Mixed-Methods Analysis of Preferences for Community-Based Violence Prevention and Intervention Approaches

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2025-12-04

Violence poses a threat to the health and safety of communities in the U.S. Prior literature has demonstrated the efficacy of violence prevention and intervention programs to advancing community safety. However, there is limited research on public beliefs surrounding violence prevention and community safety, creating an empirical and knowledge gap that can be assessed by examining care-based and fear-based safety. To evaluate this question, a Qualtrics survey was developed, and a convenient sample of approximately 200 Broome County residents, aged 18 or older, was recruited through tabling. This mixed-methods study integrates qualitative NVivo analysis and quantitative R analysis. A theory-driven qualitative analysis of open-ended survey responses demonstrates that conceptions of safety can be categorized under care-based or fear-based models, and reasons for criminality can be categorized to reflect a growth or fixed mindset. A multiple linear regression demonstrated that growth mindset (b = .57) is a significant predictor of care-based community safety interventions effectiveness beliefs (p = .011, R2 = .203), whereas a second linear regression demonstrated no association between growth mindset (b = –0.2117) and fear-based community safety intervention effectiveness beliefs (p=0.6336, R2 = 0.017). Together, these analyses suggest: 1) community safety can be viewed as care or fear-based, 2) growth and fixed mindsets are important aspects for viewing safety and criminality, and 3) growth mindset is related to care-based violence intervention support, but not fear-based. This study enabled a better understanding of the framework needed for future violence intervention effectiveness studies, as well as further insight into how communities can achieve community safety.

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1 Introduction

In the United States, community violence is a major public health issue. Although violent crime has been reduced by 49% between 1993 and 2022, the fear and impacts of community violence persist (Miller et al., 2023). The Center for Gun Violence Solutions and the Center for Suicide Prevention at Johns Hopkins Bloomberg School of Public Health (2025) report that in 2023, one person was killed by a gun every eleven minutes, which amounted to 46,728 people dying from gun violence in that one year. There was also a rise in arrests in Broome County from 3,031 to 4,479 between 2021 and 2022 (New York State Division, 2021-2022). The frequency of these violent acts contributes to the almost one million years of life cut short and the economic cost of five hundred billion dollars annually from 2021 to 2022 (Miller et al., 2023). As a result, the U.S. remains one of the leading developed countries in violent deaths (Grinshteyn & Hemenway, 2019).

Community violence affects everyone, but certain individuals experience the adverse effects of it more. This public health issue starts with direct exposure to violence, in which 50% to 96% of adolescents who reside within urban areas receive exposure to violence within their communities (Fowler et al., 2009). Thus, adolescents are more likely to experience symptoms of mental health disorders, including post-traumatic stress disorder, depression, and anxiety, which then negatively affect their educational and social-behavioral development (Oppenheim et al., 2024). Homicide is also the second leading cause of death for people between the ages of 10 and 24, as well as the third leading cause of death for people between the ages of 25 and 34 (CDC, 2024). Another group disproportionately affected by community violence is marginalized groups. Black Americans specifically are 14 times more likely to be murdered by firearms than their White counterparts

(Hopkins, 2021).Likewise, marginalized communities that lack resources to promote upward social mobility experience a 35% increase in firearm fatalities (Hans et al., 2025). The consequences of community violence are endless for all, hence the importance of a public health approach for reducing the prevalence of this issue.

1.1 Knowns and Unknowns

Previously, community violence was narrowly defined to encompass only certain physical acts, such as assaults and homicides. The issue of community violence has historically been examined through a criminal justice and law enforcement perspective, resulting in reactive interventions that have emphasized policing, isolation, and punishment (Abt & Hahn, 2024). However, with the emergence of a public health perspective within this domain, community violence is now defined as violence that occurs "between unrelated individuals, who may or may not know each other, generally outside the home," typically excluding domestic and intimate partner violence (CDC, 2024). Acts including physical assault, sexual assault, homicide, mugging, gang violence, and unnecessary force by authorities (Walling et al., 2011) are included under this definition, and an emphasis is now placed on prevention rather than reactive punishment. This study builds upon preventative research through its analysis of mindsets, namely fixed mindsets and growth mindsets, and models of safety, namely a care-based model of safety and a fear-based model of safety. A fixed mindset, also known as an entity mindset, is one in which people believe that individuals are born with certain characteristics and traits that will not change (Burnette et al., 2013). Thus, they believe that "dangerous" people are born as such and will remain that way for the entirety of their lives. Burnette defines a growth or incremental mindset as a mindset in which people believe that humans are capable of internal change. Analyzing a growth mindset is beneficial to this study as it has been previously associated with less aggression, prosocial behaviors, and support for rehabilitative measures (Dweck, 2012; Moss et al., 2019), lending an ability to build upon previous literature within the realm of violence prevention. This study also analyzes two main models of safety: a care-based model of safety and a fear-based model of safety. A care-based model of safety is an approach that promotes making physical and mental health resources more accessible, increasing economic security, and holding individuals accountable for societal wrongdoings (Norris, 2021). For example, a police-mental health correspondence program allows behavioral health workers and trained police officers to work together to respond to a mental health crisis (Townsend et al., 2023). Conversely, a fear-based model of safety is defined as an approach that relies on an in-group fearing an out-group because the out-group is viewed as "dangerous." For instance, increasing the number of police in the community after a shooting (Norris, 2021). While these definitions contribute to the world's understanding of community violence as an issue, society needs more research on how these factors influence preferences.

Both an ecological and individual perspective offer insight for this study. Individual perceptions contribute to how people generally view community violence, but there are multiple layers to these perceptions that are important to consider as well. As such, an integration of both perspectives is needed in order to explore individual beliefs about socioecological approaches to violence prevention. Risk factors for community violence include low mobility and socioeconomic background, high poverty and high-risk environment, early exposure to violence, neglect, or abuse. Protective factors that decrease the likelihood of violence and promote safety include a socially cohesive environment, high socioeconomic status, environmental values of nonaggressive behavior, and low impulsivity (Lösel & Farrington, 2012). Currently, care-based and fear-based safety are conceptions coined by

Zach Norris based on his beliefs of how society achieves public safety through his book Defund Fear. This study aims to find empirical evidence to support these models of safety by assessing community members' perceptions of effective violence prevention/intervention approaches, mindsets on criminality and anti-violence, and beliefs on violence preventability. These aspects of community safety from an individual to a group scope provide a deeper understanding of possible predictors for achieving greater community safety and how current community violence initiatives can be improved.

1.2 Research Aims

Evaluating how beliefs influence support for community-based violence prevention and intervention approaches aims to alleviate empirical and knowledge gaps within existing violence prevention and safety promotion research. Knowledge and empirical gaps surround a lack of evaluation of safety and violence beliefs/perceptions as indicators of support for intervention pathways. This mixed-methods study combines qualitative and quantitative analysis of perceptions, beliefs, and mindsets measured through Likert scale responses and open-ended questions to holistically evaluate individuals and their likelihood to support intervention strategies. This exploratory study aims to examine qualitatively and quantitatively measured variables, including gender, conceptions or beliefs around safety, changeability beliefs, and violence prevention conceptions. These gaps and research aims form the following questions: 1) What are the lay perceptions of the Binghamton and Broome County communities' surrounding effective violence prevention/intervention approaches? 2) Does the possession of a growth or fixed mindset influence preferred safety approaches? and 3) How do mindsets influence perceptions of criminality and violence and affect preferences for care-based vs. fear-based models of safety? Assuming no correlation, expectations predict a random association between growth mindsets and support for care-based community violence prevention approaches. Alternatively, analysis may support that growth mindsets are associated with support for care-based community violence prevention and intervention approaches.

2 Methods

2.1 Participants and Sampling

The study was approved by the Institutional Review Board of a public higher education institution in New York. Research was conducted ethically to protect the rights, welfare, confidentiality, and privacy of participants. Also, participants were informed of the project and provided their consent before beginning the survey. Participants were eligible for this study if they were at least 18 years old and Binghamton University students or Broome County residents. Individuals were recruited through tabling on campus and at Broome County community events for 6 weeks. Data was collected via a Qualtrics survey that had a total of 21 questions. Open-ended questions were utilized to gather qualitative data, while Likert scale and ranking questions were used to gather quantitative data. The survey reached 210 participants, with 154 responses excluded for quantitative analysis and 134 responses excluded for qualitative analysis due to incompleteness of the Qualtrics survey.

2.2 Measures

Beliefs and Perceptions of Community Safety refers to lay beliefs surrounding perceptions of safety, violence intervention, and crime. Perceived Exposure refers to the perceived level of safety one feels within their community, as well as the perceived extent to which safety and community trust is present within their neighborhood. Effectiveness Rating of Various Interventions refers to lay beliefs surrounding the effectiveness of different violence intervention approaches to achieving community safety and preventing violence, and the extent to which these preferred approaches reflect a care-based model of safety or a fear-based model of safety. Kind of Person Implicit Theory Scalemeasures lay beliefs surrounding the extent to which a person can change the kind of person they are, and reflects the extent to which respondents have a growth or fixed mindset. Preferred Approach to Creating Safetyrefers to the extent to which a person prefers care-based methods of achieving safety, as opposed to fear-based methods of achieving safety. Sociodemographics refer to the social characteristics a person holds, and includes gender identity, racial/ethnic identity, political beliefs, perceived social status, age, and zip code. Gender identity refers to an individual's personal sense of their own gender, and the extent to which they align with being a man, a woman, both, or neither. Racial identity refers to an individual's social classification on the basis of perceived phenotypic characteristics, while ethnic identity refers to an individual's cultural identity and their perceived belonging to a particular ethnic group. Political beliefs refer to an individual's perceived alignment with a set of values regarding the organization and goals of a society. Lay Beliefs on Care Promotion and Violence Prevention refers to perceptions held by respondents in reference to violence preventability and safety promotion. Most Effective Intervention refers to the perceived effectiveness of different community- and societal-level changes on achieving community safety, as well as the perceived effectiveness of different community- and societal-level changes on preventing or reducing violence.

Newly generated variables include Beliefs and Perceptions of Community Safety, Perceived Exposure, Effectiveness Rating of Various Interventions, Sociodemographics, Preferred Approach to Creating Safety, and Most Effective Intervention. Items for Beliefs and Perceptions of Community Safety were developed as open-ended questions by the authors by brainstorming, discussion with peers, and reading prior articles on similar constructs. The measure consisted of 4 items: 1) What does community safety mean to you?, 2) Do you believe community violence can be reduced? Why or why not?, 3) Who are the people that commit crimes, and who are the people that prevent crime from happening?, and 4) "These are hardcore criminals. You know, we took many people off the streets of Washington, DC. They're not going to be good… they were born to be criminals, frankly… Washington, DC is now a safe zone." Do you agree or disagree with this statement regarding recent deportations and deployment of the National Guard in DC? Explain your reasoning.

Items for Perceived Exposure were developed by the authors through brainstorming, generating a list of the constructs that would be encompassed by this variable, and reading prior articles on similar constructs. In addition to producing new statements, certain statements within this measure were adapted from previously existing validated measures. The measure consisted of 6 items: 1) My neighborhood feels like a community., 2) Most people in this neighborhood are willing to help you if you need it., 3) I trust my neighbors., 4) I do not feel safe in my neighborhood., 5) I cannot rely on my neighbors for help if I need it., and 6) I do not trust my neighbors. The items were scored using a 6-pt Likert scale with the following response options: strongly disagree (1), disagree (2), slightly disagree (3), slightly agree (4), agree (5), and strongly agree (6). Items for Effectiveness Rating of Various Interventions were developed by the authors through brainstorming, discussion with peers, and reading prior articles on similar constructs. The measure consisted of 8 items: 1) Community-based interventions are the most effective way to achieve community safety., 2) Educational programs are the most effective way to achieve community safety., 3) Hospital-based intervention programs are the most effective way to achieve community safety., 4) Increasing/enhancing mental health resources available and other social services is the most effective way to achieve community safety., 5) Inclusive social welfare policies are the most effective way to achieve community safety., 6) Utilizing legislation and policy is the most effective way to prevent violence., 7) Policing is the most effective way to prevent violence., and 8) Immigration enforcement (e.g. deportation) is the most effective way to prevent violence. The items were scored using a 6-pt Likert scale with the following response options: strongly disagree (1), disagree (2), slightly disagree (3), slightly agree (4), agree (5), and strongly agree (6).

Items for Sociodemographics, including gender identity, racial/ethnic identity, and political beliefs, were developed by the authors through brainstorming, discussion with peers, and reviewing prior articles and surveys containing similar measures. The measure for gender identity consisted of 4 items: 1) Girl or woman, 2) Boy or man, 3) Nonbinary, genderfluid, or genderqueer, and 4) I am not sure or questioning, as well as options for participants who do not understand the question and those who do not wish to answer. The measure for racial/ethnic identity consisted of 8 items: 1) American Indian or Alaska Native, 2) Asian, 3) Black or African American, 4) Hispanic or Latine, 5) Middle Eastern or North African, 6) Native Hawaiian or Pacific Islander, 7) White, and 8) Other, as as well as an option for participants who do not wish to answer. The measure for political beliefs consisted of 8 items: 1) Far left/leftist, 2) Very liberal, 3) Liberal, 4) Moderate, 5) Conservative, 6) Very conservative, 7) Far-right/alt-right, and 8) Other (please specify), as well as options for participants who do not understand the question and those who do not wish to answer.

Items for Preferred Approach to Creating Safety were developed by the authors through brainstorming, discussion with peers, and reviewing prior articles on similar constructs. In addition to producing new statements, certain statements within this measure were adapted from previously existing validated measures. The measure consisted of 2 directly opposing items: 1) Communities would be safer if less people owned firearms, less people carried firearms for self-protection, more regulations are placed on firearms, less emphasis on border patrol is placed, and individuals displaying symptoms of mental illness were diverted to health care professionals rather than arrested., and 2) Communities would be safer if more people owned firearms, more people carried guns for self-protection, less regulations are placed on firearms, more emphasis on border patrol is placed, and individuals displaying symptoms of mental illness were arrested rather than diverted to health care services. The items were scored using a 2-pt bipolar matrix scale, in which respondents were prompted to choose one statement or the other.

Items for Most Effective Intervention were developed by the authors through brainstorming and reviewing prior articles on similar constructs. The measure consisted of 8 items: 1) Economic security initiatives (e.g. raising minimum wage, Universal Basic Income), 2) Gun safety policies (e.g. universal background checks), 3) Violence prevention programs (e.g. conflict resolution, bystander training), 4) Policing initiatives, 5) Intervene in hospitals to prevent future violence (e.g. follow-up mental health services, job training referrals), 6) Positive youth development programs (e.g. mentorship, after-school programs), 7) Mental health supports (e.g. therapy, trauma recovery), and 8) Immigration enforcement (e.g. deportation). Items are then rated by participants from most effective to least effective.

Validated measures include Kind of Person Implicit Theory Scale, Sociodemographics, and Lay Beliefs on Care Promotion and Violence Prevention. Kind of Person Implicit Theory Scale was measured using the Kind of Person Implicit Theory Scale (Dweck, 2000) on a 6-pt Likert scale with the following response options: strongly agree (1), agree (2), mostly agree (3), mostly disagree (4), disagree (5), and strongly disagree (6). Sociodemographics, including subjective social status, were measured using the MacArthur Scale of Subjective Social Status (Adler et al., 2000) on a 10-pt scale going from lowest perceived social standing (1) to highest perceived social standing (10). Lay Beliefs on Care Promotion and Violence Prevention was measured using items directly pulled from a developing paper and study by McCarty et al. on a 6-pt Likert scale with the following response options: disagree completely (1), disagree a lot (2), disagree a little (3), agree a little (4), agree a lot (5), and agree completely (6).

Each response to the items for Beliefs and Perceptions of Community Safety was manually assessed, and different responses were grouped under codes based on conceptual themes that emerged. This procedure was repeated four times for each of the items underneath this measure. Responses to the open-ended question, "What does community safety mean to you?" allowed for the analysis of safety models and lay safety conceptions held by Broome County members. Responses to the open-ended question, "Do you believe community violence can be reduced? Why or why not?" allowed for the measurement and analysis of preventability beliefs amongst Broome County residents. Responses to the open-ended questions, "Who are the people that commit crimes, and who are the people that prevent crime from happening?" and "These are hardcore criminals. You know, we took many people off the streets of Washington, DC. They're not going to be good… they were born to be criminals, frankly… Washington, DC is now a safe zone." Do you agree or disagree with this statement regarding recent deportations and deployment of the National Guard in DC?" allowed for the analysis of growth vs. fixed mindsets towards criminality amongst Broome County members. The first question allowed for the identification of a growth or fixed mindset as it captured whether participants believed a certain type of person commits crimes. The second question allowed for the identification of mindset type in relation to criminality specifically.

2.3 Data Analysis Plan: Qualitative

NVivo was utilized in order to qualitatively analyze the open-ended data, consisting of the items under Beliefs and Perceptions of Community Safety, collected from the Qualtrics survey, while performing simultaneous quantitative analysis of safety perceptions. Prior to analyzing the collected data, it was screened for invalid responses. Survey responses in which participants did not consent to participating in the study, participants utilized AI to generate responses, participants were under the age of 18, participants did not respond to 50% or more of the survey questions, or participants did not respond to survey questions seriously were removed from the collected data. The valid survey responses were then imported into NVivo, where the software was used to conduct a content analysis of the collected data, and a conventional approach was used to generate thematic codes under which similar responses to the open-ended questions on the survey could be categorized. Responses were first read over in their entirety, and similar themes that arose amongst the responses were mentally noted. Survey responses were then read over a second time, going line by line, and relevant parts of each response were then turned into references from which codes could be produced. This was done by highlighting a part of the text data and selecting In-vivo Code. From then, the code produced could be renamed to reflect the broader conceptual theme, which was reflected by the reference. New codes continued to be generated in this manner as each survey response was reviewed and analyzed. References were also continually added to existing codes. Following the initial coding of each survey response, the codes produced were then refined by aggregating codes that were too specific or dividing codes that were too general. References underneath the codes that had been altered were then moved accordingly as they aligned with the new codes. This procedure was repeated until all codes had been finalized.

2.4 Data Analysis Plan: Quantitative

Utilizing Positcloud - a platform hosting R software for statistical analysis and data visualization - quantitative perceptions of safety variables were analyzed in tandem with qualitative sociodemographic, preventability belief, care-based safety conception, and fixed mindset belief variables in a mixed-methods research design. Data was imported using the package Readxl and screened for participants who opted not to consent to the survey or selected prefer not to say in response to certain questions by assigning the responses the value -99 and filtering out of the dataset for analysis. Respondents indicating the selection 'Don't know' were similarly filtered out of the dataset utilizing the value -50. Other invalid responses filtered out include respondents who refrained from completing half or over half of the survey or selected do not consent at the beginning of the survey.

The variables necessary for analysis were selected for in a new dataset: selectdata. Using the package diplyr, predictor community variables (COMM_FEEL, COMM_HELP, COMM_NEIGHBORS, NONCOMM_UNSAFE, NONCOMM_RELY, NONCOMM_DISTRUST) and fixed and growth mindset variables (FIXED PERSON1_BASIC, FIXEDPERSON2_DIFF, FIXEDPERSON3_CHANGE_R, FIXEDPERSON4_OLD, FIXEDPERSON_ALL_R, FIXEDPERSON_ALWAYS_R, FIXEDPERSON_CERTAIN, and FIXEDPERSON_MATTER_R) were transformed, assigning each response with values one through six for Likert levels of agreement from strongly disagree to strongly agree. Transformations of continuous community and mindset variables were performed, and gender was simplified into binary variables. To create visualizations to check for normality and model community safety as a single variable (COMMUNITY), COMM and reverse-coded NONCOMM variables were grouped using the psych package. Similarly, fixed and growth variables were grouped to indicate growth mindset by reverse coding variables indicating a fixed mindset (FIXEDPERSON_ALWAYS_R, FIXEDPERSON3_CHANGE_R, FIXEDPERSON_ALL_R) and averaging them with variables indicating growth mindset (FIXED PERSON1_BASIC, FIXEDPERSON2_DIFF, FIXEDPERSON_CERTAIN) . Using the diplyr package, the variable indicating growth mindset (GROWTH) was created, measuring the average level of growth mindset held by each individual. The final transformation performed for this dataset included creating a new gender variable (GENDER01), regrouping participants into binary subsets necessary for the independent variable of a Wilcoxon-Mann-Whitney U test.

Visualizations were required for both Wilcoxon-Mann-Whitney U tests and Multiple Linear Regression tests using the ggplot2 and diplyr. First, to narrow down which outcomes to investigate, using tidyr for a long data visual, a bar chart was visualized to indicate which intervention (EFFECT_CARE_EDUCATION, EFFECT_CARE_HVIP, EFFECT_CARE_COMM, EFFECT_FEAR_LEG, EFFECT_FEAR_POLICE) is perceived as most effective for both care-based and fear-based. To perform Wilcoxon-Mann-Whitney U tests of significant difference between intervention methods, a non-normal distribution of intervention preferences was required. Utilizing ggplot2, histograms of the most preferred outcomes, care-based: education and community intervention, and fear-based: policing (EFFECT_CARE_COMM, EFFECT_CARE_POLICE, EFFECT_CARE_EDUCATION), were visualized for non-normality. Additionally, outcome variables including support for community-based violence intervention (EFFECT_CARE_COMM) programs, educational intervention programs (EFFECT_CARE_EDUCATION), and fear-based policing intervention (EFFECT_CARE_POLICE) visualizations, showed non-normal distributions. Alternatively, to perform a multiple linear regression of the perceptions of safety, continuous variables (GROWTH and COMMUNITY) were first reviewed using parametric tests to determine if the response distribution is normal or not normally distributed. Both distributions were relatively normal, allowing for multiple linear regression to be performed.

With distribution requirements confirmed, three Wilcoxon-Mann-Whitney U tests were performed. Community intervention support (EFFECT_CARE_COMM) was compared to policing support (EFFECT_FEAR_POLICE) and then to binary gender variables (GENDER01). Furthermore, support for policing (EFFECT_FEAR_POLICE) was compared to binary gender variables (GENDER01). Faceted bar charts to display agreement with community-based interventions (EFFECT_CARE_COMM) and policing fear-based interventions (EFFECT_FEAR_POLICE) by gender (GENDER01) were created using ggplot2.

In the multiple linear regressions, community safety perceptions (COMMUNITY) and growth mindset (GROWTH) variables were evaluated as predictors of support for care-based community interventions (EFFECT_CARE_COMM) in one regression and fear-based policing interventions (EFFECT_FEAR_POLICE) in another using the stats package. These regressions were paired with a scatterplot visualization of agreement with growth mindset statements (GROWTH) and support for care-based interventions (EFFECT_CARE_COMM), with best-fit lines highlighting a third relationship with gender (GENDER01). Additionally,Furthermore ggplot2 was also used to visualize agreement with growth mindset statements (GROWTH) in comparison to (EFFECT_FEAR_POLICE).

2.4.1 Import

```
library(readxl)
library(dplyr)

alldata <- read_excel("alldata.xlsx", col_names = TRUE)

alldata[alldata == -99] <- NA
alldata[alldata == -50] <- NA

##explanation:Data collected using the surveying platform, qualtrics was exported to excel. Th
#source: The Quantitative Playbook for Public Health Research in R. (McCarty, 2025) https://sha
```

2.4.2 Transform

2.4.2.1 *Select Variables for Analysis*

```
library(dplyr)
selectdata <- alldata %>%
  select(AGE, FIXEDPERSON1_BASIC, FIXEDPERSON2_DIFF, FIXEDPERSON3_CHANGE_R,FIXEDPERSON4_OLD, FI
```

```
##explanation: Select dataset created to isolate variables and data used in Wilmulti linear re
#source: The Quantitative Playbook for Public Health Research in R. (McCarty, 2025) https://sh
```

2.4.2.2 *Community Indicator Transformations*

```
#Factor
selectdata <- selectdata %>% filter(!is.na(COMM_FEEL)) %>%
  mutate(
    COMM_FEEL == case_when(
    COMM_FEEL == 1 ~ "Strongly Disagree",
    COMM_FEEL== 2 ~ "Disagree",
    COMM_FEEL == 3 ~ "Slightly Disagree",
    COMM_FEEL== 4 ~ "Slightly Agree",
    COMM_FEEL == 5 ~ "Agree",
    COMM_FEEL == 6 ~ "Strongly Agree",
  )
  )
##explanation: Assigning values 1-6 for low to high level of agreement with the corresponding
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(COMM_HELP)) %>%
  mutate(
    COMM_HELP == case_when(
    COMM_HELP == 1 ~ "Strongly Disagree",
    COMM_HELP== 2 ~ "Disagree",
    COMM_HELP == 3 ~ "Slightly Disagree",
    COMM_HELP== 4 ~ "Slightly Agree",
    COMM_HELP == 5 ~ "Agree",
    COMM_HELP == 6 ~ "Strongly Agree",
  )
  )
##explanation: Assigning values 1-6 for low to high level of agreement with the corresponding
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(COMM_NEIGHBORS)) %>%
  mutate(
    COMM_NEIGHBORS == case_when(
    COMM_NEIGHBORS == 1 ~ "Strongly Disagree",
    COMM_NEIGHBORS== 2 ~ "Disagree",
    COMM_NEIGHBORS == 3 ~ "Slightly Disagree",
    COMM_NEIGHBORS== 4 ~ "Slightly Agree",
    COMM_NEIGHBORS == 5 ~ "Agree",
    COMM_NEIGHBORS == 6 ~ "Strongly Agree",
  )
```

```
  )
##explanation: Assigning values 1-6 for low to high level of agreement with the corresponding 
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(NOTCOMM_UNSAFE)) %>%
  mutate(
    NOTCOMM_UNSAFE == case_when(
    NOTCOMM_UNSAFE == 1 ~ "Strongly Disagree",
    NOTCOMM_UNSAFE== 2 ~ "Disagree",
    NOTCOMM_UNSAFE == 3 ~ "Slightly Disagree",
    NOTCOMM_UNSAFE== 4 ~ "Slightly Agree",
    NOTCOMM_UNSAFE == 5 ~ "Agree",
    NOTCOMM_UNSAFE == 6 ~ "Strongly Agree",
  )
  )
##explanation: Assigning values 1-6 for low to high level of agreement with the corresponding 
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
 selectdata <- selectdata %>% filter(!is.na(NOTCOMM_UNSAFE)) %>%
  mutate(
    NOTCOMM_RELY == case_when(
    NOTCOMM_RELY == 1 ~ "Strongly Disagree",
    NOTCOMM_RELY== 2 ~ "Disagree",
    NOTCOMM_RELY == 3 ~ "Slightly Disagree",
    NOTCOMM_RELY == 4 ~ "Slightly Agree",
    NOTCOMM_RELY == 5 ~ "Agree",
    NOTCOMM_RELY == 6 ~ "Strongly Agree",
  )
  )
##explanation: Assigning values 1-6 for low to high level of agreement with the corresponding 
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(NOTCOMM_DISTRUST)) %>%
  mutate(
    NOTCOMM_DISTRUST== case_when(
    NOTCOMM_DISTRUST == 1 ~ "Strongly Disagree",
    NOTCOMM_DISTRUST== 2 ~ "Disagree",
    NOTCOMM_DISTRUST == 3 ~ "Slightly Disagree",
    NOTCOMM_DISTRUST == 4 ~ "Slightly Agree",
    NOTCOMM_DISTRUST == 5 ~ "Agree",
    NOTCOMM_DISTRUST == 6 ~ "Strongly Agree",
  )
  )
```

```
##explanation: Assigning values 1-6 for low to high level of agreement with the corresponding 
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

2.4.2.3 *Fixed & Growth Transformations*

```
#Factor
selectdata <- selectdata %>% filter(!is.na(FIXEDPERSON1_BASIC)) %>%
  mutate(
    FIXEDPERSON1_BASIC== case_when(
    FIXEDPERSON1_BASIC == 1 ~ "Strongly Agree",
    FIXEDPERSON1_BASIC== 2 ~ "Agree",
    FIXEDPERSON1_BASIC == 3 ~ "Slightly Agree",
    FIXEDPERSON1_BASIC == 4 ~ "Slightly Disagree",
    FIXEDPERSON1_BASIC == 5 ~ "Disagree",
    FIXEDPERSON1_BASIC == 6 ~ "Strongly Disagree",
  )
  )

##explanation: Assigning values 1-6 for low to high level of agreement with the corresponding 
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(FIXEDPERSON2_DIFF)) %>%
  mutate(
    FIXEDPERSON2_DIFF== case_when(
    FIXEDPERSON2_DIFF == 1 ~ "Strongly Agree",
    FIXEDPERSON2_DIFF== 2 ~ "Agree",
    FIXEDPERSON2_DIFF == 3 ~ "Slightly Agree",
    FIXEDPERSON2_DIFF == 4 ~ "Slightly Disagree",
    FIXEDPERSON2_DIFF == 5 ~ "Disagree",
    FIXEDPERSON2_DIFF == 6 ~ "Strongly Disagree",
  )
  )

##explanation:Assigning values 1-6 for high to low levels of agreement with the corresponding 
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(FIXEDPERSON3_CHANGE_R)) %>%
  mutate(
    FIXEDPERSON3_CHANGE_R== case_when(
    FIXEDPERSON3_CHANGE_R == 1 ~ "Strongly Agree",
    FIXEDPERSON3_CHANGE_R== 2 ~ "Agree",
    FIXEDPERSON3_CHANGE_R == 3 ~ "Slightly Agree",
    FIXEDPERSON3_CHANGE_R == 4 ~ "Slightly Disagree",
    FIXEDPERSON3_CHANGE_R == 5 ~ "Disagree",
```

```
    FIXEDPERSON3_CHANGE_R == 6 ~ "Strongly Disagree",
  )
  )

##explanation:Assigning values 1-6 for high to low levels of agreement with the corresponding 
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(FIXEDPERSON4_OLD)) %>%
  mutate(
    FIXEDPERSON4_OLD== case_when(
    FIXEDPERSON4_OLD == 1 ~ "Strongly Agree",
    FIXEDPERSON4_OLD== 2 ~ "Agree",
    FIXEDPERSON4_OLD == 3 ~ "Slightly Agree",
    FIXEDPERSON4_OLD == 4 ~ "Slightly Disagree",
    FIXEDPERSON4_OLD== 5 ~ "Disagree",
   FIXEDPERSON4_OLD== 6 ~ "Strongly Disagree",
  )
  )
##explanation:Assigning values 1-6 for high to low levels of agreement with the corresponding 
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(FIXEDPERSON_ALL_R)) %>%
  mutate(
    FIXEDPERSON_ALL_R== case_when(
    FIXEDPERSON_ALL_R == 1 ~ "Strongly Agree",
    FIXEDPERSON_ALL_R== 2 ~ "Agree",
    FIXEDPERSON_ALL_R == 3 ~ "Slightly Agree",
    FIXEDPERSON_ALL_R== 4 ~ "Slightly Disagree",
    FIXEDPERSON_ALL_R== 5 ~ "Disagree",
    FIXEDPERSON_ALL_R== 6 ~ "Strongly Disgree",
  )
  )

##explanation: Assigning values 1-6 for high to low levels of agreement with the corresponding
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(FIXEDPERSON_ALWAYS_R)) %>%
  mutate(
    FIXEDPERSON_ALWAYS_R== case_when(
    FIXEDPERSON_ALWAYS_R == 1 ~ "Strongly Agree",
    FIXEDPERSON_ALWAYS_R == 2 ~ "Agree",
    FIXEDPERSON_ALWAYS_R == 3 ~ "Slightly Agree",
    FIXEDPERSON_ALWAYS_R== 4 ~ "Slightly Disagree",
    FIXEDPERSON_ALWAYS_R== 5 ~ "Disagree",
```

```
    FIXEDPERSON_ALWAYS_R== 6 ~ "Strongly Disagree",
  )
  )

##explanation: Assigning values 1-6 for high to low levels of agreement with the corresponding
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor
selectdata <- selectdata %>% filter(!is.na(FIXEDPERSON_CERTAIN)) %>%
  mutate(
    FIXEDPERSON_CERTAIN== case_when(
    FIXEDPERSON_CERTAIN == 1 ~ "Strongly Agree",
    FIXEDPERSON_CERTAIN == 2 ~ "Agree",
    FIXEDPERSON_CERTAIN== 3 ~ "Slightly Agree",
    FIXEDPERSON_CERTAIN== 4 ~ "Slightly Disagree",
    FIXEDPERSON_CERTAIN== 5 ~ "Disagree",
    FIXEDPERSON_CERTAIN== 6 ~ "Strongly Disagree",
  )
  )

##explanation: Assigning values 1-6 for high to low levels of agreement with the corresponding
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

```
#Factor NOTCOMM_DISTRUST
selectdata <- selectdata %>% filter(!is.na(FIXEDPERSON_MATTER_R)) %>%
  mutate(
    FIXEDPERSON_MATTER_R== case_when(
    FIXEDPERSON_MATTER_R == 1 ~ "Strongly Agree",
    FIXEDPERSON_MATTER_R== 2 ~ "Agree",
    FIXEDPERSON_MATTER_R == 3 ~ "Slightly Agree",
    FIXEDPERSON_MATTER_R== 4 ~ "Slightly Disagree",
    FIXEDPERSON_MATTER_R== 5 ~ "Disgree",
    FIXEDPERSON_MATTER_R== 6 ~ "Strongly Disagree",
  )
  )


##explanation:Assigning values 1-6 for high to low levels of agreement with the corresponding
#source: R for Data Science (2e), 16 Factors: https://r4ds.hadley.nz/factors.html
```

2.4.2.4 *Composite variables for GROWTH and COMMUNITY*

Prepare data for multiple linear regression test

```
all_keys <- list(
  GROWTH = c("FIXEDPERSON1_BASIC", "FIXEDPERSON2_DIFF", "FIXEDPERSON3_CHANGE_R","FIXEDPERSON4_
```

```
  COMMUNITY= c("COMM_FEEL", "COMM_HELP", "COMM_NEIGHBORS", "NOTCOMM_UNSAFE", "NOTCOMM_RELY", "N
)
##explanation: Defining list object grouping related variables under GROWTH and COMMUNITY
#source: The Quantitative Playbook for Public Health Research in R (McCarty, 2025) https://shar
```

```
all_keys_with_reverse <- list (
   COMMUNITY = c("COMM_FEEL", "COMM_HELP", "COMM_NEIGHBORS", "-NOTCOMM_UNSAFE", "-NOTCOMM_RELY"
  GROWTH = c("FIXEDPERSON1_BASIC", "FIXEDPERSON2_DIFF", "-FIXEDPERSON3_CHANGE_R", "FIXEDPERSON4
  )
#note: scale ranges from strongly agree to strongly disagree
##explanation: Grouping survey variable names- marking reversed scored items before calculatin
#source: The Quantitative Playbook for Public Health Research in R (McCarty, 2025) https://shar
```

```
library(psych)
all_scores <- scoreItems(all_keys_with_reverse, selectdata)

composite_scores <- all_scores$scores

selectdata$COMMUNITY <- composite_scores[,"COMMUNITY"]
selectdata$GROWTH <- composite_scores[,"GROWTH"]

##explanation: Automatically computing reverse scored variables for GROWTH and COMMUNITY survey
#source: The Quantitative Playbook for Public Health Research in R (McCarty, 2025) https://shar
```

2.4.2.5 *Binary Gender Variables*

```
selectdata <- selectdata %>%
  mutate(
    GENDER01 = case_when(
      GENDER== "0" ~ "0",
      GENDER== "1" ~ "1",
      GENDER == "2" ~ NA
    )
  )

##explanation: Creating a new variable (GENDER 01) recodes existing gender variables to includ
#source: (McCarty et al., 2025) https://fripublichealth.quarto.pub/zerosum/
```

```
library(dplyr)
#| label: Simplifying-Racialized-group-variables
#| eval: false
#| echo: false


selectdata <- selectdata %>%
```

```
  mutate(
    RACE.4 = case_when(
      grepl(",", RACIALIZED) ~ "Mixed/Other",
      RACIALIZED == "3" ~ "Black",
      RACIALIZED == "2" ~ "Asian",
      RACIALIZED == "7" ~ "White",
      RACIALIZED %in% c("1", "4","5","6", "8") ~ "Mixed/Other",
      TRUE ~ NA_character_)
  )


##explanation: Simplifying the selections for racialized group variables, a new variable is cr
#source: (McCarty et al., 2025) https://fripublichealth.quarto.pub/zerosum/
```

3 Results

3.1 Descriptive Statistics

3.1.1 Demographics & Representation

The majority of sample participants were between 18 and 25 years old, with a mean age of 22 years (SD=9.96), a minimum of 18 years, and a maximum of 73 years. Of the surveyed population, 27 self-identified as White and 28 as People of Color. For gender, 37 respondents self-identified as women, 19 as men, and 1 as non-binary. These descriptive statistics for qualitative responses and predictor variables are shown in Table 1. The racial/ethnic makeup within the surveyed region is 80% White and 20% persons of Color, with an average resident age of 39.4 years (Data USA, 2023). Based on the survey, the sample population was 49% White and 51% persons of color with an average age of 22 years, indicating influence from primarily surveying on Binghamton University's campus, which has a higher racial diversity than its surrounding county (50.2% white, 49.8% POC) (Data USA, 2023).

```
#|label: Count-Descriptive-Stats
#| echo: false
#| output: false
library(dplyr)
selectdata$AGE <- as.numeric(selectdata$AGE)

AGE_count <- sum(!is.na(selectdata$AGE))
EFFECT_CARE_COMM_count <- sum(!is.na(selectdata$EFFECT_CARE_COMM))
EFFECT_CARE_EDUCATION_count <- sum(!is.na(selectdata$EFFECT_CARE_EDUCATION))
EFFECT_CARE_HVIP_count <- sum(!is.na(selectdata$EFFECT_CARE_HVIP))
EFFECT_FEAR_LEG_count <- sum(!is.na(selectdata$EFFECT_FEAR_LEG))
EFFECT_FEAR_POLICE_count <- sum(!is.na(selectdata$EFFECT_FEAR_POLICE))
COMM_FEEL_count <- sum(!is.na(selectdata$COMM_FEEL))
COMM_HELP_count <- sum(!is.na(selectdata$COMM_HELP))
```

```
COMM_NEIGHBORS_count <- sum(!is.na(selectdata$COMM_NEIGHBORS))
NOTCOMM_UNSAFE_count <- sum(!is.na(selectdata$NOTCOMM_UNSAFE))
NOTCOMM_RELY_count <- sum(!is.na(selectdata$NOTCOMM_RELY))
NOTCOMM_DISTRUST_count <- sum(!is.na(selectdata$NOTCOMM_DISTRUST))
FIXEDPERSON1_BASIC_count <- sum(!is.na(selectdata$FIXEDPERSON1_BASIC))
FIXEDPERSON2_DIFF_count <- sum(!is.na(selectdata$FIXEDPERSON2_DIFF))
FIXEDPERSON3_CHANGE_R_count <- sum(!is.na(selectdata$FIXEDPERSON3_CHANGE_R))
FIXEDPERSON4_OLD_count <- sum(!is.na(selectdata$FIXEDPERSON4_OLD))
FIXEDPERSON_ALWAYS_R_count <- sum(!is.na(selectdata$FIXEDPERSON_ALWAYS_R))
FIXEDPERSON_CERTAIN_count <- sum(!is.na(selectdata$FIXEDPERSON_CERTAIN))
FIXEDPERSON_MATTER_R_count <- sum(!is.na(selectdata$FIXEDPERSON_MATTER_R))
GENDER01_count <- sum(!is.na(as.numeric(selectdata$GENDER01)))

##explanation: Converting Age to numeric variable and formulating count for each variable
#source: (Soetewey, 2020) https://statsandr.com/blog/descriptive-statistics-in-r/
```

3.1.2 *Descriptive Statistics: Table 1*

Variable	n	Mean	Median	SD	Min	Max
AGE	56	21.93	19	9.89	18	73
EFFECT_CARE_COMM	56	4.82	5	1.13	1	6
EFFECT_CARE_EDUCATION	57	4.79	5	1.25	1	6
EFFECT_CARE_HVIP	55	3.93	4	0.96	2	5
EFFECT_FEAR_LEG	57	4.28	4	1.24	1	6
EFFECT_FEAR_POLICE	58	3.17	3	1.42	1	6
COMM_FEEL	58	4.02	4	1.26	1	6
COMM_HELP	58	4.38	4	1.11	1	6
COMM_NEIGHBORS	58	4.41	4.5	1.09	2	6
NOTCOMM_UNSAFE	58	2.34	2	1.22	1	6
NOTCOMM_RELY	57	3.09	3	1.14	1	5
NOTCOMM_DISTRUST	58	2.66	2.5	1.05	1	5
FIXEDPERSON1_BASIC	58	4.48	5	1.33	1	6
FIXEDPERSON2_DIFF	58	4.07	4	1.3	2	6
FIXEDPERSON3_CHANGE_R	58	2.81	3	1.1	1	5
FIXEDPERSON4_OLD	58	4.34	5	1.21	2	6
FIXEDPERSON_ALWAYS_R	58	2.81	3	1.19	1	6
FIXEDPERSON_CERTAIN	58	4.4	4.5	1.15	1	6
FIXEDPERSON_MATTER_R	58	3.03	3	1.35	1	6
GENDER01	56	0.34	0	0.48	0	1

3.1.3 Predictors and Outcome Variables

3.1.3.1 *Data set Visualizations Pt 1: Normality*

In the following statistical tests, participants were evaluated on predictor variables related to community safety or trust, growth-mindset beliefs, and support for various forms of violence-prevention strategies. Predictor variables of community safety or trust and growth-mindset beliefs were visualized to check for normality before performing multiple linear regression tests in Figure 1. Independent variables of effectiveness of care-based community interventions, effectiveness of care-based education interventions, and effectiveness of fear-based policing interventions were visualized to check for non-normal distributions for the Wilcoxon-Mann-Whitney U tests (Figures 2 and 3).

```
#Check Normal distribution for regression test
library(ggplot2)

#Histogram for COMMUNITY
COMMUNITY_DISTPLOT <- ggplot(selectdata, mapping = aes(x = COMMUNITY)) +
  geom_histogram(binwidth = 1, fill = "#EDE3FF", color = "black", width = 0.8, position = "ide
  scale_x_continuous(
    breaks = 1:6,
    labels = c(
      "1 = Strongly Disgree",
      "2 = Disgree",
      "3 = Slightly Disgree",
      "4 = Slightly Agree",
      "5 = Agree",
      "6 = Strongly Agree"
    )
  )+ labs(
    title = "Community Safety Perception Distribution",
    x = "Level of Agreement with Safety Statements ",
    y = "Number of Responses"
  ) +
  theme_bw() +
  theme(
    axis.text.x = element_text(
      angle = 55,
      hjust = 1,
      vjust = 1,
      size = 10
    ),
    plot.margin = margin(10, 10, 20, 10)  #
  )

# Print and save to the plots folder
print(COMMUNITY_DISTPLOT)
```

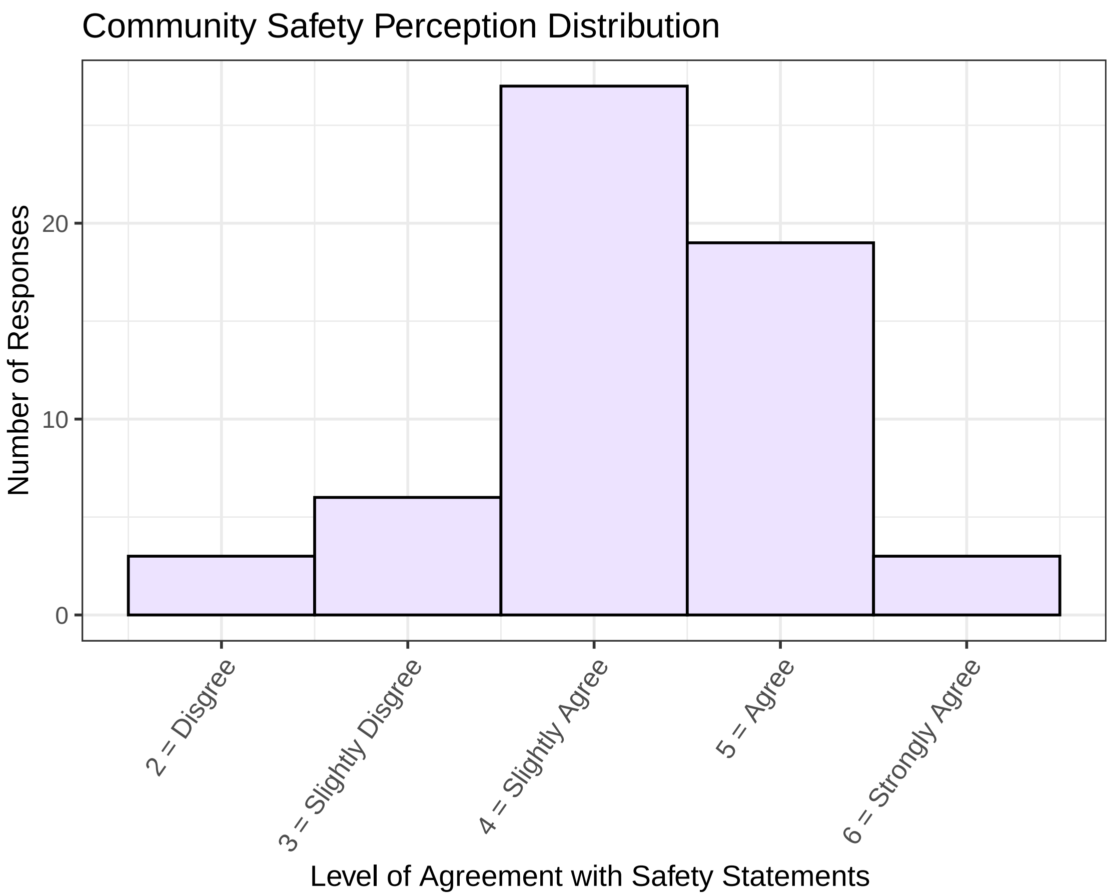


Figure 1: Figure 1. Distribution of COMMMUNITY- Fairly normal distribution allows for multiple linear regression test

```
##explanation: Visualizing Community Distribution to check for normality: relatively normal di
#source: Visualize a distribution with a histogram: https://posit.cloud/learn/recipes/visualize
```

```
#Check Normal distribution for regression test

library(ggplot2)

#Histogram for GROWTH
GROWTH_DISTPLOT <- ggplot(selectdata, aes(x = GROWTH)) +
  geom_histogram(binwidth = 1, fill = "#FFDBBB", color = "black") +
  scale_x_continuous(
    breaks = 1:6,
    labels = c(
      "1 = Strongly Agree",
      "2 = Agree",
      "3 = Slightly Agree",
      "4 = Slightly Disagree",
      "5 = Disagree",
      "6 = Strongly Disagree"
```

```
    )
  ) +
  labs(
    title = " Growth Mindset Distribution",
    x = "Level of Agreement with Growth Mindset Statements",
    y = "Number of Responses"
  ) +
theme_bw() +
  theme(
    axis.text.x = element_text(
      angle = 55,
      hjust = 1,
      vjust = 1,
      size = 10
    ),
    plot.margin = margin(10, 10, 20, 10)  #
  )
# Print and save to the plots folder
print(GROWTH_DISTPLOT)
```

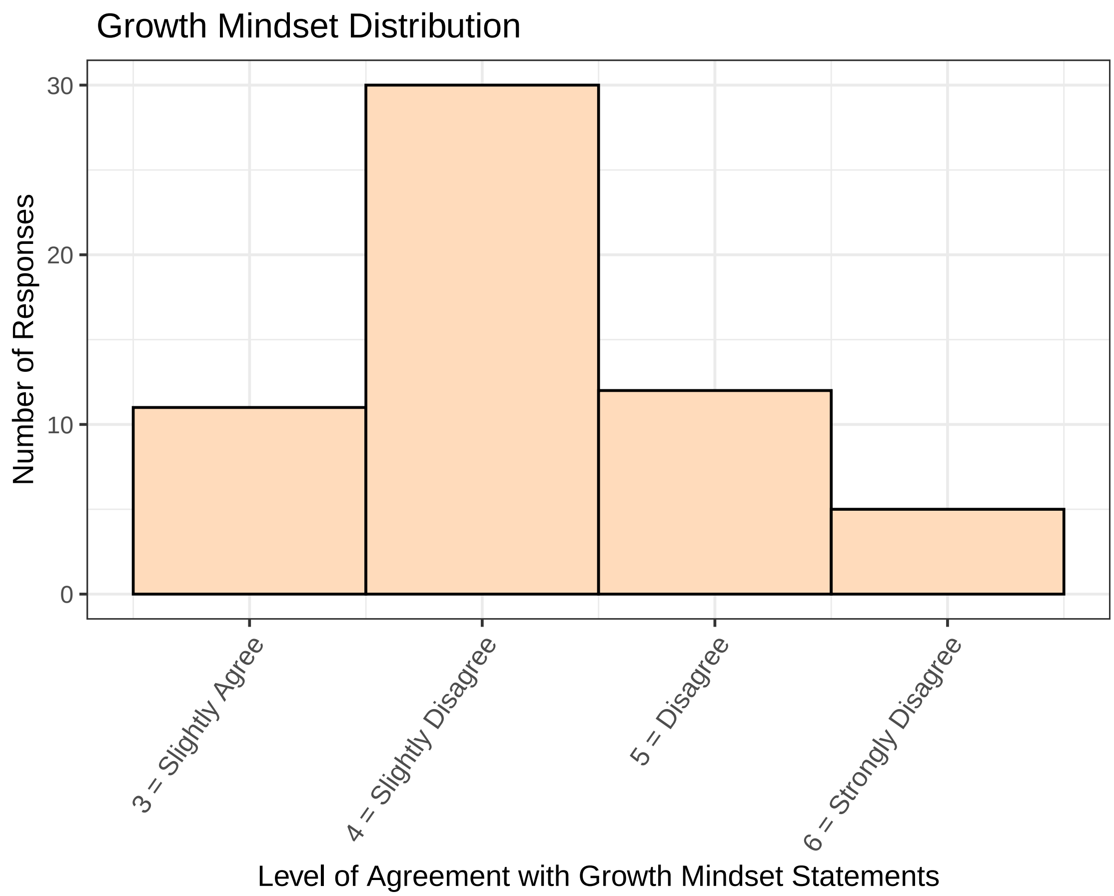


Figure 2: Figure 1. Distribution of Growth Mindset-Distribution of GROWTH- Fairly normal distribution allows for multiple linear regression test

```
##explanation: Visualizing Growth Distribution to check for normality: relatively normal distr
#source:Visualize a distribution with a histogram: https://posit.cloud/learn/recipes/visualize
```

3.1.3.2 *Data set Visualizations Pt 2: Non-normality*

```
#Check Normal distribution for regression test

library(ggplot2)

#Histogram for community-based interventions
COMM_DISTPLOT <- ggplot(selectdata, aes(x = EFFECT_CARE_COMM)) +
  geom_histogram(binwidth = 1, fill = "#C8DBC8", color = "black") +
  scale_x_continuous(
    breaks = 1:6,
    labels = c(
      "1 = Strongly Disagree",
      "2 = Disagree",
      "3 = Slightly Disagree",
```

```r
      "4 = Slightly Agree",
      "5 = Agree",
      "6 = Strongly Agree"
    )
  ) +
  labs(
    title = " Community-Based Intervention Data Distribution",
    x = "Level of Agreement that Community-based Interventions are Effective",
    y = "Number of Responses"
  ) +
theme_bw() +
  theme(
    axis.text.x = element_text(
      angle = 55,
      hjust = 1,
      vjust = 1,
      size = 10
    ),
    plot.margin = margin(10, 10, 20, 10)  #
  )
# Print and save to the plots folder
print(COMM_DISTPLOT)
```

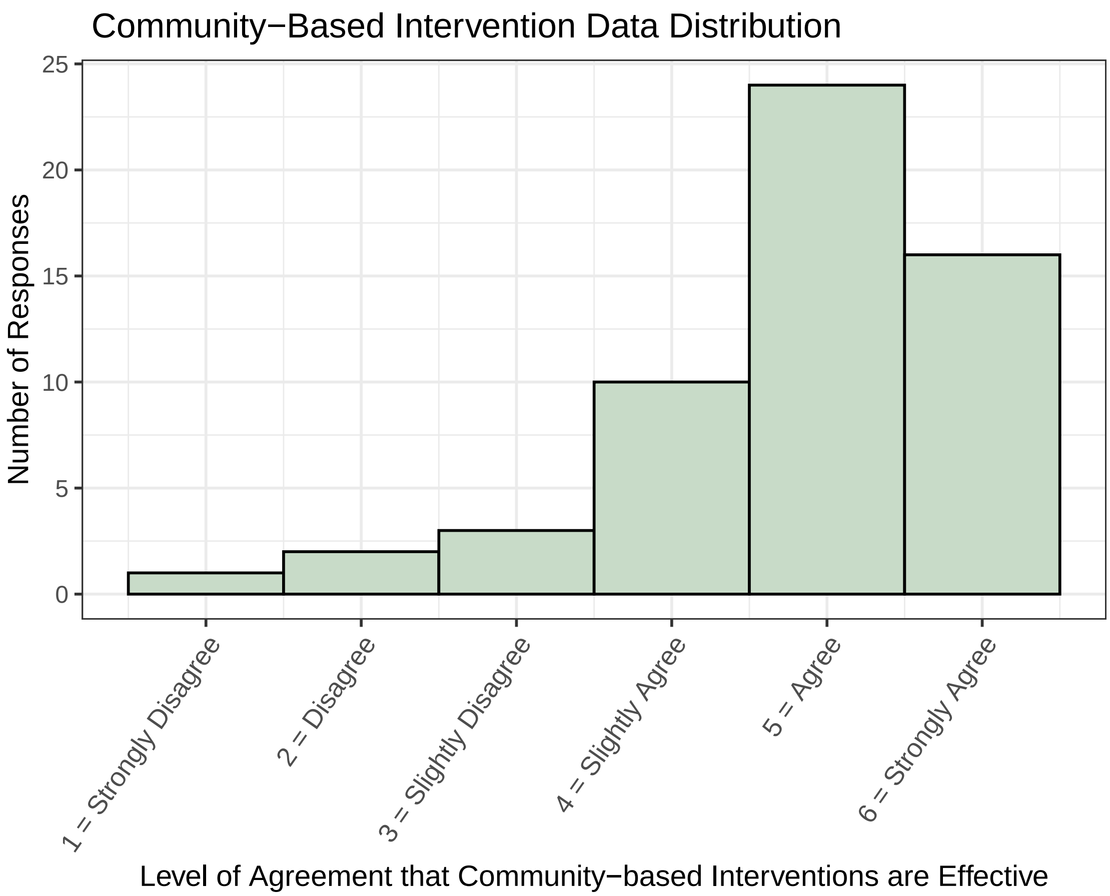


Figure 3: Figure 2. Distribution of data on Community-Based-Intervention. Non-normal distrubution allows for Wilcoxon-Mann-Whitney_U test.

```
##explanation: checking for normality within the EFFECT_CARE_COMM data set using a Histogram
#source: Visualize a distribution with a histogram: https://posit.cloud/learn/recipes/visualiz
```

```
#Check Normal distribution for regression test

library(ggplot2)

#Histogram for educational programs
EDUCATION_DISTPLOT <- ggplot(selectdata, aes(x = EFFECT_CARE_EDUCATION)) +
  geom_histogram(binwidth = 1, fill = "#C8DBC8", color = "black") +
  scale_x_continuous(
    breaks = 1:6,
    labels = c(
      "1 = Strongly Disagree",
      "2 = Disagree",
      "3 = Slightly Disagree",
      "4 = Slightly Agree",
      "5 = Agree",
      "6 = Strongly Agree"
```

```
    )
  ) +
  labs(
    title = " Educational Programs Data Distribution",
    x = "Level of Agreement that Educational Programs are Effective",
    y = "Number of Responses"
  ) +
theme_bw() +
  theme(
    axis.text.x = element_text(
      angle = 55,
      hjust = 1,
      vjust = 1,
      size = 10
    ),
    plot.margin = margin(10, 10, 20, 10)  #
  )
# Print and save to the plots folder
print(EDUCATION_DISTPLOT)
```

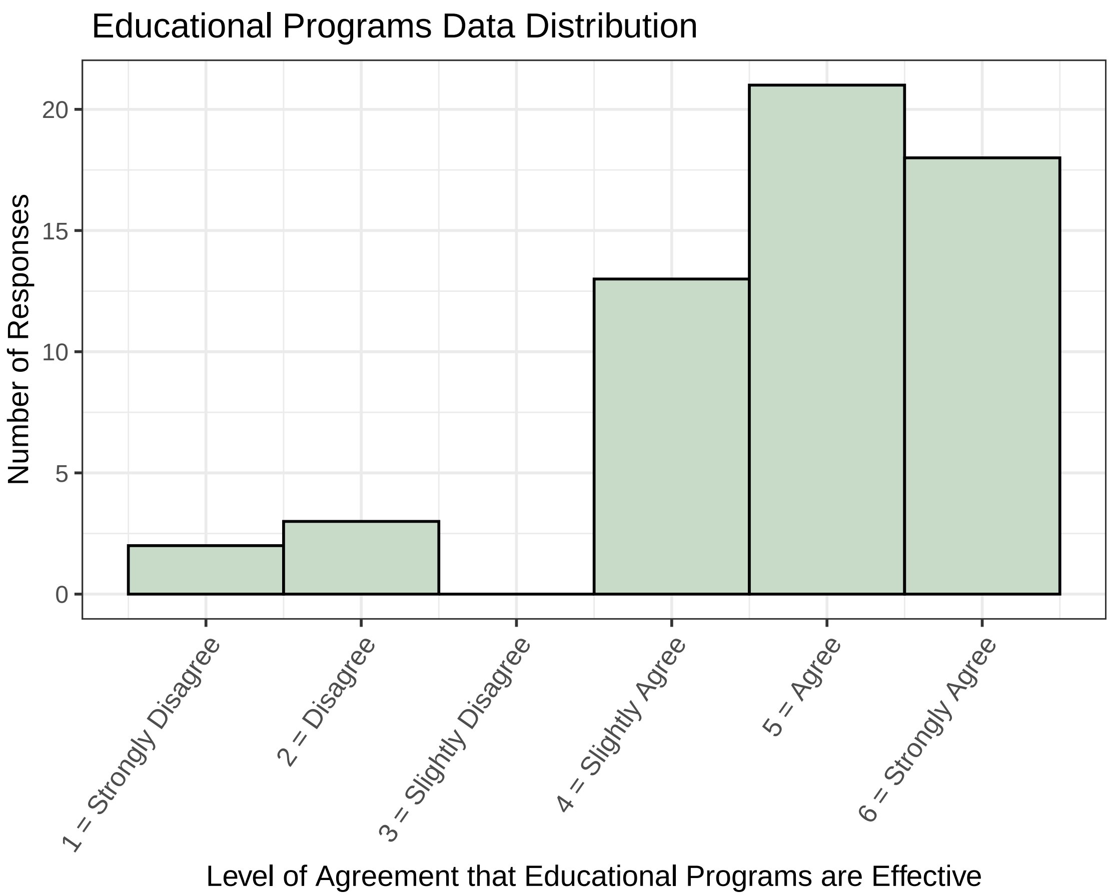


Figure 4: Figure 2. Distribution of data on Educational Programs. Non-normal distrubution allows for Wilcoxon-Mann-Whitney_U test.

```
##explanation: checking for normality within the EFFECT_CARE_EDUCATION data set using a Histog
#source: Visualize a distribution with a histogram: https://posit.cloud/learn/recipes/visualize
```

```
#Check Normal distribution for regression test

library(ggplot2)

#Histogram for Policing
POLICE_DISTPLOT <- ggplot(selectdata, aes(x = EFFECT_FEAR_POLICE)) +
  geom_histogram(binwidth = 1, fill = "#F3CDCC", color = "black") +
  scale_x_continuous(
    breaks = 1:6,
    labels = c(
      "1 = Strongly Disagree",
      "2 = Disagree",
      "3 = Slightly Disagree",
      "4 = Slightly Agree",
      "5 = Agree",
      "6 = Strongly Agree"
```

```
    )
  ) +
  labs(
    title = "Policing Data Distribution",
    x = "Level of Agreement that Policing is Effective",
    y = "Number of Responses"
  ) +
theme_bw() +
  theme(
    axis.text.x = element_text(
      angle = 55,
      hjust = 1,
      vjust = 1,
      size = 10
    ),
    plot.margin = margin(10, 10, 20, 10)  #
  )
# Print and save to the plots folder
print(POLICE_DISTPLOT)
```

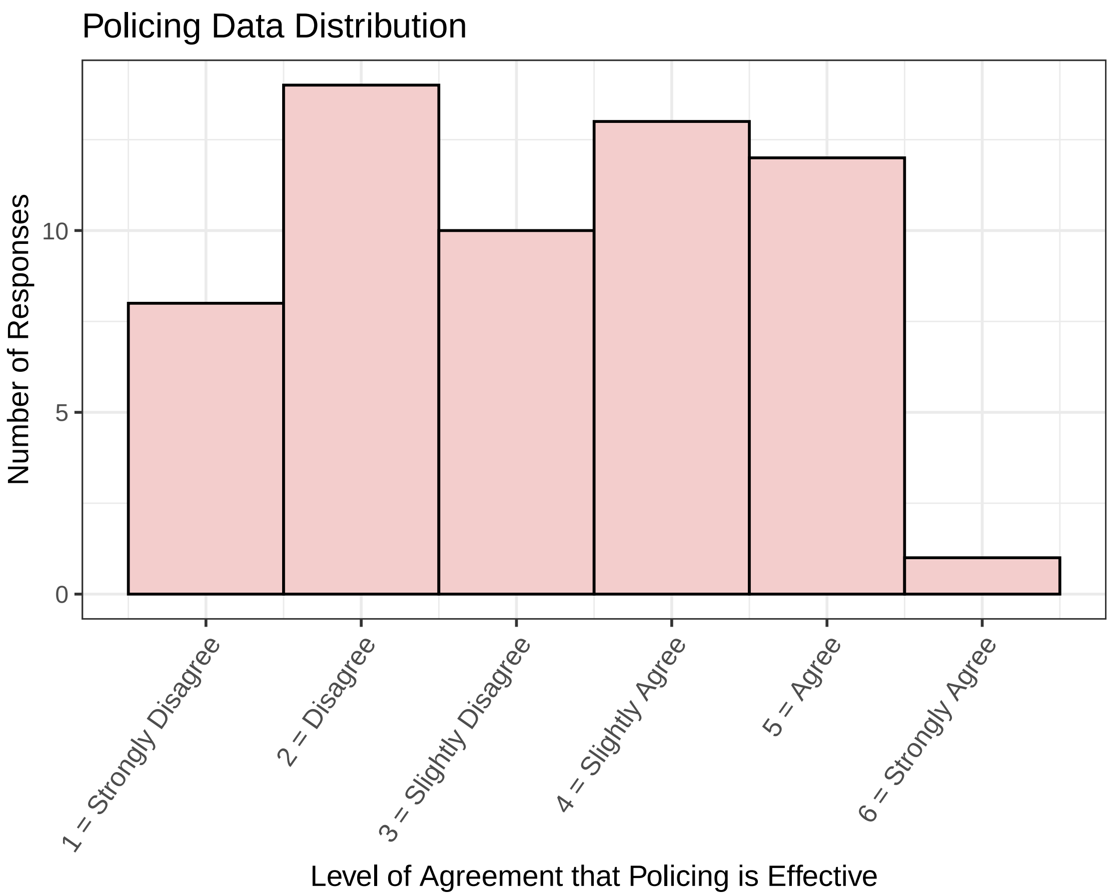


Figure 5: Figure 3. Distribution of data on Policing. Non-normal distrubution allows for Wilcoxon-Mann-Whitney_U test.

```
##explanation: checking for normality within the EFFECT_FEAR_POLICING data set using a Histogra
#source: Visualize a distribution with a histogram: https://posit.cloud/learn/recipes/visualize
```

3.2 Quantitative Results

3.2.1 *Perceived Effectiveness of Violence Prevention Approaches*

The most supported violence prevention or safety-promoting strategy was evaluated through the mean level of agreement for the effectiveness of each strategy. Figure 4 shows that care-based strategies received the highest level of agreement regarding effectiveness. Specifically, community-based interventions and educational programs had the highest means, respectively, 4.80 and 4.76. On the other hand, policing, a fear-based strategy, has the lowest-rated agreement regarding effectiveness, with a mean of 3.20.

```
library(dplyr)
library(tidyr)
library(ggplot2)
```

```
#Make data into long form
longdata <- selectdata %>%
  select(EFFECT_CARE_EDUCATION, EFFECT_CARE_HVIP, EFFECT_CARE_COMM, EFFECT_FEAR_LEG, EFFECT_FEA
  pivot_longer(cols = everything(),
               names_to = "Variable",
               values_to = "Value")

#change variable names
longdata <- longdata %>%
  mutate(
    Label = recode(Variable,
      "EFFECT_CARE_EDUCATION" = "Education",
      "EFFECT_CARE_HVIP"      = "HVIP",
      "EFFECT_CARE_COMM"      = "Community",
      "EFFECT_FEAR_LEG"       = "Legislation",
      "EFFECT_FEAR_POLICE"    = "Police"
    )
  )

#Compute means and 95% CI
means <- longdata %>%
  group_by(Label) %>%
  summarise(
    Mean = mean(Value, na.rm = TRUE),
    SD = sd(Value, na.rm = TRUE),
    N = sum(!is.na(Value)),
    SE = SD / sqrt(N),
    CI_lower = Mean - 1.96 * SE,
    CI_upper = Mean + 1.96 * SE
  ) %>%
  mutate(Label = reorder(Label, -Mean))

# Reorder longdata labels to match means
longdata <- longdata %>%
  mutate(Label = factor(Label, levels = levels(means$Label)))

#colors for each variable
custom_colors <- c(
  "Education" = "#C8DBC8",
  "HVIP" = "#C8DBC8",
  "Community" = "#C8DBC8",
  "Legislation" = "gray",
  "Police" = "#F3CDCC"
)

#Bar Plot with error bars and individual points
Plot_Strategy_Effectiveness_CI_points <- ggplot(means, aes(x = Label, y = Mean, fill = Label))
```

```
  geom_col(color = "black", alpha = 0.7) +
  geom_jitter(data = longdata,
              aes(x = Label, y = Value),
              width = 0.2,
              alpha = 0.08,  # Changed from 0.3 to 0.15 (50% lighter)
              size = 1.5,
              color = "black") +
  geom_errorbar(aes(ymin = CI_lower, ymax = CI_upper),
                width = 0.25,
                linewidth = 0.8) +
  geom_text(aes(label = round(Mean, 2)), vjust = -3.1, size = 4) +
  scale_fill_manual(values = custom_colors) +
  theme_bw() +
  scale_y_continuous(
    limits = c(0, 6.5),
    breaks = 1:6,
    labels = c(
      "1: Strongly Disagree",
      "2: Disagree",
      "3: Slightly Disagree",
      "4: Slightly Agree",
      "5: Agree",
      "6: Strongly Agree"
    )
  ) +
  labs(
    title = "Perceived Effectiveness of Violence Prevention/Intervention Approaches",
    x = "Type of Violence Prevention and Intervention Approach",
    y = "Level of Agreeance with Effectiveness"
  ) +
  theme(
    legend.position = "none",
    plot.title = element_text(size = 15, face = "bold", hjust = 0.5, margin = margin(b = 15)),
    legend.title = element_text(size = 18, face = "bold"),
    legend.text = element_text(size = 15),
    axis.title.x = element_text(size = 12, face = "bold", margin = margin(t = 12)),
    axis.title.y = element_text(size = 12, face = "bold", margin = margin(r = 12)),
    axis.text.x = element_text(size = 9, lineheight = 0.8, angle = 50, hjust = 1, vjust = 1),
    axis.text.y = element_text(size = 9, hjust = 1)
  )


Plot_Strategy_Effectiveness_CI_points
```

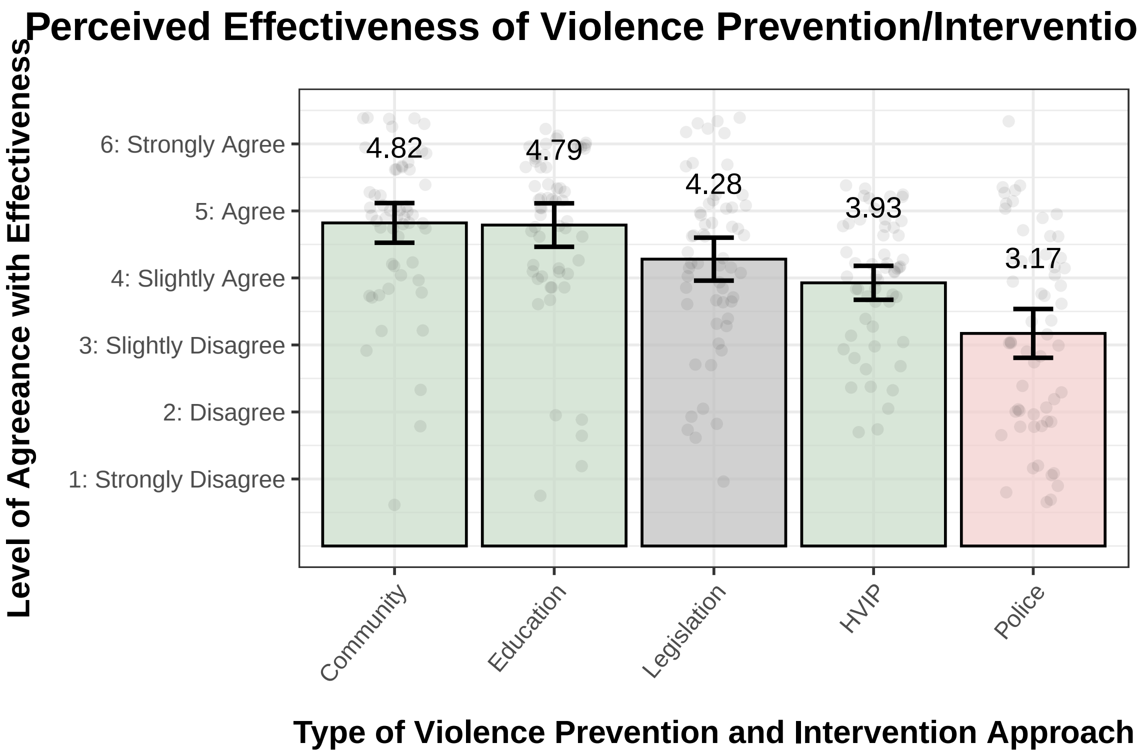


Figure 6: Figure 4. Perceived Effectiveness of Each Intervention by Mean- Bar plot shows the mean perceived effectiveness of each community violence prevention and safety promotion intervention- 6 represents there is strong agreement that the intervention is effective in reducing violence and achieving safety- while 1 represents there is strong disagreement that the intervention is effective

```
##explanation: Bar plot the mean percieved effectiveness of each community violence prevention
#source: Visualize counts with a bar chart (2025) https://posit.cloud/learn/recipes/visualize/V
```

3.2.1.1 Testing for Statistical Significance: Mann Whitney U Care & Fear

Of the intervention approaches surveyed in terms of effectiveness, community-based interventions were the highest-rated care-based intervention, whereas policing was the highest-rated fear-based intervention. A Wilcoxon-Mann-Whitney U-test determined that the difference in the level of agreement regarding effectiveness between community-based interventions and educational programs is statistically significant. However, the Wilcoxon-Mann-Whitney U-test showed no statistically significant difference between support for community-based interventions and educational programs ($p=0.974$, $p>0.001$). The strategy with the highest level of support was further evaluated in this study. Since no statistically significant difference was found between these two variables, community-based interventions were chosen for further analysis.

A second Wilcoxon-Mann-Whitney U-test was conducted between community-based interventions and policing to evaluate if there was a statistically significant difference between the highest-rated care-based intervention and the fear-based strategy. The test showed a statistically-significant difference between these two variables ($p=1.865e-06$, $p<0.001$).

3.2.1.1.1 Mann-Whitney 1:

```
wilcox.test(selectdata$EFFECT_CARE_COMM, selectdata$EFFECT_CARE_EDUCATION, paired=TRUE)
```

```

	Wilcoxon signed rank test with continuity correction

data:  selectdata$EFFECT_CARE_COMM and selectdata$EFFECT_CARE_EDUCATION
V = 254, p-value = 0.9115
alternative hypothesis: true location shift is not equal to 0
```

```
##explanation: Mann-Whitney U Test was used for non-normal distributed data. The test showed th
# source: (Cotton, 2024) https://campus.datacamp.com/courses/hypothesis-testing-in-r/non-parame
```

3.2.1.1.2 Mann-Whitney 2:

```
wilcox.test(selectdata$EFFECT_CARE_COMM, selectdata$EFFECT_FEAR_POLICE, paired=TRUE)
```

```

	Wilcoxon signed rank test with continuity correction

data:  selectdata$EFFECT_CARE_COMM and selectdata$EFFECT_FEAR_POLICE
V = 879.5, p-value = 8.049e-07
alternative hypothesis: true location shift is not equal to 0
```

```
##explanation: Mann-Whitney U Test was used because I had non-normal distributed data for my it
# source: (Cotton, 2024) https://campus.datacamp.com/courses/hypothesis-testing-in-r/non-parame
```

3.2.2 *Gender and Perceived Effectiveness of Violence Prevention Approaches*

3.2.2.1 Testing for Statistical Significance: Mann Whitney Care & Fear with Gender

A third Wilcoxon-Mann-Whitney U-Test evaluated whether there was a statistically significant difference between how men and women perceived the effectiveness of community-based interventions, a care-based approach. The test showed a lack of statistically significant difference in ratings based on gender ($p=0.3241$, $p>0.001$). Figure 5 visualizes the level of agreement with the effectiveness of community-based interventions between men and women. This indicates that both men and women show moderate to high levels of agreement that community-based interventions are an effective way to reduce violence and achieve community safety. This belief was more prevalent amongst women surveyed.

A fourth Wilcoxon-Mann-Whitney U-Test was performed to evaluate whether there was a statistically significant difference between how men and women perceive the effectiveness of policing, a fear-based approach. The test showed a statistically significant difference between these two variables ($p=2.2e\text{-}16$, $p<0.001$). Figure 6 visualizes the level of agreement with the effectiveness of the fear-based policing intervention among males and females. This evaluation indicated that women show higher levels of agreement with the effectiveness of policing than men surveyed. While both males and females surveyed showed greater variation in the level of agreement with effectiveness, males indicated more extreme levels of agreement than women, as indicated in Figure 6 below.

3.2.2.1.1 Mann-Whitney 3:

```
wilcox.test(EFFECT_CARE_COMM ~ GENDER01, data = selectdata)

##explanation: Mann-Whitney U Test was used because I had non-normal distributed data for my i
# source: (Cotton, 2024) https://campus.datacamp.com/courses/hypothesis-testing-in-r/non-parame
```

```
selectdata <- subset(selectdata, GENDER != 2)
library(ggplot2)
GENDER_CARE_BAR_EFFECTIVENESS <- ggplot(selectdata, aes(x =EFFECT_CARE_COMM, fill = GENDER01))
  geom_bar() +
  facet_wrap(~ GENDER01,
             labeller = as_labeller(c("0"= "Women", "1"= "Men"))) +
  scale_fill_manual(
    values = c("0" = "hotpink", "1" = "darkblue"),
    labels = c("Women","Men")) +
  labs(
    title = "Level of Agreement with Commmunity-Based Intervention Effectiveness by Count (Grou
    x = "Level of Agreement with Community-Based Interventions",
    y = "Number of Respondents",
    fill = "Gender"
  ) +
  theme_minimal()
  theme(axis.text.x = element_text(angle = 45, hjust= 1),
  panel.spacing = unit(1, "lines"))
```

```
List of 2
 $ axis.text.x  :List of 11
  ..$ family       : NULL
  ..$ face         : NULL
  ..$ colour       : NULL
  ..$ size         : NULL
  ..$ hjust        : num 1
  ..$ vjust        : NULL
  ..$ angle        : num 45
  ..$ lineheight   : NULL
  ..$ margin       : NULL
  ..$ debug        : NULL
  ..$ inherit.blank: logi FALSE
  ..- attr(*, "class")= chr [1:2] "element_text" "element"
 $ panel.spacing: 'simpleUnit' num 1lines
```

```
  ..- attr(*, "unit")= int 3
 - attr(*, "class")= chr [1:2] "theme" "gg"
 - attr(*, "complete")= logi FALSE
 - attr(*, "validate")= logi TRUE
```

```
    # Print and save to the plots folder
print(GENDER_CARE_BAR_EFFECTIVENESS)
```

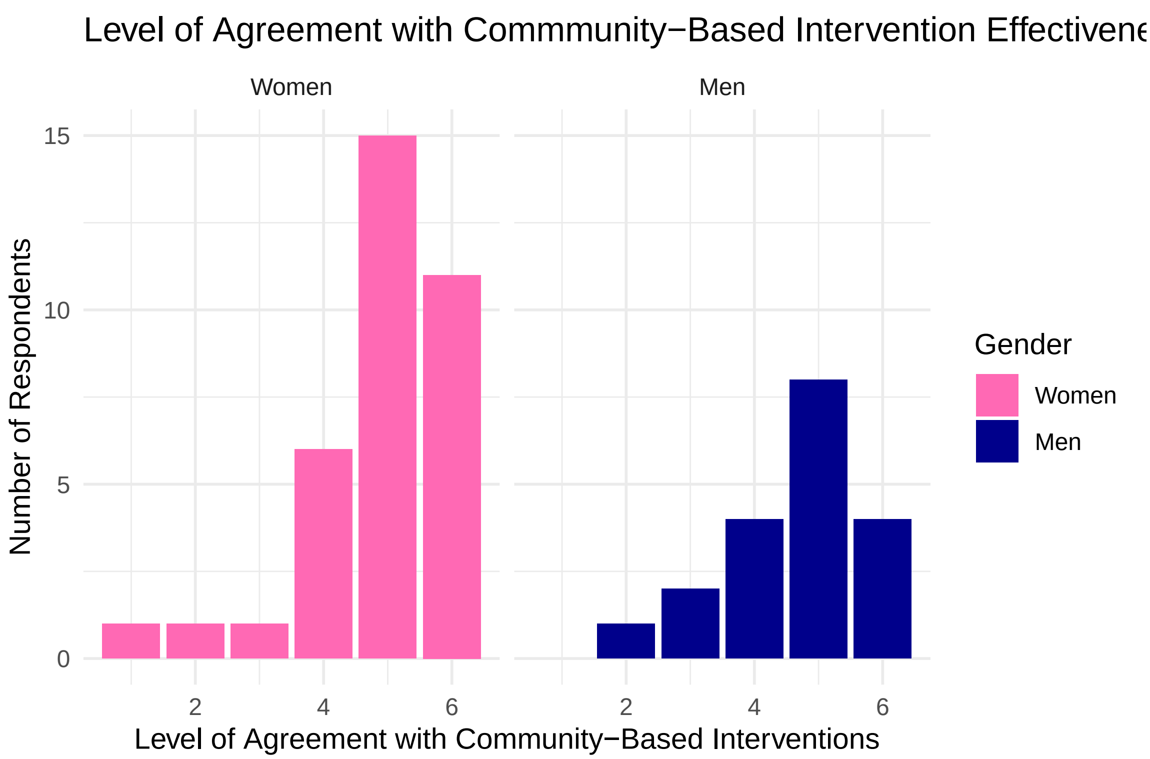


Figure 7: Figure 5. Faceted Bar plot show how women vs. men rated the level of agreeance regarding effectiveness of community-based interventions in achieving community safety and reducing violence. Both women and men rated community-based interventions moderately to highly effective, clustering around 4-6 (slightly agree to strongly agree).

```
## explanation: geom_bar was used to create a bar chart. facet_wrap was used to create two bar
# source: Facets for ggplot2 in R: https://www.datacamp.com/tutorial/facets-ggplot-r?utm_cid=1
```

3.2.2.1.2 Mann-Whitney 4:

```
wilcox.test(selectdata$EFFECT_FEAR_POLICE, selectdata$GENDER, paired=FALSE)
```

```

    Wilcoxon rank sum test with continuity correction

data:  selectdata$EFFECT_FEAR_POLICE and selectdata$GENDER
```

```
W = 3069.5, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

```
##explanation: Mann-Whitney U Test was used because I had non-normal distributed data for my i
# source: (Cotton, 2024) https://campus.datacamp.com/courses/hypothesis-testing-in-r/non-parame
```

```
# Omit Non-binary
selectdata <- subset(selectdata, GENDER != 2)
library(ggplot2)
GENDER_FEAR_BAR_EFFECTIVENESS<- ggplot(selectdata, aes(x =EFFECT_FEAR_POLICE, fill = GENDER01)
  geom_bar() +
  facet_wrap(~ GENDER01,
             labeller = as_labeller(c("0"= "Women", "1"= "Men"))) +
  scale_fill_manual(
    values = c("0" = "hotpink", "1" = "darkblue"),
    labels = c("Women","Men")) +
  labs(
    title = "Level of Agreement with Fear-Based Policing Effectiveness by Count (Grouped by Ge
    x = "Level of Agreement with Effectiveness of Policing",
    y = "Number of Respondents",
    fill = "Gender"
  ) +
  theme_minimal()
  theme(axis.text.x = element_text(angle = 45, hjust= 1),
  panel.spacing = unit(1, "lines"))
```

```
List of 2
 $ axis.text.x  :List of 11
  ..$ family       : NULL
  ..$ face         : NULL
  ..$ colour       : NULL
  ..$ size         : NULL
  ..$ hjust        : num 1
  ..$ vjust        : NULL
  ..$ angle        : num 45
  ..$ lineheight   : NULL
  ..$ margin       : NULL
  ..$ debug        : NULL
  ..$ inherit.blank: logi FALSE
  ..- attr(*, "class")= chr [1:2] "element_text" "element"
 $ panel.spacing: 'simpleUnit' num 1lines
  ..- attr(*, "unit")= int 3
 - attr(*, "class")= chr [1:2] "theme" "gg"
 - attr(*, "complete")= logi FALSE
 - attr(*, "validate")= logi TRUE
```

```
  # Print and save to the plots folder
print(GENDER_FEAR_BAR_EFFECTIVENESS)
```

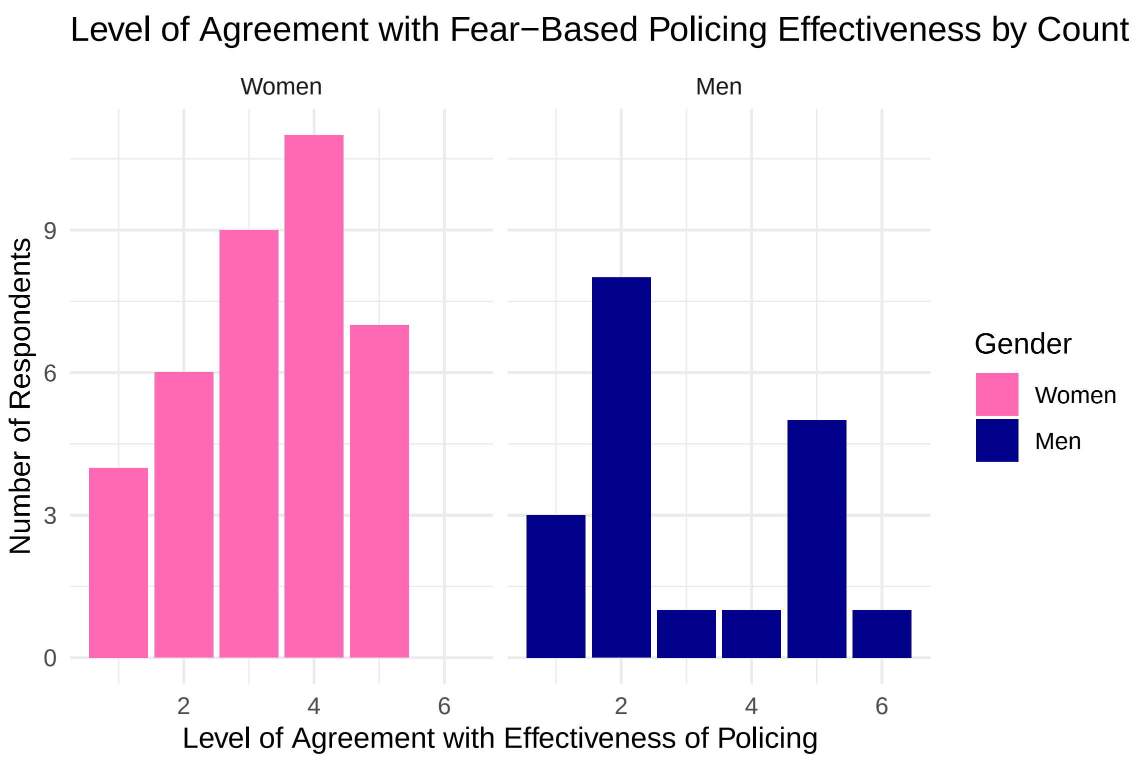


Figure 8: Figure 6. Bar plot show how women vs. men rated the level of agreeance regarding effectiveness of policing in achieving community safety and reducing violence. Women generally show higher agreement levels than men, while men are skewed more towards lower agreement.

```
 ## explanation: geom_bar was used to create a bar chart. facet_wrap was used to create two ba
# source: Facets for ggplot2 in R: https://www.datacamp.com/tutorial/facets-ggplot-r?utm_cid=1
```

3.2.3 *Predictors of Perceived Effectiveness of Violence Prevention Approaches*

3.2.3.1 Visualizing Care vs Fear with Growth Mindset

Significant differences between fear-based police interventions, care-based community interventions, and gender from prior Wilcoxon-Mann-Whitney-U tests facilitated further evaluation of relationships between the outcome and predictor variables. Evaluating these associations, the following scatterplot visualizes support for care-based community intervention based on the participant's degree of growth mindset. Due to the significance of gender from the Wilcoxon-Mann-Whitney-U tests, the following plots include gender as a third variable with best-fit regression lines for each group indicated below.

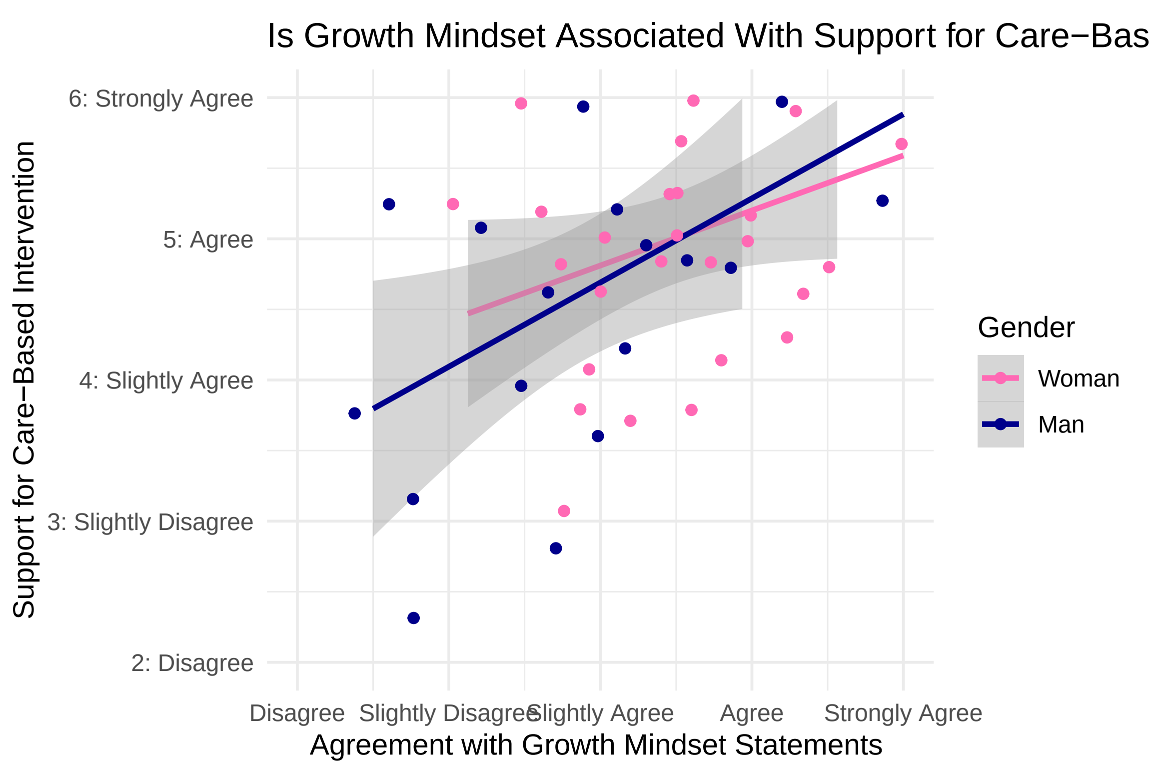
```
#|label: Visualization-Growth-Mindset-vs-Care-Based-Intervention
#| fig-cap: Figure 7. Scatter plot and linear regression of support for community care based in
#| fig-alt: Higher degrees of growth mindset positively correlating with increased support for
#| fig-width: 16
#| fig-height: 18
# Omit Non-binary
selectdata <- subset(selectdata, GENDER != 2)
#Growth Mindset vs Case Based Intervention  with 3rd Gender Variable: change color dots
GROWTH_CARE_SCAT_CARE <- ggplot(selectdata, aes(x = GROWTH, y = EFFECT_CARE_COMM, color = GENDE
  geom_smooth(method = "lm") +
  geom_point(position = position_jitter(width=0.2)) +
   scale_color_manual(
    values = c("0" = "hotpink", "1" = "darkblue"),
    labels = c("0" = "Woman", "1" = "Man")
  ) +  scale_x_continuous(breaks = 0:6, limits = c(2,6.5)) + scale_y_continuous(breaks = 0:6, l
  theme_bw() +
  scale_x_continuous(
    name = "Agreement with Growth Mindset Statements ",
    breaks = 2:6,
    limits = c(2, 6),
      labels = c(
      "Disagree",
      "Slightly Disagree",
      "Slightly Agree",
      "Agree",
      "Strongly Agree"
    )
  ) +
  scale_y_continuous(
    name = "Support for Care-Based Intervention",
    breaks = 1:6,
    limits = c(2, 6),
     labels = c(
      "1: Strongly Disagree",
      "2: Disagree",
      "3: Slightly Disagree",
      "4: Slightly Agree",
      "5: Agree",
      "6: Strongly Agree"
    )
  ) +

  labs(
  title = "Is Growth Mindset Associated With Support for Care-Based I3nterventions?",
    color = "Gender"
    ) +
   theme_minimal()
```

```
  theme(axis.text.x = element_text(angle = 45, hjust= 1),
  panel.spacing = unit(1, "lines"))
```

```
List of 2
 $ axis.text.x  :List of 11
  ..$ family       : NULL
  ..$ face         : NULL
  ..$ colour       : NULL
  ..$ size         : NULL
  ..$ hjust        : num 1
  ..$ vjust        : NULL
  ..$ angle        : num 45
  ..$ lineheight   : NULL
  ..$ margin       : NULL
  ..$ debug        : NULL
  ..$ inherit.blank: logi FALSE
  ..- attr(*, "class")= chr [1:2] "element_text" "element"
 $ panel.spacing: 'simpleUnit' num 1lines
  ..- attr(*, "unit")= int 3
 - attr(*, "class")= chr [1:2] "theme" "gg"
 - attr(*, "complete")= logi FALSE
 - attr(*, "validate")= logi TRUE
```

```
# Print and save to the plots folder
print(GROWTH_CARE_SCAT_CARE)
```



```
##explanation: Scatterplot evaluating support for community interventions and degree of growth
#source: Visualize data with a scatterplot (2025) https://posit.cloud/learn/recipes/visualize/V
```

This visualization reveals concurrent higher degrees of growth mindset positively correlated with increased support for care-based community intervention for both men and women at a relatively similar rate (Figure 7). Gender differences are negligible in this association as confidence intervals overlap significantly. Alternatively, the evaluation of associations between support for fear-based police interventions in comparison to the degree of growth mindset with gender as a grouping variable is showcased in Figure 8.

```
#|label: Visualization-Growth-Mindset-vs-Fear-Based-Intervention
#|fig-cap: Figure 8. Scatter plot and linear regression of support for fear based police based
#| fig-alt: Higher levels of growth mindsets coinciding with lowered support for fear based pol
#| fig-width: 16
#| fig-height: 18
# Omit Non-binary
selectdata <- subset(selectdata, GENDER != 2)
#Growth Mindset vs Case Based Intervention  with 3rd Gender Variable: change color dots
GROWTH_CARE_SCAT_FEAR <- ggplot(selectdata, aes(x = GROWTH, y = EFFECT_FEAR_POLICE, color = GE
  geom_smooth(method = "lm") +
  geom_point(position = position_jitter(width=0.2)) +
   scale_color_manual(
    values = c("0" = "hotpink", "1" = "darkblue"),
    labels = c("0" = "Woman", "1" = "Man")
  ) +  scale_x_continuous(breaks = 0:6, limits = c(2,6.5)) + scale_y_continuous(breaks = 0:6, l
  theme_bw() +
  labs(
    x = "Degree of Growth Mindset",
    y = "Support for FearBased Police Intervention",
    color = "Gender"
    )+  scale_x_continuous(breaks = 0:6, limits = c(2,6.5)) + scale_y_continuous(breaks = 0:6,
  theme_bw() +
  scale_x_continuous(
    name = "Agreement with Growth Mindset Statements ",
    breaks = 2:6,
    limits = c(2, 6),
     labels = c(
      "Disagree",
      "Slightly Disagree",
      "Slightly Agree",
      "Agree",
      "Strongly Agree"
    )
  ) +
  scale_y_continuous(
    name = "Support for Fear-Based Intervention",
    breaks = 1:6,
```

```r
    limits = c(2, 6),
    labels = c(
      "1: Strongly Disagree",
      "2: Disagree",
      "3: Slightly Disagree",
      "4: Slightly Agree",
      "5: Agree",
      "6: Strongly Agree"
    )
  ) +

  labs(
    title = "Is Growth Mindset Associated With Support for Fear-Based Interventions?",
    color = "Gender"
    ) +
   theme_minimal()
  theme(axis.text.x = element_text(angle = 45, hjust= 1),
  panel.spacing = unit(1, "lines"))
```

```
List of 2
 $ axis.text.x  :List of 11
  ..$ family       : NULL
  ..$ face         : NULL
  ..$ colour       : NULL
  ..$ size         : NULL
  ..$ hjust        : num 1
  ..$ vjust        : NULL
  ..$ angle        : num 45
  ..$ lineheight   : NULL
  ..$ margin       : NULL
  ..$ debug        : NULL
  ..$ inherit.blank: logi FALSE
  ..- attr(*, "class")= chr [1:2] "element_text" "element"
 $ panel.spacing: 'simpleUnit' num 1lines
  ..- attr(*, "unit")= int 3
 - attr(*, "class")= chr [1:2] "theme" "gg"
 - attr(*, "complete")= logi FALSE
 - attr(*, "validate")= logi TRUE
```

```r
# Get just the coefficients
    coefficients <- coef(GROWTH_CARE_SCAT_FEAR)
    print(coefficients)
```

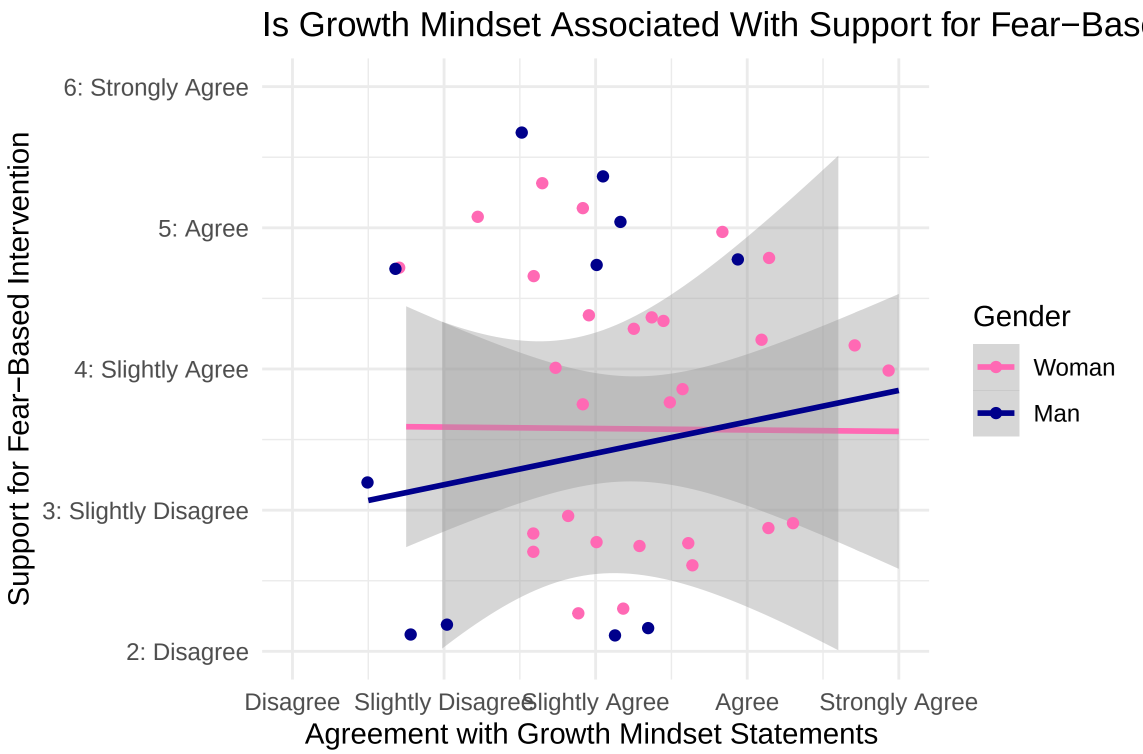
```
NULL
```

```r
    # Get a comprehensive summary including coefficients, R-squared, p-values, etc.
    summary(GROWTH_CARE_SCAT_FEAR)
```

```
data: AGE, FIXEDPERSON1_BASIC, FIXEDPERSON2_DIFF,
  FIXEDPERSON3_CHANGE_R, FIXEDPERSON4_OLD, FIXEDPERSON_ALL_R,
  FIXEDPERSON_ALWAYS_R, FIXEDPERSON_CERTAIN, FIXEDPERSON_MATTER_R,
  COMM_FEEL, COMM_HELP, COMM_NEIGHBORS, NOTCOMM_UNSAFE, NOTCOMM_RELY,
  NOTCOMM_DISTRUST, EFFECT_CARE_COMM, EFFECT_CARE_EDUCATION,
  EFFECT_CARE_HVIP, EFFECT_FEAR_LEG, EFFECT_FEAR_POLICE,
  POLITICAL_BELIEFS, GENDER, SOCIALSTATUS, RACIALIZED, ==...,
  COMMUNITY, GROWTH, GENDER01, RACE.4 [56x29]
mapping:  x = ~GROWTH, y = ~EFFECT_FEAR_POLICE, colour = ~GENDER01
scales:   colour, x, xmin, xmax, xend, xintercept, xmin_final, xmax_final, xlower, xmiddle, xup
faceting: <ggproto object: Class FacetNull, Facet, gg>
    compute_layout: function
    draw_back: function
    draw_front: function
    draw_labels: function
    draw_panels: function
    finish_data: function
    init_scales: function
    map_data: function
    params: list
    setup_data: function
    setup_params: function
    shrink: TRUE
    train_scales: function
    vars: function
    super:  <ggproto object: Class FacetNull, Facet, gg>
-----------------------------------
geom_smooth: na.rm = FALSE, orientation = NA, se = TRUE
stat_smooth: na.rm = FALSE, orientation = NA, se = TRUE, method = lm
position_identity

geom_point: na.rm = FALSE
stat_identity: na.rm = FALSE
position_jitter
```

```r
# Print and save to the plots folder
print(GROWTH_CARE_SCAT_FEAR)
```




```
##explanation:  Scatter plot and linear regression of support for fear based police based inte
#source: Visualize data with a scatterplot (2025) https://posit.cloud/learn/recipes/visualize/V
```

This figure displays higher levels of growth mindsets coinciding with lowered support for fear-based police interventions. In contrast to the similar slopes for growth mindset and care-based intervention based on gender reported previously, Figure 8 highlights potential differences between men and women, whereby women surveyed display a significant decrease in support for fear-based intervention, with increases in growth mindset, and men indicate little change in intervention support as growth mindset increases. While men indicate little variation in degree of support with a slightly positive yet flat regression line, the wide and overlapping confidence intervals suggest gender differences may remain insignificant. Potential gender differences in Figure 8 may be attributed to differences in connotations around policing held by women and men or a variety of beliefs around control elicited by the term 'policing'.

3.2.3.2 *Growth Mindset & Intervention Support: Modeling Care vs Fear-Based*

With significant associations and variable differences indicated in the scatterplot, Wilcoxon-Mann-Whitney-U Testing, subsequent steps include evaluating support for care and fear-based interventions as an outcome of predictor variables. Utilizing the level of safety and trust within one's community and degree of growth mindset as predictors of support for care vs fear-based intervention requires the use of multiple linear regression testing. The distribution of the datasets was relatively normal without any extreme outliers or skew, as shown in Figures 7 and 8, allowing for multiple linear regressions to be performed.

First, multiple linear regression modeling predicting support for care-based community violence interventions revealed significant associations between growth mindsets and engagement with care-based interventions. The predictors of perceived community safety and trust are not significant; however, a 1 unit increase in feelings of community safety indicates a 0.17 increase in care-based intervention support ($p=0.369$). More significantly, for each unit increase in growth mindset support for care-based community interventions increased by 0.57 ($p=.001$). Altogether, about 23.3% of the variation in support for care-based community interventions can be explained by feelings of community safety and growth mindset variables.

Multiple linear regression testing was also utilized to predict perceived support for fear-based police interventions based on the level of community safety/trust and growth mindset. Regression testing revealed that for each unit increase in feelings of safety and community trust, support of fear-based policing is expected to increase by 0.12 while the growth mindset is held constant. However, this value is not statistically significant ($p=0.63$) and therefore is somewhat conclusive that there is no association between growth mindset and support for fear-based policing interventions. Alternatively, for each one-unit increase in growth mindset, support for fear-based approaches to intervention decreases by 0.21, producing another insignificant result ($p=0.36$). No significant relationship between predictors and support for fear-based policing interventions exists, as both predictors have p-values > 0.001. Overall, only 1.7% of the variance in support for fear-based policing interventions is explained by community safety and growth mindset predictors. Contrasting significant predictors of support for community-based interventions, this model indicates that support for fear-based policing does not vary significantly in relation to community or growth as predictors of intervention preference. Quantitative modeling and visualizations begin to expose significant predictors of support for community violence intervention that are then explored further through qualitative analysis.

```r
library(stats)

#Perform MLR for COMMUNITY

#Create linear model of values in COMM ALL
COMMGROWTH.CARE.lm <- lm(EFFECT_CARE_COMM ~ COMMUNITY + GROWTH, data = selectdata)

summary(COMMGROWTH.CARE.lm)
```

```
Call:
lm(formula = EFFECT_CARE_COMM ~ COMMUNITY + GROWTH, data = selectdata)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.6355 -0.6527  0.1288  0.6359  1.5990 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept)   1.6480     0.9220   1.787  0.07982 . 
COMMUNITY     0.1663     0.1835   0.906  0.36907   
GROWTH        0.5715     0.1653   3.458  0.00111 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 1.017 on 51 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared:  0.2332,    Adjusted R-squared:  0.2031
F-statistic: 7.753 on 2 and 51 DF,  p-value: 0.001148
```

```
##explanation: COMMUNITY safety perceptions and GROWTH mindset as independent predictors of GR
#source:(Keita, 2022) https://www.datacamp.com/tutorial/multiple-linear-regression-r-tutorial
```

```r
library(stats)

#Perform MLR for FEAR BASED

#Create linear model of values in COMM GROWTH.FEAR
COMMGROWTH.FEAR.lm <- lm(EFFECT_FEAR_POLICE ~ COMMUNITY + GROWTH, data = selectdata)

summary(COMMGROWTH.FEAR.lm)
```

```

Call:
lm(formula = EFFECT_FEAR_POLICE ~ COMMUNITY + GROWTH, data = selectdata)

Residuals:
     Min       1Q   Median       3Q      Max
-2.33174 -1.27369 -0.08928  1.12333  2.48647

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.5584     1.2634   2.817   0.0068 **
COMMUNITY     0.1229     0.2554   0.481   0.6324
GROWTH       -0.2117     0.2276  -0.930   0.3564
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.421 on 53 degrees of freedom
Multiple R-squared:  0.01708,   Adjusted R-squared:  -0.02002
F-statistic: 0.4604 on 2 and 53 DF,  p-value: 0.6336
```

```
##explanation: COMMUNITY safety perceptions and GROWTH mindset varibles used as independent pr
#source:(Keita, 2022) https://www.datacamp.com/tutorial/multiple-linear-regression-r-tutorial
```

3.3 Qualitative Results

Several themes and codes emerged when using a combination of conventional and directed content analysis to understand the mindset of and lay conceptions of community safety for Broome County community members. These results were also developed to aid in the prediction of an individual's preference for community violence prevention and intervention methods.

3.3.1 Mindset

One of the open-ended questions in the Qualtrics survey included a quote from President Donald Trump that said, “These are hardcore criminals. You know, we took many people off the streets of Washington, DC. They’re not going to be good… they were born to be criminals, frankly… Washington, DC is now a safe zone.” and participants were asked to explain whether or not they agreed with the statement. From this question, two main themes emerged: (a) fixed mindset and (b) growth mindset.

3.3.1.1 Fixed Mindset

Broome County community members with responses that encompassed a fixed mindset agreed with the President’s quote. Four participants reasoned that “it’s hard to change someone and ensure they are going to change for the good” (participant 3), and “Washington DC is a bad environment that produces a criminal mindset” (participant 99).

3.3.1.2 Growth Mindset

Broome County community members with responses that encompassed a growth mindset disagreed with the President’s quote. There were two concepts under this theme: not born (n=35) and circumstances (n=16). The not born code explained that people were not born as criminals because “no one is born to be evil and we shouldn’t narrow it to specific people” (participant 4), “no one is born to be a criminal” (participant 12), and “criminality is taught” (participant 10). The circumstances code explained that “people become criminals out of necessity or by their environment” (participant 12), “some people may be predisposed due to their background” (participant 15), or “crimes often spawn from external circumstances that people are faced with” (participant 90).

3.3.2 Community Safety Conceptions

Another open-ended question asked participants, “What does community safety mean to you?” to understand their conceptions of community safety. From this question, two themes emerged: (a) care-based model of safety (n=68) and (b) fear-based model of safety (n=49).

3.3.2.1 Care-Based Model of Community Safety

A care-based model of community safety included methods for achieving community safety in a promotive and preventative manner. There were eight concepts under this theme: community acceptance (n=14), walking security (n=12), stable environment (9 participants), involvement of community members (n=8), community trust (n=8), secure self-expression (n=6), access to resources (n=6), and community understanding (n=5). The most relevant codes were chosen for explanation and supported with excerpts from participants.

One promotive care-based approach was community acceptance, as it referred to community members wanting to create “a welcoming/comforting environment” (Participant 143) that others want to be a part of. As part of building community, there was mention of community trust, which was when “In a dangerous situation, people are willing to rely on people within their community and have trust for them” (Participant 138). Generally, participants noted “Trusting my neighbors” (Participant 24), as well as more specifically, "reliance on strangers to aid when in need" (Participant 158) and "trust in local institutions" (Participant 23). One preventative care-based approach was walking security, which meant that a community member could walk around their neighborhood alone or without fear for their life or imminent danger ("I can walk comfortably alone," Participant 2; "feeling like I can walk down the street of a neighborhood without fearing for my life and possessions," Participant 19). Some participants mentioned walking in the nighttime as they should be able "to walk around safely at night without worries" (Participant 167).

3.3.2.2 Fear-Based Model of Community Safety

A fear-based model of community safety entailed the removal of some negative aspects of society. There were three concepts under this theme: no fear (n=27), no threat (n=18), and no crime (n=4).

The code no fear meant that community members did not feel scared for their own or their immediate circle's life in the community. That fear also included not being a witness to ("Not worrying about being harassed, robbed, or seeing people harassed or robbed," Participant 99) or having to anticipate a violent situation occurring ("Not feeling a sense of dread or anxiety being in certain spaces or locations," Participant 128). Similarly, participants highlighted no threat, which meant that community members were "not scared or threatened by potential danger and situations they can not prepare for" (Participant 159). In terms of environmental threat, participants said, "People can go to public and community spaces without being threatened or experiencing violence" (Participant 125). Participants also mentioned no crime, meaning the reduction ("reduced violence and crime," Participant 25) or absence of criminal activity in the community ("lack of crime," Participant 172).

3.4 Discussion

The mixed-methods study is the first to provide qualitative and quantitative evidence for Community Safety Activist Zach Norris's community safety conceptions of fear-based vs. care-based safety (Norris, 2021). The qualitative findings of community safety conceptions demonstrated that Broome County residents and Binghamton students view a range of care-based concepts (e.g., community acceptance, walking security, stable environment) and fear-based concepts (e.g., no fear, no threat, no crime), confirming the existence of the two theoretical models of safety. The quantitative findings demonstrated that residents prefer a care-based approach to a fear-based approach. In fact, all care-based intervention approaches–community, education, HVIP–were rated higher than the fear-based policing approach.

The findings support prior work that psychological beliefs are meaningful predictors of safety effectiveness and views on criminality. Most Broome County residents hold a growth mindset, allowing these findings to be generalized to the greater Broome County population. Quantitative Wilcoxon-Mann-Whitney U and Multiple Linear Regression tests of care-based community interventions revealed that growth mindsets are predictive of preference for community-based violence interventions. Scatter and barplot visualizations supporting these tests reveal similar levels of support for community interventions for both women and men with an increased growth mindset. However, analysis of support for fear-based interventions differs highly by gender. Overall, women are more likely than men to support fear-based interventions, yet as the degree of growth mindset amongst women increases, support for fear-based interventions decreases more significantly than in men.

A multitude of responses observed in this study confirmed that both a growth and a fixed mindset are utilized by many people, but in different domains (Burnette et al., 2013). Many participants showed a growth mindset when attributing criminal behavior to structural flaws. The second open-ended question provided responses that overall indicated a common growth mindset, and feelings that people can change with the correct and sufficient resources and circumstances. This prompts the general conclusion that many, if not most, Broome County residents hold a growth mindset and believe that character traits are developed as time goes on and through different environments. It is also clear from the variety of response themes that many Broome County residents support a social-ecological model of intervention (Sallis & Owen, 2015), with multiple levels of intervention being necessary to fully prevent crime.

Norris (2021) identified a fear-based model of safety as approaches that rely on an in-group fearing an out-group because the out-group is "dangerous", providing the increased presence of police officers as an example. Meanwhile, he identified a care-based model of safety as approaches that focus on the promotion of community resources and security, and the prevention of violent situations, which may come in the form of advancing community cohesion. These models of safety offer a lay and novel way to examine approaches to achieving safety, which have started being used in academic literature. A fixed mindset, also known as an entity mindset, is defined as a mindset in which people believe that individuals are born with certain characteristics and traits that will not change. They believe that "dangerous" people are born as such and will remain that way for the entirety of their lives (Burnette et al., 2013). A growth mindset, or an incremental mindset, is defined as a mindset in which people believe that humans are capable of internal change (Burnette et al., 2013). This study aimed to correlate the mindsets of Broome County community members with the extent of their support for community-based violence interventions. Through consulting existing literature within the realm of violence prevention as the study progressed, it was found that this correlation could be explained through an Integrated Behavioral Model. The Integrated Behavioral model encompasses a theory stating that community members' lay beliefs on community safety are dependent on attitudes towards their community, outlook on the achievability of safety, and subjective norms of their surroundings. While qualitative analysis of fear-based and fixed mindsets indicated the existence of fixed and growth mindsets in Broome County residents, as well as fear-based and care-based intervention methods, quantitatively, no prediction between fear-based policing was indicated based on community and growth mindset evaluation of the sampled population.

3.4.1 Strengths and Limitations

3.4.1.1 *Strengths*

This study exhibits many strengths, including the theoretical integration of safety conceptions (Norris, 2011) and mindsets (Dweck, 2012) research, the integrated mixed-methods analysis of quantitative and qualitative data on care/fear and fixed/growth, and the novel exploration into associations between different mindsets and conceptions of safety held by the general public. While extensive evidence of effective approaches to violence intervention exists within current literature, there is a lack of studies examining lay conceptions surrounding the methods of violence intervention that are most effective. This signifies a disconnection between the methods displayed to be effective in intervening violence within research and the public's perceptions of these intervention methods.

The strengths of the study lie in the unique methods utilized and the constructs analyzed. This study includes novel examinations of constructs such as growth and fixed mindsets regarding criminality in both quantitative and qualitative responses. Additionally, the correlation between growth and fixed mindsets and individual beliefs surrounding different conceptions of safety is largely unexplored within current literature, allowing this study to provide novel evidence of the correlation that exists between these two constructs and the extent to which these factors are related to the support an individual exhibits for community-based approaches to violence intervention. This builds upon the limited knowledge surrounding lay perceptions of effective methods of intervening in violence (Ward et al., 2022). Furthermore, existing safety reviews, including Norris' (2021) theoretical view of safety, are a novel conception of safety; however, they lack any supporting qualitative or quantitative data. Thus, this study provides a mixed-methods perspective that enables a greater understanding of the fear-based and care-based models of safety from a qualitative and quantitative viewpoint.

3.4.1.2 *Limitations*

The results of this study should be understood alongside the following limitations: sampling limitations, measurement and construct inconsistencies, and assumptions of utilizing a multiple linear regression model. There was a small sample size, as a total of 180 participants responded to the Qualtrics survey, but 104 responses were excluded because they were incomplete. As a result, there was a sample of 56 to 76 participants who completed half or more of the survey, limiting the extent to which the survey could encompass the views of all Broome County residents. In addition, many of the recruiting events took place on campus, so a majority of the participants are most likely Binghamton University students. Thus, the responses may also not be reflective of the Broome County community. Within the survey, individuals with more opinionated beliefs around safety and community trust may have decided to respond to the survey entirely or may have avoided completing the survey due to strong beliefs or feelings about phrasing or questions. This may have resulted in a more skewed dataset, not representative of a wide range of beliefs. Additionally, respondents may have held response or social desirability bias when responding to the survey questions, believing they were answering in a way that would be viewed favorably by others rather than indicating their true belief. This follows the theory of motivated reasoning, stating that one's emotions affect how information is processed within that individual (Kunda, 1990). This theory has been linked to politically motivated reasoning in that individuals who encounter information from a political figure will automatically form a response based on their prior internal beliefs (Leeper & Slothuus, 2014). Although the quote included in one of the open-ended questions in this study did not cite President Trump, the language used in the quote may have prompted participants to infer that it was his statement. This may have ultimately led to motivated reasoning in their responses. The study may also have been limited by the constructs and selected measurements. Measures may have failed to capture the key concepts or left room for survey participants to form alternative interpretations of what each measure means. Finally, the assumptions of utilizing a multiple linear regression model may have limited the study data and conclusions that can be drawn from modeling, as a linear model assumes a clear-cut relationship between a predictor and the outcome. However, this may fail to incorporate levels of nuance that exist naturally in perceptions and beliefs from influences outside the evaluated demographics.

3.4.2 *Impact and Future Work*

In the future, academic literature should adopt a care-based and fear-based safety framework model for categorizing different violence prevention and intervention approaches. This framework will help advance studies focused on approaches based on the growth mindset, and if any other mindsets influence support for these models of safety. The survey also suggested that motivated reasoning may skew a respondent's true beliefs on a situation, hence the need for further research on more nuanced influences of safety perceptions and mindsets. In these future studies, measures should be developed to capture true opinions rather than opinions influenced by social desirability or strong automatic political judgment.

Beyond the limitations of this study, a lack of relationship between demographic variables as predictors of community safety beliefs, feelings of trust, and distrust indicates a need for further exploration of what predictors influence safety perceptions. A lack of correlation, as demonstrated in this study, may imply that other existing factors influencing feelings of safety and trust are underrepresented and unexplored in existing research. This may signal a pivot towards exploring new relationships outside of basic demographic categories that may influence an individual's perceptions. Important next steps, however, may be to verify demographic variables are not significant predictors of safety and trust beliefs with a larger sample size and more validated measures. Beyond confirming the validity of study results, future research may require evaluation of more nuanced influences of safety perceptions, such as familial beliefs, media content consumed, and level of education. Evaluating the driving factors of apathy, lack of care, opinion, and thought related to safety and community trust may also require evaluation in order to devise measures that accurately unveil any existing differences in perceptions of safety and trust. Gaining a greater understanding of what key factors influence safety beliefs and perceptions of trust is key to effectively developing targeted interventions to increase safety and trust within communities. In its entirety, the findings of this study build upon existing understanding of lay conceptions of safety and violence intervention approaches through its support of the idea that possessing a growth mindset is associated with favoring community-based interventions as a preferred method of violence intervention. As such, these results could be utilized to develop future interventions that focus on the promotion of growth mindsets, in tandem with the promotion of community-based interventions.

3.5 References

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