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Quantifying Victim Associations in Hate Crimes: A Chi-Squared Analysis

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Abstract

This study investigates the associations between hate crimes and victim characteristics using data from Montgomery County, Maryland. The aim is to identify the significant relationships and trends in bias incidents, particularly focusing on different victim groups and locations. Data from Montgomery County, Maryland, were analyzed using chi-squared tests and p-values to identify the significant relationships between hate crimes and victim characteristics. Visualization techniques were employed to reveal trends and patterns in the data. The analysis revealed a rise in bias incidents, particularly in schools and colleges, with a peak in February 2023. The incidents were notably against individuals with anti-Black, anti-Jewish, anti-Asian, and anti-homosexual biases. Chi-squared values indicated an increasing association of victims with bias codes for individuals, while there was a decreasing trend for schools and colleges since 2023. The findings highlight the need for targeted interventions and increased awareness to address the rising trend of hate crimes. Continuous monitoring is essential to understand and mitigate these incidents effectively. These evidence-based findings suggest the necessity for targeted interventions and increased awareness campaigns. Additionally, continuous monitoring of hate crimes is crucial. Generative AI can assist novices in Python code generation for such analyses, but user verification remains crucial to ensure accuracy and reliability.

Keywords Hate crimes · Bias incidents · Victim analysis · Chi-squared test · *P*-value

Introduction

Despite the importance of understanding hate crimes, little is known about the associations between victims and features such as date, district, bias, and suspect information. This paper aims to fill that gap by examining hate crimes and quantifying the connections between various victims (including individuals, society, schools/colleges, businesses/financial institutions, religious organizations, governments, and others) and seven key determinants: incident date, district, bias code, bias type, victim status, the number of suspects, and whether the suspect is known or unknown. Utilizing data from 1639 instances in Montgomery County, Maryland (Data.Gov, 2024), this study categorizes 'Bias Code' into 25 types, such as anti-Black, anti-Hispanic, anti-Asian, anti-White, anti-homosexual, anti-transgender, and more. Additionally, 'Bias' is categorized into 12 types, including vandalism, assault, and flyer left behind. This comprehensive evidence-based analysis provides valuable insights into the patterns and characteristics of hate crimes, highlighting the need for targeted interventions and support for affected communities. A concise literature review was conducted using peer-reviewed publications from the National Library of Medicine, the world's largest database, to substantiate this evidence-based study.

True associations between the target (victim) and features were calculated using Chi-squared tests and *p*-values, grounded in evidence-based studies. Visualization of victim trends revealed a constant increase in bias code from January 2021 to 2024. The distribution of bias code underscores the urgent need for interventions to protect individuals. The stronger the association between victims and determinants, the more effective early interventions can be. Generative AI is employed to assist novice and non-programmers in generating Python code. However, due to inherent imperfections in generative AI, users must verify the generated code through multiple conversations to ensure accuracy. This

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study highlights the critical need for timely and targeted interventions to address the rising trend of bias-related incidents and the importance of leveraging AI tools responsibly.

Following the definition of hate crime, a comprehensive literature review was undertaken to examine victim perspectives across various dimensions such as gender, racial minorities, LGBTQ+, statistics, trends, and violence prevalence. This review utilized peer-reviewed publications from the National Library of Medicine, the largest database in the world, to analyze hate crime and victim trends.

Defining Hate Crime

A hate crime is a criminal act committed against a person or property that is motivated by bias or prejudice against a particular group. This bias can be based on race, religion, ethnicity, nationality, gender, sexual orientation, disability, or other protected characteristics. The key aspect of a hate crime is that the perpetrator's actions are driven by hatred toward a specific group, rather than a personal vendetta against an individual. These crimes aim to intimidate and harm not just the immediate victim but also the broader community that shares the victim's identity (Trickett & Lorretta, 2021).

Vergani et al. (2024) presented that defining hate crime, hate incidents, and hate speech is challenging due to differing views on protected identities, hateful behaviors, and assessing the 'hate element.' This lack of consensus hindered research, policy, and programming. Since the 1990s, these issues have persisted, affecting data quality. Their systematic review mapped original definitions and measurement tools of hate crime, hate speech, and hate incidents, highlighting the need for improved conceptual foundations and sound data to advance research and policy in this domain (Vergani et al., 2024).

Gender Hate Crime

Brayson reported that in April 2023, the U.K. government chose not to categorize misogyny as a hate crime, citing potential harm (Brayson, 2024). Brayson argued that misogyny, the hatred of women, underpins Western legal, social, and political systems, manifesting in everyday violence. Patriarchal, colonial, capitalist democracy relies on systemic misogyny. The paper explores historical and contemporary violence against women, from Greek dehumanization to contemporary femicide rates, proposing a decolonial feminist approach to disrupt this foundational misogyny. Misogyny, far from hidden, ensures women's precarity and is intrinsic to our societal structures (Brayson, 2024).

Camp et al. (2024) concluded that sexuality and gender minoritized (SGM) adolescents face higher risks of self-injury and suicide, with barriers to mental health support. Their study examined dialectical behavior therapy (DBT) outcomes for SGM adolescents and their cisgender and heterosexual peers in the UK. Treatment completion, opting out, and changes in emotion dysregulation, self-injury, and mental health symptoms were analyzed. SGM adolescents were over-represented, but no significant differences in treatment completion were found. Clinical outcomes improved for all groups. Findings suggested DBT could be beneficial for SGM adolescents in specialist settings (Camp et al., 2024).

Hate Crime Against Racial Minorities

Leander et al. (2020) showed that mass shooters often target minorities, but public opinion on their motives varies. Dominant majority members may downplay hate crimes due to personal frustrations and prejudices. Surveys after shootings in the US, New Zealand, and the Netherlands revealed that biased hate crime perceptions are linked to prejudicial attitudes and feelings of disempowerment, reflecting supremacist sympathies (Leander et al., 2020).

Clarke addressed that hate studies literature shows most hate crimes are committed by the "majority" society (Clarke, 2024). In the UK, young White, British males are often culprits, especially in racist hate crimes. Urban "super-diversity" areas reveal nuanced hate crime dynamics, including minority-on-minority targeting. This dynamic is poorly understood but may involve minority members adopting majority values to "fit in." Drawing from interviews and grassroots observations, Clarke challenged binary majority/minority theories and offered new insights into victim-perpetrator relationships and motivations (Clarke, 2024).

Zare reported that high-profile police use-of-force incidents involving people of color (e.g., George Floyd, Breonna Taylor) have deepened mistrust between communities and police (Zare, 2024). Disparities in policing are complex and require examining systemic oppression, historical discrimination, socioeconomic inequalities, and power dynamics. Theories like majority-minority communities, conflict theory of law, and minority threat hypothesis explain these disparities. Studies showed racial/ethnic minorities face more intense policing. Addressing these systemic factors is crucial to reducing police violence and improving community-police relations. Comprehensive data and accountability were essential for effective interventions (Zare, 2024).

Hwang et al. (2024) qualitatively studied and explored how COVID-19-associated xenophobia affected Asian American university students' identities. Analyzing interviews with four participants over three waves, the study identified 12 themes across four categories: experiences and events during the pandemic; categorization of Asians in America; confronting Asian discrimination; and renewed sense of identity. Findings revealed the pandemic's impact on Asian communities and the influence of social and political events like the Black Lives Matter movement and the 2020 US presidential election on their identity (Hwang et al., 2024).

Hate Crime Against LGBTQ+

Vahed et al. (2024) reported that harmful online content is common, and understanding user judgments and mitigation strategies is crucial. In a study with 294 social media users, participants evaluated objectionable content, with some acting as content moderators. Findings revealed that moral imagery and poster intention greatly influenced judgments, with negative content frequently flagged and punished. Moderation roles affected reporting but not punishment preferences. Trust in platforms negatively impacted reporting, while empathy increased it. Their research highlighted the complexities of user moderation decisions and offers insights for improving social media content regulation (Vahed et al., 2024).

Singh et al. (2024) presented that the VA's LGBTQ+ Health Program tackles health disparities for LGBTQ+ veterans. Their study investigated barriers and facilitators in LGBTQ+ affirming care through interviews with 11 VA providers and 12 LGBTQ+ veterans. Barriers include limited education and time, while peer support and openness are facilitators. Veterans face safety concerns and discrimination but benefit from positive provider relationships. Enhanced policy adherence through education and collaboration can improve healthcare outcomes for LGBTQ+ veterans, suggesting a need for inclusive, collaborative healthcare strategies (Singh et al., 2024).

Paterson et al. (2023) conclude that crimes motivated by hatred toward a person's sexual orientation or gender identity cause greater physical and emotional harm compared to non-hate crimes. Hate crime victims often receive less empathy and support and are more blamed by society and criminal justice agencies. However, such crimes may also trigger ingroup empathy bias, where LGBT+ people show more empathy, support, and less victim blaming. Across three studies, we found that indirect experiences of hate crimes strengthened LGBT+ identity, which increased empathy and support for victims. This ingroup empathy bias helps mitigate the marginalizing effects of hate crimes. Policy implications include leveraging shared identities to improve responses to anti-LGBT+ hate crimes (Paterson et al., 2023).

Flores et al. (2022) estimated the prevalence and characteristics of violent hate crime victimization among LGBT people in the US using 2017–2019 National Crime Victimization Survey data. LGBT individuals experienced 6.6 violent hate crimes per 1,000 persons, compared to 0.6 for non-LGBT individuals. LGBT victims were more likely to face sexual orientation or gender bias crimes and reported more social, emotional, and physical distress. Our findings highlight the need for support services for LGBT hate crime victims (Flores et al., 2022).

Hate Crime Statistics and Trends

Ormiston et al. (2024) concluded that adolescent suicide in the US, partly due to hate crime, is a major public health problem with understudied trends. This study examines national trends in suicide methods from 1999 to 2020 by demographics using death certificate data. Results show increases in suicide by firearm, poisoning, hanging, asphyxiation, and other means. Females had rapid increases in poisoning and hanging suicides. Firearm suicides surged among various racial groups. The study highlights the need for effective prevention strategies, especially for racial and ethnic minority youth (Ormiston et al., 2024).

Holder (2024) reported that early legal challenges to the 1990 Hate Crime Statistics Act argued that hate crimes "hurt more," but empirical gaps remain. Studies showed biased offenders cause greater harm, influenced by factors like victim/offender characteristics, bias motivation, weapon use, or crime location. Using National Crime Victimization Survey data (2010–2020), Holder found victims of bias-motivated offenses report more physical and emotional harms later, with greater trauma for crimes based on disability, gender, and sexual orientation (Holder, 2024).

Gram and Mau (2024) concluded that the COVID-19 pandemic saw a rise in racism and hate crimes against East and Southeast Asian (ESEA) individuals. Their study examined the mental health impact on young ESEA Londoners, aged 9–20, during the pandemic. Participants reported distress from racism, anxiety from hate crime news, and pervasive online racism. Responses included isolation and activism. Actions by parents and schools helped, but support was inconsistent. Findings highlighted the need for policies to combat anti-ESEA racism and support community resilience (Gram & Mau, 2024).

Franks et al. (2024) addressed that during the COVID-19 pandemic, stigmatization, hostility, and violence toward the Asian American and Pacific Islander (AAPI) community increased sharply. Their study examined whether AAPI identity factors moderated the relationship between stigmatization/threat and psychological distress/behavioral vigilance. AAPI individuals were recruited online and completed measures of perceived stigmatization, integrated threat, depression, anxiety, stress, and behavioral vigilance. Perceptions of stigmatization and threat predicted relevant outcomes, but AAPI identity factors did not moderate these effects. Instead, these moderators were predicted by stigmatization and threat variables. Implications for interventions were discussed (Franks et al., 2024).

Violence Prevalence

Abrahams et al. (2024) revealed that in most countries, reliable statistics on femicide, intimate partner femicide (IPF), non-intimate partner femicide (NIPF), and violence prevalence are scarce. They analyzed three national surveys from 1999 to 2017 to compare femicide rates and violence prevalence using age-standardized rates (ASRs) and incidence rate ratios (IRRs). Their study found a decline in femicide among women 14 years and older, with an IPF rate of 4.9/100,000 in 2017. The decline was more significant for NIPF. The reductions may be due to social and policy interventions. Their study highlighted that gender-based violence is preventable and stresses the importance of dedicated surveys (Abrahams et al., 2024).

Sheikh and Rogers (2024) reported that technology-facilitated sexual violence and abuse (TFSVA) is a global issue, notably rising in low and middle-income countries (LMICs) due to increased digital technology use. TFSVA includes image-based sexual abuse, online exploitation, and non-consensual image sharing, with severe psychological, social, financial, and health impacts. Their scoping review analyzed 14 peer-reviewed studies from six databases to explore TFSVA in LMICs, focusing on types, impacts, and coping strategies. Traditional patriarchal norms heavily influence TFSVA in LMICs. Survivors rely on informal support systems. Effective legislation, supportive policing, and better reporting awareness are crucial for tackling TFSVA, alongside more research to understand this issue comprehensively (Sheikh & Rogers, 2024).

Innes et al. (2024) reviewed evidence on physical violence against people with insecure migration status. A systematic review and meta-analysis of 31 studies with 25,997 migrants found a 31.16% prevalence of physical violence. No significant difference was found between men (35.30%) and women (27.78%). Employment-related insecure status had the highest violence prevalence (44.40%). Violence prevalence was highest in Asia (56.01%) and lowest in Europe (17.98%). Their study highlighted the significant concern of physical violence among people with insecure migration statuses (Innes et al., 2024).

Litvak et al. (2024) examined how hate crimes targeting religious identity inflict harm on both individuals and societies by systematically reviewing 44 peer-reviewed studies published from 2002 to 2022. They identified twelve distinct countermeasure types, organized into personal (e.g., camouflage, resilience strategies, routine adaptations), collective (e.g., community resilience mobilization, stereotype reduction efforts, place-based interventions), and institutional (e.g., victim–authority engagement) levels. Experimental research within this corpus chiefly evaluated the effectiveness of perception-change interventions. The authors conclude by outlining key implications for future research agendas and policy development.

Burch (2024) showed that violence is an everyday reality for many disabled people, often attributed to perceived vulnerability and passivity. It dismantles these stereotypes, highlighting disabled people's capacity to resist and respond to hate crime through collaborative research. Burch argues that hate studies must work "with," not "on," survivors, building on disabled activism and scholarship. Reflecting on a co-produced disability hate crime toolkit, it offers accessible resources and collaborative methods for addressing hate crime and violence.

Previous studies highlight essential policies for mitigating hate crimes. Improved data collection and reporting on hate crimes are crucial to understanding the problem's scope and targeting interventions effectively. Hate crimes disproportionately impact vulnerable groups, such as racial minorities, LGBTQ+ individuals, and marginalized communities. Building trust between law enforcement and these communities is vital for encouraging reporting and cooperation. Public education campaigns can raise awareness, challenge prejudice, and promote tolerance. Addressing online hate speech through regulations and holding social media platforms accountable is also important. Finally, ensuring access to victim support services, including mental health care and legal assistance, is crucial.

Drawing on previous research conclusions, this paper quantifies hate crimes and investigates victim associations using a dataset of 1639 instances. It analyzes the relationships between hate crimes and victim characteristics in Montgomery County, Maryland, employing evidence-based studies with Chi-squared tests and p-values to fill existing research gaps.

By employing Chi-squared tests and p-values, significant relationships were identified. Visualizations indicate a rise in bias incidents, particularly within schools and colleges, peaking in February 2023, and against individuals, with prevalent biases being anti-Black, anti-Jewish, anti-Asian, and anti-homosexual. The Chi-squared values reveal an increasing association between victims and bias codes for individuals, while a decreasing trend is observed for schools and colleges since 2023.

Many researchers inadvertently introduce error by applying statistical tools outside their valid scope—for example, using linear models on inherently nonlinear phenomena or fitting parametric techniques to nonparametric data. Such mismatches between method assumptions and data characteristics can distort estimates, yield misleading inferences, and ultimately compromise the validity of conclusions. This form of human-induced error is pervasive across disciplines and geographic regions. To guard against it, we recommend rigorous training in tool assumptions, routine diagnostic checks, and careful selection of analytical methods that align with the data's underlying structure.

Methods

This paper utilizes Chi-squared tests and p-values (Greenland et al., 2016; Turhan, 2020; Mirkin, 2023). The purpose of using Chi-squared tests and *p*-values in statistical analysis is to determine the significance of associations between categorical variables. The Chi-squared test calculates the test statistic, denoted as (χ^2), which measures the discrepancy between observed and expected frequencies in a contingency table. The higher the (χ^2) value, the stronger the association between the target variable (y) and one of the features ($\times 1, \times 2, \ldots, xn$): $y = f(\times 1, \times 2, \ldots, xn)$. A low *p*-value (typically ($p < 0.05$)) indicates a significant association, suggesting that the observed relationship is unlikely to be due to chance. This helps researchers identify meaningful patterns and relationships in their data, guiding further analysis and decision-making. Additionally, these statistical tools provide a robust framework for hypothesis testing, ensuring that the conclusions drawn from the data are both reliable and valid. By leveraging Chi-squared tests and *p*-values, researchers can make informed decisions, validate their hypotheses, and contribute to the advancement of knowledge in their respective fields.

In this study, we leveraged generative AI to draft Python scripts for data cleaning, analysis, and visualization, but because such tools remain imperfect, we supplemented their output with rigorous human oversight: Every line of code was reviewed, unit-tested, and, where necessary, debugged to correct the roughly 15 % error rate we observed in AI-generated routines. To achieve reliable results and trustworthy conclusions, users must craft precise prompts and perform systematic verification of all AI-produced code.

Initial query for distribution: use MCPD_Bias_Incidents.csv. remove 'ID' and '# of Victims'.

'Incident Date' indicates date with "06/17/2020" format. 'Victim Type' is the target. show the unique 'Victim Type' and user is allowed to select 1 category by number. sum instances per individual unique 'Bias Code' by monthly. 'Bias Code' contains strings. sort data based on 'Incident Date.' select top 4 'Bias Code' based on the number of incidents and plot 4 distribution black lines over month–year with 4 distinct linestyles. plot title by selected victim type and place 4 legends. show python full code.

Initial query for Chi-squared: use MCPD_Bias_Incidents.csv. remove 'ID' and '# of Victims'. 'Incident Date' indicates date with "06/17/2020" format. 'Victim Type' is the target. show the unique 'Victim Type' and user is allowed to select 1 category by number. sum instances per individual unique 'Bias Code' by monthly. 'Bias Code' contains strings. sort data based on 'Incident Date'. show two graphs of selected category for chi-squared values on *Y*-axis, plotting label and unit on *Y*-axis. *X*-axis indicates month-year with rotating 90° with 15 xticks. chi-squared values indicate associations between the target and one of four individual determinants such as 'Incident Date', 'District', 'Bias Code','Bias' in the first graph, and one of 3 determinants such as 'Status', '# of Suspects', 'Suspect Known/Unknown' for the second graph. In the first graph, 4 black lines for chi-squared should be plotted with 4 distinct linestyles only when *p*-value < 0.05. for the second graph, 3 black lines for chi-squared should be plotted when *p*-value < 0.05. show python full code.

Download the dataset (Data.Gov, 2024) before running the programs.

Results

The distribution visualization program, dist.py, and hate.py for Chi-squared are available at the GitHub site (GitHub, 2024). Download the dataset, MCPD_Bias_Incidents.csv (Data.Gov, 2024) and run the following command on the system terminal after installing Python on your system. ($) indicates the system prompt.

```
$ python dist.py.
$ python hate.py.
```

Figure 1a–g illustrate bias incidents across various categories, including School/College, Religious Organizations, Other, Individuals, Government, Business/Financial Institutions, and Society. Figure 1a specifically highlights bias incidents within schools and colleges, with a peak of over 20 incidents occurring around February 2023. The most common biases observed in this category are anti-Jewish, anti-Black, anti-homosexual, and anti-multi-racial, in that order. Figure 1d depicts the rising number of bias incidents against individuals, with the top four biases being anti-Black, anti-Jewish, anti-Asian, and anti-homosexual, respectively. The peak number of incidents in this category reaches 17. Figure 1h shows the distribution of victim types in MCPD Bias Incidents.

Figure 2a–c, display Chi-squared values for individuals and schools/colleges. Figure 2a indicates that the victim's association with bias codes against individuals is

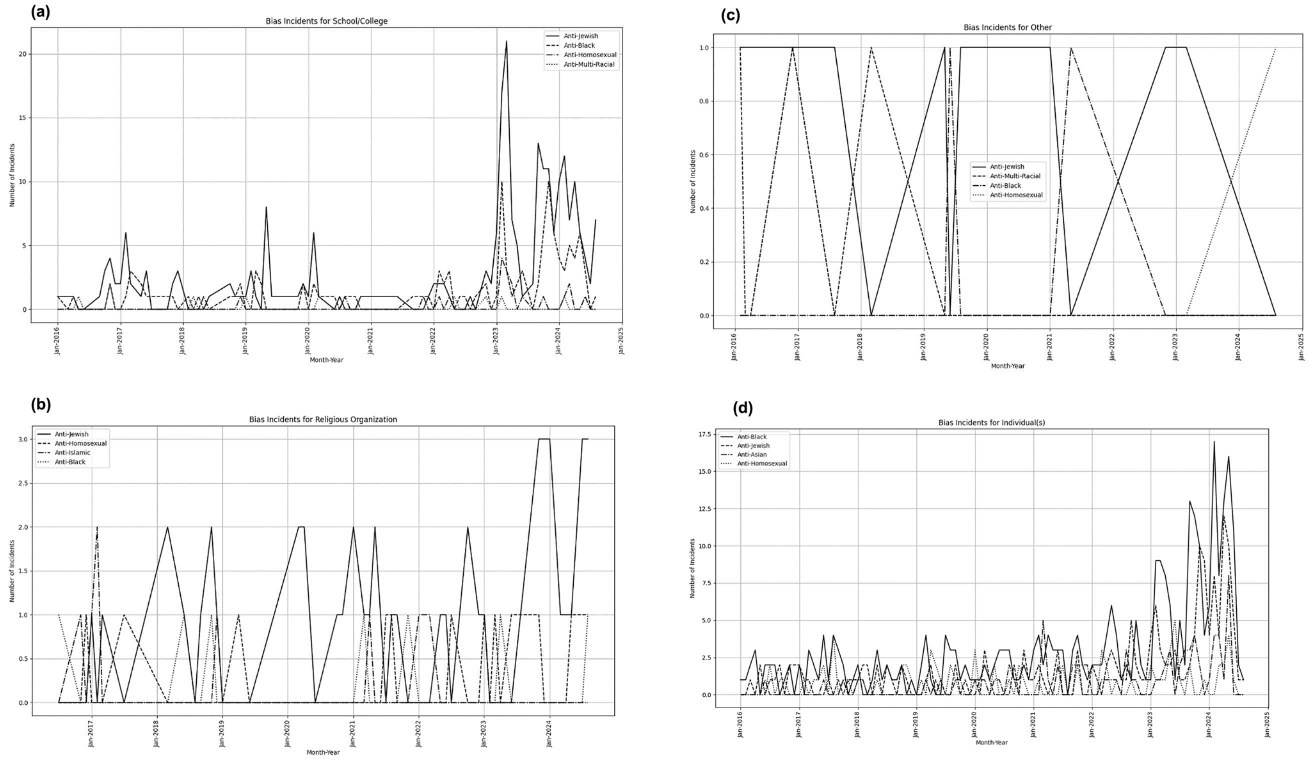

Fig. 1 **a** School/college bias incidents. **b** Religious organization bias incidents. **c** Other bias incidents. **d** Individual bias incidents. **e** Government bias incidents. **f** Society bias incidents. **g** Business/financial institute bias incidents. **h** Distribution of victim types in MCPD bias incidents

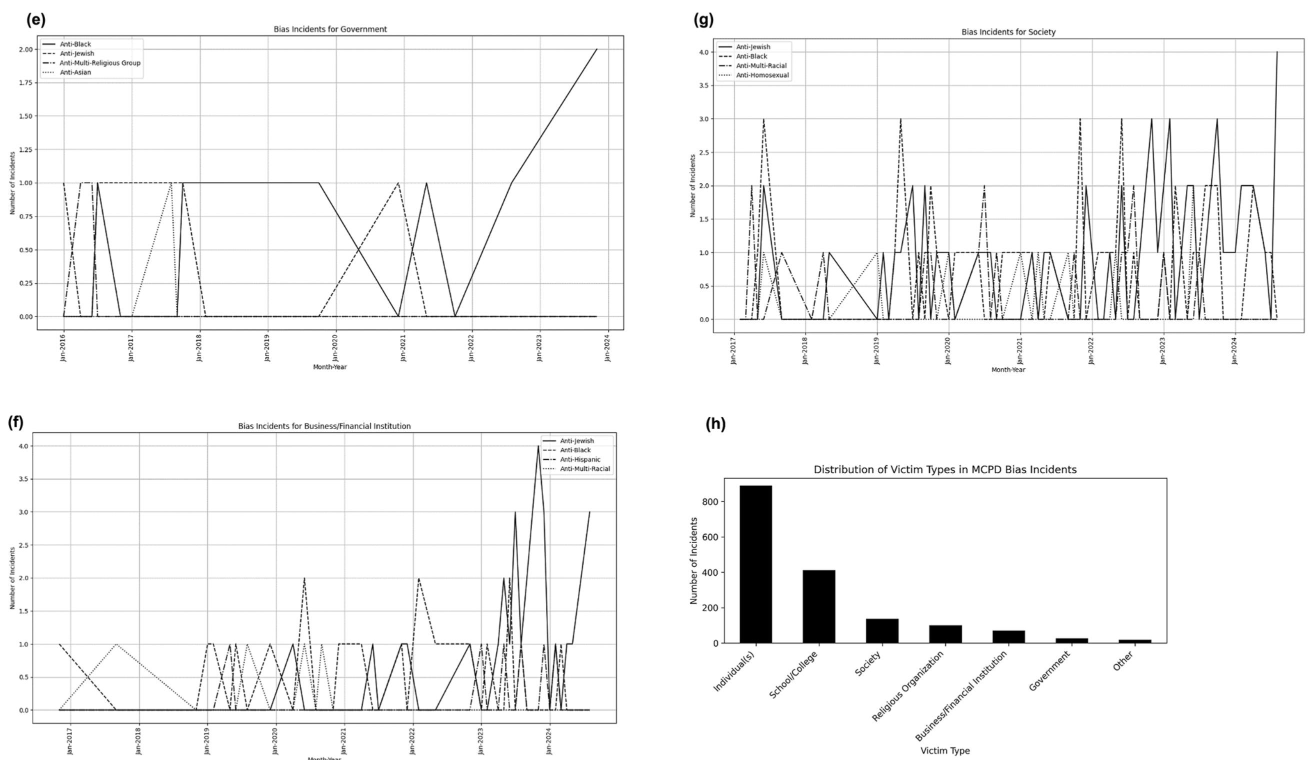

Fig. 1 (continued)

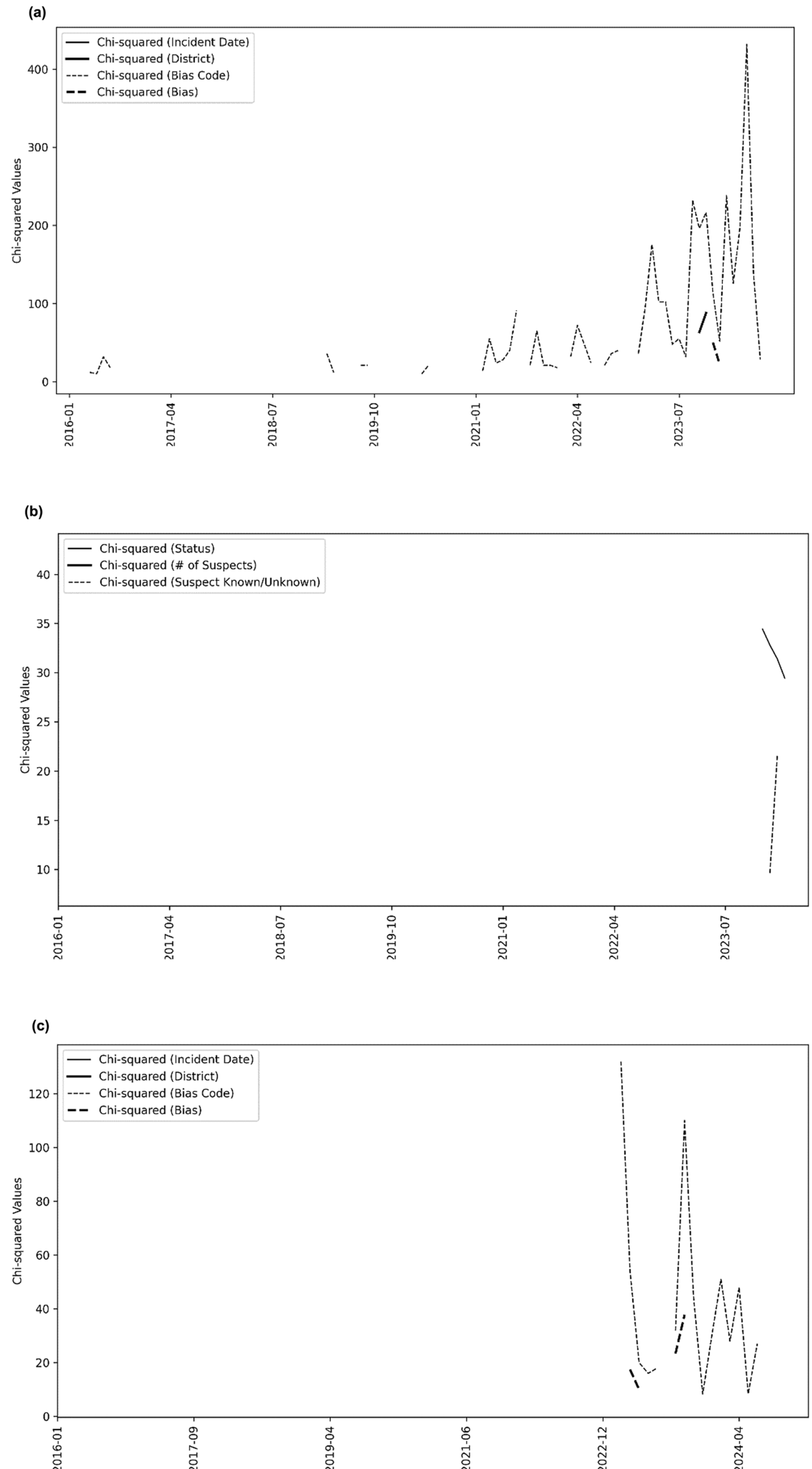

Fig. 2 **a** Chi-squared for incident date, district, bias code, and bias against individual(s). **b** Chi-squared for status, number of suspects, and suspect known/unknown against individual(s). **c** Chi-squared for incident date, district, bias code, and bias against school/college

consistently increasing, while other categories are not clearly represented. Figure 2b illustrates that the victim's association with status and whether the suspect is known or unknown has remained high recently. Figure 2c shows that the victim's association with bias codes against schools/colleges has been declining since 2023. All other figures remained empty after evaluating the Chi-squared values.

Discussion

Previous studies outline several critical policy recommendations to mitigate hate crimes. Firstly, improved data collection and reporting are vital for accurately understanding the scope of hate crimes, identifying trends, and effectively targeting interventions. Community-focused initiatives are essential for building trust between law enforcement and affected communities, encouraging the reporting of hate crimes, and fostering a sense of safety. Public education campaigns can elevate awareness about hate crimes, challenge prejudices, and promote tolerance. Regulating online hate speech and holding social media platforms accountable for harmful content is crucial to reducing hate speech. Enhanced victim support, including mental health care, legal assistance, and counseling, is necessary for victims' recovery and well-being. Targeted interventions, informed by data analysis, can be tailored to specific vulnerable groups and regions, addressing the most pressing needs and preventing future hate crimes. Previous studies emphasize the importance of these policies in tackling the root causes of hate crimes and fostering a more inclusive and equitable society. Implementing these measures enables policymakers to effectively combat hate crimes and protect vulnerable individuals and communities. This comprehensive approach ensures that hate crimes are addressed from multiple angles, creating a safer environment for all. This paper bridges the gap in previous studies by quantifying the latest dataset.

The results of this study highlight significant associations between various bias incidents and their respective categories. The Chi-squared tests and p-values were instrumental in identifying these associations, providing a robust framework for hypothesis testing and ensuring the reliability and validity of the conclusions drawn.

The analysis revealed a peak in bias incidents within schools and colleges around February 2023, with anti-Jewish, anti-Black, anti-homosexual, and anti-multi-racial biases being the most prevalent. This suggests a heightened period of bias-related activities in educational institutions during this time. Additionally, the data showed a consistent increase in bias incidents against individuals, with anti-Black, anti-Jewish, anti-Asian, and anti-homosexual biases being the most common. This trend indicates a growing concern for individual safety and the need for targeted interventions.

The Chi-squared values for individuals have consistently indicated an increase in victim's association with bias codes, whereas the values for schools and colleges have shown a decline since 2023. This divergence suggests differing trends in bias incidents across these categories. Consequently, early interventions are crucial to mitigate hate crimes effectively.

The findings of this study have several important implications. Firstly, the significant associations identified through Chi-squared tests and p-values can inform policymakers and educational institutions about the areas that require immediate attention. Targeted interventions can be designed to address the specific biases prevalent in schools/colleges and among individuals. Secondly, the results underscore the need for increased awareness and education about bias-related issues. Educational programs can be developed to address the most common biases and promote inclusivity and tolerance.

Furthermore, the study highlights the importance of continuous monitoring and analysis of bias incidents. Future research can build on these findings to explore the underlying causes of bias incidents and develop more effective strategies for prevention and intervention. Lastly, the use of generative AI for generating Python code demonstrates its potential for assisting novices and non-programmers in conducting complex statistical analyses. However, it also emphasizes the need for multiple iterations and user verification to ensure accuracy and reliability. By leveraging the insights gained from this study, researchers, policymakers, and educators can work together to create a more inclusive and equitable society.

This research, while offering valuable insights, has some limitations to consider. The study focuses on a single dataset from Montgomery County, Maryland, limiting the generalizability of the findings to other locations or demographics. The conclusions heavily rely on the accuracy and completeness of the reported data, with potential underreporting or bias in data collection. The analysis covers a relatively short period, hindering the identification of long-term trends or seasonal variations in hate crimes. While the study identifies associations between bias codes and victim categories, it cannot establish causal relationships, as other factors not analyzed might contribute to the observed trends. The use of generative AI for code generation introduces potential inaccuracies, requiring user verification and multiple iterations to ensure reliable results. These limitations highlight the need for further research with broader datasets and longer timeframes to gain a more comprehensive understanding of hate crimes across different regions and demographics. Additionally, future studies could explore the underlying causes of these crimes to develop more effective prevention and intervention strategies.

Future research should aim to increase the sample size by incorporating data from multiple jurisdictions, demographic groups, and time periods to improve the generalizability of the findings. Expanding the dataset in this way would allow for more robust subgroup analyses and enhance confidence in observed associations across different contexts. In addition, a longitudinal design that follows victims and communities over time would provide critical insights into the long-term psychological, social, and economic consequences of hate crimes. Such extended follow-up could reveal delayed effects, identify factors that promote resilience or exacerbate harm, and inform more targeted prevention and support strategies. By adopting these approaches, subsequent studies would build on the current work and yield stronger, more broadly applicable evidence to guide policy and intervention efforts.

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Code Availability The code is available at the GitHub site. https://github.com/y-takefuji/hate

Declarations

Conflicts of interest The author has no conflict of interest.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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