for the GPT Models.

	GPT-3.5-turbo			GPT-4o-mini			GPT-4o		
Category	**Precision**	**Recall**	**f-1**	**Precision**	**Recall**	**f-1**	**Precision**	**Recall**	**f-1**
Neutral	0.48	0.50	0.49	0.68	0.53	0.60	0.63	0.75	0.69
Positive	0.68	0.41	0.51	0.91	0.31	0.47	1.00	0.47	0.64
Negative	0.48	0.66	0.55	0.47	0.88	0.61	0.63	0.84	0.72
macro avg.	0.55	0.52	**0.52**	0.69	0.57	**0.56**	0.63	0.84	**0.68**
accuracy	0.52			0.57			0.69		

Based on the results, GPT-4o outperformed the other models. Although it is more costly than the other two models, due to its significant difference in performance GPT-4o is used for the stance annotation process.

7.3.2 Stance Annotation with GPT-4o

To provide a set of relevant tweets for annotation with GPT-4o, the BERTurk model developed for the topic classification is used to classify tweets from an independent random set of 1,000,000 tweets. To balance the cost of ChatGPT annotation, these tweets are predicted by the model and annotated by GPT-4o gradually until the stance models provide adequate performance. As a result, a total of 880,000 tweets are classified by the BERTurk model and 11,594 tweets are labeled as relevant. These relevant tweets are annotated by GPT-4o in terms of stance against immigration using the final prompt mentioned above. Since the priority is to expand the positive stance category, all the tweets that are labeled positive by GPT-4o are manually read and adjudicated. The negative and neutral categories are expanded proportionately to the total positive tweets at the end.

After the adjudication period, there are 222 positive tweets. For a 1:2:2 ratio in the training process, neutral and negative tweets labeled by GPT-4o are also adjudicated. As a result, in total, there are 444 negative and 444 neutral tweets to be used in the training process. With this amount of tweets in each stance category, models are evaluated for stance detection.

7.4 Model Selection for Stance Detection with the Expanded Dataset

With the expanded dataset with ChatGPT annotation, both BERTurk and TurkishBERTweet models are trained and evaluated. The dataset is split into training, test, and validation sets with 60%, 20%, and 20% distribution respectively. All the labels are distributed proportionately to train, test, and validation sets using the "stratify" parameter of the train_test_split function from the scikit-learn package.

Using 222 positive, 444 neutral, and 444 negative tweets, BERTurk is fine-tuned on training and test sets and then evaluated on the validation set. The results are shown below in Table 7.8.

Table 7.8: Evaluation Metrics of BERTurk for Stance Detection with the Expanded Dataset.

category	precision	recall	f-1	accuracy	number of tweets*
Neutral	0.45	0.40	0.43		444
Positive	0	0	0		222
Negative	0.45	0.73	0.56		444
macro avg	0.30	0.38	**0.33**		
Accuracy				0.45	

**total number of tweets used in train, test, and validation sets*

The performance metrics of the BERTurk model, as shown in Table 7.8, indicate moderate success in identifying neutral tweets, with a precision of 0.45, a recall of 0.40, and an F1-score of 0.43. It performs better with negative tweets, achieving a precision of 0.45, recall of 0.73, and F1-score of 0.56, suggesting a bias towards a negative stance. However, the model failed to predict any tweets within the positive category. Overall, BERTurk provided inadequate performance for stance detection even with the increased number of instances for each category.

Table 7.9: Evaluation metrics of TurkishBERTweet for stance detection with the expanded dataset.

category	precision	recall	f-1	accuracy	number of tweets
Neutral	0.71	0.81	0.75		444
Positive	0.76	0.49	0.59		222
Negative	0.74	0.76	0.75		444
macro avg	0.73	0.69	**0.70**		
Accuracy				0.73	

The performance of the TurkishBERTweet model shows significant improvement compared to the BERTurk model, particularly in the identification of neutral and positive tweets. For neutral tweets, the precision, recall, and F1-score are 0.71, 0.81, and 0.75, respectively, demonstrating a stronger ability to correctly identify neutral sentiments. Positive tweets are better recognized by TurkishBERTweet, with an F1-score of 0.59 compared to BERTurk's incapability to predict positive tweets, although recall is still low at 0.49. The negative tweet performance is also slightly improved, with a balanced precision, recall, and sf1-score of around 0.75. Overall, the TurkishBERTweet model achieves an accuracy of 0.73 and a macro average F1-score of 0.70, significantly outperforming BERTurk's accuracy of 0.45 and macro average F1-score of 0.33. This indicates that TurkishBERTweet handles the dataset more effectively across different stance categories.

7.4.1 5-fold Stratified Cross-Validation

To validate TurkishBERTweet for stance detection, a 5-fold stratified cross-validation is applied. Results are shown below in Table 7.10.

Table 7.10: Results of Stratified Cross Validation for TurkishBERTweet Stance Detection.

Folds	Category	Precision	Recall	f-1
1	Neutral	0.74	0.76	0.75
	Positive	0.65	0.44	0.53
	Negative	0.73	0.82	0.77
	macro avg	0.70	0.68	0.68
2	Neutral	0.72	0.76	0.74
	Positive	0.64	0.56	0.60
	Negative	0.72	0.73	0.72
	macro avg	0.69	0.68	0.69
3	Neutral	0.80	0.79	0.79
	Positive	0.81	0.66	0.73
	Negative	0.73	0.81	0.77
	macro avg	0.78	0.75	0.76
4	Neutral	0.83	0.75	0.79
	Positive	0.68	0.73	0.70
	Negative	0.77	0.81	0.79
	macro avg	0.76	0.76	0.76
5	Neutral	0.68	0.79	0.73
	Positive	0.70	0.36	0.48
	Negative	0.72	0.78	0.75
	macro avg	0.70	0.64	0.65
Average	**macro score**	0.73	0.70	0.71

The results of the stratified cross-validation for the TurkishBERTweet stance detection model show variability in performance across the three categories—neutral, positive, and negative. The neutral category consistently performed well, with relatively high precision, recall, and f1-scores across all folds. The positive category, however, displayed considerable inconsistency, with f1-scores varying significantly between folds, suggesting challenges in detecting positive stances. While more stable than the positive, the negative category still exhibited some variability, though it generally maintained better performance compared to the positive category. This indicates that while the model performs adequately in detecting neutral and negative stances, it struggles with positive stances, likely due to data imbalances or the subtlety of positive expressions in the dataset.

7.5 Model Application

The fine-tuned TurkishBERTweet model was applied to a dataset of 1,284,467 tweets from 89,827 users, categorizing each tweet based on its stance toward immigration. The distribution of tweets is shown below in Figure 7.2.

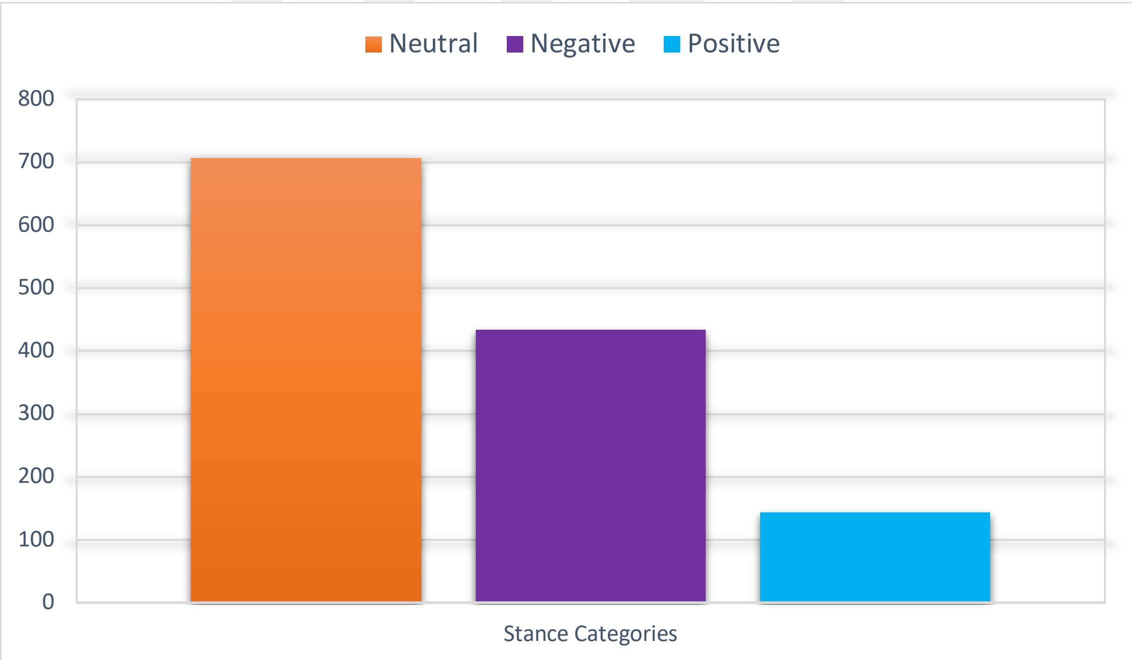


Figure 7.2: Stance Distribution within Immigration Tweets.

The results show that the majority of the tweets, **706,620** in total, were labeled as **neutral.** This suggests that most users express neither strong support nor opposition in their tweets about immigration.

In contrast, **434,286** tweets were identified as having a **negative** stance, indicating a significant portion of the conversation leans toward opposition to immigration. Finally, **143,552** tweets were classified as **positive**, reflecting a smaller but notable segment of users who express support for immigration.

These results illustrate the overall stance distribution within the dataset, highlighting that while there is a substantial amount of neutrality in the discourse, negative stances outnumber positive ones by a considerable margin. Despite its limitations especially for the detection of the “positive” category, the best option for stance detection is TurkishBERTweet which is fine-tuned with the specified conditions above.

Chapter 8:
ANALYSIS: DESCRIPTIVE STATISTICS

In the dataset, since a single user can post multiple tweets, the descriptive statistics for users and tweets are presented separately. This distinction is necessary because user-level statistics may differ from tweet-level statistics due to the varying number of tweets per user. Therefore, to provide a clear and accurate representation, the descriptive statistics are broken down into separate analyses for users and tweets.

8.1 Descriptive Statistics for Users

8.1.1 Gender Distribution

As indicated in Figure 8.1, in terms of gender distribution among users in the sampled dataset, the majority are male, accounting for approximately 83.5% (75,050 users), while female users represent about 16.5% (14,777 users).

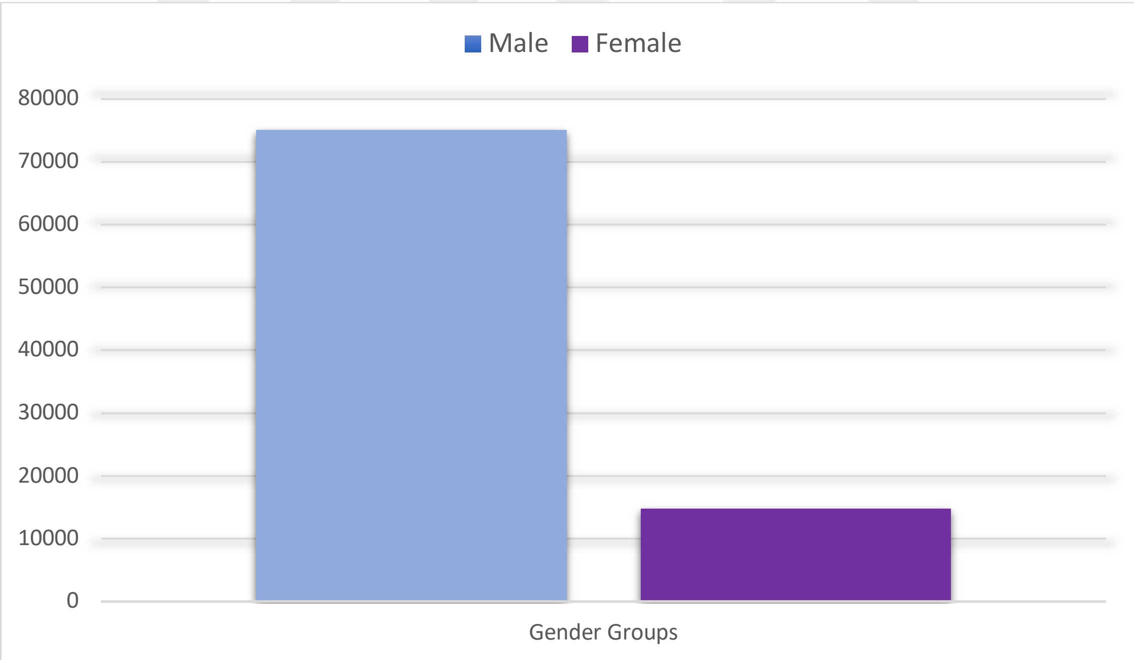


Figure 8.1: Distribution of the Users by Gender.

It's important to note that in the original dataset before sampling, male users made up about 82.7%, with female users representing 17.3%. This slight shift in the proportions suggests that the sampling process has marginally increased the representation of male users in the analysis.

8.1.2 Age Group Distribution

Figure 8.2 below shows that in terms of age distribution among users, the sampled dataset reveals that the largest age group is users aged 40 and above, comprising approximately 54.1% (48,606 users). This is followed by users aged 18 or younger, who make up about 18.5% (16,644 users). Users aged 30-39 represent 16.9% (15,191 users), while the 19-29 age group accounts for 10.4% (9,386 users).

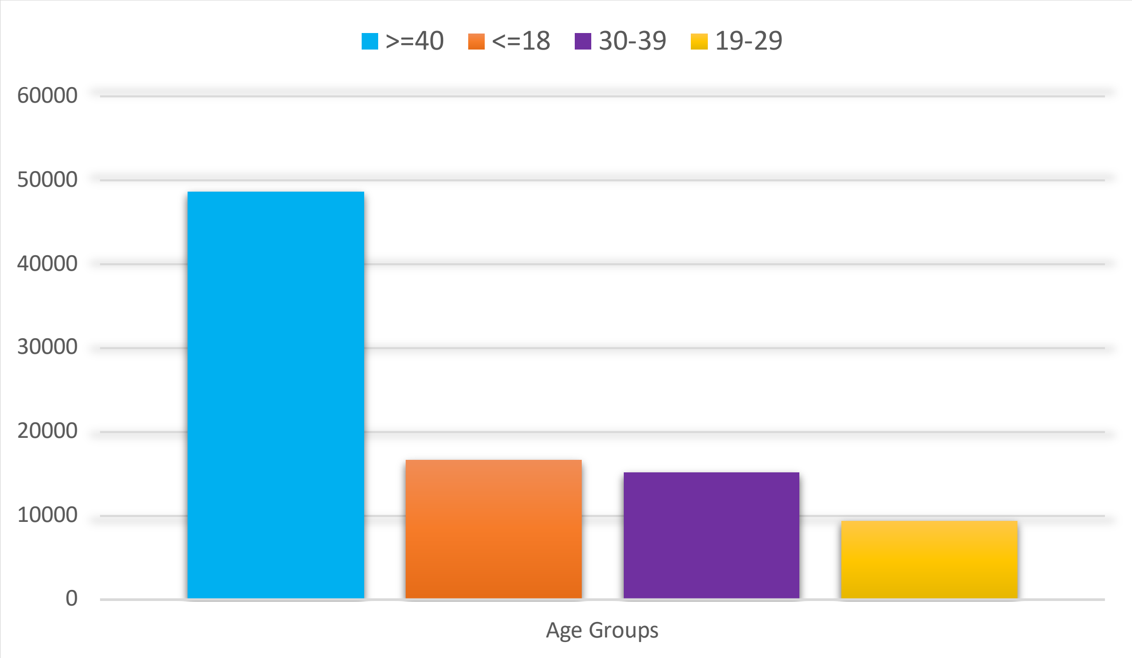


Figure 8.2: Distribution of the Users by Age Groups.

Comparing these figures to the original dataset, we see that the age distribution remains relatively consistent. In the original data, users aged 40 and above constituted 54.6%, followed by those 18 or younger at 18.0%, users aged 30-39 at 16.7%, and those aged 19-29 at 10.7%. This slight shift in proportions suggests that the sampling process has only marginally affected the distribution across age groups, maintaining a close alignment with the original data.

8.1.3 Location Distribution

In the dataset, approximately 53% (47,400) of the users have location information in the form of a province code. The province codes are assigned to users by Politus based on the 'location,' 'screen name,' and 'description' fields from their profiles. The corresponding province code is assigned if any of these fields contain relevant information regarding the user's province. Figure 8.3 shows the user distribution based on NUTS-3 level statistical provinces.

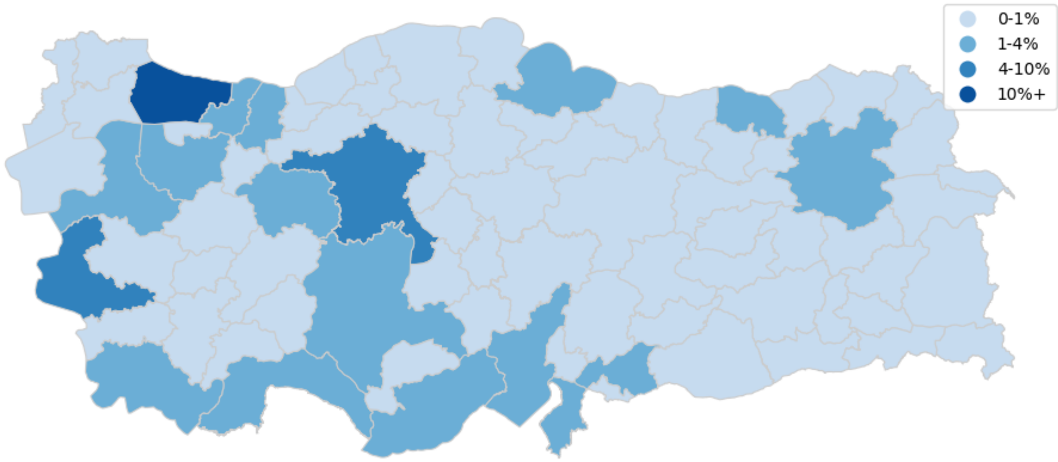


Figure 8.3: User Percentage Distribution Across Provinces.

Figure 8.3 reveals a clear concentration of users in certain key provinces. Istanbul is the most dominant contributor, with approximately 35% of users coming from this province alone, as indicated by the darkest blue shading. This is expected, given the city's large population and high level of online activity. Ankara and Izmir also show significant user representation, with 9% and 8% of the users, respectively, placing them in the 4-10% range on the map. These provinces are shaded in a darker blue, reflecting their importance as major urban centers in Türkiye. In contrast, most other provinces, especially in the eastern and less populated regions, contribute between 0-1% of users. These areas, represented by the lightest shades of blue, indicate a relatively low level of user activity. Overall, the distribution highlights the disproportionate concentration of users in Istanbul, Ankara, and Izmir, which together account for a significant portion of the total user base. These cities are also among the top four cities that host immigrants in Türkiye (Turkish Statistical Institute, 2023).

8.1.4 Ideology Distribution

Figure 8.4 illustrates the count of users categorized by the presence of each ideology among those who have posted tweets related to the immigration topic. Since each user can be associated with up to three different ideologies, a single user may be counted under multiple ideologies. As a result, the total number of users shown across all ideologies exceeds the actual number of users in the dataset. This is because the same user can be represented under multiple ideologies simultaneously.

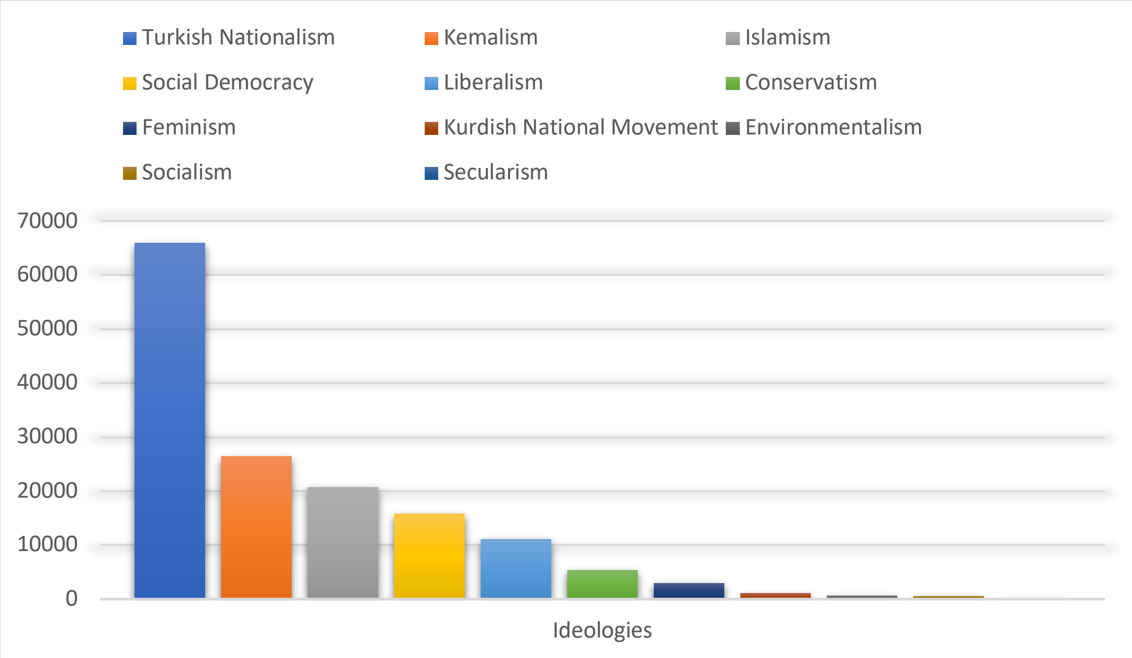


Figure 8.4: User Distribution by Ideology.

The user counts by ideology presence reveal that Turkish Nationalism is the most prevalent ideology among users discussing immigration, with 65,898 users associated with it. This is followed by Kemalism and Islamism, with 26,426 and 20,726 users, respectively. Social Democracy and Liberalism also have significant representation, with 15,840 and 11,112 users, respectively.

In contrast, ideologies such as Conservatism, Feminism, and Kurdish National Movement are less prevalent among users discussing immigration, with user counts ranging from 5,392 to 1,030. Environmentalism, Socialism, and Secularism are the least represented ideologies, each with fewer than 1,000 users.

This distribution indicates a strong dominance of Turkish Nationalism, Kemalism, and Islamism among users who are actively engaged in discussions about immigration within the dataset, while ideologies like Environmentalism, Socialism, and Secularism have relatively minimal user representation in this context.

8.2 Descriptive Statistics for Tweets

8.2.1 Gender Distribution

As illustrated in Figure 8.5 below, in terms of gender category, the majority of the tweets in the dataset are posted by male users, accounting for approximately 87% (1,121,694 tweets), while female users contribute around 13% (162,773 tweets).

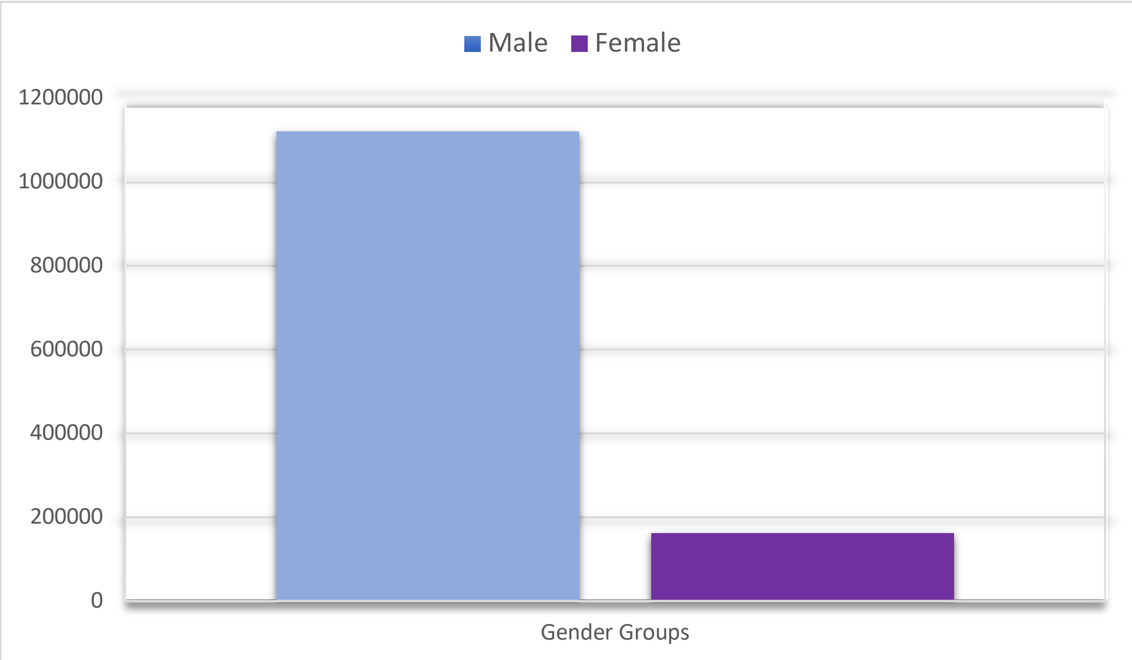
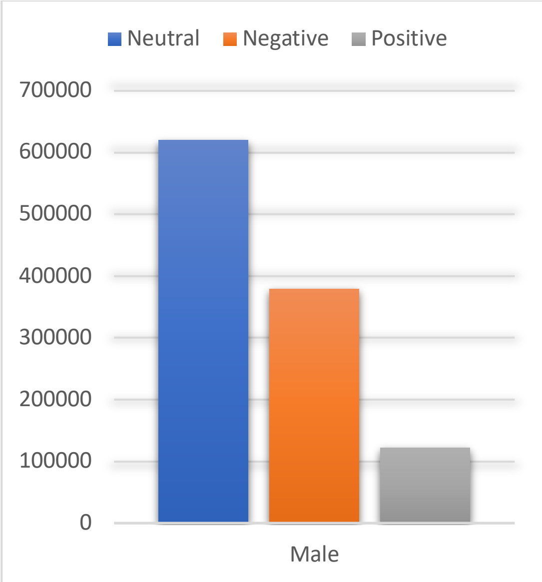


Figure 8.5: Tweet Count Distribution by Gender.

Figure 8.5 demonstrates that male users are significantly more active in discussions about immigration on Turkish social media, comprising approximately 87% of the total tweets (1,121,694 tweets), whereas female users contribute around 13% (162,773 tweets). This suggests that male users are far more engaged in this topic than female users.

Figure 8.6 indicates the distribution of tweet counts across stance categories by gender groups.



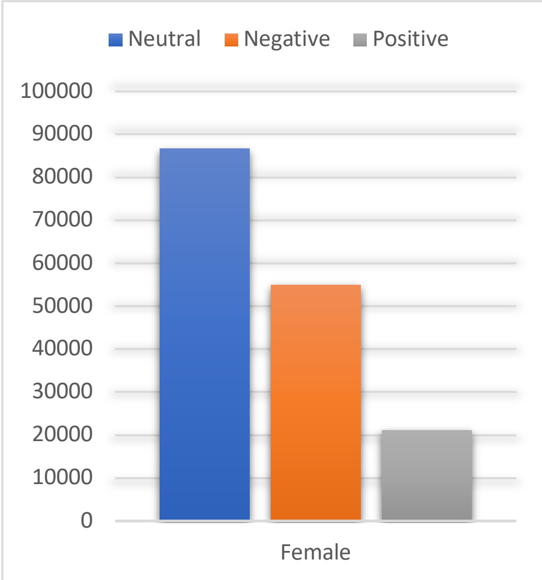


Figure 8.6: Distribution of Tweet Count Across Stance Categories by Gender.

Figure 8.6 shows the distribution of tweet counts across different stance categories by gender. The data indicates that in both gender groups, the majority of tweets related to immigration express a neutral stance, followed by negative tweets. The similarity in the proportion of stance categories between male and female users suggests that gender does not significantly influence the stance on immigration within this dataset.

However, the results of the Chi-square test challenge this initial observation. The test produced a chi-square statistic of 666.51 with 2 degrees of freedom and a p-value of 1.86e-145, which indicates a statistically significant association between gender and stance toward immigration. This suggests that despite the apparent similarity in the distribution of tweets by stance categories between males and females, gender does have a significant influence on users' stances toward immigration. The standardized residuals in the chi-square test shown in Table 8.1 highlight where the observed counts deviate significantly from the expected counts. “Expected counts” refer to the counts that would normally be expected if there were no relationship between gender and stance toward immigration.

Table 8.1: Standardized Residuals for Gender and Stance on Immigration.

Gender	Neutral Stance	Positive Stance	Negative Stance
Female	-9.67	20.10	-0.36
Male	1.03	-8.42	0.14

Based on the standardized residuals in Table 8.1, for female users, there is a strong tendency to take a positive stance on immigration, as shown by the large positive residual in this category. On the other hand, female users are less likely to remain neutral. Their stance on negative views shows little deviation from what would be expected.

For male users, there is a slight inclination toward a neutral stance, while they are less likely to take a positive stance. Like female users, their stance in the negative category closely matches expectations.

8.2.2 Age Group Distribution

In terms of age distribution, as shown in Figure 8.7, the majority of tweets are posted by users aged 40 and above, representing approximately 55% (699,265 tweets). This is followed by users aged 18 or younger, who account for about 20% (262,927 tweets). Users aged 30-39 contribute around 16% (206,088 tweets), while the 19-29 age group posts about 9% (116,187 tweets) of the total tweets.

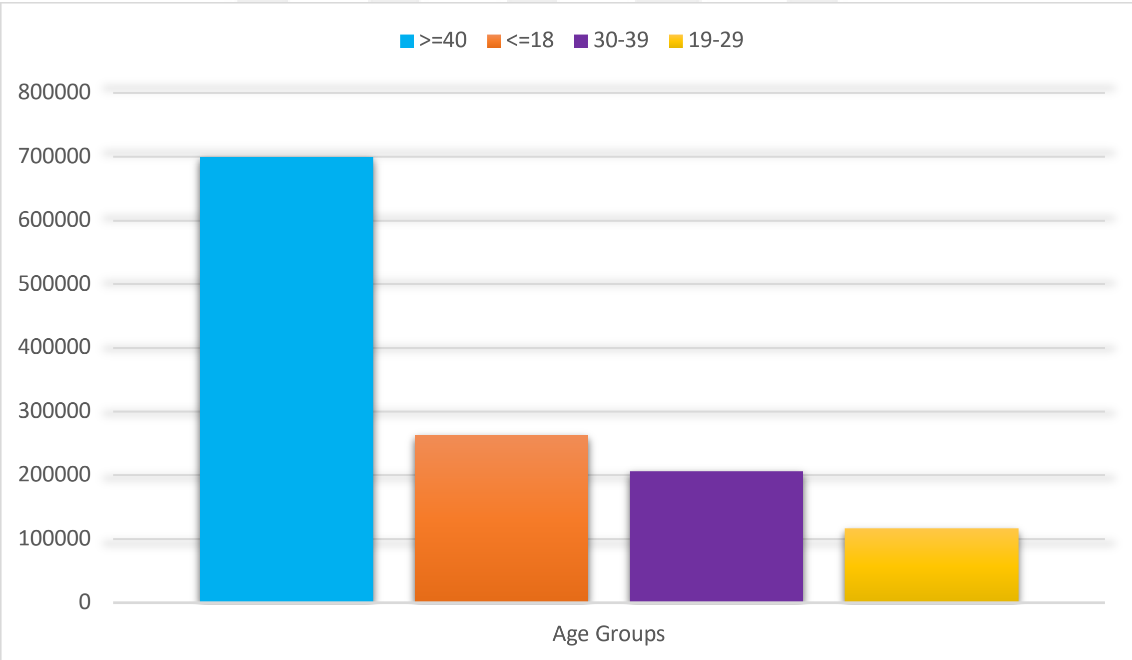


Figure 8.7: Tweet Count Distribution by Age Group.

Figure 8.8 below shows tweet count distribution across different stance categories by the four age groups.

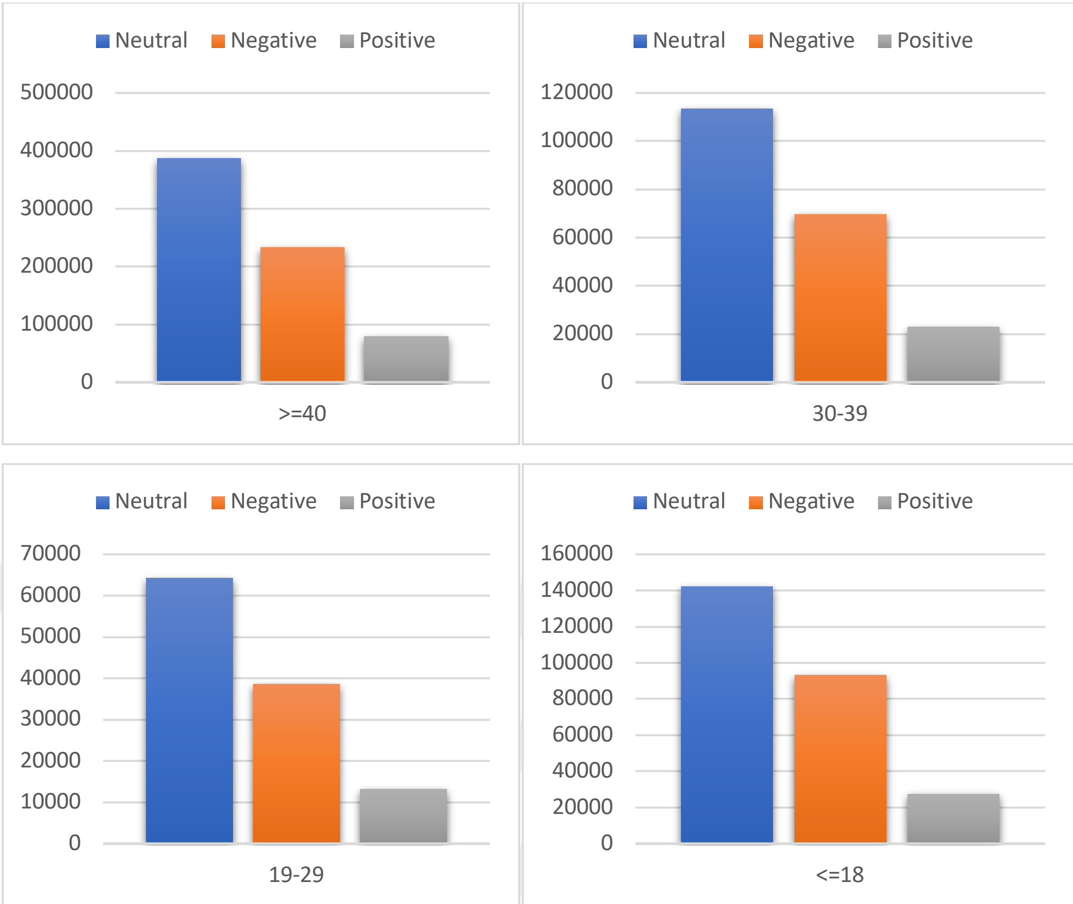


Figure 8.8: Tweet Count Distribution Across Stance Categories by Age Group.

Figure 8.8 provides a detailed breakdown of the tweet count distribution across stance categories by age group. It shows that neutral stances dominate the discussion on immigration across all age groups, with a particularly high proportion in the 40 and above age group (55.3%). Negative stances also consistently outweigh positive stances in every age group. The distribution proportions within each age group are similar, reflecting the overall distribution patterns observed in the entire dataset. This consistency suggests that age does not significantly alter the general tendency toward neutrality or negativity in the immigration discourse within this dataset.

However, the chi-square test results indicate that age group does have a statistically significant influence on the stance toward immigration. The chi-square statistic of 456.69 with 6 degrees of freedom and a p-value of 1.78e-95 shows that the relationship between age group and stance is highly significant. This means that, despite the seemingly similar proportions within each age group, the deviations between the observed tweet counts and the expected counts (if age group and stance were independent) are large enough to conclude that age group plays a significant role in determining stance. Table 8.2

highlights these differences, showing the deviations in observed values from expected values with standardized residuals in the chi-square test.

Table 8.2: Standardized Residuals for Age Groups and Stance on Immigration.

Age Group	Neutral Stance	Positive Stance	Negative Stance
19-29	1.01	1.02	-3.42
30-39	0.24	-0.91	0.22
≤18	-6.44	-10.08	14.01
≥40	1.03	1.05	-7.31

Table 8.2 suggests that younger users (≤18) are more likely to express negative views, while older users (≥40) tend to take neutral or positive stances. Overall, while the visual patterns appear consistent across age groups, the chi-square test reveals that these small differences are statistically significant, suggesting that age does influence the stance on immigration more than initially apparent.

8.2.3 Location Distribution

Figure 8.9 shows the percentage distribution of tweet counts based on NUTS-3 level statistical provinces.

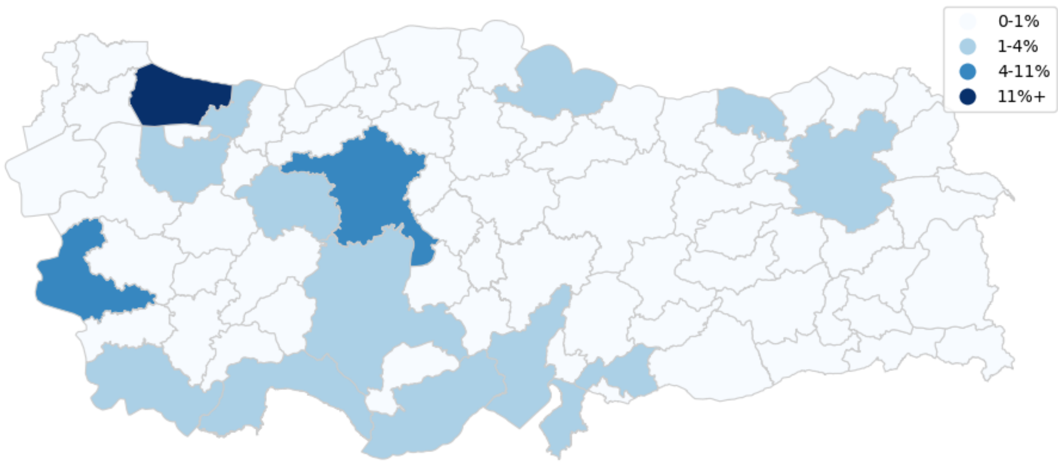


Figure 8.9: Tweet Count Percentage Distribution Across Provinces.

Figure 8.9 depicts the distribution of tweets related to immigration by province, with a significant concentration in Istanbul, which accounts for almost 40% of the total tweets. This highlights Istanbul as a focal point for online discussions around immigration. Izmir and Ankara follow, contributing 11% and 9 %, respectively. These three provinces collectively dominate the immigration discourse on social media. The map also shows much lower activity in other provinces, suggesting that discussions on immigration are highly concentrated in urban centers.

Figure 8.10 shows the percentage differences between positive and negative tweets across NUTS-3 level statistical provinces.

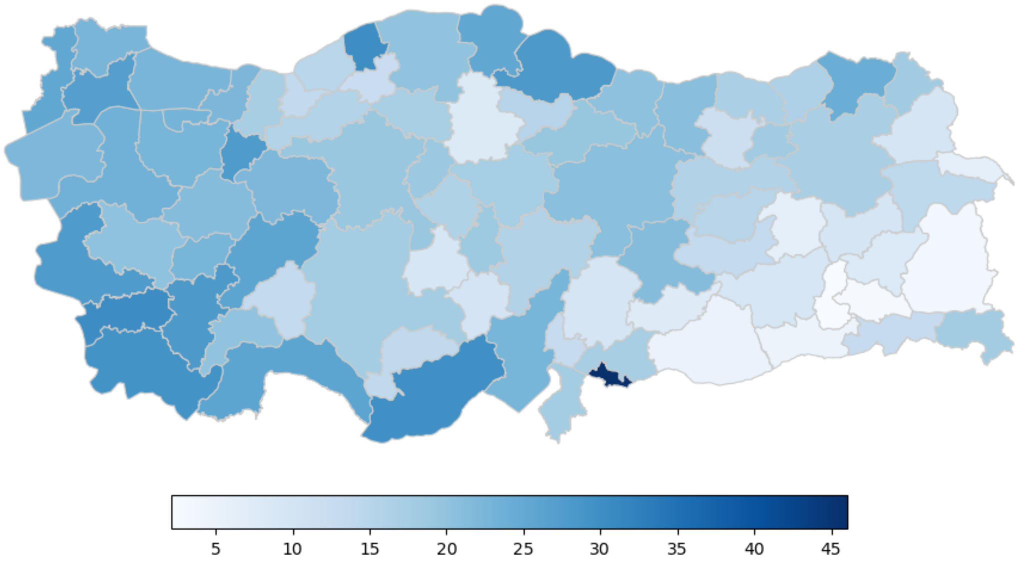


Figure 8.10: Percentage Difference between Negative and Positive Immigration-Related Tweets by Province.

Figure 8.10 visualizes the percentage difference between negative and positive immigration-related tweets across Turkish provinces. Provinces with higher values show a stronger dominance of negative sentiment over positive sentiment. Kilis stands out as a border city with the highest percentage difference (46.07%) in negative immigration-related tweets. This is significant given Kilis's unique demographic situation, where a large proportion of the population consists of Syrian refugees. According to data from the Presidency of Migration Management in Türkiye (2024), Kilis has the highest density of Syrians relative to its local population.

The map shows a significant rise in the percentage difference between negative and positive immigration-related tweets in several coastal provinces, particularly in the Aegean and Mediterranean regions. Coastal cities like Izmir, Muğla, and Antalya display increasing negative sentiment, with differences between 25% and 30%. Izmir and Antalya are among the four top cities which has the highest population of migrants (Turkish Statistical Institute, 2023).

8.2.4 Ideology Distribution

Figure 8.11 below illustrates the count of immigration-related tweets categorized by the users' associated ideologies. Since each user can be associated with up to three different ideologies, the same tweet may be counted under multiple ideologies. As a result, the total number of tweets shown across all ideologies exceeds the actual number of tweets in the dataset. This is because the same tweet can be represented under multiple ideologies simultaneously.

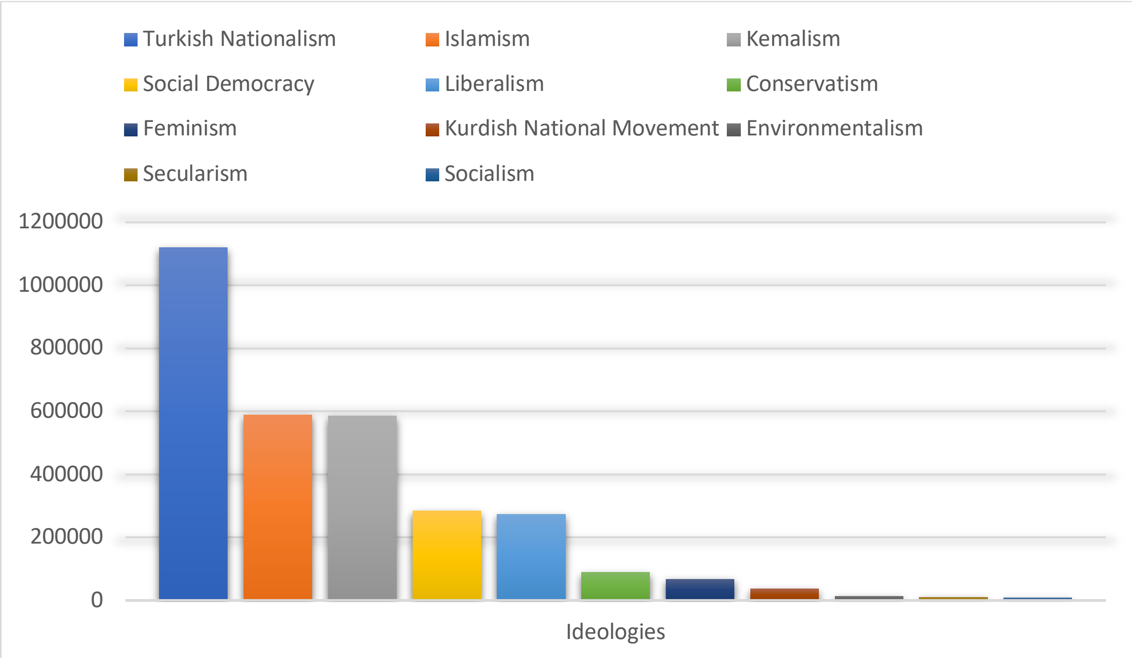


Figure 8.11: Tweet Count Distribution by Ideology.

The tweet counts by ideology presence reveal that Turkish Nationalism is the most prevalent ideology in the dataset, with over 1.1 million tweets sent by users associated with it on the topic of immigration. This is followed by Islamism and Kemalism, each with approximately 589,000 and 586,000 immigration-related tweets, respectively. Social Democracy and Liberalism also have significant representation, with around 284,000 and 273,000 tweets on immigration, respectively.

In contrast, ideologies such as Conservatism, Feminism, and the Kurdish National Movement are less prevalent in the immigration discussion, with tweet counts ranging from 89,000 to 37,000. Environmentalism, Secularism, and Socialism are the least represented ideologies in the context of immigration, each with fewer than 15,000 tweets.

This distribution indicates a strong dominance of Turkish Nationalism, Islamism, and Kemalism in the immigration discourse within the dataset, while ideologies like Environmentalism and Socialism have a relatively minimal presence in the discussion.

8.2.5 Tweet Count Distribution Over Time

Figure 8.12 below shows the distribution of tweets in the dataset over time.

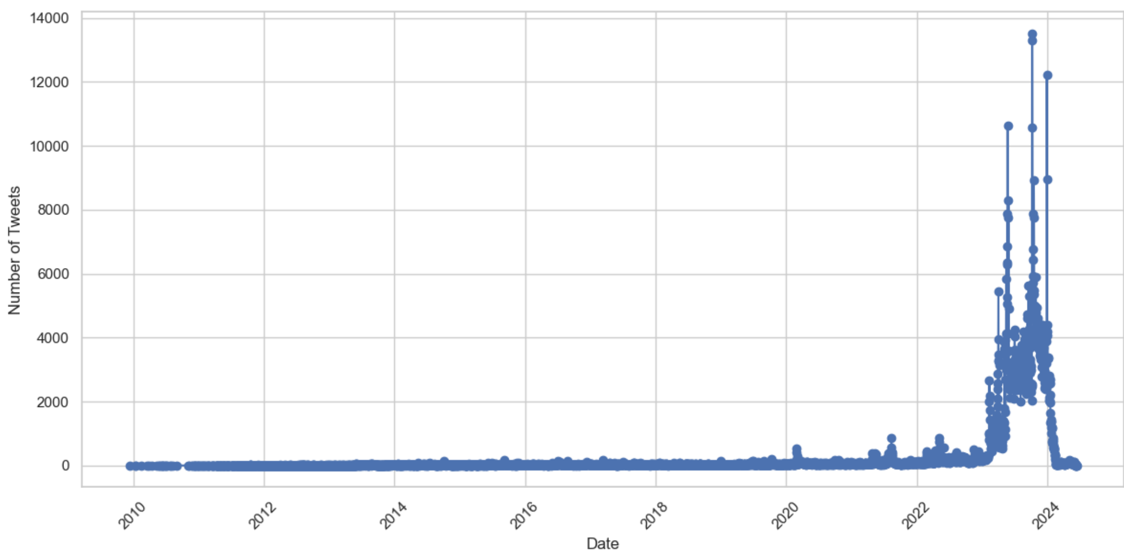


Figure 8.12: Tweet Count Distribution Over Time.

Figure 8.12 reveals that there has been a significant increase in tweet activity regarding immigration starting from around 2022 to the beginning of 2024. The num Before this period, tweet activity remained relatively low and consistent. The significant increase between 2023-2024 can be related to several reasons. 2023 is the year that the presidential election took place. It can be expected that immigrants are one of the main issues debated during electoral campaigns by the political parties. Taliban takeover of Afghanistan towards the end of 2021 and the Russian invasion of Ukraine in 2022 which are two main events causing refugee flows to Türkiye can be another reason that immigration became a hot topic between 2022 and 2024.

Below Figure 8.13 indicates tweet count distribution between 2022 and 2024 by positive and negative stances.

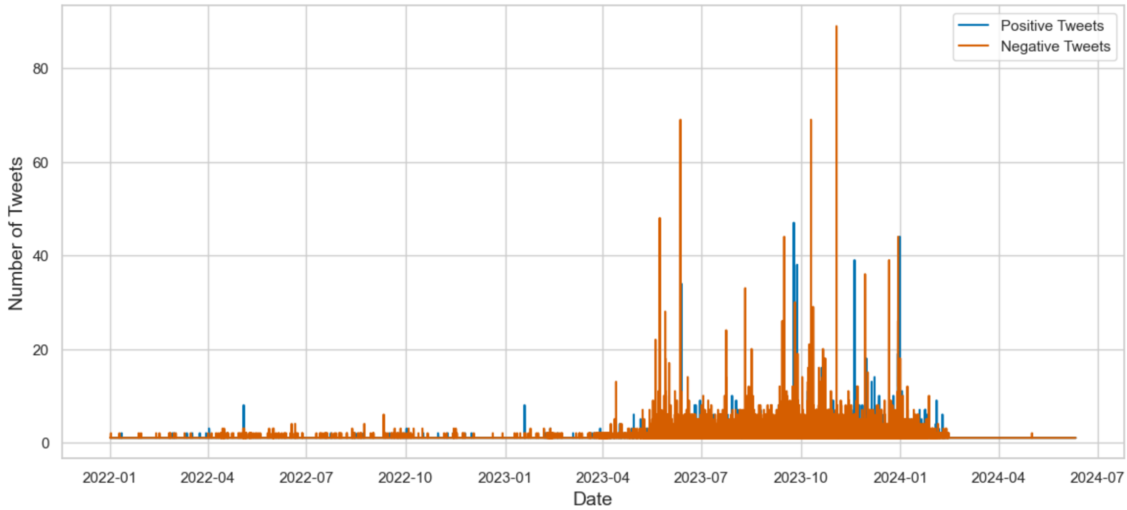


Figure 8.13: Tweet Count Distribution by Stance (starting from 2022).

As indicated in Figure 8.13, despite the peak of positive tweets during some periods, the immigration debate on Twitter is generally dominated by negative tweets.

8.2.6 *Topic Distribution*

In the dataset, there are two fields that reveal the topics discussed in tweets. One of them indicates whether the tweet is related to five main political issues those are "foreign affairs", "internal affairs", "economy", "corruption" and "national defense". The other field shows topics specifically related to welfare. These topics consist of "social policy", "labor and employment", "education", "health and public health", "disability" and "housing". The topics are not mutually exclusive meaning one tweet can be related to multiple topics.

Figure 8.14 below shows the topic distribution by five main political issues within tweets regarding immigration.

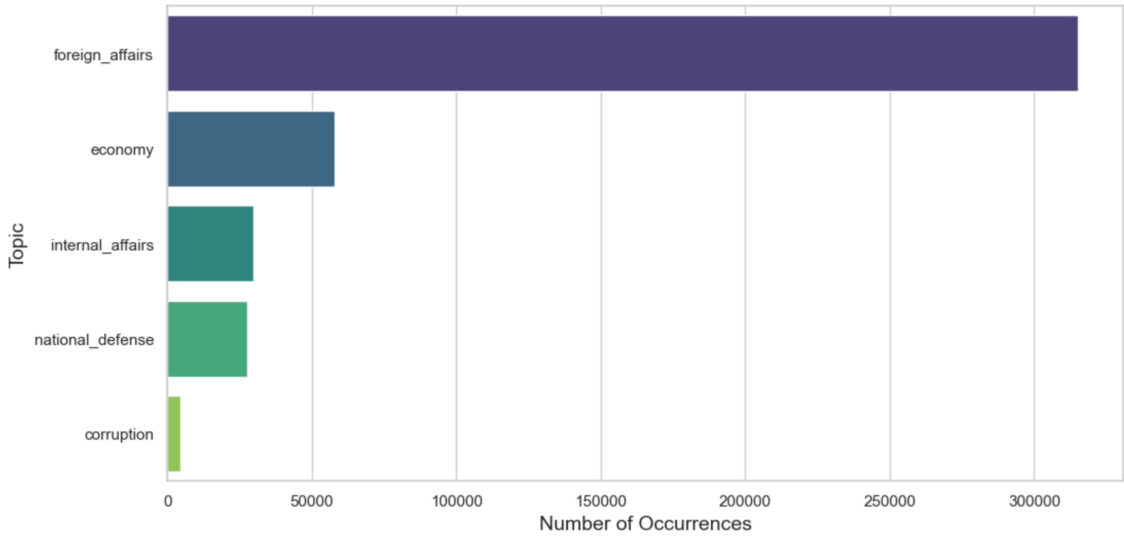


Figure 8.14: Topic Distribution within Immigration Debate by 5 Main Political Issues.

The figure illustrates that the immigration debate on Twitter is predominantly centered around foreign affairs, which is expected given the nature of the topic. The second most discussed issue is the economy, a significant concern regarding refugees in Türkiye. Internal affairs and national defense are equally represented in the tweets. The discussion of internal affairs, which includes topics like public security, maintaining order, and crime prevention, indicates a securitization of immigration in the public discourse. National defense encompasses national security and the involvement of the Turkish Armed Forces in conflicts, both within and beyond Türkiye's borders. Therefore, tweets related to national defense within the context of immigration can be related to conflicts near the Syrian border in which the Turkish Armed Forces are involved. Secondly, it can be related to the security of the Turkish borders through which refugees cross without control.

Figures 8.15 and 8.16 below show topic distribution specifically among positive and negative tweets.

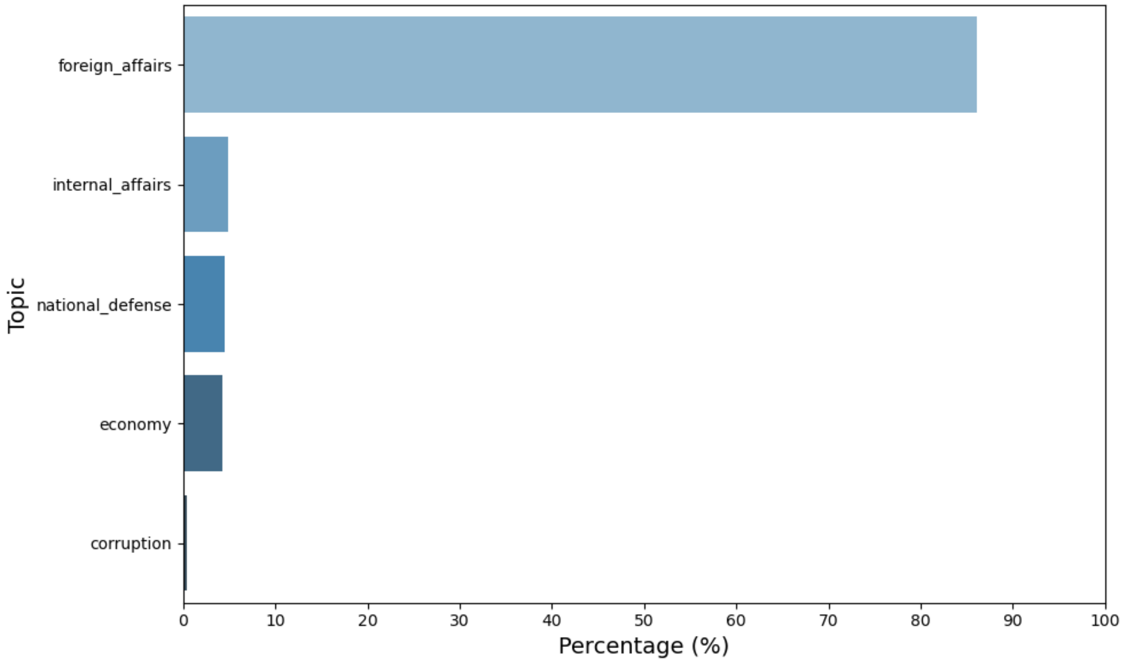


Figure 8.15: Topic Distribution among Positive Tweets by 5 Main Political Issues.

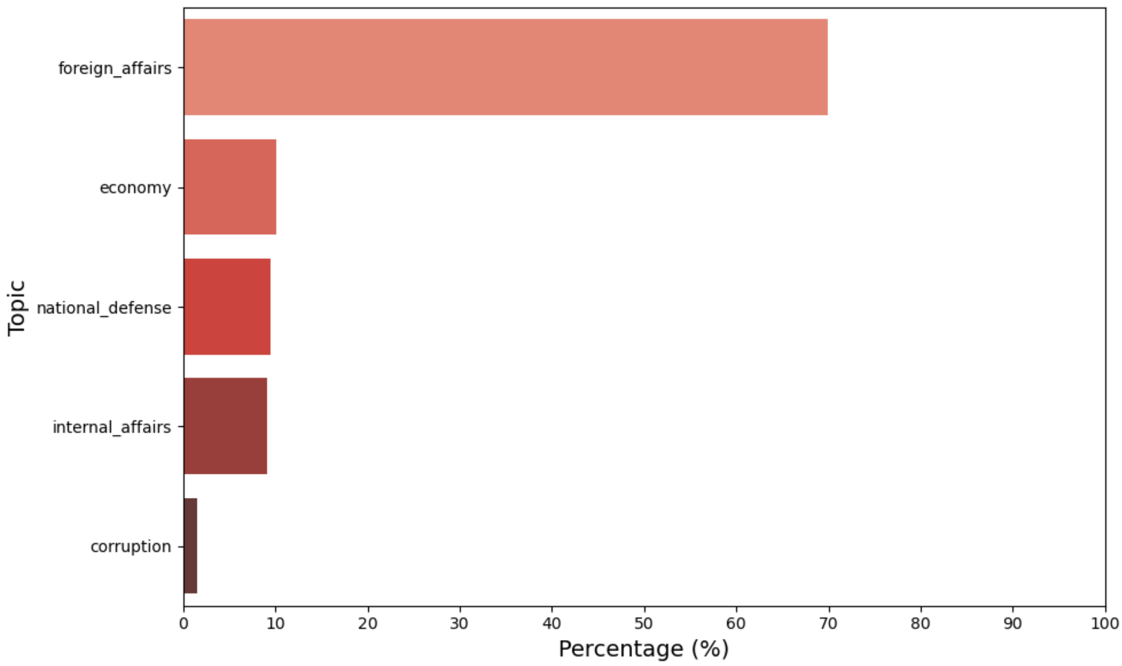


Figure 8.16: Topic Distribution among Positive Tweets by 5 Main Political Issues.

The comparison between Figures 8.15 and 8.16 highlights the differences in topic focus between positive and negative tweets related to immigration. Both stances prominently feature foreign affairs, which is expected due to the international nature of immigration. However, negative tweets are more widely distributed across topics like the economy, national defense, and internal affairs, indicating a connection between negative sentiment and concerns about the perceived realistic threats to the economy and security as ITT suggests (Stephan & Stephan, 2000). In contrast, positive tweets tend to remain more focused on foreign affairs, reflecting a diplomatic or international perspective.

For the welfare-related categories, the distribution of topics among tweets related to immigration is shown below in Figure 8.17.

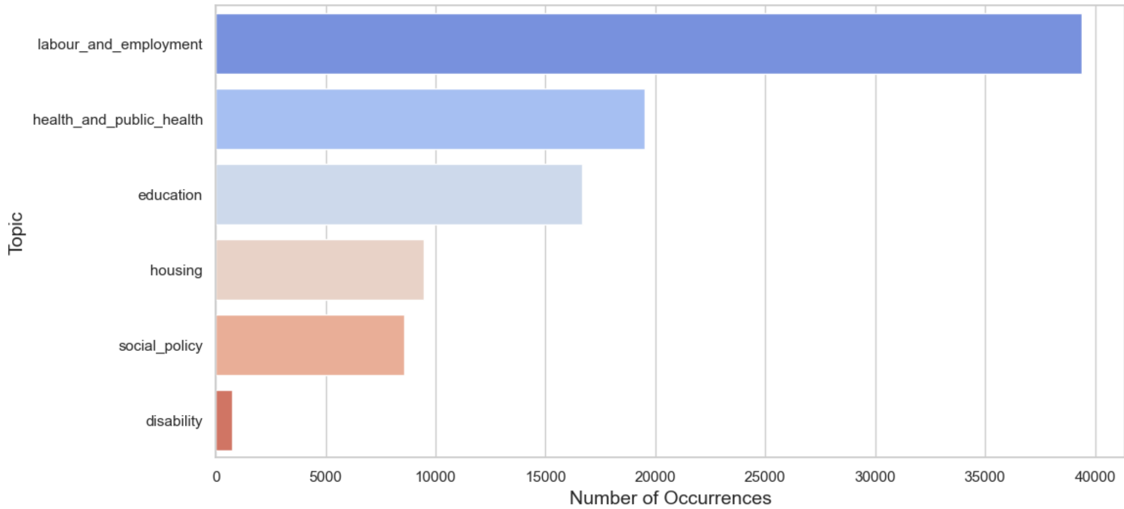


Figure 8.17: Welfare-Related Topic Distribution within the Immigration Debate.

Figure 8.17 illustrates the distribution of welfare-related topics within positive tweets regarding immigration. The most frequently discussed topic is "labor and employment," indicating that discussions around employment opportunities and labor market impacts are central to the immigration debate. "Health and public health" and "education" also appear prominently, reflecting concerns about the effects of immigration on public services and educational systems. Topics like "housing" and "social policy" are less frequently mentioned but still significant, suggesting that these areas are also relevant in the context of welfare discussions surrounding immigration.

Figures 8.18 and 8.19 show the distribution of topics related to welfare among positive and negative tweets.

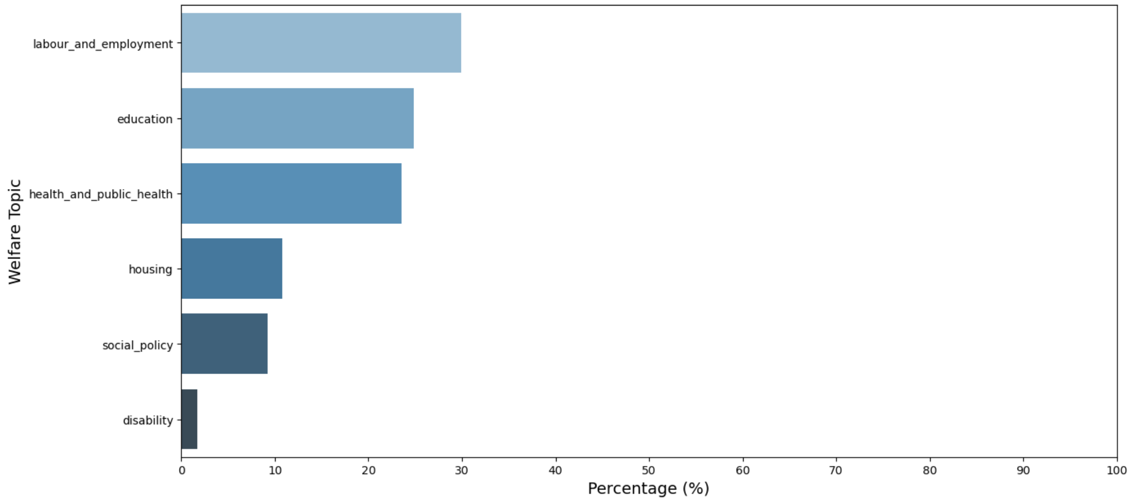


Figure 8.18: Welfare-Related Topic Distribution within Positive Tweets.

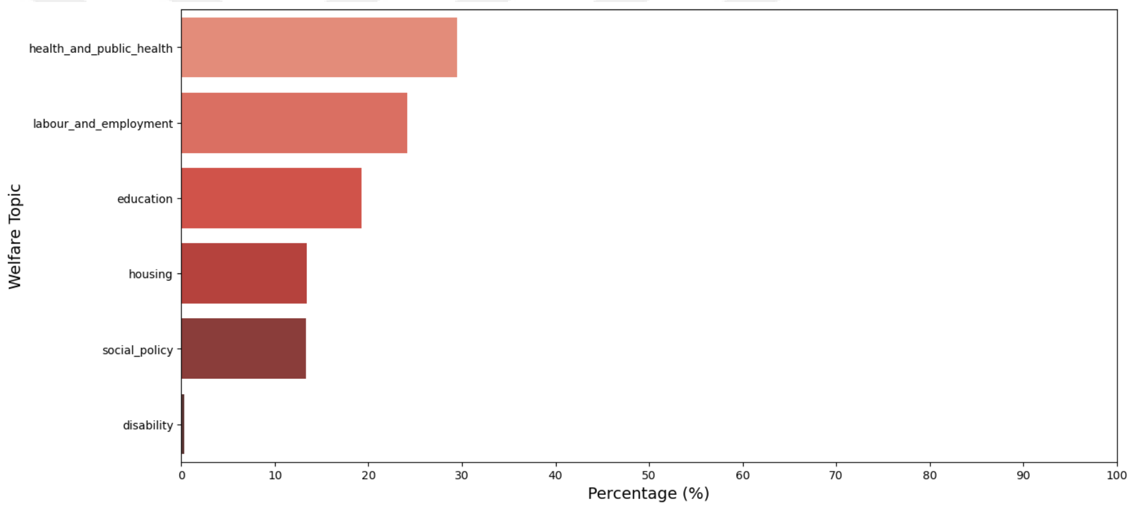


Figure 8.19: Welfare-Related Topic Distribution within Negative Tweets.

Among the positive tweets, the most discussed welfare-related topic is labor and employment which may reflect a recognition of the economic contributions immigrants can make, such as filling labor shortages or contributing to economic growth. It is also the second most discussed topic within negative tweets. Unlike the positive ones, this can be mostly related to fears about job competition, wage suppression, or the strain on job markets caused by immigration as part of realistic threats.

The overwhelming focus on health and public health in negative tweets likely stems from concerns about the burden immigrants might place on healthcare systems which is also an example of realistic threats of ITT. There could be fears of overcrowding, increased demand for services, or anxieties related to public health risks. On the other hand, positive mentions of health in the context of immigration might reflect public support for initiatives aimed at ensuring that refugees have access to necessary medical care and public health services.

The education topic with a significant portion in negative tweets can be related to the concerns about the quality of education, resource allocation, or cultural integration in schools. Positive mentions of education in this context may reflect approval of or advocacy for providing educational opportunities to refugees, including access to schools.

Housing among negative tweets can be reflecting fears of competition for housing resources, rising rents, or a shortage of affordable housing attributed to immigration. On the other hand, positive tweets can be related to support for providing access to refugees.

The negative tweets related to social policy can be linked to concerns about the cost of welfare programs, perceived exploitation of social services by immigrants, or discussions over policy priorities. The positive tweets regarding social policy likely express support for inclusive and supportive social policies aimed at assisting immigrants and refugees.

8.2.7 Emotion Distribution

In the dataset, all the emotions within tweets were pre-labeled by an emotion model. If a tweet does not contain any emotional indication the model left it empty. Around 25% of the tweets in the dataset do not express any emotion. In the figures below, it is shown as "no emotion". Figures 8.20 and 8.21 show emotion distribution within positive and negative tweets.

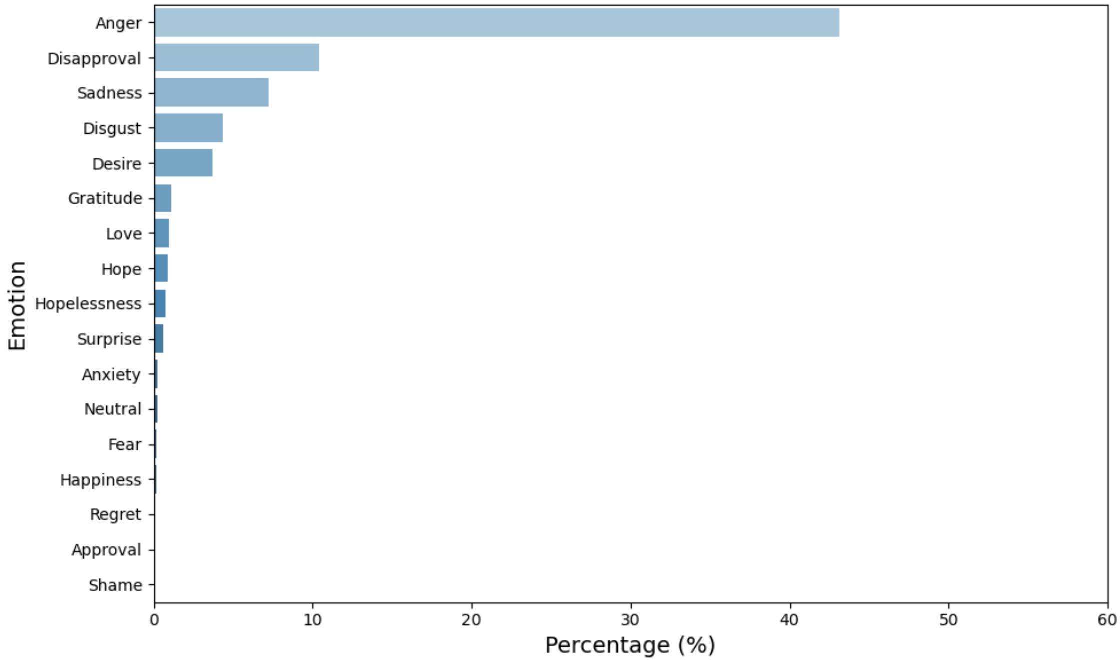


Figure 8.20 Emotion Distribution in Positive Tweets.

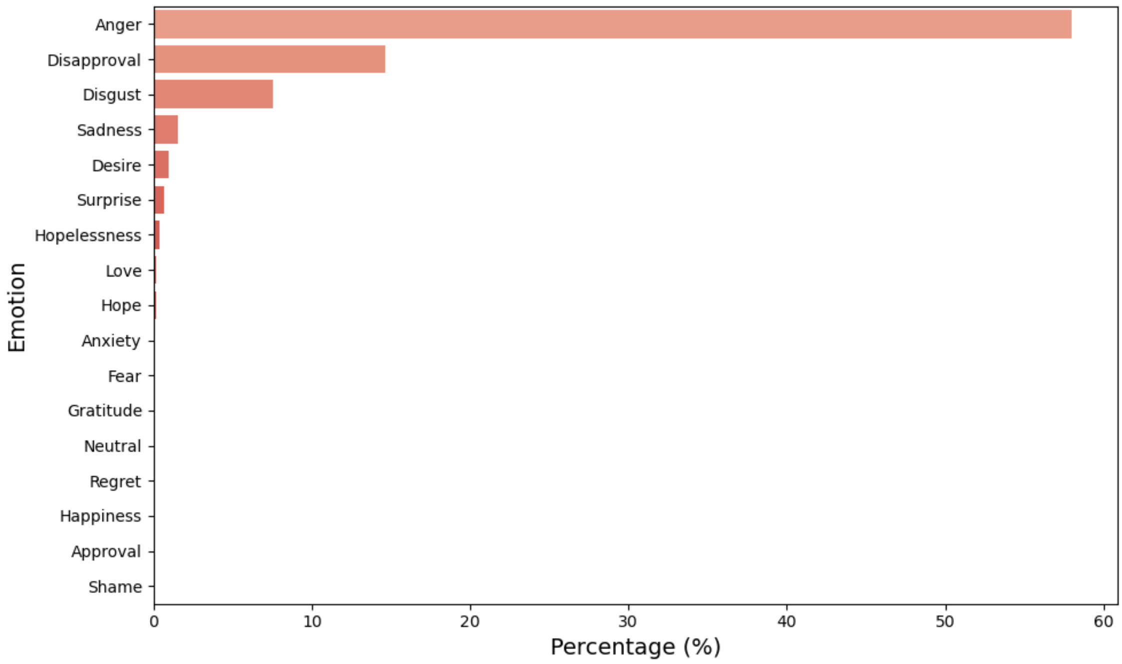


Figure 8.21 Emotion Distribution in Negative Tweets.

The figures indicate that anger is the most dominant emotion in both positive and negative tweets, but it is significantly more prevalent in negative tweets. This suggests that regardless of stance, immigration is a topic that elicits strong emotional responses, particularly anger. However, the motivations and targets of anger likely differ between those with positive and negative stances. In negative tweets, anger may be directed toward immigrants themselves, the government's policies allowing immigration to the country, or the perceived consequences of immigration itself. Conversely, in positive tweets, anger might be aimed at those opposing immigration or at governmental policies perceived as unjust or insufficiently supportive of immigrants. This underscores the complexity of emotions involved in the immigration debate, where the same emotion can stem from vastly different perspectives and motivations.

Disapproval and sadness are the next most frequent emotions in positive tweets, which might seem counterintuitive. However, this could indicate that even those with a generally positive stance might express dissatisfaction over certain aspects of immigration. Sadness might indicate empathy towards the challenges faced by immigrants, while disapproval could be directed at perceived shortcomings in how immigration is handled, either by governments or by those opposed to immigration. Positive emotions like gratitude, love, and hope do appear but are less frequent, suggesting that positive stances may not always be accompanied by traditionally positive emotions. This reinforces the idea that stance detection is more nuanced than sentiment analysis, as it involves understanding a person's position or attitude toward a topic, which can be complex and multifaceted, often involving a mix of emotions that are not strictly positive or negative.

Disapproval and Disgust are also prominent in negative tweets, which aligns with the expectation that those opposed to immigration would express strong discontent and revulsion.

Chapter 9:
DESCRIPTIVE STATISTICS: IDEOLOGY AND ANTI-IMMIGRANT STANCE

In this chapter, the stance distribution against immigration based on ideologies is analyzed. The tweet-level and user-level analysis is conducted separately.

9.1 Tweet-Level Analysis

The first part of the analysis focuses on the distribution of stances within tweets categorized by different ideologies. By examining the stance that each tweet expresses, it can be identified which ideologies are more likely to support or oppose immigration in Türkiye.

Figure 9.1 shows the distribution of tweet counts across positive and negative stance categories, broken down by ideology presence within users. It is based on all the ideologies assigned to a user causing a tweet to be counted under multiple ideologies.

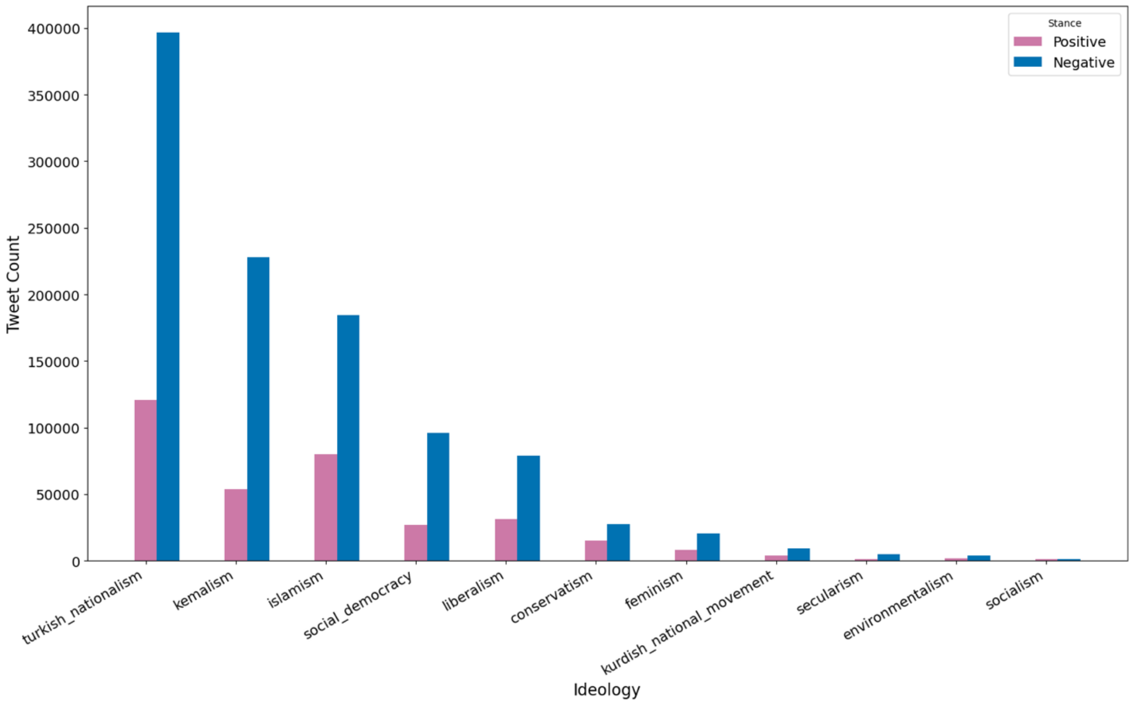


Figure 9.1: Tweet Count Distribution for Positive and Negative Stances by Ideology.

The figure reveals that immigration-related discourse is dominated by negative stances across most ideologies, with Turkish Nationalism in the leading position with the highest tweet count. Positive stances are present but are significantly outnumbered by negative stances, especially within the most active ideologies. This suggests a prevailing stance of opposition to immigration among users associated with these ideologies.

For a consistent comparison within ideologies, especially for the ones with a limited number of tweets, Figure 9.2 shows the percentage distribution of positive and negative tweets, within the total amount of tweets associated. Percentages of neutral tweets are not shown for clear visualization of the distribution of polarized tweets.

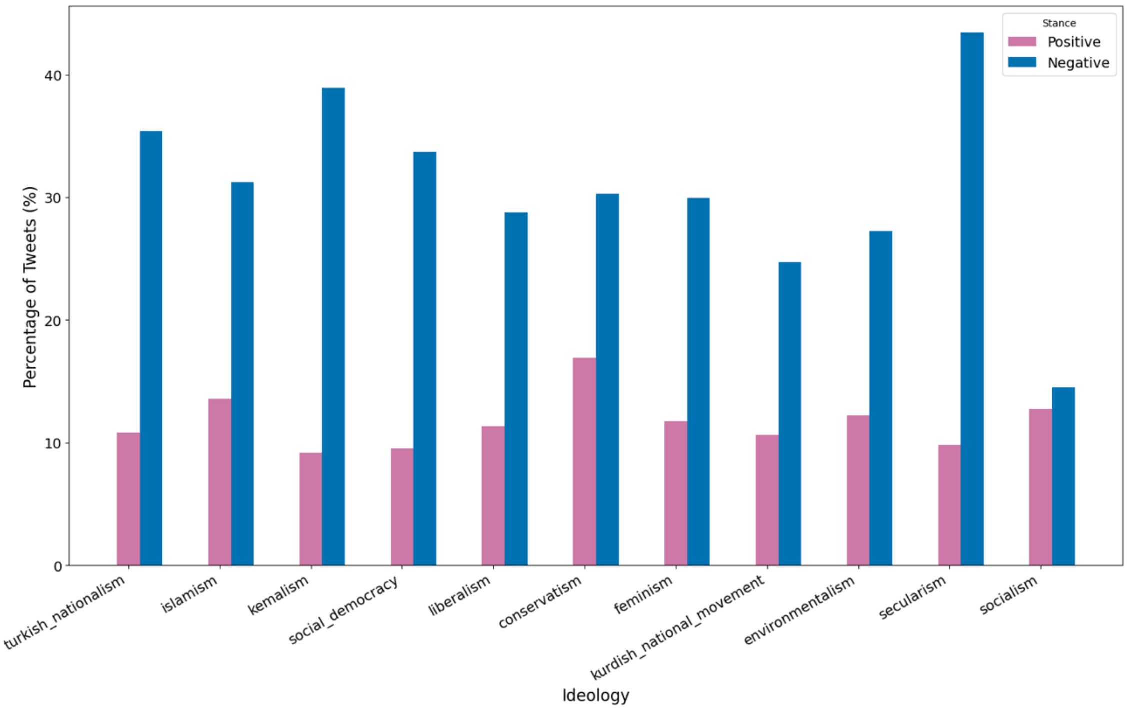


Figure 9.2: Percentage Distribution of Positive and Negative Stances by Ideology.

The figure reveals that within most ideologies, there is a predominant negative stance towards immigration. Turkish Nationalism, Kemalism, Secularism, and Social Democracy exhibit particularly strong opposition, with around 80% of tweets expressing a negative stance. Positive tweets within these ideologies are significantly fewer, making up less than 20% of the total, indicating a general resistance to immigration for users who have at least one of these ideologies assigned among the three ideologies they represent.

Islamism on the other hand, although with the majority of negative tweets, provides a more balanced view than the other four ideologies with around 30% of positive tweets.

Keeping in mind that with the limited number of tweets, ideologies such as Liberalism, the Kurdish National Movement, Feminism, and Environmentalism show a more balanced distribution, though negative tweets still outweigh positive ones. Approximately 30% of tweets in these ideologies are positive, suggesting that while opposition to immigration is common, there is also a notable proportion of support.

Conservatism, on the other hand, presents a more balanced approach compared to these ideologies, with around 60-70% of tweets being negative and 30-40% positive. This distribution indicates that while opposition to immigration is still prevalent among users associated with Conservatism as one of their ideologies, there is a significant proportion who express a positive stance, making this ideology more evenly split compared to others.

In contrast, Socialism, though with a limited number of tweets, presents the most balanced or even favorable stances towards immigration, with positive tweets comprising nearly 50% of the total in the case of Socialism. This suggests that users associated with these ideologies are more open or supportive of immigration compared to others.

Overall, the figure underscores the diversity of opinions on immigration across different ideological groups, with most leaning towards the opposition, but some, like Socialism and Conservatism showing a more balanced view.

To explore the relationship between different ideological positions and stances on immigration further, the differences in proportions of neutral, positive and negative immigration stances among various ideologies are analyzed. The results are summarized in Figure 9.3, which visualizes the deviation from the average stance on immigration for each ideology.

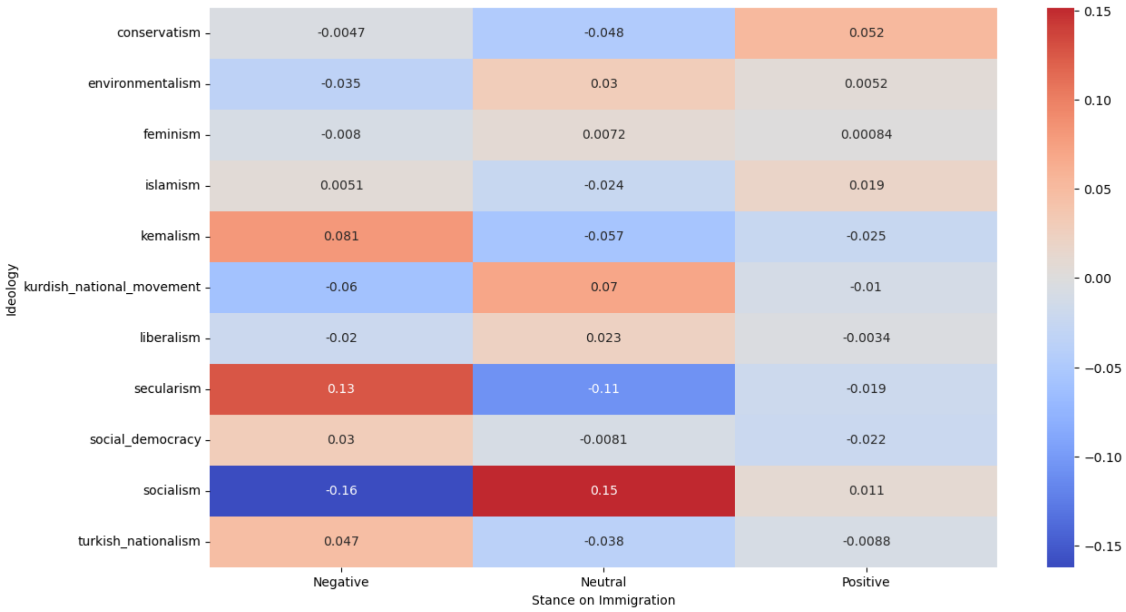


Figure 9.3: Difference in Proportions of Immigration Stances by Ideology Presence (Compared to Average).

Figure 9.3 highlights that Secularism and Kemalism exhibit the most significant deviations from the average stance on immigration, particularly in the negative stance category. These ideologies are more strongly associated with opposition to immigration compared to the average, indicating a higher likelihood of negative views.

Turkish Nationalism also shows a tendency toward opposing immigration, with a positive deviation in negative stances and a slight negative deviation in positive stances. Although Turkish Nationalism demonstrates high negativity towards immigration in terms of internal percentages, its stance does not deviate much from the average when compared to other ideologies.

Conversely, Conservatism displays a more supportive outlook, showing a positive deviation from the average in the positive stance category and a slight negative deviation in the negative category.

Socialism exhibits a strong positive deviation in the neutral category, suggesting a greater likelihood of adopting a neutral stance. However, its significant negative deviation in the negative category implies that Socialism is more inclined to support immigration.

Islamism presents a more complex pattern. While it shows a slight positive deviation in the negative stance, it leans more towards a positive stance. This suggests that Islamism is somewhat more supportive of immigration than the average, though not as polarized as Secularism or Kemalism.

The remaining ideologies do not show significant deviations in the positive and negative stance categories and are more likely to maintain a neutral stance on immigration.

In summary, based on the differences in proportions relative to the average, left-wing ideologies such as Secularism and Kemalism exhibit polarized, negative views on immigration. In contrast, Socialism tends to support immigration, while Liberalism adopts a more neutral stance. Among right-wing ideologies, Turkish Nationalism leans towards a negative stance, whereas Conservatism takes a more supportive approach. Islamism appears balanced but with a slight tendency towards supporting immigration. The other ideologies largely maintain a neutral stance.

9.1.1 Chi-square Test

The chi-square test results reveal a highly significant relationship between ideology and stance on immigration. The test produced a chi-square statistic of 24,461.63 with 20 degrees of freedom and a p-value of 0.0, indicating that the observed differences in stance across various ideologies are statistically significant. The expected frequencies, which represent the counts we would expect if there were no relationship between ideology and immigration stance, deviate considerably from the observed counts. This suggests that ideology plays a substantial role in shaping individuals' stances toward immigration, with the large chi-square statistic further underscoring the strength of this association.

The results demonstrate that the patterns of neutral, positive, and negative stances are strongly influenced by ideological alignment. These differences are visually represented below in Figure 9.4, which highlights the standardized residuals for each ideology and immigration stance.

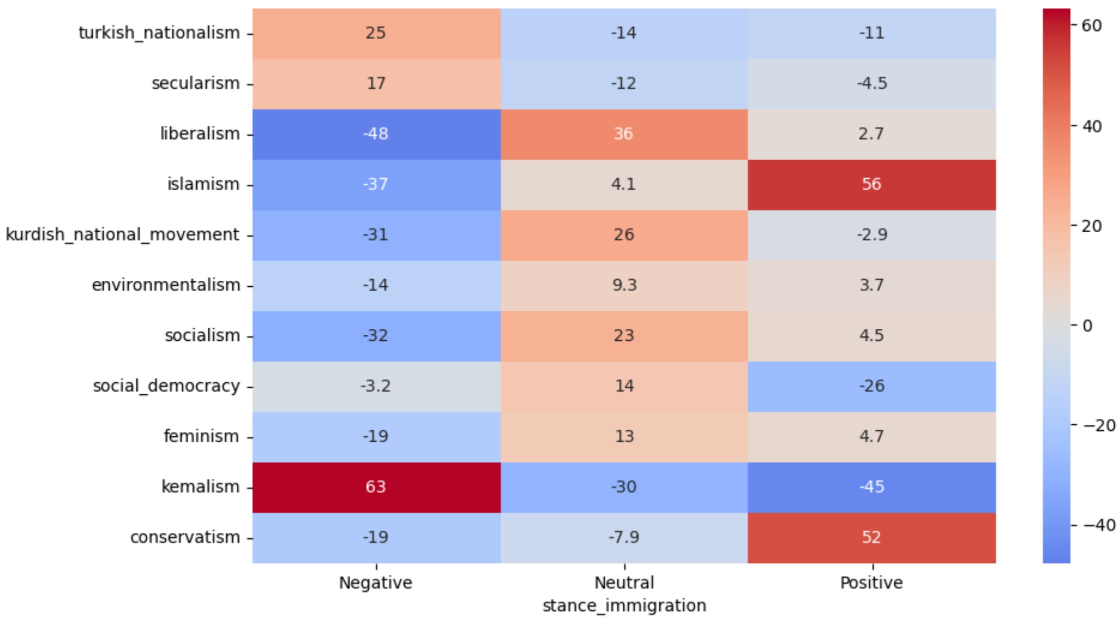


Figure 9.4: Standardized Residuals for Ideologies and Stance on Immigration.

Based on Figure 9.4, which illustrates the deviation from expected values in terms of standardized residuals in the chi-square test, ideologies such as Kemalism, Turkish Nationalism, and Secularism lean toward a negative stance on immigration. In contrast, Islamism and Conservatism demonstrate a tendency toward a positive stance. Ideologies such as Socialism, Liberalism, Environmentalism, and Feminism are primarily neutral but are less likely to oppose immigration and show a slight inclination toward a positive stance. Social Democracy and the Kurdish National Movement largely maintain a neutral stance.

9.2 User-Level Analysis

To conduct a user-level analysis, each user's stance on immigration is determined by the number of positive and negative tweets they have posted. A user is labeled as "pro-immigrant" if the majority of their tweets express a positive stance on immigration, considering only the positive and negative tweets. Conversely, if the majority of their tweets are negative, the user is labeled as "anti-immigrant." If there is no clear majority, the user is classified as "neutral." It's important to note that neutral tweets are excluded when calculating the majority. The distribution of users based on their stance against immigration is shown below in Figure 9.5.

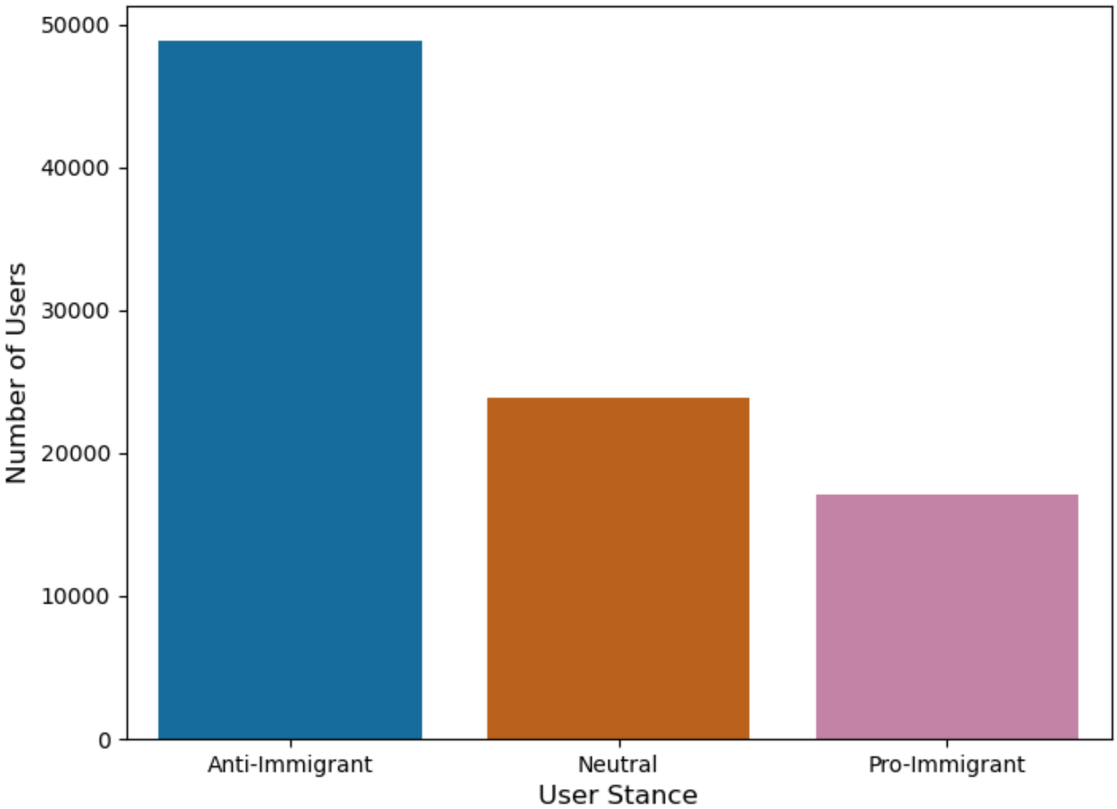


Figure 9.5: Stance Distribution by Users.

As shown in Figure 9.5, the majority of users, representing 54.4%, adopt an anti-immigrant stance. This is followed by "neutral" users, who make up 26.5% of the total. Finally, pro-immigrant users constitute approximately 19% of all users.

In this part of the analysis, the distribution of the users associated to ideologies is analyzed. Since all three ideologies are taken into consideration, a user can be counted under multiple ideologies. Figure 9.6 indicates the user count for each ideology.

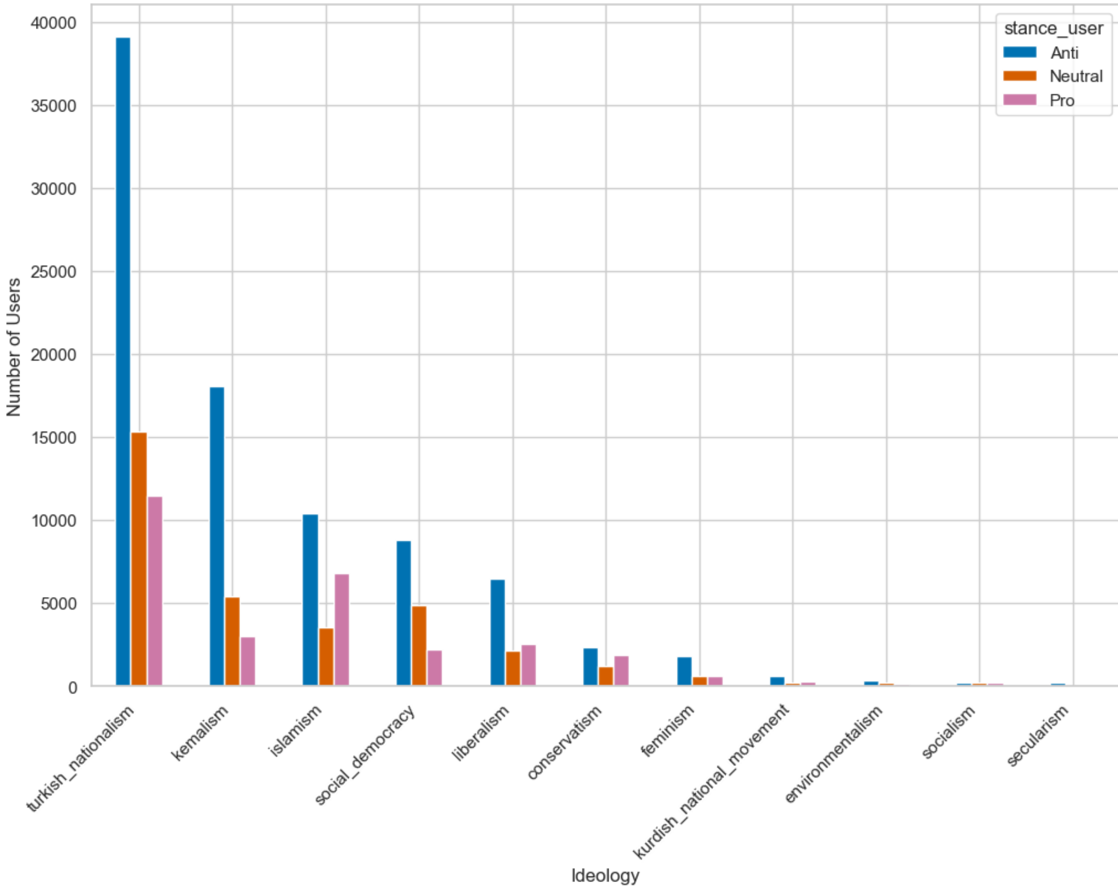


Figure 9.6 User Distribution by Ideology.

Figure 9.6 illustrates the distribution of users' stances on immigration across various ideologies, considering multiple ideology associations. Turkish Nationalism stands out with the highest number of users, predominantly adopting an anti-immigrant stance. The overwhelming majority of users associated with Turkish Nationalism oppose immigration, with only a small fraction showing a pro-immigrant stance, and a moderate number remaining neutral. Kemalism follows a similar pattern, with a significant portion of its users also leaning toward an anti-immigrant stance. Ideologies such as Social Democracy, Liberalism, have the majority of users who adopt an anti-immigrant stance. However, the difference is not as significant as the other two main ideologies.

In contrast, Islamism presents a more balanced distribution across all three stances. While there is still a substantial number of anti-immigrant users, the ideology also includes a notable proportion of neutral and pro-immigrant users, indicating a broader spectrum of opinions on immigration. This balanced distribution distinguishes Islamism from the more uniformly anti-immigrant ideologies like Turkish Nationalism and Kemalism. In terms of Conservatism, the number of users is more evenly distributed than the other ideologies.

The remaining ideologies have a limited number of users to make interpretations. However, the percentage distribution of users within those ideologies is shown below in Figure 9.7.

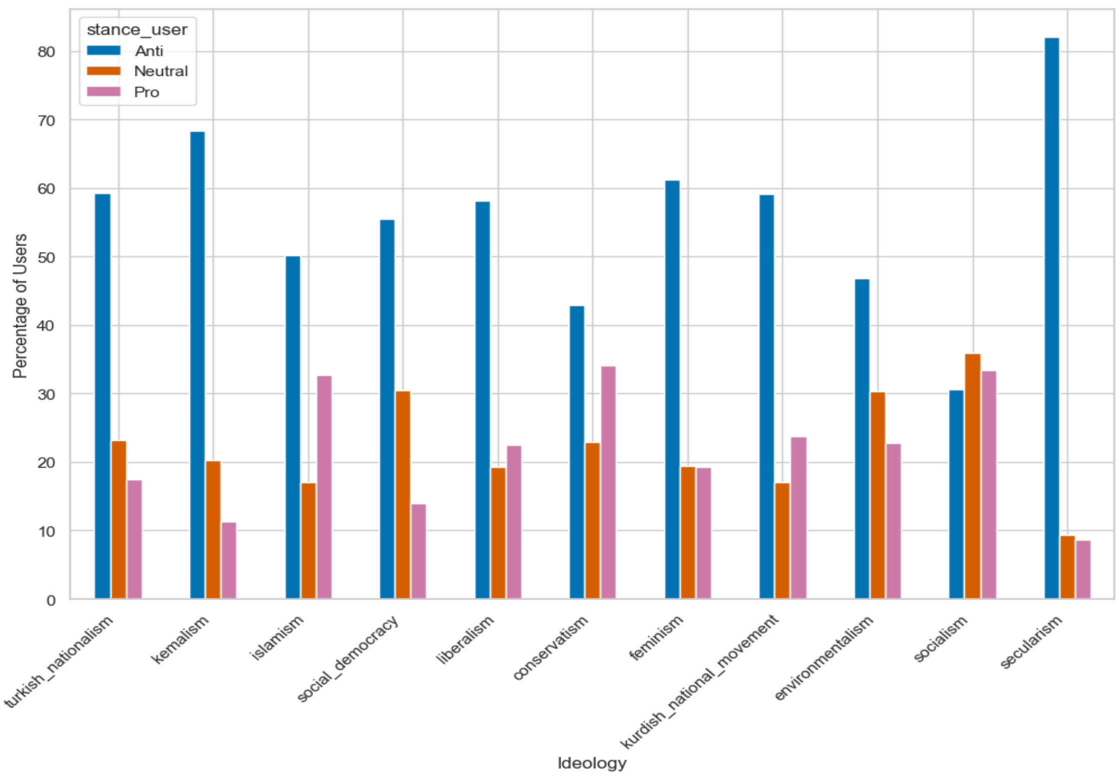


Figure 9.7 Percentage Distribution of Users by Ideology.

The remaining ideologies have a limited number of users, making detailed interpretations challenging. However, it's notable that even within these smaller ideological groups, a trend toward anti-immigrant stance persists. For example, Feminism and Environmentalism display a considerable proportion of users who are anti-immigrant, though they also feature a more balanced mix of neutral and pro-immigrant stances compared to the major ideologies. Socialism, however, presents a unique case among the smaller groups, with a distribution in favor of positive stances.

Secularism stands out with a significant skew toward an anti-immigrant stance, similar to Turkish Nationalism and Kemalism, despite its relatively smaller user base. This pattern reinforces the notion that secular ideologies in the dataset are predominantly aligned with anti-immigrant views.

Overall, the analysis highlights how user ideologies influence their stance on immigration, with certain ideologies like Turkish Nationalism, Kemalism, and Secularism showing a strong anti-immigrant stance. Whereas Islamism indicates a more balanced stance, Socialism shows a positive stance against immigrants.

For further analysis, the difference in proportions is analyzed to provide a clearer picture of how each ideology diverges from the overall average stance on immigration. This analysis helps to identify which ideologies are significantly more likely to hold either a pro-immigrant or anti-immigrant stance compared to the baseline. The results of this analysis are illustrated in Figure 9.8, offering insights into the nuanced differences in immigration attitudes across various ideological groups.

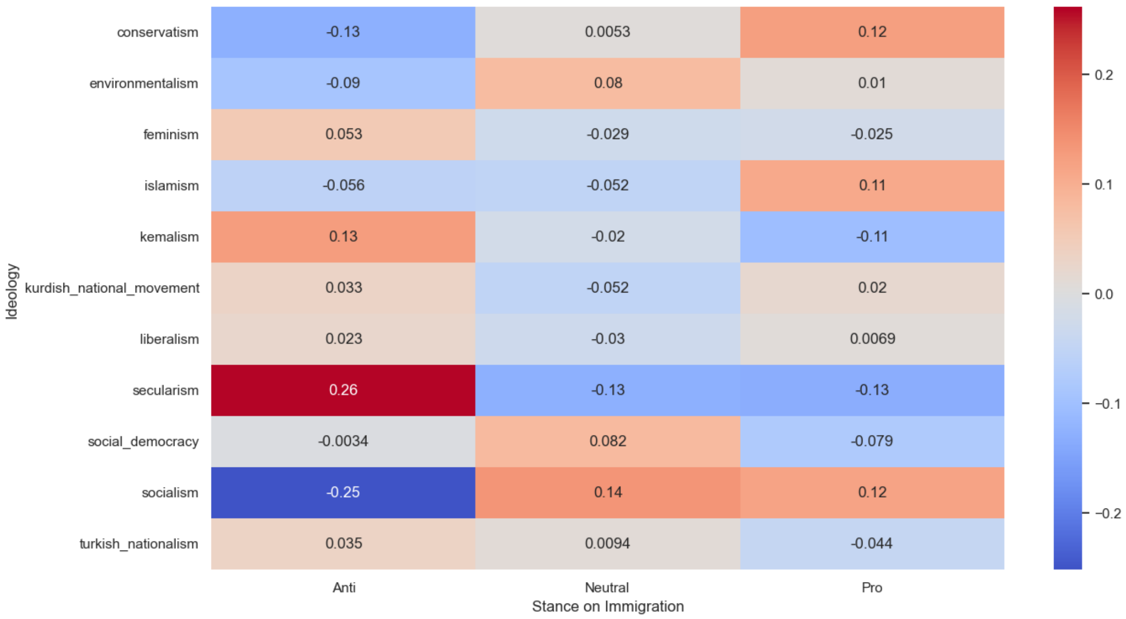


Figure 9.8: Difference in Proportions of Immigration Stances by Ideology (User-Level, Compared to Average).

Figure 9.8 reveals significant differences in immigration stances across various ideologies, with a clear polarization in the dataset. Secularism and Kemalism stand out with strong negative stances towards immigration, showing a substantial deviation towards anti-immigrant views compared to the average. Turkish Nationalism, while also exhibiting a negative stance, shows a smaller deviation, indicating a somewhat more balanced perspective. Conservatism, however, presents a slightly more positive stance compared to other ideologies, with a moderate positive deviation, suggesting that users associated with this ideology are less opposed to immigration than might be expected.

On the other hand, Socialism strongly favors a pro-immigrant stance, with a significant positive deviation from the average, suggesting a strong alignment with supportive immigration policies. Islamism also shows a slight tendency towards a pro-immigrant stance, though this is accompanied by a notable anti-immigrant sentiment, reflecting a more complex and divided view within this ideology. Environmentalism, while largely neutral, leans slightly positive, indicating moderate support for immigration. Neutral stances are more prevalent in ideologies like Social Democracy and Feminism, which do not show strong deviations in either direction, suggesting a more balanced or indifferent view on immigration.

Overall, both tweet-level and user-level analyses yield consistent findings, indicating that ideologies on both the left and right of the political spectrum exhibit diverse opinions on immigration. Individuals associated with ideologies such as Turkish Nationalism, Secularism, and Kemalism tend to oppose immigration. In contrast, those aligned with Conservatism, Islamism, and Socialism are more likely to adopt a supportive stance. Meanwhile, ideologies such as Liberalism, Social Democracy, Feminism, Environmentalism, and the Kurdish National Movement are generally inclined towards a neutral stance on immigration.

9.2.1 Chi-Square Test

The large chi-square statistic of 5,971.60 and the p-value of 0.0 suggest that the relationship between ideology and stance on immigration at the user level is statistically significant. This means that user-level stances on immigration are strongly associated with ideological alignment, and the differences between the observed stance counts and the expected counts are substantial.

The deviations from expected values, represented by the standardized residuals in previous analyses, further underscore how specific ideologies are more or less likely to be associated with neutral, positive, or negative views on immigration. The deviation from the expected counts, which would occur if there were independence between ideology and stance, is presented in terms of standardized residuals in Figure 9.9.

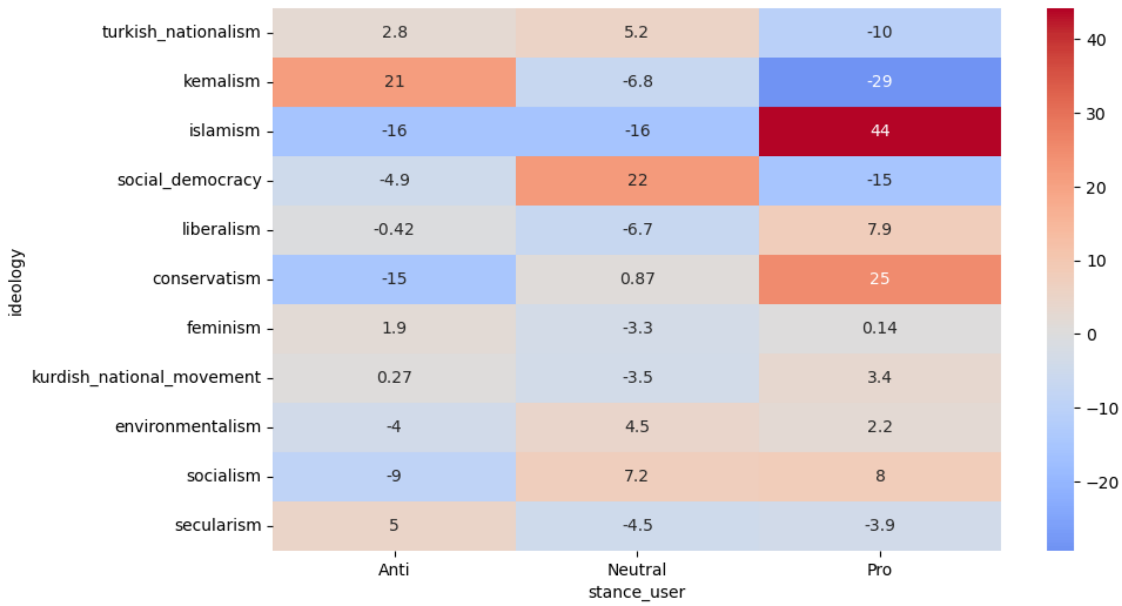


Figure 9.9: Standardized Residuals for Ideologies and Stance on Immigration (user-level).

The results shown in Figure 9.9, while displaying some differences, are largely consistent with the tweet-level analysis of ideologies and immigration stance. On the user level, ideologies such as Kemalism and Secularism still lean toward a negative stance on immigration. Turkish Nationalism, while showing a more neutral stance, continues to lean slightly toward a negative stance. Ideologies that are more aligned with a positive stance include Islamism, Conservatism, and Socialism. Interestingly, Liberalism presents a more positive stance at the user level compared to the tweet-level analysis. Social Democracy remains neutral, while Environmentalism shows neutrality with a slight inclination toward a positive stance. Feminism demonstrates a more balanced view, and the Kurdish National Movement exhibits a stronger positive stance.

Chapter 10:
ANALYSIS: STATISTICAL MODELS

In this section, a multinomial logistic regression model is applied to examine the effects of ideologies, emotions, and their interaction on anti-immigrant stance. Given that the dependent variable is a categorical variable with multiple labels, this method is appropriate. The first model investigates the isolated effect of ideologies, while the second focuses on emotions. The third model combines ideologies, emotions, and their interaction to measure their collective impact. Both ideologies and emotions are categorical variables.

In all models, demographic variables of gender and age are included as control variables. Age groups in a categorical variable consisting of four categories which are “>=40”, “30-39”, “20-29” and “<=18”. Additionally, given that economic conditions in the host country can significantly influence anti-immigrant sentiments, the unemployment rate is incorporated as an additional control variable. This decision is supported by Heizmann & Huth (2021), who argue that economic factors, particularly the unemployment rate, can have a substantial impact on anti-immigrant attitudes. The monthly unemployment rate data used in this model is sourced from the OECD (2024) and represents the percentage of unemployed individuals within the labor force aged 15 and over in Türkiye. Geographical factors are expected to influence anti-immigrant stances due to the frequency and proximity of contact with immigrants (Steinmayr, 2021; Weber, 2015). Additionally, differences in educational backgrounds, occupational skills, and income levels between individuals living in urban and rural areas can also impact anti-immigrant attitudes (Maxwell, 2019; Valentova & Alieva, 2014). However, since only half of the users in the dataset have location information, geographical factors are not included as control variables in the model.

10.1 Model 1

Model 1 is designed to explore the relationship between different ideologies and the tweet-level stance on immigration, which is categorized into three levels: neutral, negative, and positive. The primary independent variables in this model are the ideologies attributed to users. Results are shown in Table 10.1. In this multinomial logistic regression, the neutral stance serves as the baseline category for comparison.

Table 10.1 Results of Multinomial Logistic Regression (Ideologies).

Variable	Positive Stance Exp. Beta Coeficients (std error)	Negative Stance Exp. Beta Coeficients (std error)
Intercept	0.1998***	0.6481***
	(0.033)	(0.023)
Ideologies		
Turkish Nationalism	0.8625***	1.6347***
	(0.009)	(0.007)
Kemalism	0.8158***	1.2986***
	(0.006)	(0.004)
Secularism	1.0211	1.4812***
	(0.033)	(0.020)
Islamism	1.4214***	0.7996***
	(0.006)	(0.004)
Social Democracy	0.8262***	0.9971
	(0.008)	(0.005)
Liberalism	0.9414***	0.7958***
	(0.007)	(0.005)
Conservatism	1.4006***	0.9497***
	(0.010)	(0.008)
Feminism	0.9555***	0.9027***
	(0.013)	(0.009)
Kurdish National Movement	0.7964***	0.7549***
	(0.018)	(0.013)
Environmentalism	1.0039	0.8070***
	(0.027)	(0.020)
Socialism	0.9488	0.5277***
	(0.033)	(0.031)
Economic Indicator		
Unemployment Rate (monthly)	1.0329***	0.9547***
	(0.003)	(0.002)
Demographic Variables		
Gender (Male)	0.7540***	0.9566***
	(0.009)	(0.006)
Age Group (30-39)	1.0168	1.0358***
	(0.012)	(0.008)
Age Group (<=18)	0.9475***	1.0901***
	(0.012)	(0.008)
Age Group (>=40)	1.0469***	1.0080
	(0.011)	(0.007)

**** $p<0{,}001$; ** $p<0{,}01$; * $p<0{,}05$; pseudo R^2:0.01589; LLR-p-value:0.000*

Table 10.1 shows the results of the multinomial logistic regression. The model's fit is confirmed by the likelihood ratio test, with a significant LLR p-value of 0, suggesting that the overall model is a strong fit for the data and significantly improves on the null model, which assumes no relationship between the variables and immigration stance. This underscores the robustness of the relationships identified between the ideologies and stances on immigration.

The exponentiated beta coefficients represent odds ratios, which indicate how much more or less likely a particular stance on immigration is for individuals with certain ideologies. A value greater than 1 signifies a higher likelihood of the outcome, while a value less than 1 indicates a lower likelihood.

The regression results reveal distinct patterns in how various ideologies relate to stances on immigration. Turkish nationalism and Kemalism are significantly associated with negative stances on immigration, with individuals aligned with these ideologies being much more likely to oppose immigration. The odds of adopting a negative stance are particularly high for Turkish nationalism and Kemalism, while their odds of adopting a positive stance are lower. Secularism also shows a positive association with negative stances on immigration, though the relationship with positive stances is insignificant.

On the other hand, Islamism and conservatism are positively associated with supporting immigration. Islamism has a high odds ratio for a positive stance, with individuals identifying with this ideology being more likely to support immigration and less likely to oppose it. Similarly, conservatism shows a positive association with supporting immigration, with a slight reduction in the likelihood of opposition.

Liberalism, on the other hand, exhibits neutrality, with a slight negative association with both positive and negative stances, suggesting that liberals tend to adopt a neutral or weakly supportive stance on immigration. Social democracy, while negatively associated with a positive stance, does not have a significant impact on the likelihood of adopting a negative stance, indicating that those aligned with this ideology are generally neutral. Socialism shows a particularly strong inclination toward supporting immigration, with a low likelihood of adopting a negative stance, although the relationship with a positive stance is not statistically significant.

Feminism and the Kurdish national movement are similarly associated with neutrality, with both ideologies showing negative associations with both positive and negative stances, with a stronger negative association with the negative stance, suggesting a neutral or slightly positive outlook on immigration. Environmentalism shows no significant association with a positive stance but is negatively associated with a negative stance, indicating a general tendency towards neutrality or weak support for immigration.

10.2 Model 2

Model 2 explores the effects of emotions on anti-immigrant stance. This analysis is conducted on the tweet level since emotions are reflected the emotions within the tweets. As the independent variable, aims to reduce the complexity of the model, only basic and relevant emotions such as happiness, sadness, anger, fear, anxiety, and disgust are included. In the model, the neutral stance is set as the baseline category for comparison. The results are shown below in Table 10.2 in terms of exponentiated beta coefficiencts for each variable.

Table 10.2: Results of Multinomial Logistic Regression (Emotions).

Variable	Positive Stance Exp. Beta Coeficients (std error)	Negative Stance Exp. Beta Coeficients (std error)
Intercept	0.1446***	0.2578***
	(0.030)	(0.022)
Emotions		
Happiness	2.2835***	0.5677***
	(0.069)	(0.097)
Sadness	4.9435***	10.018
	(0.013)	(0.014)
Anger	1.5559***	3.9575***
	(0.006)	(0.004)
Fear	1.8201***	1.3441***
	(0.066)	(0.056)
Anxiety	1.8317***	1.4881***
	(0.057)	(0.050)
Disgust	1.3559***	1.9260***
	(0.014)	(0.009)
Economic Indicator		
Unemployment Rate	1.0196***	10.036
	(0.003)	(0.002)
Demographic Variables		
Gender (Male)	0.8064***	0.9619***
	(0.009)	(0.006)
Age Group (30-39)	1.0355**	1.0197**
	(0.012)	(0.009)
Age Group (<=18)	0.9573***	1.0443***
	(0.012)	(0.008)
Age Group (>=40)	1.0875***	10.076
	(0.011)	(0.008)

**** p<0,001; ** p<0,01; * p<0,05; pseudo R^2: 0.06117; LLR p-value: 0.000*

The model's fit is validated by the likelihood ratio test, with a highly significant LLR p-value of 0. This indicates that the model provides a substantially better fit to the data than the null model, which assumes no relationship between the variables and immigration stance. The result highlights the strength and reliability of the associations observed between emotions and immigration stances in the analysis.

The emotion model highlights the role emotions play in shaping stances on immigration. Happiness significantly increases the odds of supporting immigration, while it reduces the likelihood of opposing it. Similarly, sadness makes individuals far more likely to hold a positive stance on immigration, although it does not significantly affect negative stances.

Anger, on the other hand, strongly influences both positive and negative stances, but its effect is especially pronounced in increasing the odds of opposing immigration.

Fear similarly affects both stances, increasing the likelihood of both support and opposition, with a slightly stronger effect on negative stances.

Anxiety raises the odds of both positive and negative stances, suggesting that anxious individuals are more likely to take a stance on immigration, but tend toward opposition.

Finally, disgust is a strong predictor of both positive and negative stances, particularly increasing the likelihood of opposing immigration. Overall, these findings indicate that emotions like anger and disgust are closely tied to opposition to immigration, while emotions like happiness and sadness significantly increase the likelihood of support. Fear and anxiety influence both positive and negative stances but tend more toward opposition.

10.3 Model 3

Model 3 combines all the ideologies and six basic emotions happiness, sadness, anger, fear, anxiety, and disgust. All ideology-emotion interaction terms are included in the model. Table 10.3 shows the result by the Model 3. The neutral stance is the baseline category for comparison. For the purpose of clarity, among 77 interaction terms, only the significant ones with exponentiated beta coefficients are shown in Table 10.3. The complete table is available in Appendix A.

Table 10.3: Results of the Combined Multinomial Regression Model.

Variables	**Positive Stance Exp Beta Coefficients (std err)**	**Negative Stance Exp Beta Coefficients (std err)**
Intercept	0.1395***	0.2016***
	(0.035)	(0.027)
Ideologies		
Turkish Nationalism	0.8440***	1.5264***
	(0.012)	(0.010)
Kemalism	0.8064***	1.3384***
	(0.010)	(0.007)
Secularism	1.0085	1.2625***
	(0.055)	(0.041)
Islamism	1.3317***	0.7039***
	(0.009)	(0.007)
Social Democracy	0.7495***	0.9790**
	(0.012)	(0.009)
Liberalism	0.9143***	0.8363***
	(0.011)	(0.009)
Conservatism	1.3869***	0.7471***
	(0.015)	(0.016)
Feminism	0.9001***	0.8483***
	(0.019)	(0.017)
Kurdish National Movement	0.8066***	0.5886***
	(0.027)	(0.026)
Environmentalism	0.8106***	0.6607***
	(0.041)	(0.036)
Socialism	0.9874	0.6213***
	(0.046)	(0.050)
Emotions		
Happiness	1.7386*	0.6664
	(0.246)	(0.361)
Sadness	5.9367***	1.0026
	(0.042)	(0.052)
Anger	1.3644***	3.8212***
	(0.021)	(0.016)
Fear	1.6413*	1.4308
	(0.225)	(0.206)
Anxiety	1.6342*	1.2721
	(0.214)	(0.210)
Disgust	1.1214*	2.2128***
	(0.053)	(0.035)

Table 10.3 (cont.)

Interaction Terms		
Sadness * Conservatism	1.4879***	0.9141
	(0.049)	(0.065)
Sadness*Feminism	0.7439***	0.9656
	(0.019)	(0.056)
Sadness * Liberalism	0.8948***	0.9125**
	(0.032)	(0.037)
Sadness * Social Democracy	0.8848***	0.9910
	(0.032)	(0.034)
Sadness * Socialism	0.6371**	1.1555
	(0.144)	(0.196)
Sadness * Turkish Nationalism	0.8918***	1.0185
	(0.035)	(0.044)
Anger * Environmentalism	1.5461***	1.4160***
	(0.056)	(0.045)
Anger * Feminism	1.0732**	1.0246
	(0.027)	(0.021)
Anger * Islamism	1.1190***	1.1094***
	(0.013)	(0.009)
Anger * Kemalism	0.9984	0.9189**
	(0.013)	(0.009)
Anger * Kurdish National Movement	0.9505	1.1384***
	(0.037)	(0.031)
Anger * Conservatism	0.9261**	1.3023***
	(0.022)	(0.019)
Anger * Liberalism	1.0738***	0.9747*
	(0.015)	(0.011)
Anger * Social Democracy	1.1047***	0.9661**
	(0.016)	(0.011)
Anger * Socialism	1.0421	0.7921*
	(0.067)	(0.065)
Anger * Turkish Nationalism	4.5383**	1.0271
	(0.018)	(0.015)
Fear*Liberalism	1.4093*	0.8616
	(0.166)	(0.151)
Fear * Social Democracy	1.1820	1.4758**
	(0.181)	(0.140)
Anxiety * Liberalism	1.0704	1.3440*
	(0.145)	(0.124)
Disgust * Environmentalism	1.5633***	1.0950
	(0.118)	(0.091)
Disgust * Feminism	1.0785(0.054)	0.8173*(0.036)

Table 10.3(cont.)

Disgust * Islamism	1.0689* (0.030)	0.9867
	(0.030)	(0.018)
Disgust * Kemalism	1.0210	0.8962***
	(0.031)	(0.019)
Disgust * Kurdish National Movement	1.1498*	1.0835
	(0.076)	(0.049)
Disgust * Liberalism	1.0562	0.8525***
	(0.036)	(0.023)
Disgust * Social Democracy	1.2405***	1.0258
	(0.039)	(0.024)
Economic Indicator		
Unemployment Rate	1.0450***	1.0001
	(0.003)	(0.002)
Demographics		
Gender (Male)	0.7780***	0.9507***
	(0.009)	(0.007)
Age Group (30-39)	1.0267*	1.0346***
	(0.012)	(0.009)
Age Group (<=18)	0.9472***	1.0563***
	(0.012)	(0.008)
Age Group (>=40)	1.0632***	1.0222**
	(0.011)	(0.008)

*** $p<0,001$; ** $p<0,01$; * $p<0,05$; pseudo R^2: 0.07567; LLR p-value: 0.000*

The fit of the emotion-ideology interaction model is confirmed by the likelihood ratio test, with a highly significant LLR p-value of 0. This demonstrates that the interaction model provides a considerably better fit to the data than the null model, which assumes no interaction between emotions, ideologies, and immigration stances. The result underscores the robustness of the identified relationships between the combined effects of emotions and ideologies on immigration stances.

The analysis demonstrates that emotions play a pivotal role in modulating the influence of ideologies on anti-immigrant attitudes. Emotions like anger, disgust, and sadness interact with different ideological positions, leading to either reinforcement or significant shifts in these stances. This underscores the intricate relationship between affective states and political beliefs.

Anger emerges as the most influential emotion, exhibiting significant interaction effects across almost all ideologies except for Secularism. Anger tends to shift ideological stances. For instance, Conservatism, which typically supports immigration, becomes more likely to adopt an anti-immigrant stance when anger is present. Conversely, Kemalism, which is usually strongly anti-immigrant, becomes less likely to oppose immigration when anger is introduced, although it does not shift to a pro-immigrant stance. Turkish Nationalism, which normally adopts an anti-immigrant stance, becomes more likely to support in the presence of anger. For ideologies that are neutral on immigration, anger often pushes them toward more definitive stances. Feminism, Social Democracy, and Liberalism are more likely to express pro-immigrant sentiments when influenced by anger, while supporters of the Kurdish National Movement, another neutral ideology, tend to adopt a more anti-immigrant stance when anger is involved. Anger also has a strengthening and shifting effect on the positions of Islamism (pro-immigrant). Although it affects Islamism both ways, its strengthening effect is slightly stronger. The shifting or strengthening effect of anger can be due to the target to which it is directed. Its effect may depend on whether it is against immigrants or the ones who are against them. It can also be related to economic, social, or cultural conditions in the country in which any negativity is associated with the high number of refugees in the context of Türkiye.

Disgust is the second most impactful emotion. Similar to anger, disgust reduces the likelihood of Kemalism opposing immigration, softening its typically anti-immigrant stance. For Islamism, disgust strengthens the pro-immigrant stance, increasing the likelihood of support. Among neutral ideologies, disgust promotes pro-immigrant attitudes within Environmentalism, Social Democracy, and the Kurdish National Movement. For Feminism and Liberalism, disgust reduces the likelihood of opposing immigration, aligning these ideologies more with pro-immigrant views. The dual impact of disgust may also be related to the target. It can be a reaction to the individuals who have racist motives to be against refugees, or it can be directly related to immigrants. Based on the target, it can have a strengthening or shifting effect.

Sadness interacts significantly with Turkish Nationalism, Socialism, Social Democracy, Conservatism, and Liberalism. For each ideology, it has a strengthening effect on the current position toward immigration. Its positive effect may be related to pity felt for refugees, whereas the negative impact can be related to feeling sad about the country’s economic or cultural conditions.

Fear has a unique interaction with Social Democracy, making it the only emotion that drives supporters of Social Democracy to oppose immigration. Fear and Anxiety interact with Liberalism, pushing it toward an anti-immigrant stance, which is otherwise uncharacteristic of this ideology. This can be related to economic or security concerns, which are associated with refugees in Turkish public opinion.

Happiness, while generally associated with a pro-immigrant stance, seems to exert a more uniform influence across ideologies, rather than interacting with specific ideological positions. This might indicate that positive emotions promote inclusivity and support for immigration broadly, without being tied to particular ideological perspectives. In contrast, negative emotions appear to be more potent in shaping and possibly intensifying the effects of specific ideologies, making them crucial factors in understanding the dynamics of anti-immigrant stance. This emphasizes the complexity of how emotions and ideologies interplay, particularly in the context of controversial issues like immigration.

These findings underscore the importance of considering both ideological beliefs and emotional states when analyzing political attitudes toward immigration. The interaction between emotions and ideologies is complex, with various emotions moderating ideological positions in different ways. Anger, disgust, and sadness, in particular, have a substantial impact on how ideologies align with or oppose immigration, highlighting the need for a nuanced understanding of the affective dimensions in political opinion formation. This analysis reveals that emotions can significantly alter or reinforce ideological stances, shaping public opinion on immigration in multifaceted ways.

10.4 Model 4

Model 4, in addition to Model 3, includes topics mentioned within tweets. Topics that are expected to affect the anti-immigrant stance indirectly consist of the economy, internal affairs, health and public health, education, and social policy. Differently from the previous models, the emotion of "happiness" is not included in this model. The effect of happiness is one side, which is positive on the positive stance and has no interaction effect with any ideologies, as shown in the models above. Additionally, it is an emotion that represents an overall mood rather than a feeling against a specific topic or a target; it is excluded from this model to reduce complexity.

Table 10.4 shows exponentiated coefficients for ideologies, emotions, topic, and their two-way and three-way interactions. Since the model involves around 300 variables only the significant variables are included in the table for a clear presentation of results[6].

Table 10.4: Results of Multinomial Logistic Regression (Ideologies, Emotions and Topics).

Variable	Positive Stance Exp(Beta)	Negative Stance Exp(Beta)
Intercept	0.1342***	0.2012***
	(0.0354)	(0.0269)
Sadness	5.9530***	10.355
	(0.0460)	(0.0571)
Anger	1.4114***	3.8689***
	(0.0212)	(0.0169)
Fear	2.1002**	1.7786**
	(0.2332)	(0.2186)
Anxiety	2.0410**	1.6709*
	(0.2286)	(0.2279)
Disgust	1.0748	2.1138***
	(0.0550)	(0.0360)
Islamism	1.3152***	0.6959***
	(0.0091)	(0.0075)
Kemalism	0.8106***	1.3393***
	(0.0095)	(0.0072)
Conservatism	1.4021***	0.7428***
	(0.0153)	(0.0160)
Feminism	0.9022***	0.8492***
	(0.0195)	(0.0165)
Environmentalism	0.8172***	0.6642***
	(0.0407)	(0.0363)
Kurdish_National_Movement	0.7785***	0.5683***
	(0.0272)	(0.0266)
Liberalism	0.9259***	0.8418***
	(0.0108)	(0.0089)
Secularism	1.0017	1.2653***
	(0.0554)	(0.0409)
Social_Democracy	0.7984***	1.0297***
	(0.0120)	(0.0089)
Socialism	0.9784 (0.0464)	0.5992*** (0.0116)

[6] Complete table is available on https://github.com/AlkanCan/ideology-emotion-interaction-effect-on-anti-immigrant-stance

Table 10.4(cont.)

Turkish_Nationalism	0.8465***	1.5062***
	(0.0124)	(0.0116)
Topics		
Economy	0.2541*** (0.0382)	0.5212*** (0.0211)
Internal_Affairs	0.4493*** (0.0484)	1.5618*** (0.0238)
Health_And_Public_Health	0.6010***	0.5261***
	(0.0405)	(0.0336)
Social_Policy	0.7756***	0.6497***
	(0.0696)	(0.0543)
Education	0.8672***	0.3979***
	(0.0363)	(0.0385)
Two-Way Interactions		
Sadness * Kemalism	0.9022***	10.050
	(0.0307)	(0.0338)
Sadness * Conservatism	1.4171***	0.9465
	(0.0517)	(0.0699)
Sadness * Feminism	0.7298***	0.9334
	(0.0542)	(0.0616)
Sadness * Liberalism	0.8902***	0.9113*
	(0.0346)	(0.0405)
Sadness * Social_Democracy	0.8808***	0.9668
	(0.0356)	(0.0386)
Anger * Islamism	1.1307***	1.1026***
	(0.0130)	(0.0095)
Anger * Kemalism	0.9932	0.9201***
	(0.0136)	(0.0094)
Anger * Conservatism	0.9176***	1.3086***
	(0.0221)	(0.0197)
Anger * Environmentalism	1.5236***	1.4010***
	(0.0582)	(0.0469)
Anger * Kurdish_National_Movement	0.9431	1.1414***
	(0.0374)	(0.0315)
Anger * Liberalism	1.0734***	0.9732*
	(0.0157)	(0.0116)
Anger * Social_Democracy	1.1169***	0.9793
	(0.0169)	(0.0115)
Anger * Socialism	0.8692	0.7922***
	(0.0728)	(0.0683)
Anxiety * Feminism	0.7994	0.5730*
	(0.2723)	(0.2699)

Table 10.4 (cont.)

Disgust * Kemalism	1.0190	0.8974***
	(0.0322)	(0.0194)
Disgust * Feminism	1.1090	0.8079***
	(0.0563)	(0.0375)
Disgust * Environmentalism	1.4288** (0.1265)	1.0516 (0.0964)
Disgust * Kurdish_National_Movement	1.1936*	1.0733
	(0.0787)	(0.0508)
Disgust * Liberalism	1.0527	0.8555***
	(0.0376)	(0.0243)
Disgust * Social_Democracy	1.1934***	0.9852
	(0.0413)	(0.0253)
Anger * Internal_Affairs	2.6816***	0.9294
	(0.1110)	(0.0695)
Anger * Social_Policy	0.6092*	1.0135
	(0.2327)	(0.1276)
Anger*Education	0.2389***	0.9474
	(0.1607)	(0.0995)
Three-Way Interactions		
Sadness*Islamism*Education	0.2850***	1.011
	(0.3240)	(0.2956)
Sadness * Kemalism * Economy	1.4385*	1.3869**
	(0.1589)	(0.1145)
Sadness * Kemalism * Social_Policy	0.4525*	1.2058
	(0.3604)	(0.2981)
Sadness * Kemalism * Education	2.9542***	1.5343
	(0.1737)	(0.2245)
Sadness * Conservatism * Social_Policy	3.5289*	0.8970
	(0.5410)	(0.7298)
Sadness * Feminism * Economy	1.8987*	1.2880
	(0.2623)	(0.2158)
Sadness * Liberalism * Health_And_Public_Health	1.9686**	0.8346
	(0.2186)	(0.2327)
Sadness * Liberalism * Education	0.6004*	0.7543
	(0.2361)	(0.2773)
Sadness * Social_Democracy * Internal_Affairs	1.0236	1.5362*
	(0.2376)	(0.2072)
Sadness * Social_Democracy * Health_And_Public_Health	0.6215*	1.1061
	(0.2205)	(0.1954)

Table 10.4

Sadness * Social_Democracy * Social_Policy	1.1929	0.3829**
	(0.3707)	(0.3158)
Sadness * Social_Democracy * Education	1.6599*	0.9364
	(0.2166)	(0.2563)
Sadness * Turkish_Nationalism * Internal_Affairs	0.5378*(0.2712)	1.0786 (0.2850)
Sadness * Turkish_Nationalism * Education	0.4639***	0.8303
	(0.1994)	(0.2714)
Anger * Islamism * Economy	0.6609***	1.0788**
	(0.0720)	(0.0282)
Anger * Islamism * Internal_Affairs	0.7587***	1.0700
	(0.0616)	(0.0372)
Anger * Islamism * Health_And_Public_Health	0.7469**	1.2723***
	(0.0894)	(0.0529)
Anger * Islamism * Social_Policy	0.7029*	1.0319
	(0.1724)	(0.0879)
Anger * Islamism * Education	1.3274**	1.1450*
	(0.1032)	(0.0623)
Anger * Kemalism * Economy	1.2492**	1.0400
	(0.0697)	(0.0270)
Anger * Kemalism * Internal_Affairs	0.7932***	0.9836
	(0.0659)	(0.0375)
Anger * Kemalism * Health_And_Public_Health	1.4424***	1.1735**
	(0.0863)	(0.0504)
Anger * Kemalism * Social_Policy	1.9161***	0.8917
	(0.1471)	(0.0773)
Anger * Conservatism * Internal_Affairs	0.7453**	1.0175
	(0.1068)	(0.0658)
Anger * Conservatism * Health_And_Public_Health	0.6594*	0.7657*
	(0.1809)	(0.1109)
Anger * Feminism * Economy	1.3467*	1.1722**
	(0.1313)	(0.0606)
Anger * Feminism * Internal_Affairs	1.4808***	1.3342***
	(0.1048)	(0.0716)
Anger * Feminism * Social_Policy	2.2245**	0.9095
	(0.2683)	(0.1951)
Anger * Kurdish_National_Movement *Economy	2.8389***	1.4625**
	(0.2135)	(0.1240)
Anger * Kurdish_National_Movement *Internal_Affairs	0.8441(0.1224)	0.8334* (0.0763)

Table 10.4

Anger * Liberalism * Social_Policy	0.7144*	0.9196
	(0.1624)	(0.0811)
Anger * Secularism * Health_And_Public_Health	1.2817	2.2026**
	(0.5594)	(0.2725)
Anger * Social_Democracy * Economy	1.2146**	0.8596***
	(0.7000)	(0.0278)
Anger * Social_Democracy * Internal_Affairs	1.0564	0.8605***
	(0.0690)	(0.0417)
Anger * Social_Democracy *Health_And_Public_Health	1.2559*	1.1023
	(0.0898)	(0.0531)
Anger * Social_Democracy * Education	2.1186***	1.0728
	(0.1064)	(0.0624)
Anger * Socialism * Economy	7.4669***	0.8405
	(0.1458)	(0.1663)
Anger * Socialism * Internal_Affairs	0.5504*	1.0433
	(0.2417)	(0.1735)
Anger * Socialism * Social_Policy	0.7260	3.7633***
	(0.5896)	(0.3199)
Anger * Turkish_Nationalism * Economy	1.1182	1.1085**
	(0.0842)	(0.0394)
Anger * Turkish_Nationalism * Internal_Affairs	1.2504**	1.2201***
	(0.0833)	(0.0556)
Anger * Turkish_Nationalism * Health_And_Public_Health	1.4480***	1.1085
	(0.1119)	(0.0711)
Anger * Turkish_Nationalism * Social_Policy	1.8476***	1.2236*
	(0.1657)	(0.0854)
Anger * Turkish_Nationalism * Education	1.8827***	1.2679**
	(0.1199)	(0.0776)
Disgust * Kemalism * Internal_Affairs	0.9826	0.7765*
	(0.1860)	(0.1285)
Economic Indicator		
Unemployment_Rate (Monthly) (%)	1.0534***	1.0047*
	(0.0029)	(0.0022)
Demographic Variables		
Gender_Male	0.7730***	0.9463***
	(0.0091)	(0.0066)
Age_Group_30-39	1.0353**	1.0365***
	(0.0124)	(0.0087)

Age_Group_<=18	0.9511***	1.0563***
	(0.0119)	(0.0082)
Age_Group_>=40	1.0743***	1.0243**
	(0.0109)	(0.0076)

***** $p<0,001$; ** $p<0,01$; * $p<0,05$; pseudo R^2: 0.08114:; LLR p-value: 0.000*

The fit of the emotion-ideology-topic interaction model is confirmed by the likelihood ratio test, with a highly significant LLR p-value of 0. This demonstrates that the interaction model provides a substantially better fit to the data than the null model, which assumes no interaction between emotions, ideologies, topics, and immigration stances. The result underscores the robustness of the relationships identified between the combined effects of emotions, ideologies, and key policy topics on immigration stances. It further emphasizes the importance of considering the nuanced dynamics of how these factors jointly shape public opinion on immigration.

According to results by Model 4, the individual impacts of the topics on immigrant stance is neutral as all the topics, except for internal affairs, reduces the likelihood of expressing pro or anti-immigrant stance. This indicates that when these are the concern there is no emphasis on immigration in tweets. However, concerns regarding internal affairs which indicates mentions about security increases the likelihood of negative stance while also reducing the probability of positive stance.

Model 4 reveals that topics alone generally reduce the likelihood of expressing a pro- or anti-immigrant stance, with one exception: internal affairs. Mentions of internal affairs, which often relate to security concerns, increase the probability of a negative stance while reducing the likelihood of a positive stance on immigration. This suggests that security issues trigger more polarized views toward immigration.

However, the introduction of emotions into the analysis significantly alters the impact of topics on immigration stance. Among the emotions, sadness and anger emerge as the most influential, particularly when combined with discussions on economy, social policy, education, public health, and internal affairs.

One of the key findings is the shift in Islamism's stance when emotions and topics interact. While Islamism generally holds a pro-immigrant stance, anger over topics like internal affairs, public health, and economy can drive Islamists towards a negative stance. Although anger usually strengthens Islamism's pro-immigration stance, the presence of these specific topics triggers the opposite effect, leading to more negative views. Similarly, sadness in relation to education weakens Islamism's support for immigration.

The model also highlights how anger interacts with Kemalism and Turkish nationalism, ideologies that typically oppose immigration. When anger is associated with social policy and public health, Turkish nationalism surprisingly shifts toward a more pro-immigrant stance. A similar pattern is observed with Kemalism, which also becomes more supportive of immigration when anger is directed at the economy and social policy. In both cases, anger has the overall effect of softening or shifting their traditionally anti-immigrant positions. Additionally, sadness regarding education has a similar impact on Kemalism, making it less opposed to immigration.

Lastly, Socialism shows a complex interaction with emotions and topics. While anger drives Socialists toward a negative stance on immigration when discussing social policy, it has the opposite effect in the context of the economy, leading to a more positive stance.

Chapter 11:
RESULTS & DISCUSSION

The study emphasizes the complex relationship between ideologies and emotions, consistent with Affective Intelligence Theory (Marcus, 2000). AIT suggests that emotions shape ideological positions, with their impact varying across different ideological perspectives. Some emotions, like anger, tend to reinforce existing ideological stances, while others, such as anxiety and fear, can provoke shifts. The findings indicate that emotions moderate ideological stances on immigration, either reinforcing the current position or prompting a shift. Anxiety and fear, as a negative emotion, drive individuals associated with liberalism—typically neutral on immigration—toward a more anti-immigrant stance. Fear also pushes Social Democracy, another neutral ideology, towards an anti-immigrant position. In contrast, anger and disgust have the opposite effect on Social Democracy and Turkish Nationalism, shifting them toward a more pro-immigrant stance. Anger, in line with AIT, bolsters the pro-immigrant stance of Islamism. While anger can cause a shift in Islamist ideological position, its primary effect is to reinforce it. However, anger also influences Conservatism—typically seen as pro-immigrant in Türkiye—causing a shift toward an anti-immigrant stance. Lastly, sadness tends to reinforce the existing ideological positions on which it has a significant effect rather than causing shifts.

One of the main findings of this study is the nuanced relationship between ideological dispositions and anti-immigrant stances in Türkiye. Unlike the established literature (Callens & Meuleman, 2016; Gorodzeisky, 2011; Halikiopoulou & Vlandas, 2020), there is no direct correlation between right-wing ideologies and anti-immigrant sentiment. In fact, as Leykin & Gorodzeisky (2024) also suggest, the anti-immigrant stance in Türkiye is not exclusive to the political right. This study highlights that both right- and left-wing ideologies encompass diverse views on immigration, making it necessary to move beyond traditional left-right political binaries. For instance, Turkish Nationalism, a prominent right-wing ideology, tends to oppose immigration, while Islamism and Conservatism show a more pro-immigrant stance. On the other hand, left-wing ideologies like Secularism and Kemalism adopt a more anti-immigrant position, whereas Liberalism and Socialism lean toward neutrality. This can be related to the political atmosphere within Türkiye, where the right-wing Islamist incumbent party holds a pro-immigrant stance, whereas the left-wing main opposition party adopts an anti-immigrant stance. It is also related to the fact that most immigrants flowing into Türkiye are from Muslim countries, leading to a more positive stance from the Islamist factions of the country. In summary, the study underscores the complexity of ideological influences on anti-immigrant sentiment in Türkiye, demonstrating that a broad right-left distinction is insufficient to capture the range of opinions on immigration. The anti-immigrant stance is not confined to the right, as several left-wing ideologies also exhibit opposition, indicating the need to analyze ideologies in a more detailed and context-sensitive manner.

The findings regarding emotions are consistent with Intergroup Threat Theory (Stephan, 2009), which suggests that perceived threats from out-groups trigger emotional responses that, in turn, shape anti-immigrant sentiment. Emotions such as disgust and, particularly, anger fuel negative attitudes toward immigrants in general. The results indicate that anger is not only the most prevalent emotion in discussions about immigration but is also strongly linked to a negative stance. However, in contrast to the findings of Aarøe et al. (2017), disgust although negatively associated with anti-immigrant stance in general, does not push left-wing ideologies such as Kemalism, Social Democracy, and Liberalism toward anti-immigrant positions. Instead, its interaction with these ideologies produces the opposite effect.

The findings demonstrate that the effect of emotions on ideologies is not uniform but rather context-dependent, shaped by the specific topics associated with those emotions. For example, anger generally amplifies Islamism's pro-immigrant stance, reinforcing a positive outlook toward immigration. However, when anger is directed at topics like the economy, public health, and internal affairs, its influence shifts, driving Islamist individuals toward a more negative stance. This illustrates how the same emotion can have contrasting effects depending on the target of that emotion or the topic being discussed. These findings align with Integrated Threat Theory (ITT), which suggests that realistic perceived threats—related to topics such as economic stability, health, and security—fuel anti-immigrant sentiment (Stephan & Stephan, 2000).

The findings reveal an overall negative stance toward immigrants in Türkiye, indicating that the country is experiencing immigration fatigue, as suggested by the UNHCR report (2023b). The most frequently discussed topics in this study support the labor market competition hypothesis as part of a perceived economic threat (Dražanová et al., 2022; Gerber et al., 2017; Gorodzeisky, 2011). After foreign affairs, one of the most prominent topics in the tweets expressing a negative stance is the "economy," underscoring the role of perceived economic threats in shaping anti-immigrant sentiment in Türkiye. "Labor and employment" is the second most discussed welfare-related topic, suggesting that labor market competition influences the anti-immigrant stance, consistent with previous studies in Türkiye (Ceritoglu et al., 2017; Erdogan & Semerci, 2020; Koca, 2016). Moreover, "health and public health" were discussed even more frequently than labor and employment, supporting the finding that there is a perception of migrants exploiting social and health services in Türkiye, in line with Koca (2016). These are also realistic threats as suggested by Integrated Threat Theory (Stephan & Stephan, 2000) Finally, the frequent mention of "internal affairs" in negative tweets points to the association between immigrants and security concerns in public discourse in Türkiye (Cirakoglu et al., 2021; Erdoğan & Semerci, 2020; Gökçe & Hatipoğlu, 2021; Koca, 2016).

Chapter 12:
CONCLUSION

This study aims to investigate the interaction effect of ideologies and emotions on anti-immigrant sentiment within the context of Türkiye. Using Twitter data from the Politus Project, which includes pre-labeled ideologies and emotions, Natural Language Processing (NLP) methods are employed for automated topic classification and stance detection. The BERTurk-128k cased model, a BERT-based deep learning model tailored for the Turkish language, is fine-tuned to classify tweets related to immigration in Türkiye. Additionally, a second BERT model, TurkishBERTweet, is fine-tuned and utilized specifically for stance detection, distinguishing between pro- and anti-immigrant sentiment in immigration-related tweets. To analyze the data, a multinomial logistic regression model is applied, controlling for demographic variables and economic indicators, allowing for a more nuanced understanding of how emotions and ideologies influence attitudes toward immigration.

This study highlights several key findings regarding the interaction between ideologies, emotions, and immigration stances in Türkiye. Firstly, the results confirm that the relationship between right-wing ideologies and anti-immigrant sentiment, commonly observed in Western contexts, does not fully apply to Türkiye. Ideologies such as Turkish Nationalism, Secularism, and Kemalism show a strong opposition to immigration, but right-wing ideologies like Islamism and Conservatism demonstrate more support for immigration. This suggests that ideological positions in Türkiye are more nuanced than previously thought, diverging from typical patterns seen in other countries.

Emotions also play a significant role in shaping immigration stances. While all the emotions are highly significant in the emotion-only model, their influence changes when ideologies are introduced. The interaction between emotions and ideologies reveals that emotions can either reinforce or shift ideological stances on immigration. Moreover, specific emotions interact differently with each ideology. Anger, for instance, has the most widespread effect, influencing nearly all ideologies in some way, whether by intensifying or shifting anti-immigrant sentiment or pro-immigrant views. Disgust and sadness, while impactful, have more targeted interactions with certain ideologies. Happiness, on the other hand, tends to promote a pro-immigrant stance across the board but does not show significant interaction with specific ideological positions.

Overall, the findings suggest that emotions play a critical role in moderating ideological positions on immigration in Türkiye, with anger, disgust, and sadness being particularly influential. These results underscore the complexity of political attitudes toward immigration, where both emotions and ideological beliefs interplay to shape public opinion. This study thus contributes to a deeper understanding of the affective dimensions of immigration discourse, particularly in the unique political context of Türkiye.

12.1 *Limitations and Future Work*

One of the major advantages of this study is its use of large-scale social media data, which provides real-time public opinions that are often difficult to capture through traditional survey methods. Social media platforms like Twitter allow individuals to express their emotions and opinions freely and instantly, offering a vast and diverse dataset that can reveal nuanced trends and shifts in public sentiment. Using social media data also allows to conducting of retrospective studies as such using past data.

The combination of natural language processing (NLP) techniques with deep learning models like BERTurk and TurkishBERTweet enhances the accuracy and scalability of analyzing massive datasets. These models, fine-tuned for the Turkish language, make it possible to automatically classify immigration-related content and detect stances on a large scale. By automating this process, the study can handle a far larger dataset than would be feasible with manual analysis, providing a more comprehensive picture of public attitudes. Additionally, the incorporation of both emotions and ideologies into the analysis allows for a more sophisticated understanding of how these two factors interact to shape immigration stances, offering insights that would be missed by more simplistic approaches.

However, there are also limitations to using social media data for such analyses. First, not all segments of the population are equally represented on social media, leading to potential sampling biases. For instance, urban and male individuals may be overrepresented, while female or rural populations may be underrepresented, as is the case in the sample used for this study. This can skew the findings and make it difficult to generalize the results to the entire population. To address this representation problem, the analysis could be validated using alternative real-world data sources, such as traditional surveys. Alternatively, post-stratification can be applied for a better representation of the actual population.

In terms of ideology assignment, setting a threshold of five tweets for associating a user with an ideology can increase precision but reduce recall causing some of the ideologies to be underrepresented in the dataset. Another limitation is the difficulty in accurately assigning ideological labels to users based solely on their social media posts. While NLP models like BERTurk and TurkishBERTweet are highly advanced, they still depend on the quality and comprehensiveness of their training data. Errors in ideology, stance, or topic detection can occur, especially in instances involving sarcasm, irony, or context-specific language.

In this study, there is room for improvement in the BERT model used for stance detection. Although it performed well in capturing neutral and negative stances, it could be enhanced to better identify positive stance tweets. One approach to achieving this would be increasing the size of the annotated dataset, a strategy that has proven effective in improving performance for neutral and negative categories. Additionally, the annotation process could be optimized. In this study, the majority of categories were annotated by ChatGPT and adjudicated by a single annotator. Introducing a second annotator and having final adjudication by a domain expert could lead to a more reliable annotated set, especially given the ambiguity and lack of context often present in tweets.

Additionally, due to computational limitations, the data for this study was randomly sampled, with only one-fourth of the users included in the analysis. Under ideal conditions, this sampling would not be necessary, and using the full dataset could yield more reliable and comprehensive results.

Furthermore, the interaction effect between ideologies and emotions, while revealing, is still a relatively new area of study, and the findings may be influenced by factors not fully captured by the models used.

Finally, while this study focuses on Türkiye, the findings may not be directly applicable to other non-European contexts without careful consideration of local political, cultural, and social dynamics. The unique political landscape in Türkiye, where the right-wing government adopts a pro-immigrant stance, diverges from patterns seen in Western nations. Therefore, while this study provides valuable insights, further research is needed to explore how these dynamics play out in other regions with different political and ideological landscapes.

In conclusion, while there are clear advantages in using social media data and NLP techniques to analyze public sentiment on immigration, researchers must be mindful of the limitations posed by data representation, potential biases, and the accuracy of automated models. Nevertheless, this study highlights the potential of combining emotions and ideologies to deepen our understanding of public stances on immigration, particularly in non-Western contexts like Türkiye.

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APPENDIX A: RESULTS OF COMBINED MULTINOMIAL LOGISTIC REGRESSION MODEL

Variable	**Coefficient for Positive Stance (Std. Error)***	**Coefficient for Negative Stance (Std. Error)***
Intercept	-1.9700***(0.035)	-1.6014***(0.027)
Happiness	0.5531**(0.246)	-0.4059 (0.361)
Sadness	1.7811***(0.042)	0.0026 (0.052)
Anger	0.3107***(0.021)	1.3406***(0.016)
Fear	0.4955**(0.225)	0.3582 (0.206)
Anxiety	0.4911**(0.214)	0.2407 (0.210)
Disgust	0.1145**(0.053)	0.7942***(0.035)
Islamism	0.2865***(0.009)	-0.3512***(0.007)
Kemalism	-0.2152***(0.010)	0.2915***(0.007)
Conservatism	0.3271***(0.015)	-0.2916***(0.016)
Feminism	-0.1052***(0.019)	-0.1645***(0.017)
Environmentalism	-0.2100***(0.041)	-0.4144***(0.036)
Kurdish National Movement	-0.2149***(0.027)	-0.5300***(0.026)
Liberalism	-0.0896***(0.011)	-0.1788***(0.009)
Secularism	0.0084 (0.055)	0.2331***(0.041)
Social Democracy	-0.2883***(0.012)	-0.0212**(0.009)
Socialism	-0.0127 (0.046)	-0.4760***(0.050)
Turkish Nationalism	-0.1696***(0.012)	0.4229***(0.012)
Happiness*Islamism	0.0475 (0.148)	0.0875 (0.218)
Happiness*Kemalism	-0.1230 (0.151)	0.1024 (0.202)
Happiness*Conservatism	-0.0141 (0.213)	-0.0223 (0.361)
Happiness*Feminism	0.2226 (0.262)	-0.1403 (0.416)
Happiness*Environmentalism	-0.0493 (0.608)	0.0590 (0.925)
Happiness*Kurdish National Movement	0.0999 (0.461)	-0.0289 (0.862)
Happiness*Liberalism	-0.0953 (0.180)	0.0019 (0.255)
Happiness*Secularism	-0.0323 (0.833)	-0.0094 (1.022)
Happiness*Social Democracy	0.2428 (0.186)	-0.2288 (0.256)
Happiness*Socialism	-0.0222 (0.869)	-0.0166 (1.799)
Happiness*Turkish Nationalism	0.3370 (0.215)	-0.2054 (0.325)
Sadness*Islamism	0.0070 (0.028)	-0.0021 (0.033)
Sadness*Kemalism	-0.0371 (0.029)	0.0229 (0.031)

Sadness*Conservatism	0.3974***(0.049)	-0.0898 (0.065)
Sadness*Feminism	-0.2958***(0.051)	-0.0349 (0.056)
Sadness*Environmentalism	-0.1432 (0.118)	0.0287 (0.136)
Sadness*Kurdish National Movement	-0.1455 (0.090)	0.1778 (0.107)
Sadness*Liberalism	-0.1111***(0.032)	-0.0915**(0.037)
Sadness*Secularism	-0.0801 (0.173)	0.1680 (0.168)
Sadness*Social Democracy	-0.1224***(0.032)	-0.0091 (0.034)
Sadness*Socialism	-0.4509**(0.145)	0.1445 (0.194)
Sadness*Turkish Nationalism	-0.1145***(0.035)	0.0183 (0.044)
Anger*Islamism	0.1124***(0.013)	0.1038***(0.009)
Anger*Kemalism	-0.0016 (0.013)	-0.0846***(0.009)
Anger*Conservatism	-0.0768***(0.022)	0.2641***(0.019)
Anger*Feminism	0.0707**(0.027)	0.0243 (0.021)
Anger*Environmentalism	0.4357***(0.056)	0.3479***(0.045)
Anger*Kurdish National Movement	-0.0508 (0.037)	0.1297***(0.031)
Anger*Liberalism	0.0712***(0.015)	-0.0256**(0.011)
Anger*Secularism	-0.0481 (0.070)	-0.0507 (0.048)
Anger*Social Democracy	0.0995***(0.016)	-0.0345***(0.011)
Anger*Socialism	0.0412 (0.067)	-0.2330***(0.065)
Anger*Turkish Nationalism	0.0455**(0.018)	0.0268 (0.015)
Anxiety*Islamism	0.2107 (0.126)	0.0745 (0.110)
Anxiety*Kemalism	-0.0173 (0.130)	0.0638 (0.108)
Anxiety*Conservatism	0.0393 (0.216)	-0.0726 (0.232)
Anxiety*Feminism	0.0012 (0.246)	-0.2518 (0.239)
Anxiety*Environmentalism	0.2507 (0.378)	-0.2628 (0.410)
Anxiety*Kurdish National Movement	0.1040 (0.399)	-0.0306 (0.418)
Anxiety*Liberalism	0.0680 (0.145)	0.2956**(0.124)
Anxiety*Secularism	0.0150 (0.644)	-0.0227 (0.494)
Anxiety*Social Democracy	0.1642 (0.148)	0.0671 (0.122)
Anxiety*Socialism	0.0405 (0.650)	0.0250 (0.742)
Anxiety*Turkish Nationalism	-0.0574 (0.174)	-0.0032 (0.180)
Disgust*Islamism	0.0667**(0.030)	-0.0133 (0.018)
Disgust*Kemalism	0.0207 (0.031)	-0.1095***(0.019)
Disgust*Conservatism	0.0256 (0.050)	0.0344 (0.034)
Disgust*Feminism	0.0755 (0.054)	-0.2018***(0.036)

Disgust*Environmentalism	0.4468***(0.119)	0.0908 (0.091)
Disgust*Kurdish National Movement	0.1396*(0.076)	0.0802 (0.049)
Disgust*Liberalism	0.0547 (0.036)	-0.1596***(0.023)
Disgust*Secularism	-0.0004 (0.122)	-0.0579 (0.071)
Disgust*Social Democracy	0.2155***(0.039)	0.0254 (0.024)
Disgust*Socialism	-0.0351 (0.180)	0.2033 (0.139)
Disgust*Turkish Nationalism	0.0726 (0.045)	-0.0560 (0.031)
Fear*Islamism	0.2379 (0.147)	-0.1554 (0.125)
Fear*Kemalism	-0.1534 (0.151)	-0.0541 (0.121)
Fear*Conservatism	-0.1343 (0.249)	-0.0787 (0.246)
Fear*Feminism	0.1028 (0.240)	0.1383 (0.211)
Fear*Environmentalism	0.0142 (0.504)	-0.0289 (0.434)
Fear*Kurdish National Movement	0.1585 (0.414)	-0.0379 (0.426)
Fear*Liberalism	0.3431*(0.166)	-0.1489 (0.151)
Fear*Secularism	0.0554 (0.754)	0.0597 (0.560)
Fear*Social Democracy	0.1672 (0.181)	0.3892**(0.140)
Fear*Socialism	0.1303 (0.703)	0.0397 (0.852)
Fear*Turkish Nationalism	-0.1285 (0.187)	-0.0580 (0.180)
unemployment_rate	0.0440***(0.003)	0.0001 (0.002)
gender_male	-0.2511***(0.009)	-0.0506***(0.007)
age_group_30-39	0.0263*(0.012)	0.0340***(0.009)
age_group_<=18	-0.0542***(0.012)	0.0547***(0.008)
age_group_>=40	0.0613***(0.011)	0.0219***(0.008)

*coefficients are beta coeeficients, not exponentiated betas