

Fear of crime, neighborhood disorder, and official crime rates: Evidence from three waves of a Brazilian victimization survey

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Abstract

Although previous research has documented the influence of neighborhood disorders on fear of crime (FOC), limited attention has been given in Brazil to how these effects differ from behavioral predictors such as actual crime rates. This study examined how physical disorder, social disorder, and official crime rates shape FOC among residents of a large Brazilian metropolitan area, drawing on data from three waves (2015, 2016, 2018) of the Brazilian Federal District Victimization Survey. Generalized estimating equations were used to test the effects of physical disorder, social disorder, and crime rates on FOC. Physical and social disorders emerged as significant predictors of FOC, with physical disorder exerting the strongest influence, while crime rates showed minimal association with FOC once perceptual variables were accounted for; this pattern remained consistent throughout the study period. These findings indicate that perceived neighborhood disorder accounted for more variation in FOC than the official crime-rate measure examined. Hence, we suggest that urban policies targeting environmental improvements and public communication about crime may be more effective in mitigating FOC than reporting official crime rates alone.

Introduction

Over the years, fear of crime has become a prominent topic within the social sciences, including psychology and sociology, while also playing an important role in fields such as criminology and victimology (Ferraro, 1995). Furthermore, it emerged as a fundamental part of political decisions on anti-crime interventions worldwide (Brunton-Smith & Sturgis, 2011; Lee, 2007). Through the years, this topic has drawn increasing attention from criminologists, victimologists, policymakers, law enforcement agencies, the media, and the general public. Academic interest in fear of crime dates from the 1960s, as highlighted in influential literature reviews (Ditton & Farrall, 2000; Hale, 1996). Despite significant social changes in the 21st century and a growing body of research, interest in the topic remains strong. Understanding fear of crime and its antecedents inform resource allocation and the development of effective crime prevention strategies (Hale, 1996). While these concerns are shared across many nations, most research (e.g., Hodgkinson & Lunney, 2021) focuses on WEIRD countries (Henrich et al., 2010) – an acronym for *Western, Educated, Industrialized, Rich and Democratic* societies – with seminal exceptions in the Brazilian context (e.g., Costa & Durante, 2019a). The present study addresses this gap by examining how physical disorder, social disorder, and official crime rates jointly and independently predict FOC among residents of a large Brazilian metropolitan area.

Setting aside the conceptual confusion between the fear of crime and other terms and theoretical constructs – such as victimization, actual crime rate, and risk perception – it is essential to define fear of crime for the purposes of this particular study. The term *Fear of Crime* seems to have been coined in 1967 by a commission established by the U.S. Federal Government on Law Enforcement and Administration of Justice. The ‘President’s Commission’ sought to gather, for the first time, data on victimization and police investigations into what was then called the *Fear of Crime* (President’s Commission, 1967). However, their resulting publication seems to equate Fear of Crime – FOC with

victimization. According to Lee (2007), the construct was adopted by specialized literature as early as the 1970s, albeit with different definitions and interpretations. From a psychological perspective, *fear* can be understood as either an emotion – an immediate reaction to a specific stimulus (e.g. the sudden sound of a gunshot) and depend on the relationship with the external stimuli to arise (Ekman, 1992) – or as a feeling – which is not related to a single stimulus and requires cognitive effort, such as memory activation, social and individual values, reasoning, imagination etc. (Buck, 1980). Emotions elicit chemical and neural responses (e.g., sweating, trembling) triggered by sudden environmental stimuli without prior preparation. These two concepts are inherently interconnected: feelings represent responses to emotions, describing the mental and subjective experience of the initial emotional response.

Regarding FOC, Garofalo (1981) defined it as an emotional reaction characterized by a sense of danger of being a victim of physical harm, triggered by an individual's perception of their environment in relation to crime. Other definitions expand this concept, describing FOC as a broader concern about crime based on direct or indirect experiences of criminality (Skogan, 1989), emotional reactions to risk perceptions (Jackson & Gouseti, 2012), or a feeling of alarm or dread caused by an awareness or expectation of danger (Warr, 2000). Additionally, FOC has been framed as an individual distress in response to the phenomenon of criminality, extending to the community and fostering a state of insecurity (Dantas et al., 2007). For this study, Hale's (1996) definition is adopted, which describes FOC as the fear of being a victim of a crime, irrespective of the actual probability of victimization.

Given this definition, this study aims to investigate differences in FOC based on evaluations of neighborhood features, such as level of physical or social disorder, and how these features influence FOC. Physical disorders refer to visible environmental cues that signal vulnerability and heighten the individuals' perceived victimization probability (Kang & Seo, 2020). Examples include poorly lit streets, urban decay, abandoned buildings, and other aspects of the neighborhood's physical infrastructure, as described in the 'broken windows' theory (Kelling & Wilson, 1982). Social disorders, on the other hand, are behavioral indicators perceived by the individuals as evidence of a lack of social control in the area, contributing to residents FOC. These include behaviors such as public indecency, vandalism, or destruction of public property (Oh et al., 2019), as well as other aspects described in the social disorganization theory (Shaw & McKay, 1942).

Previous research suggests that individuals' subjective experiences – both emotions and feelings – are influenced by the evaluation of social cues and factors (Warrier et al., 2018), alongside individual differences in the processing of stimuli, resulting in a multifactorial interpretation. Critics of the effect of disorders on FOC emphasize the lack of a causal relationship between these variables, highlighting instead the correlational nature of the influence of neighborhood disorders on FOC. They argue that behavioral-based variables might offer a more robust explanation than perceptual ones. For instance, Sridhar (2006) describes how the decrease in crime rates in major American cities may have contributed to a corresponding decrease in FOC, challenging the effectiveness of explanations solely based on neighborhood disorders. These critiques underscore the necessity to investigate the extent to which

social and physical disorders interact with FOC and to examine the role of actual crimes in this relationship. Such an approach is essential to substantiate claims about the connection between FOC and neighborhood disorders.

Hypotheses formulation

Neighborhood disorders are frequently cited as predictors of FOC (Jackson, 2004). Rader et al. (2012) propose that physical and social disorders are the key factors explaining why certain groups in specific neighborhoods exhibit higher FOC compared to those in more affluent areas. Lane et al. (2014) suggest that individuals' perceptions of physical and social disorders directly correlate with the risk of victimization, emphasizing the relevance of both direct and indirect victimization experiences to the concept of FOC. Conversely, some researchers incorporate behavior-based variables as alternative explanations for neighborhood disorders. Criticizing explanations rooted in the 'broken windows' theory, Taylor (2001) argues that addressing physical and social disorders provides only short-term and partial predictions of FOC. Using a materialist framework, Taylor suggests that physical decay and visible social disorder have minimal impact on FOC, while economic decline plays a significantly more influential role. Investigating FOC in an American major city, Oh et al. (2019) found that the relationship between perceived social disorder and FOC emerges only when police effectiveness mediates this connection. Additionally, Franklin et al. (2008) concluded that variables from the 'vulnerability model', which considers the impacts of sociodemographic variables as predictors of FOC, explain significantly less variation in FOC when compared to the disorder model, questioning the directional consistency of the former. In a rare example of a non-Western study, Kang and Seo (2020) identified a differential effect of physical and social disorders on FOC, stressing the greater importance of social disorder in FOC prediction.

In Brazil, the results regarding neighborhood disorders and FOC are similar to those described in international literature (e.g., Plassa et al., 2023). Rodrigues and Oliveira (2012) identified the effect of perceived physical disorder on the sense of safety and the association between social disorder and FOC, while Beato et al. (2004) found a direct effect of perceived physical and social disorders on FOC. Analyzing victimization surveys in a large Brazilian city, Natal and Oliveira (2021) observed a relationship between disorders and FOC, corroborating the findings of Valente and Vacchiano (2021), which were based on victimization surveys conducted in state capitals of four Brazilian states. Examining data from the initial data collection of the Federal District Victimization Survey, Costa and Durante (2021) found that disorders and the quality of public services were strongly associated with FOC. However, no studies were found in the Brazilian literature that addressed the relationship between neighborhood disorder variables, behavioral variables, and FOC, addressing the aforementioned critiques on influence of disorders on FOC. Based on these and other studies mentioned so far, the present investigation proposes the following hypothesis:

Hypothesis 1

Neighborhood physical and social disorders will be positively associated with fear of crime.

Hypothesis 2

Official crime rates will contribute additional predictive value for fear of crime beyond neighborhood physical and social disorders.

Method

As a district, the region has a unique administrative structure, which does not include cities or mayors. Its geographic division is organized through Administrative Regions (ARs). The physical boundaries of the ARs are established by the Government of the Federal District (DF), defining the jurisdiction of government action for the purposes of decentralization and coordination of local public services. Depending on the demands of the DF, the Governor has the discretion to create or extinguish ARs. Given differences in their territorial delimitation and population coverage, the number of ARs has varied over the years; for instance, there were 31 ARs from 2015 to 2018, compared to the 35 established in 2024.

The governor is also solely responsible for promoting public security in the DF through the State Secretariat for Public Security (SSP-DF), which seeks to optimize use resource use for greater operational effectiveness in reducing crime and violence in all Ars, incorporating input from public opinion and experience.

The Brazilian Federal District Victimization Survey, conducted by the SSP-DF, served as the database for the present study. The survey annually examined various economic and environmental variables related to Fear of Crime (FOC) across the DF from 2015 to 2019. The survey was discontinued after 2019 due to the SARS-COV-2 (COVID-19) pandemic and had not resumed at the time this article was produced. Data collection involved administering a survey to a representative sample of the DF population, following the International Crime Victims Survey framework. Data analyzed in this study represent the SSP-DF's effort to achieve its objective through the DF Victimization Survey.

Participants

A total of 28,168 individuals from the 31 administrative regions then established in the district took part in the survey over three years of data collection (2015: $n = 19,669$; 2016: $n = 3,277$; 2018: $n = 5,232$)¹. Among the participants, 54.3% were female, and 33.8% were aged between 40 and 59 years. The survey categorized participants into the following age groups: 16 to 24 years (16.4%), 25 to 39 years (30.8%), and 60 years or older (19.1%). Detailed demographic data by administrative region and by year of data collection are presented in the Supplementary Materials, Table S1.

Instruments and Procedures

The research included samples of AR residents aged 16 years or older. Participants were selected through a two-step process: (a) random selection of households to be visited in each AR based on the national address register, and (b) random selection of a resident to be interviewed from the list of household members provided by the National Census. Survey items were developed by SSP-DF in collaboration with the *DF Planning Company* based on the International Crime Victims Survey – ICVS (van Kesteren et al., 2014), a large-scale international survey on crime and victimization carried out in over 80 countries. Data collection was carried out by research companies hired by the local government, using both in-person and telephone interviews (depending on the year), with an average application time of 45 minutes and a margin of error of 0.7%. This study analyzed items consistently used across all years of data collection. Fear of Crime was assessed using six items regarding perceived insecurity and risk of victimization (e.g., “[Do you feel safe] walking on the streets where you live during the day /night”, “[Do you feel safe] walking on the streets of other neighborhoods”, “[Do you feel safe] staying at home alone/with someone” etc.). Responses were recorded on a 4-point scale (1 = Very unsafe; to 4 = Very safe). Measures of Social Disorder and Physical Disorder were also included in the survey. Physical Disorder (PhyDis) measure comprised six items (e.g. "Do you hear gunshots in your AR?"; "Are there any abandoned buildings, houses or warehouses?"), while Social Disorder (SocDis) included nine items, (e.g. "[In your AR do you see] are there people carrying out obscene or indecent acts on the street?"; "[In your AR do you see] are there people breaking windows, graffiti tagging, or destroying collective equipment such as public telephones?"). Responses to the disorder measures were recorded on a 4-point scale (1 = Infrequent; 4 = Very frequent). Demographic data (e.g., gender, age group) were also collected from respondents.

The database also included the Violent Intentional Deaths index – VID to examine behavior-based variables in comparison to perceptual-based self-reported variables (i.e., disorders). VID is a record of crimes compiled by the National Public Security Secretariat (SENASP) to aggregate the most socially relevant crimes in each city across the country, serving as an objective registry of past behavior. The VID encompasses the rate of intentional homicide, feminicide, bodily injury resulting in death, robbery and other crimes leading to death, excluding fatalities caused by state intervention. Data contributing to the VID are collected by the city’s Medico-Legal Institute, Scientific Police, State Police and intelligence services of each state and are analyzed by the General Management of Criminal Analysis and Statistics of SENASP. Data analyzed were obtained with authorization from the State Secretariat of Public Security of the Federal District, according to DF Government Consent Agreement No. [hidden by authors].

Data Analysis

The original survey suggests that the measures of FOC, Social, and Physical Disorders each produce a single factor. To test this assumption, Exploratory factor analyses (EFA) were conducted for each year using polychoric correlation matrices, with analysis performed in Stata 16.1 (StataCorp, 2021). Factor scores were calculated by averaging scores of items with factor loadings equal to or greater than |.40| were computed. The reliability of the scales was examined using Cronbach's alpha. All solutions were

factorable (e.g., for Fear Of Crime: $KMO=.88$; $\chi^2 = 8416.694$; d.f.=187; $p<.001$). For SocDis, two items did not reach adequate loadings (i.e., “[In in your AR do you see] parking attendants, or individuals who look after the parking spaces on public roads?” and “[In in your AR do you see] street vendors, people selling counterfeit products on the street?”) and were excluded. The percentage of explained variance explained by single-factor solutions was 51.22% for FOC (6 items), 37.61% for PhyDis (6 items), and 36.25% for SocDis (7 items). Regarding FOC, reliability indexes obtained by year were $\alpha = .81$ for 2015, $\alpha = .74$ for 2016, and $\alpha = .81$ for 2018. For PhyDis, reliabilities were $\alpha_{2015} = .77$; $\alpha_{2016} = .74$; and $\alpha_{2018} = .71$, whereas for SocDis these indexes were $\alpha_{2015} = .79$; $\alpha_{2016} = .78$; and $\alpha_{2018} = .80$. All reliability indexes were considered adequate for the present study (Ursachi et al., 2015).

Although collected in the same ARs in the three periods, the data were treated as cross-sectional as the same respondent was not controlled from the first collection. After checking the database for outliers and missing cases, hypothesis test was carried out with generalized estimating equations (GEE) using the Statistical Package for Social Sciences – SPSS (IBM, 2023), version 29.0. Originally proposed by Liang and Zeger (1986), GEE uses least squares procedures involving extensive minimization of the estimated parameter change to generate more efficient estimates. GEE allows the analysis of various types of data, such as continuous, binary, or ordinal, making it adaptable to secondary databases, as in the present study (França, 2024). This method extends generalized linear models to accommodate grouped data, with a notable feature for the present study being the estimation of a correlation matrix that represents the dependencies between subjects as part of the model (Højsgaard et al., 2006), making it more robust. GEE is considered a semiparametric analysis method because it relies on the specification of the first two moments, thus allowing the analysis of linear models with non-normal data and providing models for grouped data (Zuur et al., 2009).

In this study, the data did not follow a normal distribution but rather a Gamma exponential distribution, exhibiting positive leptokurtic asymmetry (e.g., FOC_{total} ; Fisher’s $g^1_{skewness/standard\ error} = 20.64$; Fisher’s $g^1_{kurtosis/standard\ error} = 8.25$; Tabachnick & Fidell, 2021). Given these characteristics, GEE was selected as an appropriate analytical method. GEE is particularly suited for large multi-site cohort studies due to its capacity to manage different types of unmeasured dependence between outcomes (O'Brien et al., 2006). To verify the effect of the independent variables (IVs) on FOC (the dependent variable – DV), the variable Year (2015, 2016, 2018) was included to account for the influence of the year of data collection on FOC and its interaction with the IVs.

Two models were tested: one with 2 IVs (PhyDis and SocDis) and another one that included VID as an additional IV. As previously discussed, explanations for the discrepancy between FOC and actual crime rates emphasize the importance of disorders in explaining FOC while highlighting its multidimensional nature (Rountree & Land, 1998). This multidimensionality captures the differential effects on fear arising from perceptual variables (e.g., disorder) versus behavior-based variables (e.g., crime rate). To address this complexity, the second model investigated the effect of violent crimes (VID) on FOC alongside the effects of the disorder variables and the interactions. Models 1 and 2 tested distinct sets of main

effects, along with the respective interactions between IVs (PhyDis*SocDis; PhyDis* VID; SocDis* VID; and PhyDis*SocDis* VID).

Sex was relatively evenly distributed across the samples; however, the age range distribution was not. Therefore, age effects were controlled for in the analyses to address their potential influence on the relationships examined. The AR variable was initially included as a control variable solely to guide the selection of the covariance matrix, but, due to residuals' pattern, it was later incorporated as a covariate variable. Nonetheless, the present study only reports results for the full dataset (DF). To better accommodate cross-sectional data characteristics (Rountree & Land, 1998), an independent correlation structure was used. A Gamma Log Link was applied to account for the non-normal distribution of the data, with hybrid parameter estimation and the restricted maximum likelihood (REM) method. As a contrast test, the *Bonferroni* test was employed, and comparison of main effects were conducted.

Results

Table 1 displays the means, standard deviations, and frequencies of the variables investigated for each year and the total sample.

Table 1
Means and Frequencies of Variables by Year of Data Collection

Year	Control Variables		Tested Variables			
	Sex %	Age %	Fear of Crime (Mean/SD)	Social Disorder (Mean/SD)	Physical Disorder (Mean/SD)	VID (number; Mean;SD)
2015 (n = 19,659)	F: 55.1% M: 44.9%	a: 16.5% b: 29.7% c: 33.8% d: 20.0%	M = 2.40 (SD = 0.49)	M = 3.78 (SD=.25)	M = 3.70 (SD=.26)	671 Cases (M = 28.02; SD = 29.75)
2016 (n = 3,719)	F: 51.9% M: 48.1%	a: 13.2% b: 30.8% c: 36.2% d: 19.8%	M = 2.56 (SD = 0.73)	M = 3.76 (SD=.25)	M = 3.68 (SD=.26)	635 Cases (M = 26.33; SD = 26.93)
2018 (n = 5,230)	F: 52.9% M: 47.1%	a: 17.7% b: 34.8% c: 32.5% d: 15.0%	M = 2.35 (SD = 0.78)	M = 3.62 (SD=.28)	M = 3.61 (SD=.29)	486 Cases (M = 21.59; SD = 23.02)
Total sample (N = 28,608)	F: 54.3% M: 45.7%	a: 16.1% b: 30.8% c: 33.8%	M = 2.41 (SD = 0.59)	M = 3.75 (SD=.26)	M = 3.68 (SD=.27)	1.792 Cases (M = 26.55; SD = 28.32)

Note = F: Feminine; M: Masculine; a: 16 to 24 years old; b: 25 to 39 years old; c: 40 to 59 years old; d: more than 60 years old.

Year	Control Variables		Tested Variables			
	Sex %	Age %	Fear of Crime (Mean/SD)	Social Disorder (Mean/SD)	Physical Disorder (Mean/SD)	VID (number; Mean;SD)
		d: 19.1%				
Note = F: Feminine; M: Masculine; a: 16 to 24 years old; b: 25 to 39 years old; c: 40 to 59 years old; d: more than 60 years old.						

[Table 1 NEAR HERE]

FOC averages were $M = 2.40$ ($S.D.=0.49$) in 2015, in 2016 $M = 2.56$ (0.73) and in 2018 $M = 2.35$ (0.78). An ANOVA suggested a significant difference between the FOC means ($F = 153.60$; $p<.001$), with the *Bonferroni* test indicating significance of $p<.001$ for all pairs of means between the years. For correlations between FOC, PhyDis, SocDis and VID, Pearson Coefficient r was calculated, which is appropriate for relationships between continuous variables (see Table 2).

Table 2
Correlations between Fear of Crime, Disorders, and VID by year.

Year	Correlations of Fear of Crime with		
	SocDis	PhyDis	VID
2015 (n = 19,659)	.14**	.22**	.21**
2016 (n = 3,719)	.07*	.20**	.22**
2018 (n = 5,230)	.08*	.15**	.20**
Total sample (N = 28,608)	.10**	.19**	.20**
Note: SocDis=Social Disorder; PhyDis= Physical Disorder; VID = Violent Intentional Deaths index; **p < 0,01; *p < 0,05			

[Table 2 NEAR HERE]

The Quasi Likelihood Under Independence Model Criterion (QIC) was used to assess the goodness of fit between models. For the first model, which included two IVs, QIC was 1,704.75. In contrast, for the second model, which incorporated three IVs (two disorder variables plus crime rates) the QIC was 9,246.40. As the model with the smaller statistic is preferred (Pan, 2001) model with PhyDis and SocDis as predictors was retained. The statistical significance of the predictors in each model is summarized in Table 3.

Table 3
Test of Model Effects.

Model 1 (Two IVs)	Wald's Chi-Square	d.f.	Sig.
QIC = 1,704.75			
Physical Disorder	384.37	12	< .001
Social Disorder	253.43	28	< .001
Physical*Social Interaction	274.31	28	< .001
Model 2 (Three IVs)			
QIC = 9,246.40			
Physical Disorder	354.32	12	< .001
Social Disorder	235.62	28	< .02
Crime Index	235.02	42	< .001
Physical*Social Interaction	145.29	28	< .02
Physical*Crime Interaction	259.70	12	< .001
Social*Crime Interaction	101.60	12	< .05
Physical*Social*Crime Interaction	188.28	42	< .05

[Table 3 NEAR HERE]

Considering that Model 2 was rejected, Hypothesis 2 was not supported. The main interest of the following analyses is to examine the variation in FOC based on PhyDis and SocDis, and their interaction. Results obtained through GEE are presented in Table 4.

Table 4

Parameters and p-values estimated with GEE for variation in fear of crime predicted by physical and social di in 2016 and 2018, based on the year 2015.

Parameter	Effect Estimate	Standard Error	95% Confidence Interval for Wald		Hypotheses Test		
			Inferior	Superior	Wald's Chi-Square	d.f.	Sig.
(Intercept)	2.02	1,273.411	-2,493.82	2,497.86	.000	1	.999
Year 2015*	---	.	.	.	.	.	.
Year 2016	.11	1,271.892	-2,492.76	2,492.97	.000	1	1.000
Year 2018	.25	1,273.411	-2,495.58	2,496.09	.000	1	1.000
Physical Disorder	.56	.082	.13	.46	384.37	12	< .001
Social Disorder	.31	.077	.41	.71	253.43	28	< .001
Physical Disorder * Social Disorder	.40	.047	.49	.31	274.31	28	< .001
Note: * Set to zero because this parameter is redundant. d.f.= degrees of freedom; Sig.= p value.							

[Table 4 NEAR HERE]

The base year of 2015 was used as the intercept for the effect of the predictors. In the test of FOC variation across years, the estimate of $\beta_1 = 0.56$ indicates that PhyDis is the most effective predictor of FOC, although SocDis also contributes to prediction, albeit to a lesser but significant extent, along with the interaction between the two, supporting Hypothesis 1. All predictors show significant variations over the years, with a decrease in absolute values in 2016 followed by an increase in 2018. Along with the results from Model 1 (Table 3), these results suggest that there was variation in FOC prediction across at least two of the three years. The Bonferroni post-hoc test was performed, and since the interaction was significant, the main effects were not analyzed. The test revealed that mean FOC scores were significantly, with $p < .001$, which indicates that the prediction of FOC by PhyDis and SocDis over time in a lesser degree for SocDis, and in 2016.

Discussion

Before delving into the discussion of the model, it's important to highlight that the measures used for data collection, all based on the ICVS (van Kesteren et al., 2014), presented unifactorial structures, confirming the original survey design (van Dijk, 2010). Furthermore, Cronbach's alphas were adequate across all three measures, reassuring the reliability of the data obtained.

Analyzing the model retained, the Wald Chi-Square values were used to check the predictive power of the variables, so that the higher the indexes, the more relevant the prediction (Hardin & Hilbe, 2003). Results suggest that physical disorder is the best predictor of FOC, and it's complemented by its interaction with social disorder.

Even though only the first model was retained, meaning Hypothesis 2 was not supported, it is interesting to note that when the actual crime rate is included in Model 2 the significance of the social disorder for the explanation diminishes. This may indicate that these variables would be redundant or complementary. Such effect of redundancy and/or complementarity could be related to the large number of observations in the database, which can obstruct the extraction of useful patterns in the data, often proving to be detrimental to the subsequent findings (Tsanas, 2022). However, that was not the case in the present study. First, the correlations between these variables are low across the years ($r=.10^*$, $r=.06$, and $r=.06$ for 2015, 2016 and 2018 respectively) and are all lower than the respective maximum-likelihood estimations, indicating the absence of redundancy. Secondly, the criterion for complementarity is that the two predictors should have a negative correlation between them (Tabachnick & Fidell, 2021), what did not happen in our data. Thus, the more plausible interpretation for the rejection of Model 2 is that actual crime rate is as a spurious variable in the prediction of the second model, leading to Type II error. This corroborates Roman's (2023) statement that FOC is not related to the actual occurrence of crime, since FOC is a perceptual variable and is not necessarily based on real data. This conclusion has been reiterated over time, as it had already been suggested by other studies about 30 years ago (e.g. Ferraro & LaGrange, 1992; Hale, 1996). Costa and Durante (2019a) also observed this effect when analyzing the same data in 2015, which is again reinforced by the VID drop in 2018 in the present analysis (see Table 1). Our results indicate a stronger effect of the perceptual-based variables, such as physical and social disorders, on FOC, when compared to this observed behavioral-type variable (VID).

The variation in FOC over the years can derive from a perceptual bias termed 'social nostalgia' (Farrall et al., 2021), a feeling of longing for a way of life now past and irretrievable. Similar biases have been discussed by other authors, who have described how increased exchange of information about crime due to news reported in the formal press or social media (Caldeira, 2003), and how decrease trust in the police (Roman, 2023) can increase FOC. Therefore, such variation in FOC would not be related to the increase in crime rates, but to individuals' exposition to information about it. In fact, VID in the studied community dropped from 2015 to 2016, and then again in 2018. Official data (Damaceno, 2018; Pera, 2016) associate this drop to public policies and programs aimed at educational campaigns for the population (mainly regarding risk behavior), and crime reduction actions focused not only on policing, but also as setting goals for law enforcement agencies. Also, environmental factors are associated with this drop-in crime rate, such as improved public lighting, cleaning of abandoned areas, and other measures related to Crime Prevention Through Environmental Design – CPTED (Cozens & Love, 2015). Considering this perceptual characteristic of FOC, it's suggested that the association between public policies and police actions designed for crime reduction, and greater investment in publicizing crime rates mitigation could reduce FOC in the population. Since FOC does not seem to be affected by the

simple reduction of crime occurrence, as already observed by several authors (e.g., Costa & Durante, 2021), we propose that its reduction depends on public knowledge about the increase in security rates.

GEE results present a more detailed description of the relationship between FOC and predictor variables. The correlations found pointed to stronger and more significant relationships between FOC and physical disorder when compared to social disorder (see Table 2). GEE results expand on the results of these correlations (Table 4). For every 1-point increase in physical disorder there is an increase of .56 in FOC and for every 1 point in social disorder, there is an increase of .31 in FOC, while the increase of 1 point in the interaction between the predictors represents an increase of .40 in FOC. This relationship remained stable across the years of collection, confirming the findings of LaGrange et al. (1992) of the relationship between FOC and disorders, suggesting that our results are aligned to a large body of literature that has consistently found neighborhood disorders to be positively associated with higher levels FOC, both internationally (e.g., Di Rocco et al., 2023), and in Brazil (Villarreal & Silva, 2006). Moreover, these findings suggest that neighborhood social and physical disorders increase FOC but do not affect residents' interpretation of the decrease in crimes occurrence in the city, suggesting peoples' disregard of victimization rates when describing their FOC. Still, previous studies (e.g., Natal & Oliveira, 2021) in large cities of Brazil, such as São Paulo, suggested that disorders have low effect on FOC prediction ($\beta = .09$), which would be diminished when behavioral variables were included ($\beta = .05$).

To better understand those findings, it's important to consider the socioeconomic characteristics of the study population. The classical theory of social disorganization (Shaw & McKay, 1942) suggests that neighborhood characteristics such as poverty and low education levels disrupt the social organization of communities and reduce their capacity to exercise social control, therefore increasing crime. On the other hand, although cohesive communities may be more efficient in controlling and preventing crime, they may paradoxically exhibit more FOC (Markowitz et al., 2001). To further discuss the societal development interaction with FOC, we adopt the Municipal Human Development Index (MHDI), which evaluates human development in the country through three indicators: schooling (expected years of schooling for children of school age and average schooling in years for adults over 25), longevity (life expectancy at birth) and income (per capita income). The DF has systematically achieved high MHDI. In 2015, DF's index was 0.814 (IPEA, 2019), the highest in the entire country, and quite discrepant when compared to the second in the national ranking (São Paulo, MHDI = 0.783). This highest within-country position continued in 2016 and 2018, with the DF presenting scores of 0.836 in 2016 and 0.859 in 2018 (CODEPLAN, 2023). Furthermore, the DF's VID scores reflect the low crime rate when compared to other large cities (e.g., number of violent crimes for DF in 2018 was 486, while in São Paulo it reached 3,464 in that same year). Together, our results confirm weak correlation between crime and FOC found in affluent areas when compared to disadvantaged neighborhoods; this phenomenon is known as the 'paradox of fear', describe by Breetzke and Pearson (2015). The authors found that residents of wealthy neighborhoods had higher levels of FOC than those reported in poorer areas. Then, according to the 'paradox of fear' proposal, people who live in wealthier areas perceive a higher risk of crime, hence report higher FOC, when in fact there is a lower risk of victimization. This effect is reinforced by the results of the present study.

In sum, our findings suggest that Fear of Crime is in fact impacted by social and physical disorders, highlighting the importance of perception-based variables over behavioral-based variables to understand this phenomenon, especially in more affluent areas. These findings reiterate the need for public policies, focused on community engagement and accurate information disclosure, specifically designed to reduce FOC and increase residents' life quality.

Conclusions

The present study aimed to investigate the impacts of neighborhood features on Fear of Crime (FOC), particularly Social and Physical Disorders. The results suggest that such features directly impact FOC, supporting Hypothesis 1, and are proven to be more relevant to FOC explanation than the actual crime rates in the studied area, which did not support Hypothesis 2. The observed increase in FOC in 2016 when compared to 2015, which was not accompanied by an increase in criminality, suggests variables other than crime rate are increasing FOC in this population. We propose that media dissemination of crimes might play an important part in this result, making it an essential variable to be considered in future public policies elaboration.

Taken together, these findings suggest that residents' fear of crime is shaped mainly by visible signs of neighborhood disorder – such as abandoned buildings, vandalism, and other physical and social incivilities – rather than by official crime statistics. From a policy standpoint, interventions that improve the physical and social environment of neighborhoods, combined with a clearer public communication of crime trends, may reduce fear of crime more effectively than the mere disclosure of crime rates.

The lack of significance of the prediction model that included Violent Intentional Deaths index suggests that in fact criminality may not influence FOC, however, there is still need for studies specifically designed for testing this effect, and longitudinal studies seem to be a relevant alternative to explore the relationship between criminality on fear. Such studies should investigate individuals throughout their contact with criminality over time examining the nature of the crime inflicted upon the individuals, especially sexual crimes, which have shown to impact FOC in previous studies (Hodgkinson & Lunney, 2021). There's still need for future research on specific crime types to determine to what extent actual crime rate is a variable of interest for FOC interpretation. Finally, results suggest that the impact of neighborhood social and physical disorders on FOC should be interpreted along with societal development characteristics of the sample, as previously proposed in scientific literature (Breetzke & Pearson, 2015).

For the purpose of this study, data collection used a set of instruments based on the ICVS. Even though the instruments met acceptable statistical indexes, it remains the need to verify the equivalence of measures across different cultural samples. When dealing with theoretical constructs of interest in comparative research, one should not just *assume* the measure invariance, i.e., that the same constructs are measured in the same way across different samples, as it appears to be the case in several studies that also used items coming from ICVS (e.g., Costa & Durante, 2019b; Plassa et al., 2023; Valente &

Vacchiano, 2021). Instead of just assuming it, the investigator must test for invariance across versions of the instrument to establish that by using the same set of items in different groups, they will measure the same construct in the same way (Davidov et al., 2014). Considering that, there is need for further research to investigate the invariance of the instruments so that comparisons between groups are possible (Cieciuch et al., 2019). This involves testing the equivalence by comparing the instrument performance in the original group it was created for with its performance in other samples of the population of interest (e.g., Brazil). Once these invariances are met, researchers may carry on any comparison across the groups in question with confidence (van de Vijver & Leung, 2011), which will provide a much broader comprehension of Fear of Crime within Brazil and abroad.

Declarations

Ethics Approval

The data analyzed were obtained with authorization from the Federal District's State Department of Public Security (SSP-DF), in accordance with Term No. [hidden by authors. All procedures were conducted in accordance with the ethical standards of the Institute of Psychology of the University of Brasília, Brazil, and with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards. Informed consent from respondents followed the protocol of the Federal District Victimization Survey; as this study relied on secondary data, the authors did not have direct access to the original consent forms.

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Author Contribution

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Data Availability

The data that support the findings of this study are available from the Government of the Federal District of Brazil (Governo do Distrito Federal, GDF), but restrictions apply to their availability. These data were used under special authorization for the present study, as they include additional participant information beyond that used here, some of which might be identifiable; they are therefore not fully available with the article. The specific data used in this study are available from the authors upon request and with the permission of the GDF. For more information, please visit <https://segov.df.gov.br/fale-com-a-secretaria/>. Because these data are owned by the GDF and cannot be deposited in a public, open-access repository, the authors are not applying for the Open Data badge.

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Footnotes

1. Data on victimization in the DF were also collected in 2017 and 2019. However, due to significant differences in the procedure and survey used, which did not allow for comparison, they were not included in this article.

Supplementary Files

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