

Revisiting workplace mobbing: tweets and qualitative analysis in Türkiye case

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Abstract

The globality of mobbing points to huge influence of economic issues over social and societal aspects in the life dynamics of work. COVID-19 presents a new kind of crisis that transforms these factors and establishes new norms in working life simultaneously. Mobbing is to be defined, in this perspective, as the modifications of situation of work and expectations of workers retraining the boundaries and manifestation of mobbing. This study examines the impact of dislocating mobbing, which is a kind of violence that deteriorates the quality of life for employees as well as workplace productivity, in terms of the new dynamics of mobbing and existing dimensions of mobbing-the COVID-19 perspective. Mixed methods research was carried out through macro-level collection and analysis of tweet data alongside micro-level focus group interviews. While macro findings identified general mobbing dimensions, micro findings revealed more indirect, implicit and specific means of power imbalance. The findings of the research identify emerging gaps in organisational practice regarding diversity and inclusion via the lens of increasing and latent specific power imbalances. In both data analyses, a new dimension of mobbing was identified: the perception of injustice. The emergence of injustice as a new dimension provides a more comprehensive perspective on current practices. The findings of this research are expected to provide valid approaches towards reiteration of existing organisational practices and human resources training.

Keywords Workplace mobbing · Sentiment analysis · Qualitative analysis · Post-COVID-19 · Bullying · Injustice perception

1 Introduction

The mobbing phenomenon has existed as a destructive power struggle since the beginning of business life. Since the emergence of structured work environments, individuals have sought to assert dominance over others, driven by complex motives such as dark side of personalities, and workplace dynamics. In order to establish dominance and pressure, they exhibit unethical behaviors such as humiliation, verbal harassment, exclusion, ignoring, gossiping and even physical violence in the workplace [1–3]. The expected result of these behaviors is to make the targeted employee uncomfortable, unhappy or distant from work. From this perspective, although mobbing is a



very old concept, it was first systematically investigated in the field of organizational psychology by Leymann [1]. Mobbing refers to intentional, systematic, and repeated psychological attacks against an individual in the workplace. These attacks aim to leave the individual defenseless and emotionally drained [1, 4]. Groups or individuals in power regularly put pressure on the person by emotionally attacking them with various psychological methods and leaving them defenseless. The concept of mobbing has a very complex structure [5]. In other study [6], the authors point out many difficulties in the field of research. The most important of these difficulties is understanding the interaction between personal characteristics, group dynamics, organizational culture-climate and social factors within a multi-layered structure of mobbing. The variety, frequency, power imbalance and covertness of behaviors also cause discussions about which behaviors are considered and classified as mobbing [6]. Power imbalance refers to the creation of power differences among individuals based on social, gender, or professional factors, often resulting in negative consequences that the target is unable to resist or stop due to their disadvantaged position [7]. For these reasons, researchers argue that mobbing has not yet been clearly framed and has aspects open to research [3, 6, 8]. Another important definition is the concept of harassment. Harassment denotes adverse, unwelcome actions aimed at an individual due to personal attributes such as gender, ethnicity, or religion. It includes psychological or physical harm [9]. The terms used in this study, along with their definitions, are presented in a tabular form in Appendix 1.

Mobbing has increasingly attracted scholarly attention as a significant form of workplace aggression with complex social and psychological dynamics. While debates on the conceptualization and classification of mobbing continue, the COVID-19 pandemic [10, 11], widely described in the literature as an unprecedented disruption, has emerged. This global crisis not only reshaped working conditions but also intensified various organizational stressors, creating new contexts and dynamics in which mobbing behaviors could manifest [12]. Indeed, COVID-19 may cause changes in the sub-elements of mobbing and the behaviors that define them. COVID-19 has changed organizational structures and ways of doing business [13]. In particular, the spread of remote work and digital communication tools has reshaped the dynamics of relationships among employees who do not share a physical workspace [14]. Under these conditions, behaviors that were previously less likely to be exhibited may now emerge through digital channels, potentially expanding the boundaries of mobbing as interactions become more invisible and implicit. The Workplace Bullying Institute investigated whether remote working conditions were associated with mobbing during the COVID-19 period in 2021. The study revealed that the rate of employees being subjected to bullying was 43%. It was determined that remote workers faced more mobbing than non-remote workers during this period. However, in studies conducted before COVID-19, working from home was associated with positive outcomes such as job performance, well-being and ensuring work-family balance on employees [15]. This situation proves that the level of spread, and impact of mobbing differed in the context of remote working before and after COVID-19. In other words, it is seen that this negative phenomenon is experienced in different ways after the COVID-19 pandemic. Here, it is useful to explain the definition of the concept of bullying in literature. Bullying is when someone is subjected to repeated, systematic abuse and psychological pressure. It frequently entails isolating the subject, instilling fear, and causing emotional injury [16, 17]. On the other hand, the economic disruption caused by COVID-19 pandemic transformed employment and labor policies and reshaped the interaction between businesses and employees. The accompanying high-performance expectations and power imbalances often lead to job insecurity [18, 19], which can also cause mobbing to take new forms. A review of studies conducted during the COVID-19 period reveals that they generally focus on three main themes: (1) types of mobbing (e.g., cyber, school, and workplace cyberbullying) [20, 21], (2) psychological and social consequences (e.g., resilience, commitment, well-being, stress) [22–24], (3) detection and prevention strategies [25]. In the light of this information, although no study has been found that directly investigates the dimensions of mobbing, it is predicted that the investigation of the dimensions of mobbing has been ignored.

This literature review explores how various dimensions of mobbing have been influenced by rapid changes triggered by COVID-19. It examines whether the attitudes and behaviours traditionally associated with mobbing have been reconstructed in the post-pandemic context. Furthermore, it questions whether phenomena previously identified as mobbing remain conceptually valid or whether shifts in workplace behavior have rendered the

notion partially obsolete. To address these questions, a mixed-methodology approach was adopted, diverging from conventional research designs that treat qualitative and quantitative methods separately. Previous studies have highlighted several limitations in such traditional methodological separations [26, 27]. Quantitative studies typically require large sample sizes to support robust analysis. In this regard, the available sample was not sufficiently representative to capture the full scope of problem cases, as all data was collected simultaneously. In qualitative research, critics have also questioned the reliability and generalizability of interviews with mobbing victims [27]. To address these limitations, social media was employed both for qualitative analysis of beliefs and perceptions [8] and for building dataset analysis that enables generalization of findings [28]. Thus, working together with platforms such as Twitter would allow for the collection of data relevant to the problem, especially as it is an open-source social media tool [29]. Most studies examining mobbing during COVID-19 have focused on online mobbing (cyberbullying) and have primarily been conducted with samples from developed countries [30]. However, investigating potential shifts in mobbing patterns in developing countries such as Türkiye can enhance the generalizability of research findings. The authors in [31] further emphasize that bullying behaviors vary across cultural settings. Examining mobbing in different cultural contexts therefore offers an opportunity to deepen the understanding of how its dynamics evolve.

In this study, two methodological approaches were applied simultaneously in a Turkish sample. Twitter data were used to capture a large-scale, real-time dataset, while qualitative methods, including focus groups, were employed to explore perceptions of mobbing in greater depth. The first methodological contribution of this research lies in combining Tweet-based data analysis with qualitative research, thereby addressing the limitations of traditional single-method designs. A review of the current literature reveals that such an integrated, multidisciplinary approach remains rare; most studies rely on either traditional qualitative methods or data-driven analyses in isolation. By bringing these perspectives together, the present study aims to fill this gap. Additionally, focusing on a specific national context and the post-COVID-19 period provides further analytical value. The second contribution of this research is to update and enrich the understanding of mobbing's dynamic structure and behavioral characteristics through the lens of employees' perceptions.

1.1 Conceptual perspective on mobbing

Mobbing is generally defined in literature as a person or group in business life who consciously, unethically and systematically harms an individual emotionally and physically and leaves the individual defenseless [1, 6]. When this definition is examined, it is seen that mobbing has similarities and differences with other mistreatment concepts both structurally and theoretically [1, 9]. In the theoretical context, mobbing is associated with bullying, emotional abuse and conflict-based approaches [16, 17]. Conceptually, emotional abuse is a form of psychological abuse in which individuals systematically degrade and diminish the emotional well-being of others. Such behaviors can significantly undermine an individual's self-esteem [17]. Reasons such as interests, power balances, lack of communication, differences in purpose, division of labor, etc. cause various disagreements within the company and turn into conflict over time. Conflicts that cannot be resolved over time can turn into mobbing or tyranny. The source of behaviors such as emotional abuse or harassment is often personality disorders and abuse of authority. In addition, while behaviors defined as bullying are more direct and intentional in order to harm, mobbing represents more covert and indirect behaviors exhibited by more individuals. Emotional abuse, on the other hand, aims to psychologically destroy the individual. As can be understood, the multiplicity of these structures leads to confusion and suggests that the complexity stems from examining forms of maltreatment only with different terminologies [7]. On the other hand, some researchers argue that the concepts are closely related and that different concepts (mobbing, bullying, emotional abuse) can be used interchangeably in studies [4, 32, 33].

Although researchers and practitioners cannot agree on an acceptable definition for workplace mobbing due to the complexity of the phenomenon [34], a consensus is emerging in determining the basic characteristics of this phenomenon [35, 36]. Three basic characteristics stand out for a behavior to be considered mobbing: conscious intent to harm, power imbalance, and systematic repetition [1, 7]. As the first behavioral characteristic is

examined, it is seen that the behavior begins with the intention to harm, has the characteristics of being negative, beyond ethical boundaries, and irrational [4, 37]. Systematic and conscious attempts to psychologically wear down the individual are made through conflict-based communication. Behavior is considered goal-oriented when it is planned, conscious, and has the intention to harm without provocation. These behaviors often occur through verbal communication, involve less physical violence, and can be overt or covert [17]. Although three basic behaviors that determine the structure of mobbing are mentioned, the main issue is whether behaviors experienced in face-to-face situations can be considered mobbing [1, 7]. Although the emotions experienced by individuals exposed to mobbing vary from person to person, they usually emerge as negative emotions [28]. For example, Nielsen and colleagues [38] defined mobbing as a constant source of stress for employees. In their study, researchers pointed out that situations such as being targeted, attacked, or excluded cause employees to be in constant anxiety and stress and lead to serious mental health problems such as depression and anxiety. Moreover, efforts to psychologically wear down employees can even lead them to consider suicide. Leach and colleagues [39] concluded that workplace bullying creates suicidal thoughts in employees.

The second behavioural characteristic of mobbing behaviour is power imbalance [7]. Individuals who are subject to mobbing are usually in a situation where they feel vulnerable in terms of some individual factors (gender, personality traits, etc.) or environmental factors (occupation, status, etc.). The aim is to negatively affect the individual's emotional, psychological and physical health through these behaviours [16]. The first studies on the subject point to managers who use their power for their own interests as the source of bullying behaviour [40]. However, later studies have shown that when informal power is obtained, subordinates also engage in bullying behaviour towards their superiors [6]. Therefore, mobbing can occur between superiors, subordinates and peers. The important point here is that the person using power, whether formal or informal, intends to abuse that power maliciously. The third and final characteristic is the duration and repetition of the abusive behaviour. This repetition can range from less than six months to sometimes fifteen months and from twenty-nine to forty-six months [1, 3]. The main point here is that an individual's sense of victimization is constantly escalating. On the other hand, it is suggested that in cases where there is a high probability of occurrence in a single instance, such as sexual harassment or dismissal, these behaviors can be evaluated within the scope of mobbing regardless of the number of repetitions, given their potential to create the same negative perceptions and consequences in the individual [41]. In the framework of all this information, mobbing is accepted as all hostile and negative behaviors that occur in workplaces, target a specific person or group, are carried out intentionally, are continuous, and leave psychological/physical damage on the victims.

1.2 Types and classifications of mobbing

The diversity and similarity of mobbing behaviours as well as the different perspectives of researchers have necessitated a systematic classification of this phenomenon. Among the classifications commonly used in literature are those of Leymann [1], Zapf et al. [3] and Rayner and Hoel [42]. Leymann classifies forty-five behaviours into five categories: attacks that prevent individuals from expressing themselves and communicating, attacks on social relationships, attacks on the individual's social reputation, attacks on the individual's quality of life and work, and attacks that affect the individual's health. Zapf et al. examined Leymann's five-part classification and defined seven dimensions of mobbing: organisational mobbing, social isolation, attacks on the victim's private life, physical violence, attacks on the victim's attitudes, verbal attacks and gossip. Rayner and Hoel created five categories according to the way mobbing is applied: threat to the individual's position at work, threat to the individual's personality, exclusion, excessive workload and instability. These common aspects of mobbing classification include attacks on the victim's social relations, work life and personality. All classifications emphasise the negative impact of mobbing on the individual's psychological and professional life. On the other hand, while Leymann's and Zapf's classifications focus more on the effects suffered by the victim, Rayner and Hoel's classification focuses on the ways in which mobbing is applied. Zapf et al.'s model differs from the others in that it

includes indirect types of attacks such as mobbing through organisational means and gossip. Rayner and Hoel's classification include elements specific to working life such as excessive workload and instability.

In addition to the widely accepted classifications, mobbing is also classified according to its types (physical, psychological, digital, etc.), how it is applied (active–passive), its source (vertical-horizontal-reverse mobbing) and its causes (competition, power, normative, strategy-based) [43–45]. When classified according to its type, physical mobbing includes direct physical attacks, threats and actions that endanger the physical safety of the individual; while psychological mobbing includes humiliating and discrediting behaviors that negatively affect the emotional and cognitive health of the individual. Digital mobbing, on the other hand, manifests itself in the form of cyberbullying, online threats, and psychological pressure carried out through digital platforms. The classification of mobbing according to the way it is applied includes a distinction between active and passive mobbing. While active mobbing includes open attacks such as insults directly directed at the individual; passive mobbing refers to systematic pressure processes applied indirectly, such as exposing the individual to social isolation, restricting the flow of information, or obscuring task-authority definitions. Mobbing can be applied vertically from managers to subordinates within the hierarchical structure, as well as inversely from subordinates to managers, and can also occur horizontally among employees of equal status. Structurally, mobbing is associated with power imbalances and organizational structures in the workplace. The source of mobbing is influenced by power dynamics between managers and employees or among peers, while organizational culture and the work environment also play a significant role in shaping this phenomenon [46].

Although various theoretical frameworks and classifications have been developed in previous research on the concept of mobbing, challenges and gaps persist in fully comprehending and explaining this phenomenon [38]. However, two main approaches are observed in research on mobbing. In the first approach, quantitative analyses focus on the antecedents and sequels of mobbing [47] and qualitative analysis results generally based on the experiences of the victims. The second approach is research that focuses on the definition, classification and theoretical basis of mobbing, proceeding with systematic literature reviews and meta-analysis methods [48]. In this context, Moayed et al. [49] draws attention to the effects that environmental factors can have on individuals and businesses and suggests that they be re-investigated. Findings reveal that dynamics such as environment, society and market can differentiate the responses given to organizational changes and conflicts. In addition, it is emphasized that bullying individuals is also affected by these external factors. The research shows that workplace bullying should be addressed not only with individual and organizational factors but also within a broader socio-economic and environmental context, drawing attention to the research gap in this area. In this direction, [50] tried to re-evaluate the behaviors defined as mobbing from the perspective of Human Resources (HR). Although the research attempted to determine new behaviors defined as bullying by HR professionals, the general perspective considered is not examined comprehensively.

1.3 Cultural context to mobbing

In the 1980s, Geert Hofstede identified four distinct cultural dimensions that help to understand how cultural values shape the behaviour of individuals; in subsequent years, he added two new dimensions, increasing the number of dimensions to six [51]. A further study examined many organisational behaviour issues, such as human resources and leadership, in more than 60 countries and how they are shaped by social and cultural differences [52]. Studies support this claim by highlighting the impact of cultural factors on workplace bullying and how the prevalence of bullying varies across different national cultures. However, studies are limited to a few countries (USA, Switzerland, China, Japan, Finland, etc.) [4, 31].

International Labor Organization published a report in 2020, revealing the prevalence and dynamics of workplace bullying worldwide. The report estimates that 6% of employees in Europe experience social harassment, an estimated 36 million people in the US experience workplace bullying, and cyberbullying cases are observed among academics in Canada. Psychological violence and unethical managerial practices are prominent in Latin American countries such as Brazil and Chile. In the African continent, cases of physical and sexual harassment

in the workplace are quite high in Nigeria, Ethiopia, Kenya and South Africa. In Asia, hierarchical mobbing is common in countries such as South Korea and Japan, and employees are subject to pressure from managers. In the Oceania region, a significant portion of employees in Australia and New Zealand report that they have experienced workplace bullying in the last six months. In addition, female employees are more likely to be victims of sexual harassment than men. In Cambodia, Ethiopia and Kenya, workplace sexual harassment has been identified as one of the biggest problems for women. The report summarizes. According to the data of the Anti-Mobbing Association in Türkiye, it is estimated that approximately 9.5 million people are exposed to mobbing. According to the hotlines, 1,168 reports were made in 2022, and there was a 23% increase compared to the previous year.

It is evident that both the types of mobbing and the prevalence rates vary significantly between countries. Each country has different dynamics according to its own cultural and socioeconomic structure. Türkiye is a developing country and according to the GLOBE research [61], it has the characteristics of in-group collectivism, power distance, assertiveness/assertiveness, social collectivism, uncertainty avoidance, human orientation, performance orientation, future orientation and gender equality values from high to low. Due to these cultural characteristics, it has a structure that includes both Eastern and Western cultural dynamics. In addition, as a developing economy, it is thought to contribute to understanding how mobbing is shaped in work environments in other developing countries. Competition and job insecurity in the labor market can cause employees to experience stress and become more susceptible to mobbing.

1.4 Assessing mobbing: traditional method research

Studies on mobbing utilizing traditional research methods are observed to employ qualitative, quantitative, and mixed methods. When evaluated from the perspective of method and content, it is evident that researchers predominantly focus on the prevalence, antecedents, and consequences of mobbing [53]. A meta-analysis conducted in 2022 predominantly found associations between mobbing and intentions to leave the job, job satisfaction, burnout, and organizational commitment.

Although qualitative analysis was generally preferred in the first studies on mobbing [7] methodologically, most of the research on mobbing uses quantitative methods that include numerical approaches [54]. Two main streams emerge for measuring mobbing in quantitative studies, differing in their approach to assessing the prevalence rates of mobbing. These streams are: (1) Researchers provide a definition of mobbing based on theoretical foundations, followed by asking participants whether they have been exposed to a behavior within this framework. The participant's perception of recognition is measured, which is also known as self-labeling. (2) Participants are given a list of various mobbing behaviors, and they are asked how frequently they have experienced them. This approach is known as behavioral experience [4]. In literature, the most used scales for querying behavior lists include the Inventory of Psychological Terror developed by Leymann [1] and the Negative Acts Questionnaire-Revised developed by Einarsen and others [16, 37].

Traditional research methods also include qualitative research methods that encompass various techniques such as interviews, focus group discussions, individual personal experiences, case studies, and text analysis are used. Among these, in-depth interviews are the most preferred data collection technique for researching mobbing [55]. This methodology, called phenomenology [56], reveals the common perspective of the target audience by comparing the interpretations, perspectives, and interpretations of people who have had the same experience.

Mixed methods, combining both qualitative and quantitative methods, provide a rich perspective in terms of collecting multiple data. This approach allows researchers to both deeply understand the event and generalize their findings [57]. While qualitative methods enable exploring participants' experiences and emotions in more detail, quantitative methods offer statistical analyses and generalization capabilities based on broad sampling. This combination provides researchers with the opportunity to achieve a more comprehensive and in-depth understanding [58]. Systematic literature reviews reveal that most studies employing mixed methods are conducted in the education (students) [26, 59] and health (nurses) [60] sectors.

Studies conducted on post-COVID periods, utilizing qualitative, quantitative, and mixed methods, appear to be concentrated in the fields of health and education. In health studies, mobbing is associated with burnout, intention to leave the job, and post-work stress, and both qualitative and quantitative methods are utilized [62, 63]. In educational research, cyberbullying within the context of mobbing has been predominantly investigated through quantitative studies.

1.5 Tweets-based studies

In this subsection, the mobbing issue is evaluated from the perspective of social media, which plays an important role in the new era, rather than traditional approaches and methods. In this regard, studies conducted in literature from this line of vision are taken as basis. Recently, in a wide range of areas such as psychology and social analyses, product reviews, political issues, and health reviews, Twitter flows are classified, and Twitter sentiment analysis is carried out based on them. Accordingly, Tweets and data analysis are important for various comments and inferences. In this context, studies in the literature investigating mobbing based on tweet data were examined. As mentioned before, mobbing is expressed in different words, so a wide range of literature searches were conducted. However, as mobbing incidents in the workplace have become more common today due to various reasons, as explained in the previous section, studies that approach the incident from this perspective have been focused on. It is worth noting that in literature, there are very few studies on the relevant problem after COVID-19 pandemic on a country basis.

Recent studies, a wide variety of sentiment analysis or opinion mining studies have been carried out on the data obtained from Twitter in the MERS-CoV outbreak, H1N1 and swine flue outbreak, and Ebola outbreak [64, 65]. Karaca and Aslan [66] focused on sentiment analysis of COVID-19-related tweets. It would provide background information on the COVID-19 pandemic and the importance of analyzing public sentiment. The authors outlined their goal, which generally involved analyzing sentiment in tweets to understand public perception during the pandemic, and in this regard, they used Long Short-Term Memory (LSTM) as a deep learning model for sentiment analysis. The methodology also discusses data collection and preprocessing steps. They sorted tweets into sentiment categories such as positive, negative, or neutral. Its results include statistics on the distribution of sentiments across tweets and possibly some samples of tweets from each sentiment category. The article explored the key findings and their significance in the context of understanding public sentiment during the COVID-19 pandemic.

Chaurasia and Shrekar [67] evaluated the issue of mobbing in the workplace through Turkish tweets. The purpose of the study was to analyze individuals' thoughts about mobbing and to determine the consequences experienced because of the mobbing process. Researchers working on a data set of approximately one month concluded that mobbing victims were mostly from the education and health sectors and were mostly individuals who had mental health problems and were forced to resign. This valuable study has not focused much on the limitations of traditional methods and their dependence on dynamic structure and cultural characteristics. Additionally, it is noteworthy that the fixed model was used instead of the dynamic structure and model in the data analysis. In the field of computer and data engineering, it is more common and acceptable for data to guide us. Ciplak and colleagues [68] made inferences by finding accuracy and F1-score values with the code they wrote in Python using the machine learning method on a Twitter (now known as X) dataset. However, the results of this study were mainly numerical, and they did not discuss the phenomenon from the social dimension. In another study [69] used Naïve Bayes, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classifier model to detect cyberbully threats. The distribution of people's opinions on social media as positive, neutral or negative was examined through sentiment analysis, and in this context, the accuracy of each classifier was evaluated in this study.

2 Method and material

Given the evolving nature of mobbing, particularly in response to crises such as the COVID-19 pandemic [70] and changing perceptions of the workforce, this study seeks to examine how perceptions of mobbing have changed in the post-pandemic era and to question the need to broaden the conceptual scope of mobbing. Due to the complex and evolving phenomenon of mobbing, a mixed-methods approach was adopted to provide a comprehensive analysis. Surveys and large-scale quantitative studies have provided valuable statistical information about workplace mobbing, but they often lack the depth to provide a comprehensive understanding of the evolving perceptions of employees. In light of the evolving nature of mobbing in the post-pandemic era, qualitative methods such as focus groups can offer rich, in-depth insights. Additionally, sentiment analysis of Twitter data can facilitate real-time, large-scale discourse analysis. The integration of these methodologies can ease a more comprehensive understanding of the evolving structure of mobbing.

Twitter-based sentiment analysis and focus group qualitative analysis used in our study have complementary strengths. Twitter analysis provides the opportunity to evaluate social trends and mobbing perception from a broad perspective by collecting various data from a wide range of users. Thanks to machine learning models and NLP techniques, it classifies the sentiment of tweets with high accuracy and reveals negative, positive and neutral emotions. In addition, users' free expressions have enabled the analysis of uncensored and authentic views. On the other hand, focus group analysis provides the opportunity to examine individual mobbing experiences in detail by providing in-depth insight and contextual information. This method provides more clarity in understanding the types, causes and processes of mobbing, while also revealing a new concept added to mobbing, such as injustice. Injustice in the workplace refers to unfairness in the distribution of outcomes (distributive injustice), in decision-making processes (procedural injustice), or in the way people are treated (interactive injustice) [71]. The use of these two methods together allows us to evaluate both the general perception of the mobbing phenomenon at the macro level and individual experiences at the micro level with a holistic approach. In short, the main reason for the simultaneous use of 'tweets' data and 'qualitative methodology' is that mobbing is accepted as a personal and often traumatic experience involving subjective perceptions and emotional reactions [37, 72]. For this reason, we used self-reported data retrieved from qualitative methods that are crucial for capturing subjective perceptions and emotional responses [73]. This study focuses primarily on participants of medium and large-sized business organisations in the private sector where hierarchical structures are established. Given that hierarchical organizations have the potential to create power asymmetry between managers and subordinates [74] and generate negative effects on employees, such as bullying [75]. This sample allows for an investigation of mobbing in workplaces where formal relationships exist. Recognising that alternative work models, including freelance, gig work, may create different power dynamics, such as algorithmic management, which may also exacerbate bullying behaviours [76], this study findings should be interpreted in the context of hierarchical organisations.

To enhance data validity of qualitative methods, themes emerging from the focus group interviews were reviewed independently by three researchers. Additionally, participants were reconvened to verify whether their statements were accurately represented. This cross-validation process [77] helped reduce subjective distortions in reporting mobbing incidents. However, we have acknowledged that this process may be subject to recall bias, social desirability bias, and emotional impact, particularly in qualitative interviews. To mitigate these limitations, we used triangulation techniques, combining focus group interviews with Twitter sentiment analysis providing both subjective accounts and broader social discourse insights on mobbing. Applying sentiment analysis to social media data provides a complementary understanding of mobbing experiences by analyzing real-time, unfiltered public discussions. This approach helps to address potential biases in self-reported qualitative data and provides a more diverse and large-scale perspective on mobbing.

2.1 Mobbing investigation based on tweets data analysis

The current studies demonstrate that combining social science with computer science can advance our understanding of key social issues like mobbing. Therefore, most future studies are expected to be multidisciplinary and widespread. This situation is inevitable, especially in our world where artificial intelligence and social media have become widespread. In this study, the mobbing issue is discussed through Twitter (now known as X), one of the important social media channels. The general operating principle of this model is presented graphically in Fig. 1.

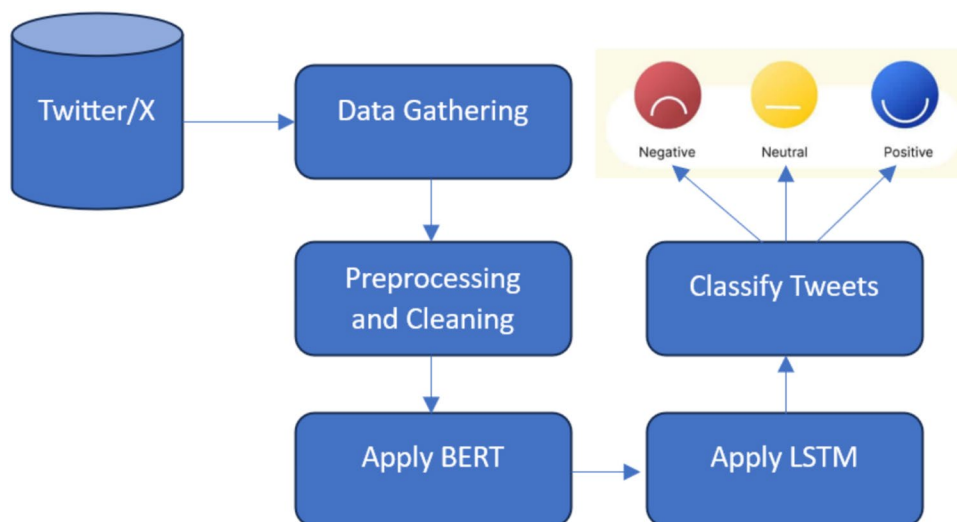
2.1.1 Data gathering

The importance of data collection plays a huge role in many different contexts, from scientific research in a variety of fields to business. Some of these areas include Decision-Making Processes, Customer Relationship Management, Performance Evaluation, Government Policies and Public Services, and Analysis of Social Problems. In this study, the issue of mobbing, which is one of the current social problems and is becoming more and more widespread today, is discussed and in this regard, data was collected from Twitter.

As it is known, until Twitter (now known as X) changed hands, data access was unlimited and free for data analysts and researchers. However, restrictions started in the process with the name X, and as of July 2023, the free access rate has been further limited. Despite this, in connection with the content of this study and research, data for 2023 was collected based on the following methods. Moreover, since the focus of the study is Türkiye as a case study, tweets sent in Turkish were taken as a basis. Relevant tweets posted between March 2023 and December 2023 were pulled and various analyses were made based on these tweets. These tweets consist of tweets with multiple keywords and hashtags, comments made on the tweets, and similar actions. Please note that the imbalanced data resulted from the nature of the problem and not from the dataset itself and will not affect the results of training and other classification tasks. To gather the dataset from the Twitter/X platform, we used three methods:

1. *Twitter (X) API*: a set of web services and endpoints provided by Twitter to allow developers to interact with the Twitter platform programmatically. It enables developers to access and interact with Twitter’s data and functionalities, such as reading tweets, posting tweets, retrieving user information, and more, by making HTTP requests to Twitter’s servers. The Twitter API offers various endpoints and functionalities, such as User Timeline, Search, and Posting Tweets. In this study, to gather the tweets, the “search” endpoint is used to search for the keyword “mobbing” and the hashtag “#mobbing”.

Fig. 1 The steps of the model to classify the gathered tweets



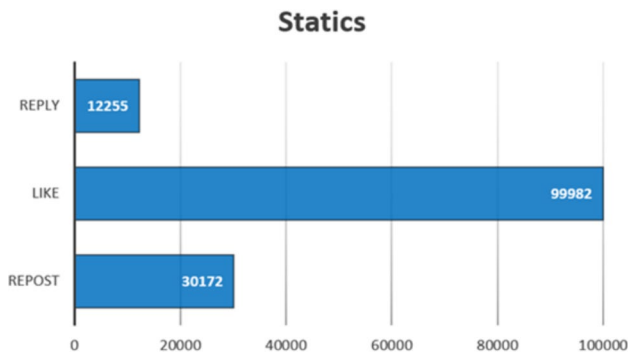


Fig. 2 Statistical results based on collected data

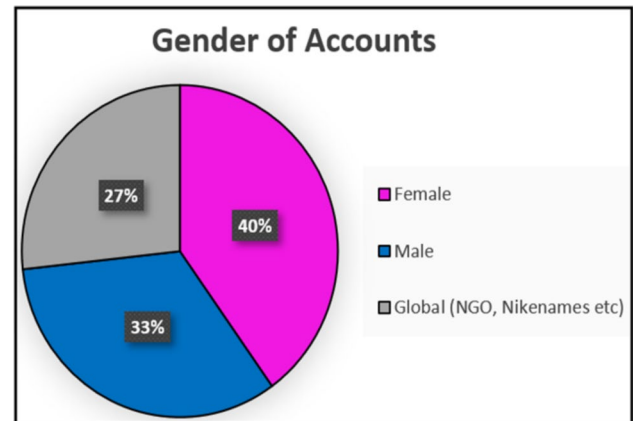


Fig. 3 Distribution of users according to collected data

- Twint Package*: Twint is an advanced and powerful Python library for scraping and collecting data from Twitter without using the official Twitter API. It allows users to search for, retrieve, and store large amounts of Twitter data, including tweets, user profiles, and follower/following information, for various purposes, such as data analysis, research, and social media monitoring. This study utilized this package for faster and clearer results.
- Manual Gathering*: some tweets were gathered manually directly from the Twitter platform after it changed its rules for downloading tweets' data from its API.

Preprocessing tweets before using them as training data or in analysis is a critical step in ensuring the quality and effectiveness of the machine learning model. In our work, this process typically involves several tasks designed to clean and standardize the text data. First, non-informative elements such as URLs, hashtags, mentions, and special characters (e.g., punctuation and emojis) are removed. It is also common to convert all text to lowercase to avoid case sensitivity issues. Additionally, stop words, which are commonly used but carry little meaning (e.g., “and” “the”), are often removed to focus on the most informative parts of the tweets before using the tweets as input to Bidirectional Encoder Representations from Transformers (BERT) and other algorithms. These preprocessing steps ensure that the tweets are in a form suitable for model training, improving accuracy and reducing noise.

2.1.2 Statistical results based on collected data

Specifically, the total retweets, likes, and comments of the gathered tweets were also analyzed. According to the results, approximately 6 times more replies ($N=12,255$), 50 times more likes ($N=99,982$) and 15 times more repost ($N=30,172$) transactions were made of the total of 2031 tweets collected. These results are presented in Fig. 2.

In addition, it also analyzed who sent the tweets. The analysis was conducted by categorizing the users into three groups, as illustrated in Fig. 3. We named two groups, male (27%) and female users (40%), and the third category, global users (33%). The Global category is based on users such as various NGOs, news agencies, and research centers focusing on social issues. Based on the results, it is quite striking that the users are predominantly female. This means that Turkish society (especially in business life) draws more attention to this problem or suffers from it. In this analysis, it should be noted that a high rate does not mean that women are exposed to more mobbing. These results also indicate that institutions operating in the global category are not as active as expected (even if it is to raise awareness).

At the same time, the hours of the day when these users posted tweets were analyzed. Accordingly, evaluation was made in two different categories. The first of these are the tweets sent during working hours and the other are

the tweets outside working hours (including meal/rest hours). The results here are presented without discrimination between men and women. Figure 4 demonstrates that normal users (male/female) mostly shared relevant tweets outside working hours, while members of the Global group did so during working hours. All collected tweets are in Turkish, and the times of tweets sent from outside Türkiye were taken into account according to their local time.

2.1.3 Sentiment analysis and data result

Sentiment analysis of tweets, also known as Twitter sentiment analysis, is a Natural Language Processing (NLP) technique used to determine and analyze the sentiment or emotional tone expressed in tweets on the social media platform Twitter/x. The goal is to understand the overall sentiment of a tweet, which can be positive, negative, neutral, or even a specific emotion like joy, anger, sadness, etc. It typically involves text processing and sentiment classification. In text processing, tweets often contain informal language, abbreviations, hashtags, and emojis. The first step is to preprocess the text, which may include tasks like tokenization (splitting text into words or phrases), removing special characters, converting text to lowercase, and handling hashtags and mentions. In sentiment classification, each tweet is classified into one or more predefined sentiment categories. The most common categories are:

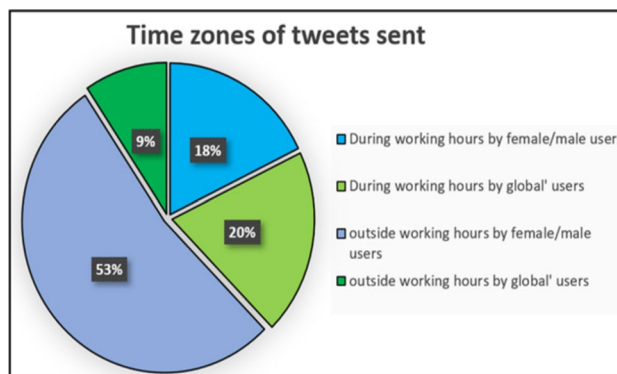
Positive: If the tweet expresses a positive sentiment, such as happiness, satisfaction, or excitement.

Negative: If the tweet conveys a negative sentiment, such as anger, sadness, frustration, or disappointment.

Neutral: If the tweet doesn't express a clear positive or negative sentiment.

In this research work, the BERT algorithm [30] is used to classify the sentiment of the gathered tweets. BERT is a finely tuned deep learning model developed to understand context by looking at words in a sentence in both directions—considering information not only coming from the past, but also from the future. The pre-trained BERT model was fine-tuned for sentiment classification on a labeled dataset of thousands of tweets (described in the following section), and then it was evaluated on a held-out test set, achieving 87.5% accuracy, 86.2% precision, and an F1-score of 86.6%. These values are reflective of the performance range of other studies, reported in the recent literature, where BERT-based models were applied to other tasks of sentiment classification. The values also reflect reliability and balance by the model in recognizing positive and negative sentiments without significantly favoring one class over another. The high accuracy (87.5%) reflects overall correctness across predictions, and the precision score (86.2%) reflects how effective the model is in minimizing false positives. The F1-score (86.6%) reflects the harmonic mean of precision and recall and verifies that the model is well balanced between those two significant variables. As we will discuss in detail below, the low proportion of predicted neutral tweets (1%) and high number of predicted negative tweets (88%, below), indicates the overall ability of the model to capture the highly polarized nature of the discourse around mobbing. These results confirm the BERT model's effectiveness as a method for classifying sentiment in relation to mobbing-related tweets. The BERT model

Fig. 4 Hours of activity of users based on collected data



used uses transformer architecture to achieve state-of-the-art performance on natural language understanding tasks, including question answering and language inference. Unlike the previous models, BERT's bidirectionality means it gets most of the subtleties in meaning, which in turn makes it well-suited for contextual understanding tasks. After training BERT on labeled sentiment data, predictions on our newly collected mobbing tweets can be made. The selected BERT model is trained using a public dataset, known as the Turkish sentiment analysis set, available on Hugging Face [30, 78], which contains 441 k labelled rows as either positive, negative, or neutral. BERT with LSTM means BERT plus an LSTM when it combines the language understanding power of BERT with the sequential modeling capabilities of LSTM networks. The general approach would be to use BERT's contextualized word embeddings and feed that into an LSTM for further sequential processing.

After using the pre-trained BERT model as the backbone for our sentiment analysis task, the results of classifying the gathered tweets dataset are presented in Fig. 5. As expected, most of the posted tweets (with a percentage of 88%) are classified as having a negative sentiment. These results show that 88% of the tweets about mobbing were posted by the victims which makes the data seem like imbalanced data. On the other hand, 11% of tweets are classified as positive and only 1% of tweets are classified as neutral. The sentiment analysis results for mobbing-related tweets show a strongly negative sentiment of the tweets classified as negative. This suggests that people share their negative experiences, emotions, or opinions about mobbing. It could be indicative of a serious and distressing issue that people are discussing on Twitter. The low percentage of positive tweets (11%) suggests that some tweets express positive sentiments, but the negative ones vastly outnumber them. It is possible that these positive tweets are outliers or that they represent a different perspective on the issue. The very low percentage of neutral tweets (1%) indicates that there is minimal or no ambiguity in the sentiment of the tweets. Most tweets are clearly express either positive or negative emotions or opinions. These results suggest that there may be a significant issue related to mobbing that is being discussed on Twitter. Organizations or authorities concerned with addressing mobbing should pay attention to this sentiment analysis to better understand the public's sentiment and potentially take some real actions to address the issue.

We also performed additional analyses on the gathered tweets to identify the key topics or themes within the negative tweets to understand different perspectives to gain a more comprehensive understanding. One of the most used methods to do this is the word cloud figure. This figure is an effective way to visually display the most common words in each dataset or piece of text, making it easy to identify the most prominent and frequently occurring terms. Figure 6 shows the word cloud graphical representation of tweets' text data, where the size of each word in the cloud is proportional to its frequency or importance in the text. According to the results shown in Fig. 6, the most common words relate to mobbing actions-pandemic (COVID-19), oppression, bullying, violence, discrimination, and ignoring- and the topics most discussed were universities (educational institutions) and the health sector.

To draw a word cloud for our dataset of tweets, the tweets were preprocessed using the following steps:

Fig. 5 The results of classifying the gathered tweets based on the pre-trained sentiment analysis BERT model

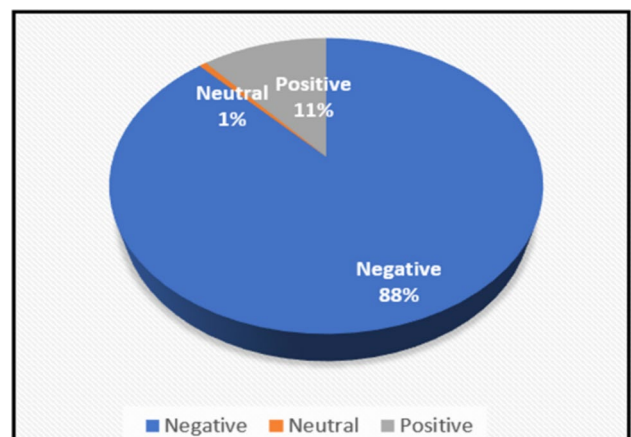
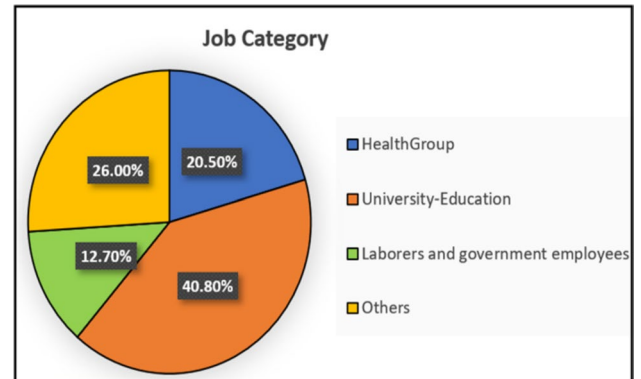


Table 1 The clustering results of the mobbing tweets according to work sectors

Cluster	Percent of Tweets (%)	Some used words
Education sector	40.8	School, university, primary school
Health sector	20.5	Hospital, health, doctor
Laborers and government employees	12.7	Worker, workplace, officer
Others	26.0	Those outside the three general groups

Fig. 7 Clustering by sectors

The use of $K=4$ in our clustering analysis was determined by the elbow method and silhouette score [79, 80]. First, the elbow method was used to assess the Within Cluster Sum of Squares (WCSS) across different K values and there was an ‘elbow’ at $K=4$. This showed that any increase in the K value beyond $K=4$ did not greatly reduce variance therefore providing strong evidence that $K=4$ was the appropriate number of clusters. Next, the silhouette score for each value of K was determined and $K=4$ had the highest score, thus confirming this number of clusters generated distinguishable and well-separated clusters. The parallel application of the elbow method and silhouette score provides strong evidence for establishing $K=4$, which ensure the clusters are valid and reliably classified. The produced clusters (education sector, health sector, labourers and government employees, and other sectors) represent the qualitative insights from the focus groups, therefore providing additional credibility of the confidence in the categorisation approach employed. To accomplish this, we gathered the most used words from the word cloud and word analysis that was done in the previous experiment and then every word was used as a feature to cluster every tweet. Table 1 shows the four clusters and the percentage of tweets in each one. According to our analysis, mobbing tweets can be classified into four main categories according to the sector: health sector, education sector, laborers and government employees, and other sectors. According to our results, the education sector is the highest sector where persons (employees or students) may be exposed to mobbing. The health sector comes in the second rank with around 20.5% percentage. The laborers and government employee’s category comes in the third rank with around 12.7%.

It is clear from results in the education sector there are many complaints about mobbing, and it is common for several factors such as: Educational institutions often have hierarchical structures with administrators, teachers, and staff. This hierarchical nature can create power imbalances, making it more likely for bullying to occur, especially when those in positions of authority misuse their power. Educators face high levels of stress and pressure due to factors like classroom management, curriculum planning, and student performance. Stress can lead to tensions among colleagues and superiors.

On the other side, health sector employees, including doctors, nurses, and other healthcare professionals, can be exposed to workplace mobbing for various reasons. In Fig. 7, these results obtained from the analysis are presented graphically as a percentage. While the healthcare industry provides care and support to patients, it is not immune to the workplace issues that exist in many other sectors. Some reasons why health sector employees may be exposed to mobbing include the high stress and pressure, long working hours, professional disagreements about treatment approaches, protocols, patient care, and patient and family expectations. These results show

themselves more clearly, especially during the Pandemic (COVID-19) period, and the results and analyses in the word cloud also support this. Based on this, although the pandemic problem and these new working conditions have affected every sector, they have negatively affected healthcare workers the most.

In another experiment as shown in Table 2, we clustered the tweets based on the keywords that indicate the type of mobbing. Accordingly, the word bullying was used the most (with a rate of approximately 44% in the different user groups). Additionally, the words violence and harassment emerged as more than 10% of the other words as a result of the analysis. Detailed results are presented in Table 2.

As a result of the analysis conducted on Twitter (X), the sectors that were found to be most exposed to mobbing were education and health, and focus group research, which is a qualitative research method, was conducted simultaneously with this analysis.

2.1.5 Validation process

To strengthen the reliability and accuracy of sentiment classification, a multifold validation process adhering to idiomatic flavour, inclination and linguistic acts and behaviour has been adopted. Once again, considering aspects of the colloquial nature of language on social media-laced with sarcasm, colloquial slang and ambiguities in textual context-we applied manual filtering processes and contextual cross-validation with manually derived qualitative findings. This further included manual validation on a few misclassified tweets by BERT, checking user intent behind the sentiment labels to have them accurate.

Data Preprocessing and Misclassification Management: Prior to model training, we conducted comprehensive preprocessing to reduce classification errors stemming from sarcasm, slang, and ambiguous language. This involved the elimination of URLs, emojis, special characters, and excessive punctuation, succeeded by case normalisation and stopword removal to guarantee linguistic uniformity. Automated keyword identification and manual evaluation were employed to identify tweets containing sarcasm or regional vernacular that can skew sentiment analysis. A random sample of 100 tweets was juxtaposed with qualitative focus group findings to enhance the contextual precision of the model and reduce misclassifications. To further investigate the effects of language differences, we analysed prevalent misclassification instances. For instance, the tweet “Our manager is truly remarkable!” Bizi sürekli küçümsüyor ve cesaretlendiriyor. Teşekkür ederim! Our boss is exceptional! Consistently belittling us while simultaneously inspiring us. Thank you! was inaccurately classified as positive by the BERT model but subsequently rectified as negative, due to a misinterpretation of sarcasm. Likewise, the tweet states, “Everyone at the company treats me like an ox.” “Am I normal?” (Everyone at work treats me like a beast of burden.) Is this typical? Initially categorised as neutral, it was then reclassified as negative following a manual assessment that acknowledged the symbolic implications of workplace harassment.

This work further enriched the original model classification by manually verifying and annotating a sample of 300 tweets classified as either erroneous or ambiguous sentiment-tagged tweets. Thereafter, they were classified by a three-member panel of independent annotators, expert in languages and social sciences, in the categories of good, negative, or neutral. Kappa was used to compute inter-annotator agreement, wherein a value above 0.75 was regarded as credible. Annotated items where the annotators disagreed were discussed and finally resolved with an assigned sentiment label. This marked the last, albeit critical, tuning of our preprocessing models and

Table 2 The clustering results of the mobbing tweets according to mobbing type

Cluster	Percent of Tweets (%)
Bullying	44.0
Violance	18.5
Harassment	14.6
Oppression	9.7
Discrimination	8.8
Injustice	2.5
Neglectedness	1.9

classification criteria, which gave rise to an approximate 6.8% boost in classification accuracy for the sentiments and reductions of errors from cultural and contextual differences. All stages of validation gave a huge weight to our discussions on workplace mobbing and preventing misclassifications stemming from linguistic subtleties.

2.2 Mobbing investigation in microenvironment: qualitative research

In accordance with the literature and objectives presented above, a simultaneous application of Twitter-based studies and qualitative research methods has been employed. Twitter findings and traditional research methods were conducted concurrently, attempting to overcome the limitations of traditional methods as claimed in the literature [27]. To explore employee experiences and observations in more detail, a qualitative research technique, namely focus group interviews, was utilized to answer the question: “*What attitudes and behaviors do employees define as mobbing in the workplace?*” Qualitative research is recognized as an umbrella term encompassing scientific frameworks such as phenomenology, narrative, action research, grounded theory, case study, content analysis, historical study, and ethnography [81]. Phenomenology (phenomenological science) was employed as the research design. Phenomenology is a suitable qualitative research method that allows individuals to express their experiences and perceptions uniquely. This descriptive and qualitative research through focus group interviews was conducted in February–March 2022. It is asserted that a focus group interview is one of the significant gathering techniques in qualitative research [82]. The number of participants in focus groups may vary, with commonly 10–12 individuals participating [83]. Themes obtained from the focus group interviews were reviewed twice by three researchers and participants who attended the focus group meetings, and the emerging sub-dimensions were evaluated in line with the existing literature [84].

2.2.1 Qualitative research sample, data collection techniques, and result

In the qualitative research section, the “purposive sampling” method was utilized [56]. The primary aim of using this method is to select the unit of study (individuals, organizations, entities) in line with the research questions, gather sufficient information, and increase the representativeness ratio to the general population concerning the research topic [57]. The qualitative research sample consists of 11 participants working in the private sector in Istanbul. Participants were selected purposively and focus group interviews were conducted with them. The selection criteria included intensive interactions between superiors and subordinates and having at least five years of experience in the same company. Seven participants are female, four are male. All participants have a master’s degree in terms of educational background. Their ages range from 37 to 52, five are married, and seven are single. Three participants specialize in marketing, four in HR management, two in the energy sector, and three in MIS. Each participant works in medium and large-scale enterprises. Three consecutive focus group sessions were conducted in February–March 2023. During the first meeting of the focus group interview sessions, participants were asked questions in line with the purpose of research, such as: “hat types of behaviors have you encountered or witnessed as mobbing in the workplace?” “How do you define attitudes and behaviors as mobbing?” “In which direction do behaviors defined as mobbing occur within the organizational structure?”.

As a result of the focus group interview sessions, the participants’ statements were compiled to create an item pool. After compiling and classifying the statements, the same group came together again to check whether the statements accurately conveyed the intended meaning. Thus, common expressions among participants were grouped under a single expression in accordance with Krippendorff’s [85] content analysis. Additionally, in content analysis, a “directed approach” was used to confirm and expand a statement conceptually [86]. Initially, the data obtained from the focus group study were evaluated independently for each sub-dimension to ensure reliability and prevent misunderstandings. The expressions given by the participants were compared with common expressions identified in the literature. It was determined that the given expressions were consistent with previously conducted scaling studies on Workplace Incivility [87], Workplace Aggression [88], and Workplace Harassment [89]. The identified expressions were grouped and compared with the definitions found in the literature,

and they were consolidated under a single expression in accordance with Krippendorff's [85] content analysis. By the conclusion of the qualitative research process, the identified themes and codes were derived, as shown in Table 3. As depicted in this table, nine distinct categories have been identified, namely, manipulative behaviors, disregarding the individual, positional pressure, creation of difficulty, devaluation, discrimination, stigmatization, inappropriate treatment, and injustice. Notably, there is a clear consensus among all participants regarding the classification of manipulative behaviors and inappropriate treatment. However, the perception of injustice as a component of mobbing is recognized by only a limited number of participants.

3 Discussion and conclusion

Mobbing is a multifaceted global issue that, despite decades of discussion and legal interventions, continues to expand its scope in parallel with evolving work conditions and changing employee expectations. Understanding how employees' perceptions of mobbing have shifted, particularly in the aftermath of COVID-19, is therefore critical to keeping the scholarly debate current and relevant. Given these altered working conditions, it is reasonable to assume that established require renewed examination.

To address the research question "*What attitudes and behaviors do employees define as mobbing in the workplace?*" regarding mobbing, two complementary methodologies were applied simultaneously: a macro-level analysis of tweet data and a micro-level the qualitative analysis. The tweet data analysis identified seven different classifications associated with mobbing: bullying, violence, harassment, oppression, discrimination, injustice, and neglectedness. Qualitative findings revealed nine classifications: manipulative behaviors, marginalization, positional pressure, obstruction, devaluation, discrimination, stigmatization, inappropriate treatment, and injustice. These classifications are largely consistent with categories and subdimensions identified in earlier literature [1, 3]. Although both methodologies were produced similar themes, it is noteworthy that physical violence and harassment were not explicitly mentioned during the focus group discussions. This absence may reflect participants' tendency to consider physical violence and harassment as determinants of bullying rather than distinct mobbing behaviors.

A particularly significant finding that diverges from previous literature is the emergence of injustice as a core sub-classification in both methodologies. Both the tweet analysis and qualitative analysis findings indicate that employees increasingly perceive workplace injustice as one of the determinants of mobbing. While the concept of justice is not new to organizational studies, its identification by employees as a direct component of mobbing represents a novel contribution of this study. To substantiate this finding, we conducted a systematic search of the Web of Science database using the keywords "mobbing," "bullying," "workplace mobbing," and "justice" or "injustice" in titles, abstracts, and keywords. This yielded 374 articles; after filtering for research articles, 323 studies remained for review.

The literature review revealed that prior research employs a variety of theoretical lenses to explain the emergence of mobbing in the workplace. However, most studies conceptualize justice perceptions as an external or moderating factor rather than an inherent dimension of mobbing. In contrast, this study positions justice perceptions as an integral component of how employees define mobbing. Previous studies have treated justice perception as an independent concept, focusing on the relationship between organizational justice or injustice and mobbing [90–93]. These studies emphasize how the distributive, procedural, and interactional dimensions of organizational justice shape employees' experiences of mobbing and the outcomes of this mechanism [94–96]. Our findings similarly indicate that perceived procedural and distributive injustice is directly associated with mobbing behaviors.

In conclusion, this study reassesses the mobbing phenomenon in the post-pandemic through a mixed-methods design: in-depth focus group discussions with employees and managers, and a large-scale analysis of tweets from users in Türkiye referencing mobbing. A review of 323 studies from Web of Science underscores the originality of the findings, particularly the integration of injustice as a central dimension. Our results suggest that perceptions

Table 3 Qualitative research themes and codes

	Themes	Codes	Frequency	Per-centage (%)
1	Manipulative Behaviors	1. Manipulation of dialogues by top-level executives 2. Manipulative behaviors in peer. to. peer dialogues 3. Manipulative behaviors from subordinates 4. Distortion	11	100
2	Disregarding the Individual	1. Concealing the individual's contributions in work by col-leagues or superiors 2. Disregarding the person through body language and/or writ-ten language, isolation 3. Not consistently giving the floor to the person in meetings 4. Disregarding/excluding/not greeting women in a male. dominated workplace 5. Withholding information among peers	8	72
3	Positional Pressure	1. The dominance of the thoughts of top-level executives 2. Forcing a subordinate to undertake a task they do not want through coercion 3. Behaviors that silence an employee 4. Constant threats of termination, forcing resignation 5. Inability to express thoughts openly	6	54
4	Creation of Difficulty	1. Workload 2. Unattainable goals 3. Making the task difficult to accomplish 4. Imbalance of authority and responsibility 5. Constantly demanding overtime 6. Changing the work location without request 7. Frequent messaging/calling outside of working hours/leave days 8. Creation of an overly competitive environment	9	82
5	Devaluation	1. Being engaged in unimportant tasks 2. Exclusion from the group with various words and/or behaviors 3. Delayed or incomplete payment of entitlements 4. Constantly criticizing the person for work results 5. Demotion/non-promotion	6	54
6	Discrimination	1. Managerial discrimination 2. Inequality between peers 3. Gender-based discrimination 4. Discrimination based on different beliefs/ethnicity	7	54
7	Stigmatization	1. Constantly labeling a person with similar patterns of jokes 2. Use of certain patterns related to physical appearance/cloth-ing style in the workplace 3. Making jokes and implications about "being someone's favorite" 4. Stigmatization due to age 5. Stigmatization due to gender-based jokes 6. Stigmatization due to different sexual orientation	6	54
8	Inappropriate Treatment	1. Inappropriate jokes 2. Use of profanity 3. Sending emojis, etc. expressions via applications like WhatsApp 4. Provocation/leading to the person making a mistake 5. Responding harshly to suggestions or feedback	11	100
9	Injustice	1. Low payment of insurance premiums 2. Less contribution to insurance days 3. No salary increases 4. Forced annual leave without request 5. Revoking given rights 6. Unequal pay for equal work 7. Not keeping promises	3	27

of mobbing among employees in Türkiye have evolved after the pandemic, with injustice now perceived as a defining element of mobbing. Broader social and economic development such as the pandemic, ongoing conflicts, and employment uncertainties may have amplified employees' sensitivity to perceived inequities [97]. It is thought that employees are reassessing their definitions and expectations regarding work (gig work, freelance, flexible work, etc.). In this regard, employees increasingly associate violations of employment rights, unfulfilled promises, and unequal pay for equal work with mobbing behaviors, explicitly identifying them as forms of injustice. This perception aligns with their emphasis on feeling devalued and treated unfairly in the workplace. Moreover, the combination of remote work, increased performance pressures, time management concerns, and job insecurity during the pandemic may have intensified employees' vulnerability to unjust practices. These factors collectively contribute to heightened perceptions of mobbing and a redefinition of its boundaries.

3.1 Theoretical contributions

The most significant finding of this study is that, considering the changing working conditions, the boundaries of the mobbing definition have expanded. First and foremost, the perception of injustice, which had not been included in the definition of mobbing, emerged as a common finding in both the Twitter sentiment analysis and focus group qualitative analyses. This study also indicates that, lately, workers are more inclined to see procedural and distributive injustices such as mobbing above others, expanding the conceptual horizon of the phenomenon. This finding, within the ambit of equity theory [71], was in light of the Employees' experiencing at the workplace unequal treatment that was unjust, as per their perceptions. In the context of both samples, procedural and distributive inequalities in the workplace were defined as mobbing. According to Equity Theory, comparing one's efforts and outcomes with those of other colleagues has now become a component of mobbing in today's work environment, particularly within the Turkish context. The cultural setting of the country may have supported this outcome. This study contributes to Equity Theory by demonstrating that workplace mobbing is not only about direct aggression, but also about indirect systemic inequalities that create perceptions of unfair practices.

From the viewpoint of the Conservation of Resources (COR) theory [98], an unjust working environment can be interpreted as a psychological and a material resource threat to the employees. With regard to recovery and preservation of resources, individuals try to acquire, protect and retain, on the one hand, justice and fair treatment in the workplace and, on the other hand, great status or at least some security of the company in the workplace. The present study augments COR theory by proving that workplace injustice serves as a psychological stressor that magnifies the vulnerability of an employee to experiences of mobbing. Employees who feel injustice may feel they are more insecure regarding their resources, which may make them more vulnerable to workplace pressure or even being mobbed. Literature on mobbing has largely addressed verbal abuse, social exclusion and psychological harassment [1, 4], whereas quite little attention has been paid to systemic organisational factors, such as perceptions of justice. It is in this light that we have revealed perceived injustice as a core factor in mobbing. Our results can enlarge the scope of knowledge for the existent mobbing research by integrating justice theories into the mobbing framework. In addition, this study suggests that traditional mobbing classifications should not consider only behavioural aggression in the categorization of mobbing, but systemic and structural injustice should also influence perceptions of mobbing. Based on the findings, we may argue that the cultural context can play a vital role in how mobbing is perceived. It could be that the Turkish work environment has been informed by contextuality within the country, with increasing sensitivity toward justice and equality.

Moreover, the four main dimensions of organisational justice theory [99], namely distributive justice (fairness of results), procedural justice (fairness of processes), interactional justice (respect and dignity in interpersonal treatment) and informational justice (communication), can be used to robustly understand the emergence of injustice as a component of mobbing. According to our research, employees increasingly classify perceived unfair incentive distribution, vague decision-making procedures or impolite communication from superiors as mobbing rather than administrative failures. A growing body of research suggests that perceptions of injustice can have psychological effects similar to those of traditional mobbing practices, particularly in high-pressure,

post-pandemic environments [91, 93]. Our study offers a more comprehensive and systemic understanding of workplace aggressiveness by incorporating these justice elements into the mobbing paradigm. This goes beyond overt animosity to encompass procedural and structural injustices as acceptable types of psychological harm.

3.2 Practical implications

These findings highlight the importance of integrating justice principles into human resource management. It is evident that employees need a more equitable and just work environment. Taking concrete steps to enhance employees' emotional well-being is critical for the long-term success of the organisations. HR professionals should recognize that workplace justice is not only merely a normative value, but also a potential psychological stressor leading to perceptions of mobbing. To operationalize these insights, organizations can implement transparent communication, establishing clear and accessible reporting mechanisms for mobbing incidents, and embedding fairness into performance evaluation and decision-making processes. Regular training on implicit power dynamics and proactive monitoring of digital communication channels in hybrid or remote environments can further help prevent the normalization of mobbing behaviors. Collectively, these justice-oriented strategies may reduce employees' perceptions of inequity and foster a more inclusive and psychologically safe organizational climate.

3.3 Limitations and future works

This study offers significant insights on workplace mobbing via Twitter-based sentiment analysis and qualitative focus group talks; however, some limitations must be acknowledged. Mitigating these limits will facilitate future study aimed at achieving a more thorough comprehension of workplace mobbing in various circumstances. Given the complex and evolving nature of mobbing, we used a mixed-methods approach, combining tweet sentiment analysis with qualitative focus group research to obtain a comprehensive and multi-dimensional understanding of the concept. We were pragmatic in our approach and used a convenience-based purposeful sampling strategy for conducting the qualitative analysis [100] allowing us to select participants who experienced or witnessed workplace mobbing behaviours. One of the main limitations of this study is its focus on private sector employees in hierarchical organisations, which excludes the perspectives of freelancers, gig workers and employees in non-traditional work arrangements. Given the increasing prevalence of these alternative work models, workplace mobbing may manifest differently in teleworking and platform-based work than in traditional workplace settings. In contrast to hierarchical organisations where power asymmetries are structured through formal managerial authority, gig workers and freelancers operate in decentralised work environments with algorithmic dependencies. The exclusion of freelancers and gig workers was not intended to overlook their experiences, but rather to ensure methodological rigour, as mobbing is often manifested differently in hierarchical organisations than in flexible or decentralised working environments. The findings of this study are based on current workforce perceptions, but it is possible that definitions of mobbing will continue to evolve as organisations adapt to new working conditions. While this study on workplace mobbing explores employees in hierarchical organizations in the private sector, we recognize it has limited sample size. This study did not capture unpleasant situations among freelancers, gig workers, and the contingent workforce, which occurs in some public institutions, or other arrangements, such as those where work is performed telecommuting. As alternative work arrangements, such as teleworking and gig working, proliferate it would be prudent for future studies of workplace mobbing to explore non-traditional work settings. Similarly, as research into mobbing grows, studies that include different settings will improve the generalizability of the findings. Future studies of mobbing should aim to have a wider and more diverse sample involving different sectors, including various public institutions, healthcare and manufacturing, and examining different cultural and organizational factors. This would create a base for examining how mobbing behaviors develop in different settings.

This study relies on self-reported data, which is crucial for understanding subjective perceptions of mobbing. However, self-reported data may be susceptible to recall bias, emotional influence and social desirability bias -especially when discussing sensitive workplace issues. To alleviate these challenges, we used multiple validation techniques, including (1) cross-checking of focus group responses by three independent researchers to ensure consistency, (2) thematic verification with participants to confirm that the categorised themes accurately reflected their experiences, (3) the sentiment analysis of social media data. One of the limitations of the sentiment analysis is the possible demographic bias in the collecting of social media data. Twitter users mostly consist of younger, technologically proficient workers who actively participate in digital platforms, whereas older employees or those with restricted digital access may be inadequately represented. This raises issues about the generalisability of findings, as experiences of workplace mobbing may differ across various age groups and sectors. As is stated above; to address this issue, we included the qualitative methodology, and the convergence of qualitative and quantitative data significantly bolsters the scientific validity of the study. A further constraint arises from the language intricacies and cultural disparities in sentiment analysis. Twitter speech frequently incorporates irony, regional vernacular, and implicit contextual nuances, potentially resulting in the misclassification of feelings. Despite the utilisation of powerful NLP models like BERT, we acknowledge that these issues remain. To resolve this, we implemented manual filtering, contextual cross-verification using qualitative data, and secondary validation by human annotation. These measures improved classification accuracy but did not completely eradicate the danger of linguistic misunderstanding.

This study provides important information about workplace mobbing by means of Twitter sentiment analysis and qualitative focus group discussions; however, there are some limitations to consider. The dataset has inherent limitations such as language bias and sampling bias. The limitation of only using Twitter as a source of data means the sample may not adequately represent other demographic groups, particularly older cohorts or individuals without widespread access to technology. Twitter users are typically younger and more technologically literate individuals, so the dataset has the potential to provide a biased representation of mobbing situations. Furthermore, Twitter is a public platform so the data extracted may only be those who are willing to engage publicly and developmentally exclude those who prefer to be private or are less willing to speak up. In consideration of these limitations, future research should attempt to include a broader and more representative sample, not just from the social media platform (> investors) but that incorporated various different data sources such as LinkedIn, professional communities, industry-specific networks to reduce bias from one source. Future research could also try to seek out how mobbing takes place in non-public environments, and further investigate the attributes behind social media discussions as compared to in person workplace situations. The trends and circumstances surrounding mobbing have changed with the new working environment since COVID-19. To monitor changes in attitudes and behaviours over time, it would be beneficial to engage in longitudinal studies. This research would generate some interesting engagement with what mobbing looks like over the lifespan of individuals and employees and across three continuums; (a) various sectors; (b) different regions; and (c) varying working styles or methods.

Future research might rectify the demographic bias present in social media data collecting by integrating multi-platform analysis, including LinkedIn conversations, workplace forums, or industry-specific platforms where older workers and less digitally engaged employees convey their views. Moreover, targeted surveys or structured interviews with varied employee demographics, including individuals in conventional, non-digital environments, might yield a more comprehensive picture of workplace mobbing. A further interesting avenue is the expansion of industry-specific analytics. This study largely examined overall trends in workplace mobbing; however, future research should investigate variations across other industries, including manufacturing, public institutions, and healthcare. This may offer profound insights into the manifestation of mobbing across various workplace conditions and cultural contexts. Moreover, the use of hybrid sentiment analysis methodologies, such as the amalgamation of rule-based sarcasm detection with machine learning techniques as context aware and metaheuristic methods [101–103], may enhance classification precision in social media research. Future studies may also investigate longitudinal analyses of mobbing trends, monitoring the evolution of perceptions over time

in relation to policy changes, distant work culture, or global emergencies such as pandemics, so facilitating the formulation of effective public policies and strategies.

Appendix 1: Operational definitions of key terms used in the study

Term	Definition
Mobbing	Mobbing refers to intentional, systematic, and repeated psychological attacks against an individual in the workplace. These attacks aim to leave the individual defenseless and emotionally drained [1, 4]
Power imbalance	Power imbalance refers to the creation of power differences among individuals based on social, gender, or professional factors, often resulting in negative consequences that the target is unable to resist or stop due to their disadvantaged position [38]
Injustice	Injustice in the workplace refers to unfairness in the distribution of outcomes (distributive injustice), in decision-making processes (procedural injustice), or in the way people are treated (interactional injustice) [71]
Bullying	Bullying encompasses a repeated, systematic pattern of harm consisting of negative incidents such as harassment, social exclusion, verbal abuse, or isolating the victim [16, 17]
Harassment	Harassment signifies negative, unwanted behaviours toward an individual based on personal characteristics (e.g., gender, ethnicity, religion) and potentially leading to psychological and/or physical harm [9]
Emotional Abuse	Emotional abuse is a psychological bullying strategy that systematically fools and humiliates another person's emotional health/emotional well-being. These types of behaviours can severely damage a person's self-esteem [17]
Psychological Harassment	Psychological harassment refers to continuous, systematic psychological harm against an individual with the intent of emotionally exhausting the victim and isolating them [16]
Social Isolation	Social isolation denotes the intentional exclusion of an individual from workplace activities, thereby isolating them socially and emotionally, constituting a sort of mobbing [1]
Verbal Abuse	Verbal abuse refers to the use of verbal insults, belittling, and threats directed at an individual. These behaviors aim to damage the person's self-esteem and create emotional harm [17]
Exclusion	Exclusion refers to deliberately leaving an individual out of workplace activities interactions, or communications, which is a form of mobbing used to isolate the person [3]
Workplace Bullying	Workplace bullying involves continuous mistreatment, humiliation, and isolation of an individual in the workplace, and includes verbal, emotional, and psychological abuse [6]
Organizational Justice	Organizational justice refers to employees' perceptions of fairness within the workplace, which include perceptions of the fairness of outcomes (distributive justice), procedures (procedural justice), interpersonal treatment (interactional justice) and communication (informational justice) [99]
Toxic Work Environment	A toxic work environment is characterized by negative elements such as mobbing, bullying, unfair treatment, and poor organizational culture, which negatively affect employees' mental and emotional well-being [28]

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Declarations

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