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Access to Support Services and Mental Health Consequences of Gender-Based Violence among Sex Workers in Abuja, Nigeria

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Abstract *Gender-based violence (GBV) remains a significant public health and human rights challenge globally, with sex workers disproportionately affected due to criminalization, stigma, economic vulnerability, and social exclusion. This study assessed access to support services and the mental health consequences of GBV among sex workers in Abuja, Nigeria. A mixed-methods comparative cross-sectional study involving 455 sex workers was conducted across Abuja Municipal Area Council, Bwari, and Gwagwalada. Quantitative data were collected using interviewer-administered questionnaires, while qualitative insights were obtained through focus group discussions. Findings revealed that although awareness of healthcare and legal support services was relatively high, actual utilization remained poor due to fear of arrest, stigma, discrimination, financial barriers, lack of confidentiality, and mistrust of law enforcement agencies. Respondents reported high levels of anxiety, depression, emotional trauma, fear, and post-traumatic stress disorder associated with repeated exposure to violence. Qualitative findings highlighted persistent psychological distress, social isolation, and discrimination within healthcare institutions. Criminalization of sex work and structural inequalities significantly contributed to poor mental health outcomes and limited healthcare utilization. The study concludes that GBV among sex workers in Abuja has profound psychosocial consequences and that existing support systems remain inadequate. Comprehensive interventions including trauma-informed mental health services, stigma reduction, legal reforms, and survivor-centered healthcare approaches are urgently needed.*

Keywords *Gender-Based Violence, Mental Health, Nigeria, Sex Workers, Support Services.*

Introduction

Gender-based violence (GBV) remains one of the most significant global public health and human rights challenges, disproportionately affecting women and other vulnerable populations worldwide. The World Health Organization (WHO) estimates that approximately one in three women globally experiences physical and/or sexual violence during her lifetime, with marginalized populations such as sex workers facing substantially higher levels of violence and exploitation than the general population [1]. GBV encompasses a broad range of harmful acts, including physical assault, sexual violence, emotional and psychological abuse, economic deprivation, coercion, intimidation, and social discrimination. Among sex workers, violence is frequently perpetrated by clients, intimate partners, brothel managers, criminal groups, and law enforcement personnel [2].

Sex workers experience unique vulnerabilities that increase their exposure to violence and limit their ability to seek protection and support. In many low- and middle-income countries, including Nigeria, sex work remains highly stigmatized and criminalized, creating environments in which violence is often normalized and underreported. Criminalization, social exclusion, poverty, and gender inequality collectively contribute to unsafe working conditions and poor access to healthcare and legal services [3]. Consequently, many sex workers experience repeated exposure to violence without adequate support or protection.

The consequences of gender-based violence extend far beyond immediate physical injuries. Numerous studies have demonstrated strong associations between violence and adverse mental health outcomes, including anxiety, depression, post-traumatic stress disorder (PTSD), substance abuse, emotional exhaustion, and suicidal ideation [4]. Persistent exposure to violence often results in chronic

psychological distress, reduced quality of life, and poor health-seeking behavior. Furthermore, stigma and discrimination discourage many survivors from accessing available healthcare and psychosocial support services, thereby exacerbating the long-term effects of violence [2, 3].

Globally, a variety of interventions have been proposed and implemented to address violence against sex workers and improve their health outcomes. These include decriminalization of sex work, harm-reduction programs, community empowerment initiatives, peer-support networks, trauma-informed mental health services, legal aid programs, and integrated sexual and reproductive healthcare services [5, 6]. International organizations such as UNAIDS, Amnesty International, and Human Rights Watch have consistently advocated for rights-based approaches that promote healthcare access, legal protection, social inclusion, and violence prevention among sex workers [7, 8, 13].

Among the available interventions, community empowerment and decriminalization strategies have demonstrated considerable effectiveness in reducing violence and improving health outcomes. Shannon et al. [9] reported that decriminalization improves access to healthcare services, reduces police harassment, and promotes reporting of violence. Similarly, Kerrigan et al. [10] found that peer-led community empowerment interventions enhance social support, resilience, and access to health services among sex workers. Evidence also suggests that trauma-informed healthcare approaches can improve psychological wellbeing and facilitate recovery among survivors of violence [11].

Despite these advances, substantial challenges remain. Existing interventions are often constrained by inadequate funding, weak implementation mechanisms, persistent social stigma, cultural resistance, and restrictive legal environments [12]. In many African countries,

criminalization continues to push sex workers into hidden and unsafe environments where violence is normalized and rarely reported [13]. Fear of arrest, discrimination, and victimization discourages many survivors from seeking medical care, legal assistance, or psychological support [14].

Research conducted over the past decade has significantly improved understanding of the relationship between violence, stigma, and mental health among sex workers. Studies from Africa, Asia, and North America consistently demonstrate that repeated exposure to violence is associated with depression, PTSD, anxiety disorders, emotional trauma, and social isolation [15, 16]. Deering et al. [2] and Argento et al. [17] further demonstrated that violence and stigma substantially reduce healthcare utilization and increase vulnerability to chronic psychological distress among sex workers.

In sub-Saharan Africa, the burden of violence and its associated mental health consequences remains alarmingly high. Scorgie et al. [3] documented widespread experiences of stigma and discrimination within healthcare facilities among sex workers in Kenya, Uganda, Zimbabwe, and South Africa. Similarly, Muluneh et al. [16] reported a high prevalence of violence among female sex workers across the region. In Nigeria, Oyefara [19] identified poverty, stigma, and criminalization as major contributors to violence and poor psychosocial wellbeing among sex workers.

More recent evidence from Nigeria further demonstrates the persistence of gender-based violence despite ongoing interventions. Ochonye et al. [20] reported that sexual violence, physical assault, extortion, and police harassment remain common experiences among female sex workers. The authors noted that although grassroots interventions have improved awareness and reporting of violence, structural barriers such as criminalization, stigma, and inadequate legal protection continue to limit their effectiveness. Similarly, another Nigerian study reported high levels of

physical, sexual, and emotional violence among sex workers, highlighting the urgent need for comprehensive prevention and response strategies [23].

Abuja, the Federal Capital Territory of Nigeria, presents a unique socio-economic context characterized by rapid urbanization, migration, unemployment, inequality, and expanding informal economic activities. These conditions contribute significantly to the vulnerability of sex workers and may increase exposure to violence. Despite the growing recognition of gender-based violence as a public health issue, there remains limited evidence specifically examining access to support services and the mental health consequences of violence among sex workers in Abuja.

Understanding the extent to which sex workers can access healthcare, legal assistance, counselling, and psychosocial support following experiences of violence is essential for informing effective policy and intervention strategies. In addition, documenting the psychological consequences of violence provides important evidence for strengthening mental health services and developing survivor-centered care models.

This study therefore assessed access to support services and the mental health consequences of gender-based violence among sex workers in Abuja, Nigeria. The findings are expected to contribute to violence prevention efforts, mental health programming, policy reforms, and the development of comprehensive survivor-centered interventions aimed at improving the health, wellbeing, and human rights of sex workers.

Materials and Methods

Study Design

This study employed a mixed-methods comparative cross-sectional research design involving both quantitative and qualitative approaches. The mixed-methods approach was considered appropriate because it enabled

comprehensive assessment of the prevalence of gender-based violence (GBV), access to support services, and the associated mental health consequences among sex workers in Abuja, Nigeria. The quantitative component provided measurable estimates of violence, service utilization, and psychological outcomes, while the qualitative component offered deeper understanding of the lived experiences, perceptions, and coping mechanisms of respondents.

Study Area

The study was conducted in the Federal Capital Territory (FCT), Abuja, Nigeria, specifically within Abuja Municipal Area Council (AMAC), Bwari, and Gwagwalada. Abuja is the administrative capital of Nigeria and is characterized by rapid urbanization, migration, socio-economic inequalities, and diverse informal economic activities, including commercial sex work. The selected locations were chosen because they represent major sex work hotspots within urban, peri-urban, and semi-rural settings of the FCT. These areas host various categories of sex workers including brothel-based, street-based, club-based, and mobile sex workers.

Study Population

The study population comprised male, female, transgender, and non-binary sex workers aged 18 years and above who were actively engaged in sex work within the selected study areas during the period of data collection.

Inclusion Criteria

Participants were eligible for inclusion if they:

1. Were aged 18 years and above;
2. Self-identified as sex workers;
3. Had lived or worked within the selected study areas for at least six months;
4. Were willing to provide informed consent;
5. Were mentally and physically capable of participating in the study.

Exclusion Criteria

Participants were excluded if they:

1. Were below 18 years of age;
2. Were critically ill at the time of data collection;
3. Declined participation or withdrew consent;
4. Were unable to communicate effectively during interviews or discussions.

Sample Size Determination

The sample size was determined using the formula for comparison of two independent proportions:

$$n = [(Z\alpha/2 + Z\beta)^2 \times \{P_1(1 - P_1) + P_2(1 - P_2)\}] / (P_1 - P_2)^2$$

Where:

N = minimum sample size required per group

$Z\alpha/2$ = standard normal deviation corresponding to the desired confidence level (1.96 for a 95% confidence interval)

$Z\beta$ = standard normal deviation corresponding to the desired statistical power (0.84 for 80% power)

P_1 = estimated proportion in the first group

P_2 = estimated proportion in the second group

$P_1 - P_2$ = expected difference between the two proportions

After obtaining the minimum sample size, adjustment for non-response was performed using the following formula:

$$N = n / (1 - r)$$

Where:

N = final adjusted sample size

n = calculated minimum sample size

r = anticipated non-response rate

This approach ensured that the study had adequate statistical power to detect the expected difference between the two groups while accounting for potential participant non-response or incomplete data.

Using a 10% non-response rate ($r = 0.10$), the final sample size obtained was 462 respondents. However, 455 participants successfully completed the study questionnaires.

For the qualitative component, 45 participants were purposively selected for focus group discussions (FGDs), with 15 participants recruited from each study location.

Sampling Technique

A multistage cluster sampling technique was employed for the quantitative survey. In the first stage, the three area councils (AMAC, Bwari, and Gwagwalada) were purposively selected because of their high concentration of sex work activities. In the second stage, sex work hotspots including brothels, clubs, bars, hotels, and street locations were identified with the assistance of peer educators and community mobilizers.

Respondents were subsequently recruited proportionately from identified hotspots using convenience and snowball sampling techniques due to the hidden and stigmatized nature of the study population.

For the qualitative component, purposive sampling was used to recruit participants with diverse experiences relating to violence, healthcare access, and mental health challenges.

Data Collection Instruments

Quantitative data were collected using structured interviewer-administered questionnaires developed after extensive review of related literature and standardized GBV assessment tools. The questionnaire consisted of the following sections:

1. Socio-demographic characteristics;
2. Experiences of gender-based violence;
3. Access to healthcare and support services;
4. Mental health consequences of violence;
5. Barriers to healthcare utilization;
6. Coping mechanisms and social support systems.

The questionnaire included both closed-ended and Likert-scale questions.

Qualitative data were collected using Focus Group Discussion (FGD) guides designed to explore:

1. Experiences and perceptions of violence;
2. Psychological and emotional consequences of GBV;
3. Access to healthcare and legal support services;
4. Experiences with healthcare providers and law enforcement agencies;
5. Coping strategies and recommendations for interventions.

Validity and Reliability of Instruments

The instruments were reviewed by experts in public health, gender studies, and mental health to ensure content and face validity. A pilot study was conducted among sex workers outside the selected study sites to assess clarity, appropriateness, and reliability of the instruments.

Necessary modifications were made following pilot testing. Internal consistency reliability of the questionnaire items was assessed using Cronbach's alpha coefficient, which yielded acceptable reliability values above 0.70.

Data Collection Procedure

Data collection was conducted over a period of eight weeks by trained research assistants familiar with key population research and ethical handling of sensitive information. Interviews were conducted in private and secure locations to ensure confidentiality and participant comfort.

Prior to data collection, informed consent was obtained from all participants after explaining the purpose, procedures, benefits, and potential risks of the study. Participants were assured of anonymity and confidentiality. Focus group discussions were conducted in English and local languages where necessary. Each discussion lasted approximately 60–90

minutes and was audio-recorded with participants' permission.

Data Analysis

Quantitative data were entered, cleaned, and analyzed using Statistical Package for Social Sciences (SPSS) version 25. Descriptive statistics including frequencies, percentages, means, and standard deviations were used to summarize socio-demographic characteristics, prevalence of violence, mental health outcomes, and healthcare utilization patterns.

Inferential statistics including chi-square tests and logistic regression analyses were performed to assess associations between socio-demographic variables, exposure to violence, mental health outcomes, and access to support services. Statistical significance was set at $p < 0.05$.

Qualitative data obtained from FGDs were transcribed verbatim and analyzed thematically. Thematic analysis involved familiarization with the data, coding, categorization, and identification of recurring themes related to violence, stigma, healthcare access, and psychological wellbeing.

Ethical Considerations

Ethical approval for the study was obtained from the appropriate Institutional Research Ethics Committee before commencement of the study. Permission was also obtained from relevant community gatekeepers and peer

network leaders. Participation in the study was entirely voluntary. Written informed consent was obtained from all participants prior to data collection. Confidentiality and anonymity were strictly maintained by excluding identifying information from questionnaires and transcripts. Participants who experienced emotional distress during interviews were referred to available counselling and psychosocial support services. All procedures were conducted in accordance with international ethical principles governing research involving human participants.

Results

Socio-Demographic Characteristics of Respondents

The study involved a total of 455 sex workers recruited from Abuja Municipal Area Council (AMAC), Bwari, and Gwagwalada. The findings revealed that the majority of respondents were female, and most participants were within the economically active age group of 25–44 years. Secondary and tertiary education levels were the most commonly attained educational qualifications among respondents. In addition, most participants identified as heterosexual, although a considerable proportion identified as homosexual or bisexual. The socio-demographic characteristics of respondents are presented in Table 1.

Table 1. Socio-Demographic Characteristics of Respondents

Variable	Frequency	Percentage (%)
Female	374	82.29
Male	49	10.82
Non-binary	20	4.33
Transgender	12	2.59
Age 25–34 years	148	32.47
Age 35–44 years	128	28.14
Secondary education	197	43.29
Tertiary education	179	39.40

Awareness and Utilization of Support Services

The findings demonstrated relatively high awareness of healthcare and legal support services among respondents; however, actual utilization of these services remained considerably low. Awareness of healthcare services was reported by more than two-thirds

of respondents, while less than one-third utilized healthcare services following experiences of violence. Similarly, awareness of legal support services was moderate, but only a small proportion of respondents had sought legal assistance after experiencing violence. These findings are summarized in Table 2.

Table 2. Awareness and Utilization of Support Services

Variable	Percentage (%)
Awareness of healthcare services	72.0
Utilization of healthcare services	31.0
Awareness of legal support services	45.0
Utilization of legal support services	12.1

Barriers to Accessing Support Services

Respondents identified several important barriers limiting access to healthcare, psychosocial, and legal support services. Fear of arrest and harassment by law enforcement officers emerged as one of the most commonly reported barriers. In addition, stigma and discrimination within healthcare facilities

significantly discouraged respondents from seeking care and support services.

Other commonly reported barriers included financial constraints, fear of exposure, lack of confidentiality, negative attitudes from healthcare workers, and mistrust of police and judicial institutions. Figure 1 presents the major barriers to accessing support services among respondents.

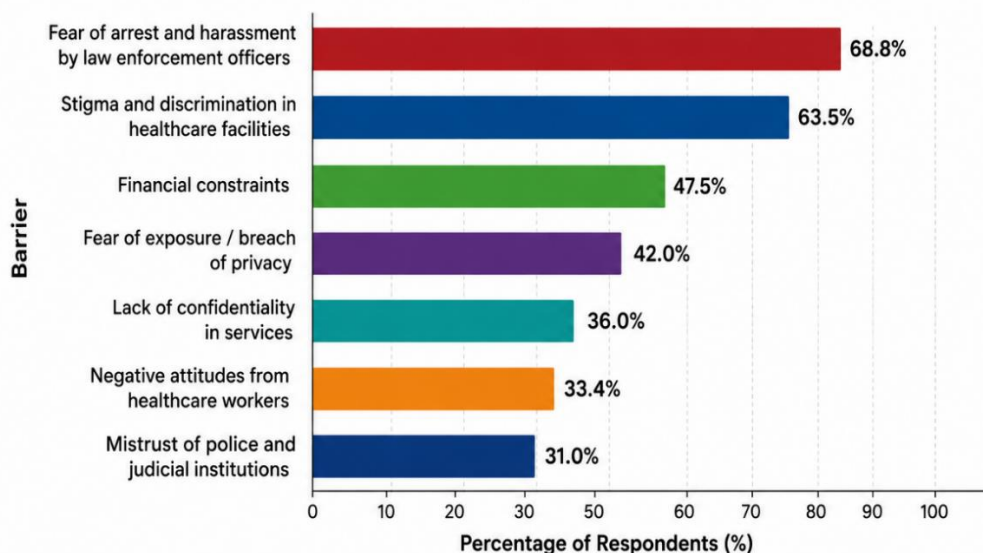


Figure 1. Major Barriers to Accessing Support Services among Respondents

The majority of respondents explained that healthcare providers often judged or discriminated against them because of their

occupation. Some respondents also reported receiving disrespectful treatment while seeking healthcare services.

Mental Health Consequences of Gender-Based Violence

The study revealed high levels of psychological distress among respondents who had experienced gender-based violence. Fear and insecurity were the most commonly reported mental health consequences, followed closely by anxiety. More than half of

respondents also reported symptoms of depression, while nearly half experienced symptoms suggestive of post-traumatic stress disorder (PTSD), including nightmares, insomnia, flashbacks, intrusive memories, emotional numbness, and hypervigilance. The distribution of mental health consequences is presented in Table 3.

Table 3. Common Mental Health Consequences Reported by Respondents

Mental Health Outcome	Percentage (%)
Fear and insecurity	72.0
Anxiety	68.0
Depression	54.0
PTSD symptoms	49.0

Experiences of Emotional and Psychological Trauma

Respondents described persistent emotional and psychological trauma associated with repeated exposure to violence, social rejection, and discrimination. Many participants reported feelings of hopelessness, loneliness, shame, and emotional exhaustion. Repeated experiences of violence were also reported to negatively affect self-esteem and trust in clients, healthcare providers, and law enforcement agencies.

Several respondents further explained that they resorted to alcohol consumption and substance use as coping mechanisms to manage emotional distress and traumatic experiences.

Qualitative Findings From Focus Group Discussions

The qualitative findings provided deeper insights into the lived experiences of sex workers regarding violence, mental health challenges, institutional discrimination, and barriers to support services. Several important themes emerged from the focus group discussions, including fear and insecurity, stigma in healthcare settings, psychological distress, and mistrust of law enforcement agencies.

Experiences of Fear and Insecurity

Participants consistently described living in fear due to frequent exposure to violence, unsafe working environments, and police harassment. Many respondents reported persistent anxiety and feelings of insecurity in their daily lives.

One participant stated:

“I feel trapped. Every day I wake up, I feel anxious, scared, and alone.”

Another respondent explained:

“We are afraid to report violence because the police often harass us instead of helping us.”

Stigma and Discrimination in Healthcare Settings

Many participants reported experiencing discrimination, judgment, and disrespect while seeking healthcare services. Respondents explained that healthcare workers often stigmatized them because of their occupation, which discouraged future healthcare-seeking behavior.

One respondent noted:

“We are judged when we go to hospitals. Some nurses insult us or refuse to attend to us.”

Another participant added:

“Society sees us as worthless, and the clients treat us like we are disposable.”

Psychological Impact of Violence

Participants reported severe emotional distress resulting from repeated violence and social exclusion. Frequently reported psychological symptoms included fear, sadness, insomnia, hopelessness, emotional withdrawal, and low self-esteem.

Several respondents explained that fear of discrimination and lack of emotional support prevented them from seeking counselling or mental health services.

Mistrust of Law Enforcement Agencies

A recurring theme across the focus group discussions was widespread mistrust of police and legal institutions. Participants described experiences of extortion, intimidation, verbal abuse, and harassment by law enforcement officers.

One respondent explained:

“We don’t trust the police because they harass us instead of protecting us.”

Overall, the qualitative findings supported the quantitative results by demonstrating that gender-based violence among sex workers in Abuja is strongly associated with psychological distress, social exclusion, institutional discrimination, and poor utilization of support services.

Discussion

This study assessed access to support services and the mental health consequences of gender-based violence among sex workers in Abuja, Nigeria. The findings revealed that although awareness of healthcare and legal support services was relatively high, actual utilization of these services remained considerably low. The study further demonstrated that exposure to gender-based violence was associated with substantial psychological consequences, including fear, anxiety, depression, emotional trauma, and

symptoms consistent with post-traumatic stress disorder (PTSD). These findings highlight the persistent structural, social, and institutional barriers that prevent sex workers from accessing appropriate support services despite their availability.

The relatively high level of awareness of healthcare and legal support services observed in this study may be attributed to ongoing public health interventions, community outreach activities, and peer-education programs targeting key populations within the Federal Capital Territory. However, awareness alone did not translate into service utilization. Similar findings have been reported in previous studies conducted in sub-Saharan Africa, where sex workers often possess knowledge of available services but remain reluctant to utilize them because of fear of discrimination, stigma, criminalization, and concerns about confidentiality [3, 7]. The discrepancy between awareness and utilization observed in the present study suggests that increasing service availability alone is insufficient unless accompanied by measures that address social and structural barriers.

Fear of arrest and harassment by law enforcement agencies emerged as one of the most important barriers to accessing support services. This finding is consistent with reports from Amnesty International and Human Rights Watch, which documented widespread fear of police victimization among sex workers operating in criminalized environments [8, 13]. Criminalization creates a climate of fear that discourages survivors from reporting violence or seeking legal protection. Similar observations were reported by Platt et al. [12], who demonstrated that restrictive legal frameworks negatively affect health outcomes and reduce access to justice among sex workers. The findings therefore support growing international calls for legal reforms that prioritize the safety, health, and human rights of sex workers.

Stigma and discrimination within healthcare settings were also identified as major obstacles to service utilization. Many participants reported experiences of judgment, disrespect, and discriminatory treatment by healthcare providers. These findings corroborate those of Scorgie et al. [3], who reported widespread stigma against sex workers in healthcare facilities across several African countries. Healthcare-related stigma has been shown to reduce trust in healthcare systems, discourage treatment-seeking behavior, and contribute to delayed utilization of essential health services. Similarly, UNAIDS [7] reported that discriminatory healthcare practices remain significant barriers to service access among key populations globally.

The present study revealed substantial mental health consequences associated with exposure to gender-based violence. Fear and insecurity were the most commonly reported psychological outcomes, followed by anxiety, depression, and PTSD-related symptoms. These findings are consistent with previous studies demonstrating strong associations between violence and poor mental health among sex workers [4, 17, 18]. Argento et al. [17] reported that repeated exposure to violence significantly increases the likelihood of depression, anxiety disorders, emotional exhaustion, and suicidal ideation among sex workers. The high prevalence of psychological distress observed in the current study underscores the need for routine mental health screening and trauma-informed care within services targeting vulnerable populations.

The widespread occurrence of PTSD-related symptoms among respondents is particularly concerning. Participants reported recurrent nightmares, insomnia, intrusive memories, emotional numbness, hypervigilance, and persistent fear. These symptoms are characteristic of trauma-related psychological disorders and reflect the cumulative effects of repeated exposure to violence. Similar findings have been reported among sex workers in

multiple settings, where chronic exposure to violence contributes to long-term psychological dysfunction and reduced quality of life [1, 11]. The findings emphasize the importance of integrating mental health services into existing healthcare programs serving sex workers.

Economic vulnerability emerged as another important factor influencing both exposure to violence and poor mental health outcomes. Many respondents indicated that financial constraints limited their ability to access counselling services, legal aid, and safe accommodation. Economic dependence often reduces the ability of sex workers to avoid abusive situations or seek alternative livelihoods. Similar findings were reported by Puri et al. [21], who found that financial insecurity significantly increased vulnerability to violence and psychological distress among female sex workers. Economic empowerment interventions may therefore play a critical role in reducing vulnerability and improving overall wellbeing.

The qualitative findings provided important contextual insights into the lived experiences of respondents. Participants consistently described feelings of fear, loneliness, hopelessness, emotional exhaustion, and social isolation. Many reported that experiences of violence had eroded their self-esteem and trust in both healthcare providers and law enforcement agencies. These narratives complement the quantitative findings and reinforce previous evidence indicating that the effects of gender-based violence extend beyond physical harm to include profound emotional and psychological consequences [17].

Mistrust of law enforcement agencies emerged as a recurring theme throughout the focus group discussions. Participants described experiences of harassment, extortion, intimidation, and verbal abuse by police officers. Such experiences contribute to underreporting of violence and discourage survivors from seeking legal redress. These findings support the theory of structural

violence proposed by Farmer [22], which argues that social institutions and unequal power structures can perpetuate violence and poor health outcomes among marginalized populations. The persistent mistrust observed in this study demonstrates the need for institutional reforms that promote accountability, human rights protection, and equitable access to justice.

The findings of this study are also consistent with previous Nigerian studies examining violence among sex workers. Oyefara [19] reported that stigma, poverty, and criminalization contribute substantially to violence and poor psychosocial wellbeing among sex workers in Nigeria. Similarly, Ochonye et al. [23] documented high levels of violence and barriers to healthcare access among female sex workers in Benue State. More recently, Ochonye et al. [20] demonstrated that despite increased awareness of violence prevention initiatives, significant gaps remain in access to mental health services, legal support, and survivor-centered care. These findings collectively suggest that violence against sex workers remains a persistent public health and human rights challenge in Nigeria.

Overall, the findings of this study demonstrate that gender-based violence among sex workers is not merely an issue of individual victimization but rather a manifestation of broader structural inequalities involving poverty, criminalization, stigma, gender discrimination, and inadequate institutional support. Effective responses therefore require comprehensive, multisectoral, and rights-based approaches that address both immediate support needs and the underlying determinants of vulnerability. Such interventions should include trauma-informed mental health services, stigma-reduction initiatives, legal reforms, economic empowerment programs, strengthened community support systems, and improved access to survivor-centered healthcare services.

Conclusion

This study demonstrated that gender-based violence remains highly prevalent among sex workers in Abuja and is associated with substantial psychological consequences including anxiety, depression, fear, emotional trauma, and symptoms of post-traumatic stress disorder. Although awareness of healthcare and legal support services was relatively high, utilization remained low due to stigma, fear of arrest, discrimination, lack of confidentiality, and mistrust of law enforcement agencies. The findings highlight the urgent need for trauma-informed mental health services, strengthened legal protection mechanisms, community empowerment programs, and policy reforms aimed at reducing structural inequalities affecting sex workers. Addressing these barriers is essential for improving mental health outcomes and ensuring equitable access to survivor-centered support services.

Study Limitations

This study has several limitations. First, the cross-sectional design limits the ability to establish causal relationships between exposure to gender-based violence and mental health outcomes. Second, data were based on self-reported experiences and may therefore be subject to recall bias and social desirability bias. Third, the use of convenience and snowball sampling techniques may limit the generalizability of findings to all sex workers in Abuja and Nigeria. Despite these limitations, the mixed-methods approach provided valuable insights into the experiences of violence, service utilization, and mental health challenges among a hard-to-reach population.

Conflict of Interest

The authors declare no conflict of interest.

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Author Contributions

Derby Ifeanyichukwu Collins-Kalu: Conceptualization, Data Collection, Methodology, Writing Formal Analysis and Project Administration. Christina Mbongueh Mohnchimbare: Writing – Original Draft Preparation. Henri Lucien Kamga: Supervision – Review and Editing.

Ethical Approval

Ethical approval for this study was obtained from the relevant institutional ethics review

board. Written informed consent was obtained from all participants before data collection.

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Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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A Behavioral Systems Theory of Investor Decision-Making under Market Stress: A Narrative Analysis of Interacting Behavioral Biases

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Abstract Psychological biases affecting investor behaviour in financial markets have gained traction over the years but little has been published about their interactions when uncertainties arise. This paper proposes a theoretical Behavioral Systems Theory (BST) of investor behaviour as a complex system defined by the cognitive, emotional and social behavioral finance biases, particularly loss aversion, overconfidence effect, anchoring bias, herd behaviour and systems theory is employed to understand cognitive dissonance and bias during economic turmoil. Qualitative narrative methodology is used to study the outcomes of investor behavior during the Global Financial Crisis of 2008, COVID19-induced market crash and speculative post-pandemic growth (2021-2025). Combination theory provides the basis for hypothesizing the numerous structural interaction possibilities for the bias system: at most six for two-way, four for three-way interactions and one for four-way interactions. Investor irrationality as revealed by the interactions functions as a feedback-loop system exhibiting recurring cognitive dissonance, emotional and social bias. Its effects are observable in the forms of speculative bubbles, panic-selling, procrastinating recovery, volatility expansion, clustering of trading activity and financial contagion. BST yields new contribution to behavioral finance as a system theory and a discovery of the dynamics that govern investor behavior during uncertainties. This theory also has practical implications for investors allocating to different asset classes, financial institutions, regulators and policymakers in maintaining order in the financial system, professional financial advisers to their clients. Quantitative and mixed-method research design is prescribed for future testing of the BST theory.

Keywords Anchoring, Behavioral Systems Theory, Herd Behaviour, Loss Aversion, Narrative Methodology, Overconfidence.

Introduction

The financial markets, playing an important role in the economic growth of a country, reallocates the available resources, transfers the financial risks, and generates the wealth for the nation. Financial economists over decades have built their theoretical models on the assumptions of rationality provided by investors who extract data out of the received information efficiently and decide to maximize the expected utility. These assumptions lay the groundwork of traditional financial theories such as Efficient Market Hypothesis (EMH) and Modern Portfolio Theory (MPT). Efficient Market Hypothesis believes that the security prices reflect all available information and information is efficiently processed. Hence, consistently outperforming the market to realize positive abnormal returns become almost impossible due to outperformance based on effective research or forecasting for future events from an investor to another [1]. Likewise, the Modern Portfolio Theory posits that the rational investor optimally assembles their portfolios to maximize the expected return at every level of risk based on dividing their investment funds across different asset classes and implementing the optimization procedures [2]. Nonetheless, these theories (which are fundamentals of the financial economics) have been increasingly criticized for their apparent inability to account for recurrent episodes of instability and irrationality in the markets. Documentary evidence have shown that investors usually do not behave as predicted; that is, they do not always adhere to rational choice and utility maximization principles. The most recent price bubbles and major financial crises such as the Dot-Com Bubble (late 90s), the Global Financial Crisis (2008) and the COVID-19 market crash (2020) were described by incautious and over-optimism behavior of investors, panic selling, speculative trading and herd behavior – all the phenomena that are

hard to fit into the traditional financial model [4, 9].

The broadly known Dot-Com Bubble is one of the first and most conspicuous examples of irrational market behavior in modern financial history. At that time, the extreme optimism of investors regarding internet IT companies with dubious and often no earnings allowed inflating the investment valuations of such enterprises to unprecedented heights. The overly heated-enthusiasm about digital technology developments spread in the markets and beyond fostered never-before-seen speculative investments. When the market reality disillusioned investors with overly optimistic prospects, the severe depreciation of corresponding assets ensued, leading to considerable economic losses. Emphasizing irrational market behavior, existing theories could not explain how thousands of investors had disregarded valuation principles for such a long time. Global financial crisis in 2008 likewise highlighted extreme shortcomings in the traditional financial theory. Prior to the crisis, overconfidence in the housing market, financial innovations, risk management and more led to extreme speculation by investors and financial firms. Confidence began to erode quickly, leading to panic selling in the housing market, a loss of confidence spreading to other financial institutions and creating a contagion in the market, and systemic instability. The crisis had shown that investors are subject to human behavioral, psychological, and emotional biases that may have negatively influenced their decisions besides just economic factors [14]. The role of behavioral effects in financial markets gained even additional attention during the COVID-19 pandemic. Global financial markets faced unprecedented volatility due to investors' response to the uncertainties of the public health threat, the prospect of the economic slowdown, and government policies to address these uncertainties. The abnormal price swings

in financial markets during that time were driven not only by economic fundamentals but also by emotions, the uncertainties in the evolving story on the prospects of the global economy. These developments reemphasized the understanding that the investors' behavior cannot be explained only using the rational-choice theory [17, 18].

There were some limits of classical finance which led to the emergence of and continually growing fame of behavioral finance. Behavioral finance contains the cognitive and psychological features that influence how individuals make financial decisions under uncertainty. Behavior finance assumes that investors don't rely on perfectly rational reasoning. Their decision-making is influenced by various cognitive distortions, emotional upheavals, societal influences, and automatic judgments or thought processes that affect reasoning and decision-making systematically [4, 8, 9, 16]. The behavioral biases most commonly discussed in the literature include loss aversion, overconfidence, anchoring, and herd behavior. Loss aversion is a behavioral bias that describes the tendency of people to experience losses stronger than symmetric gains, leading the investor to prefer to avoid losses rather than making profit and be risk-averse in uncertain situations [4]. Overconfidence is an excessive overestimation of one's intuition, prediction ability and capability to make price moves predictions, which results in excessive trading and speculation [7]. Anchoring describes the tendency of people to interrelate the decisions taken with the first information or certain point of reference, even when the information that changes the situation appears later [3]. Herd behavior describes the tendency to follow the behavior of the rest of the investors and not to analyze independently during uncertain and stressed market situations [5].

Much literature had been published regarding the identified behavioral biases; however, most of these studies looked at the

biases in isolation. The loss aversion, overconfidence, anchoring, and herd behavior were mostly diagnosed and analyzed as independent from each other. But in reality, and most of the time, not just one bias is influencing an investor's decision-making behavior. It should be noted that after the recent economic crisis, investors are probably affected by several combined psychological, emotional, and social influences. Thus, studying each bias independently might not provide a more detailed and clearer understanding of how behavioral biases could influence investors' decision-making in uncertain market environments.

Emerging behavioral finance research has provided evidence that irrationality of investors is a result of interplay of numerous behavioral biases rather than the isolated operational effect of each bias on its own [20-24]. Individual investors facing a loss can be anchored to the prior value of their portfolio, exhibit herd behavior to seek social confirmation, and overconfidently believe they are able to predict the recovery of the asset value. As a result, these combined elements create a vicious feedback system where the joint behavior becomes disproportionate to the prediction of the single-bias system. Likewise, increasing complexity of current financial markets also reinforces the need to study behavioral interactions. The investment landscape has fundamentally changed with the appearance of new digital technologies, algorithm-based trading systems, social media, online trading and investment platforms, and widespread instant availability of information. Information has become ubiquitous and spreads faster than ever, allowing emotions, ideas, and general optimism or pessimism to propagate via the herd influence among large numbers of investors within a short period of time. These phenomena have raised the risks of behavioral contagion, speculative bubbles, and correlated dynamics of financial markets much further [20, 21].

The aim of this study is to respond to these changes in environment by proposing a Behavioral Systems Theory (BST) of investor decision-making under market stress. The core idea of the proposition is that investor decisions can be considered as a behaviour system consisting of cognitive, emotional and social biases. Instead of viewing behavioral biases as isolated psychological distortions, BST argues that investor behavior is not a result of any single cognitive distortion, but a multidimensional interactive effect of loss aversion, overconfidence, anchoring and herd behavior. This study will make use of the principles and ideas from behavioral finance, complexity theory, narrative economics and combination theory in order to provide a novel and more realistic explanation of an investor behavior in times of economic crisis.

Core Research Question

How do interacting behavioral biases influence investor decision-making and investment strategy during periods of economic crisis?

Objectives of the Study

1. To examine the interaction among loss aversion, overconfidence, anchoring, and herd behaviour during economic crises.
2. To develop a Behavioral Systems Theory explaining multidimensional investor irrationality.
3. To apply combination theory in identifying possible interaction structures among behavioral biases.

Basic Assumptions

1. Investor behavior during crises is influenced by multiple interacting biases rather than isolated psychological tendencies.
2. Economic crises amplify emotional and cognitive distortions due to uncertainty and volatility.

3. Narrative methodology is appropriate for understanding investor interpretation of crisis events.

Limitations of the Study

The study adopts a conceptual and narrative approach and therefore does not include empirical testing. The analysis focuses primarily on four dominant behavioral biases and may exclude other relevant psychological constructs such as confirmation bias or mental accounting. Furthermore, crisis narratives may vary across institutional and geographical contexts.

Review of Related Literature

Behavioral Finance has been one of the significant advances in the evolution of financial economics over the past 50 years. It has emerged to explain the phenomena that existing financial theories could not accommodate; still many investors are trapped into irrationality, speculative bubbles, market crashes, over and under reaction, excessive volatility and the financial contagion. Behavioral Finance assumes that unlike traditional financial theories, which assume that investors are rational and their actions maximize utility through rational processing of information, there is plenty of evidence describing that the investor is influenced by cognitive biases, emotional response, and social influence and interaction [1, 4, 9]. Behavioral finance theory is used to justify the study of evolution and dynamics of the perception of the financial decisions of investors. Due to psychological biases, investors do not follow rational expectations, which also systematically distort both the perception and processing of information, risk perception and investment decision-making. Behavioral finance theory has fostered situations in which the investors' behavior deviates from the conventional financial theories predictions.

Despite the evident advances since the understanding of the investors as behavioral finance, the literature still presents itself poorly integrated. Most of the studies deal with the behavioral bias in an isolated manner – more central or less in a specific cognitive error: loss aversion, overconfidence, anchor, herd effect, etc. Despite the importance of this perspective as an explanatory centrality, this dispersion often does not allow us to understand how a set of biases put together intervene simultaneously in complex financial situations. This is even more aggravated in days of financial turmoil when so much uncertainty, fear, social pressure and over-information push the behavioral biases to the extreme. It therefore important that behavioral biases should be considered in an interrelated manner. Recent developments in behavioral finance, theory of complexity and theory of narrative economics postulate the premise that the behavioral finance should rather be seen as a multidimensional behavioral finance phenomenon than merely a behavioral finance anomaly - where cognitive, emotional and social mechanisms interact and collude in a systematic manner to influence the investor behavior and decisions [6, 17, 18].

Traditional Finance and the Rational Investor Paradigm

The traditional finance theory is founded on the assumption that investors' behavior is rational and the information is processed efficiently by the markets. The Efficient Market Hypothesis, proposed by Francis Fama [1, 19], states that the asset pricing reflects all the information that is available in the market. This implies that there cannot be consistent gains by the investors, as the information will be included in a timely manner to the level of the prices of the securities.

Modern Portfolio Theory (MPT) applied by Harry Markowitz [2] also assumes that the rational investor will make optimal choices for constructing a portfolio on the basis of the

trade-off between expected return and risk. It is further assumed that investors can objectively evaluate the choices available to them and select the alternative portfolio that provides them the maximum utility for a given level of risk. Grounded in the rationalists' perspectives, many of the modern financial theories have been developed. This includes theories about portfolio management, asset pricing, corporate finance, and risk management. However, many of these theories have been increasingly questioned since certain systematic anomalies have been demonstrated which deviated from rationality.

The traditional finance theory is highly criticized for its failure to consider any plausible theories for speculation bubbles and market crashes. The discovery of market crash during the dot-com bubble in which investors continued buying technology stocks with weak fundamentals and positive return was hard to comprehend in view theory. This was also true when investors and institutions ignored evidences of unstable housing and credit markets during the global financial crisis with collective underestimating of risks. It was easy for market players to assume rational expectations and precise conveyance of information [14]. The foremost argument of the critics against the established models is that these models consider human behavior too simplistic, as it considers that humans hold super rationality; people have perfect knowledge and always take the best decisions. People, however, invest under unpredictable circumstances with lack of information, pressure of emotions and social contexts, which render them prone to systematic errors in judgment and decision making [4]. It is therefore the shortcomings of classical finance that formed the intellectual basis for the emergence of the emerging paradigm of behavioral finance.

Emergence of Behavioral Finance

The areas of accomplishments of behavioral finance are economic theory with a deep influence of psychology. The efforts of Daniel Kahneman and Amos Tversky signify a great step forward in verifying that the choices of any group of individuals are not exclusively in accordance with the rational decision hypothesis [3, 4]. Heuristics and cognitive biases are described by the researchers on how people made their decisions in the uncertainty situation. Cognitive bias as a decision – making heuristic makes it easier for people, however, the researchers also identified the systematic errors that cognitive bias brought out to the risk and payoff judgment.

The development of Prospect Theory was an important breakthrough in understanding how our brains work while making investment decisions [4]. This theory opposed expected utility models by showing that individuals make decisions not according to their wealth level, but according to gains and losses relative to a reference point. The theory also suggests that the impact of losses has a more pronounced effect on decision making as compared to the same valued gain; the treatment of positive and negative outcomes is therefore asymmetric prospectively. Stemming from behavioral economics, Prospect Theory revolutionized financial decision-making research as it provided a psychological explanation for many market anomalies. Investors were not the optimal rational agents, but rather bounded rational agents perceiving and overreacting to diverse emotions and cognitive biases. With subsequent work, Richard Thaler made significant studies on mental accounting, how things are framed for the individual, and the concept of bounded rationality [8]. His work significantly proved that human economic decision-making was directed by the perception of information rather than economic values.

The qualitative element of the research emphasizes the role of behavioral finance, which has become an established area of research with an ample amount of empirical evidence. The behavioral finance empirical evidence links the established biases to excessive trading, speculative bubbles, under-diversification, market overreaction, momentum, and financial contagion [7, 9]. Nonetheless, there is a major limitation in the literature surrounding behavioral finance. Most published papers are focused on prediction and measurements of different types of the individual biases influencing the decision-making process, consequently the methods and tools used to evaluate the relationships between them are missing. Thus, behavioral finance examines the investors' psychology as independent biases instead of nonlinear behavior.

Theoretical Foundations of Behavioral Systems Theory

The Behavioral Systems Theory (BST) is built on the synthesis of four theoretically sound frameworks-Prospect Theory, Behavioral Finance Theory, Complexity Theory and Narrative Economics. Prospect Theory offers an emotional basis of BST as it explains how decision-makers assess gains and losses against reference points and loss aversion impact is greater than corresponding gain impact [4]. It helps to understand how loss aversion affects irrational investor behavior in times of uncertainty and market recession. The Behavioral Finance Theory forms the cognitive emotions of BST and provides systematic cognitive prejudices such as overconfidence and anchoring which distort the perception of market information, risk perception, and financial decision-making [3, 7, 9]. Both theories deny rationality assumptions of classical finance, proving that investor decisions are influenced by psychological factors rather than economic realities alone.

Besides individual level, Complexity Theory and Narrative Economics could explain behavioral influence in financial systems. Complexity Theory defines financial markets as complex adaptive systems that operate in nonlinear feedback loops, are emergent in structures, and contain dynamically complex interactions among agents, or market participants [6]. In accordance to the complexity theory, financial systems outcomes are influenced more by interplay between many behavioral determinants than just one singular determinant. Narrative Economics also explains the behavioral determinant of stories, beliefs, and expectations that are formed and transmitted socially, in which investors and market agents behave according to pre-held ideas or beliefs [17, 18]. Financial narrative could affect investor pool sentiment, produce shared reference points, positively or negatively boosts market player confidence and fear, and create high tendency to mimic other player's actions, or herding. Combining the four theories, it is hypothesized in Behavioral Systems Theory that investors' decision making in financial crises and uncertain economic climate is asystem of interrelated emotional, cognitive, and social influences.

Behavioral Biases and Their Interactions in Financial Decision-Making

Loss Aversion and Investor Behavior

The loss aversion theory is one of the best known in behavioral finance and was studied under the Prospect Theory. It states that people are affected more by the losses than by the increases of the same magnitude [4]. This asymmetric function of the theory takes the investor's profile to a more prejudiced and certain loss issue, contrary to the economist's line of rationality. In the financial market, the loss aversion theory influences all stages of the investor's portfolio construction, asset

allocation, risk perception and eviction, and is more significant in periods of uncertainty. When faced with a loss situation, the investor usually does not proceed with an eviction process just for the sake of admitting that the result is unfavorable. The theory defends that the investor retains the non-appreciated assets for a much longer period than would be expected by market fundamentals [4, 15].

However, loss aversion is not only relevant for individual financial decision making, but its scope increases in uncertain times when the market is volatile. Fear and uncertainty usually accompany financial crises and as a result of loss aversion, investors are more sensitive to losses and shun riskier assets. Previous literature has explored relationships between loss aversion and other phenomena such as panic selling, reluctance to portfolio rebalancing, overreaction to negative news in down markets, etc. [20-24]. There is ample evidence from empirical research supporting the effect of loss aversion in financial decision making, though numerous studies still investigate the bias in isolation, addressing only a small piece of the assessment of how emotional responses and their interactions with cognitive and social factors affect an investor's decision making process.

Overconfidence and Excessive Risk-Taking

Overconfidence refers to an investing bias where investors tend to overestimate their knowledge, forecast accuracy and ability to predict market movements [7]. According to overconfidence mechanisms, investors believe to possess some information, or they comprehend data better than the average market participants. Overconfident traders tend to trade excessively, underestimate risk and hold strongly biased beliefs regarding investment outcomes. Numerous empirical studies support findings that overconfident trader trades more excessively than confident trader and has lower returns due to higher transaction costs and decision errors [7, 25].

Overconfidence bias tends to be more prominent during bull market conditions, when increasing prices of assets contribute to feeling of increased competence and ability to successfully predict the future of some financial tools. Market participants may feel like they got lucky when their decision making leads to profits and brush off the losing decisions by attributing them to the “short term” or external circumstances. Overconfidence, therefore, encourages market participants to engage in further speculation and risk-taking behavior, ultimately leading to the formation of financial bubbles themselves [17, 18]. However, despite the available evidence, research on the overconfidence bias and its co-existence with other biases, particularly during periods of increasing uncertainty and emotional turmoil, still barely scratches the surface.

Anchoring and Cognitive Rigidity

The second one is anchoring, which refers to the mental habit relating to disproportionate weight of the first price or benchmark used to make further assessments regarding the prospect of the investment - stock price acquired, high and low values from the past, price estimates from analysts or simply the previous price of a portfolio. The investor used to get back to the previous reference to assess whether the future of their investment will payback even when there is evidence that this reference is no longer valid. Anchoring leads to mispricing, delay and resistance to change in the stock market [22, 23].

Also, the anchoring role in market persistence comes from a wider phenomenon of cognitive rigidity. An investor anchored to previous expectations is not able to adapt to a new perspective, even in the face of a change in the economic climate and basic values of the asset. Cognitive rigidity can cause serious consequences in a crisis. More recent studies are indicating theories about the anchorage that affect groups more than individuals and is

promoted by media headlines, consensual thinking and socially shared expectations [22, 23]. So, anchoring is not a cognitive bias but a social bias that enhances the persistence of mispricing and delays the adjustment.

Herd Behavior and Collective Decision-Making

Herd behavior/herd mentality is when an individual follows what majority of others do instead of taking an independent assessment of the situation [5]. An investor will assume that the majority are better informed than he is and therefore will follow market trends even if these are against all rational judgment. The informational cascade theory states that an individual will discard his private information in favor of the signal observed by the majority, especially when uncertainty is high [5]. Numerous studies have identified herding behavior among retail/institutional investors and such a tendency significantly correlates with co-movements and volatility in the market.

Emerging financial technologies relate to herd behavior in the market, particularly in terms of its theory. The fast spread of information from social networks, online identities, and financial influencers can stir narratives, emotions, and sentiments, growing rapidly in the investor community [20-24]. In terms of the current hype, the “crypto mania” and “meme stock trading” can demonstrate how herd behavior can impact the “buying” decisions much more than any visible indicators of financial soundness. However, despite its relevance, the study of herd behavior as a part of the social network analysis paradigm requires more connections with cognitive and affective biases, especially focusing on the role of behavioral contagion in financial market phenomena during instability (financial) crises.

Comparative Analysis of Behavioral Biases

Loss aversion, overconfidence, anchoring, and herd behavior are different but related facets of the investor's mental makeup. Loss aversion refers to the tendency of investors to weigh losses more than equivalent gains in their decision making. Overconfidence refers to the cognitive trait of over-estimating one's own market acumen [4, 7]. Anchoring affects the interpretation of new information as it refers to the tendency of the investor to base new knowledge on the current information [3, 5]. Herd behavior showcases the tendency of investors to obey their social network in making stock brokering decisions. However, all of these factors show instances where investors deviate from the rationality rule and succumb to emotional, cognitive, and social pressures.

Even so, there is a great level of overlap between the biases despite their theoretical differences; loss aversion may be influenced by anchoring, in the sense that the investors are influenced by the value of their portfolio prior to the effect; overconfidence may be influenced by herd behavior, in the sense that the investor is led to believe their belief stronger due to social consensus. Moreover, anchoring may be influenced by loss aversion, in the sense that the loss associated with the reference point is given more prominence; herd behavior may be influenced by optimism and fear, in the sense of social contagion. In this context, it appears that behavioral bias – if at all present – works along with one another to provide an additional layer of influence over the investment decision.

Emerging Evidence on Behavioral Interactions

Importantly, fresh discoveries in the behavioral finance have unveiled that instead of isolated psychological distortions the behavior of the investors is a result of a more complex landscape of biases [20-24]. Some of

the studies have analyzed the emotional, cognitive and social biases during the uncertain times in the market and concluded that the self-reinforcing feedback mechanisms have linked those biases with each other. For example, the loss aversion of investors, during bear market periods, possesses a powerful anchoring bias while the blindfolded optimism and herd behavior during Bull market periods threatens speculating investors. The interaction of those biases may lead to even more different results compared to those supported only by single bias.

With the creation of digital financial ecosystem, the channels for information and idea sharing, story-treading, and building of investor sentiment have become even more accessible and broadened. The recommendations based on algorithms and the exposure on social network and online forums allow for the spread of behavioral contagion across various groups of investors to happen more quickly and at larger scale [20-24]. While the recognition of the impact of these biases have increased, there is yet a literature that combines the different biases to create a framework for the interplay and effect on crises, therefore the development of a Behavioral Systems theory that analyzes stock market behaviour as a system with emotional, cognitive and social biases may be appropriate.

Critical Evaluation of Existing Literature

Overall, the literature reviewed illustrated how behavioral finance has expanded knowledge of the disregard of rationality among investors. The concepts of loss aversion, overconfidence, anchoring, and herd mentality have provided substantial evidence that investor decision-making processes are heavily influenced by psychological, emotional, and social factors [3, 4, 7, 9]. It also has supported explanations of various market inefficiencies such as overtrading, speculative bubbles, underreaction and

overreaction to information, and financial contagion. Moreover, Narrative Economics and Complexity Theory have also contributed to market knowledge by further indicating the role of investor beliefs, market narratives, and adaptive interactions on the behavior of markets [6, 17, 18]. Overall, the theories provided have successfully articulated the foundations for the neglect of rationality, while also supporting the role of psychological influences in the financial market.

Nevertheless, the current literature still has its significant drawbacks. The behavioral finance studies are still mostly reductionist in their nature, investigating behavioral biases as mutually exclusive independent determinants of marketplace and individual investor behavior [20-24]. Such approach cannot allow the researchers and practitioners to understand that an investor could be affected by a bundle of behavioral biases at the same time, emotion, information overload, social contagion, hubris, basic fear, and many others, and especially during crisis times characterized by uncertainty. Furthermore, the existing behavioral models explain individual behavior, while they cannot provide justification of how cognitive, emotional, and social influences operate through feedback loops for larger markets. Digitalization of financial operations, the emergence of social media, digital investment networks, algorithm-driven information flows facilitate behavioral contagions and collective behavior more than ever, and our existing theories do not allow explaining such processes adequately [20-24]. Finally, the existing behavioral models have low explanatory power to understand high perturbation events and crises in financial markets.

As a result of this close study of the literature, the theory and the concept gap emerge is an understanding of the interplay among behavioral biases in relation to the actor's financial decisions. While loss and overconfidence, anchoring, and herd behavior

have been demonstrated in earlier studies, very few studies have simultaneously examined the interaction of behavioral biases in crisis conditions and their impact on investor behavior [20-24]. Current behavioral finance theories do not have a mechanism to explain how emotional, cognitive, and social influences may impact each other through a feedback loop. Such effects include speculative bubbles, panic sales, non-recovery of the market, excessive volatility, and financial contagion. In addition, the rapid spread of the impacts of digital communication technology - such as the evolution of market narratives that affect the dynamics in the markets - point to a new way for interaction and the spread of behavioral biases. There are still many paths for these digitalized influences in terms of the impact of behavioral bias and isolate-bias approaches have shown their limitations. The approach proposed by this study takes into account this integration and introduces Behavioral Systems Theory (BST) as an alternative theory and a system approach framework that integrates the theory of behavioral finance including Prospect Theory, Complexity Theory, Narrative Economics, and Combination Theory. BST intends to explain the behavior of the investor's actions as part of the interconnected behavioral system that occurs in conditions of economic uncertainty and market stress.

Methodology

Philosophy, Design and Approach

This study adopts an interpretivist research philosophy combining inductive qualitative research as a means to propose BST. The research design opted for the narrative inquiry technique to critique the interacting role of loss aversion, overconfidence, anchoring and herding behavior in times of economic distress and market uncertainty. The data collection process employed secondary data compilation from peer-reviewed journal articles, seminal

books and publications reports, documentation depicting the history of financial crises, behavior narratives from institutions and archetypal files on the Dot-Com Bubble, Global Financial Crisis, the collapse of the market from COVID-19 and speculative post-pandemic developments. The approach for data analysis employed narrative synthesis of the reviews and critiques and behavior narratives from economic and market crises to identify recurring patterns and interactions among the four biases. The arguments revealed through the narrative analysis informed the development of BST. To ensure methodological rigour, the research employed triangulation of sources, clear strategy of the analysis and the five qualitative trustworthiness standards of credibility, dependability, conformability and transferability. In terms of ethics, there was no involvement of human participants and no requirement for ethical approval.

In this regard, the qualitative narrative inquiry methodology is appropriate for the research questions because it aims to understand interactions among behavioral biases in a situation of crisis in complex and uncertain financial markets. Ultimately, behavioral finance research has used quantitative approaches – surveys, experimentations, and econometric models – to explain individual behavioral bias and its influence on the investment decision process [4, 7, 9]. While this body of work has expanded knowledge on the psychology of investor behavior, it typically isolates a behavioral variable in an econometric model and lacks an appreciation of the complex, dynamic, and interrelated context in which investors make decisions during financial crises. The defining features of financial crises are uncertainty, evolving information, emotional responses, contagious behavior, and time-dependent processes. These characteristics make the narrative inquiry methodology particularly suitable because it

aims to understand how persons and groups make sense, create meaning, and adapt to changing situations through stories and shared experiences [10-13]. Also, the Narrative Economics perspective on the influence of narrative on financial markets suggests that informed belief and expectation now determine investor behavior instead of facts and information [17, 18].

In a theory-building perspective, the current behavioral finance constructs cannot fully explain why multiple biases happen at the same time during a stressful market situation. Furthermore, Complexity Theory suggests that market phenomena do not result from isolated variables but rather from connections and nonlinear interactions across agents [6], reinforcing the preference of an inclusive approach. Thus, an interpretive and theory-building approach can successfully demonstrate interaction patterns of behaviors and suggest an explanation with broad reach. The results of the synthesis from behavioral finance, crisis narrative, complexity theory, and narrative economics aim at an increase in understanding of investor behavior and the foundations of a theoretical model that future empirical tests of the Behavioral Systems Theory [6, 17, 18, 20-24] may be based on.

Combination Theory of Behavioral Bias Interaction

A distinctive feature of this study is the application of Combination Theory to systematically identify all possible interaction structures among the four focal behavioral biases: loss aversion (L), overconfidence (O), anchoring (A), and herd behavior (H). Using the combination formula:

$$nC_r = n! / (r!(n - r)!)$$

Where:

- (n) = total number of items
- (r) = number of items selected
- (!) = factorial

This formula calculates the number of possible combinations of (r) items selected from (n) items without considering order as follows.

- 2-way interactions:

$$4C2 = 4!/(2!(4-2)!) = 6$$

- 3-way interactions:

$$4C3 = 4!/(3!(4-3)!) = 4$$

- 4-way interactions:

$$4C4 = 4!/(2!(4-4)!) = 1$$

The analysis generated six two-way interactions, four three-way interactions, and one four-way interaction, resulting in a total of eleven unique behavioral interaction structures.

Figure 1 illustrates the derivation process.

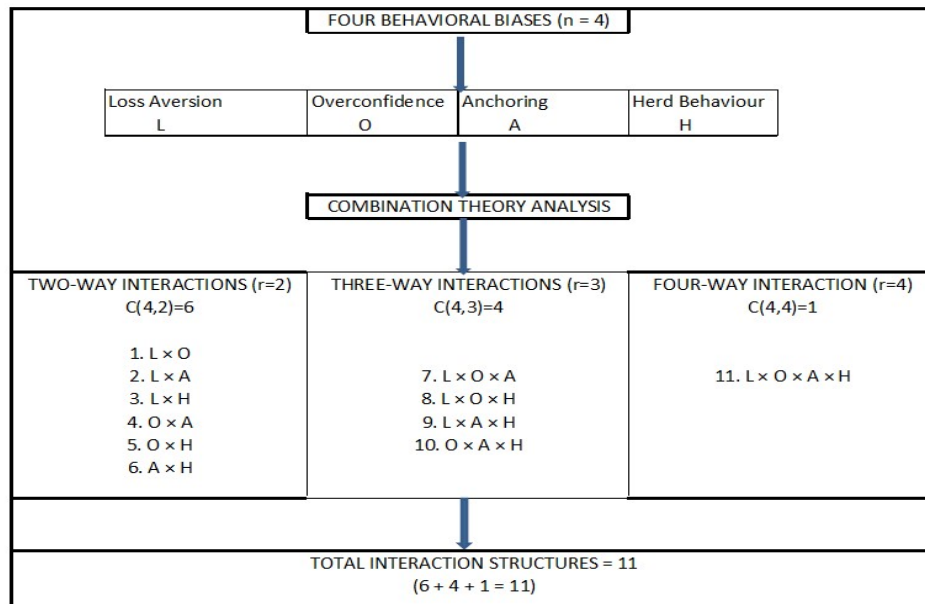


Figure 1. Combination Theory Analysis of Biases

Source: Developed by the Author

Summary of the Result

The loss aversion with overconfidence, anchoring, and herd behavior's interplay during the time of economic crises and bearish markets is analyzed. This results show that investor irrationality arises from behaviour individual alone, but recursive interactions

between emotional, cognitive and social (visible). This interactions developed behaviour amplification mechanism that leads to speculate bubbles, panic selling, long-recovery, overlearning, extreme volatility and financial contagion. Table 1 shows the interactions of the four behavioural biases.

Table 1. Behavioural Interaction Matrix

No.	Interaction Type	Bias Combination	Core Behavioral Effect	Likely Investment Outcome
1	Two-way	Loss Aversion × Overconfidence	Excessive risk-taking followed by fear of realizing losses	Holding losing assets too long
2	Two-way	Loss Aversion × Anchoring	Investor anchors to purchase price or previous high and avoids accepting loss	Delayed selling; portfolio rigidity

3	Two-way	Loss Aversion × Herd Behaviour	Fear of loss pushes investor to follow the crowd	Panic selling; market contagion
4	Two-way	Overconfidence × Anchoring	Investor over-trusts initial judgment or forecast	Slow adjustment to new information
5	Two-way	Overconfidence × Herd Behaviour	Investor believes they are independent while following market sentiment	Speculative trading; bubble formation
6	Two-way	Anchoring × Herd Behaviour	Collective market narratives become shared reference points	Valuation persistence; delayed correction
7	Three-way	Loss Aversion × Overconfidence × Anchoring	Investor takes risk, anchors to original belief, then refuses to realize loss	Disposition effect; prolonged losses
8	Three-way	Loss Aversion × Overconfidence × Herd Behaviour	Confidence-driven speculation turns into collective fear during crisis	Boom-to-panic reversal
9	Three-way	Loss Aversion × Anchoring × Herd Behaviour	Investors collectively anchor to past prices and fear selling at a loss	Clustered holding or selling behavior
10	Three-way	Overconfidence × Anchoring × Herd Behaviour	Investor confidence, shared narratives, and collective enthusiasm reinforce each other	Speculative bubble; overvaluation
11	Four-way	Loss Aversion × Overconfidence × Anchoring × Herd Behaviour	Full behavioral feedback system: confidence, reference points, social imitation, and fear reinforce one another	Panic selling, bubbles, delayed recovery, excess volatility

Source: Developed by the Author

Discussion

Analysis of Two-Way Behavioral Interactions

Loss Aversion × Overconfidence

An additional psychological bias that influences the decision-making of investors that stems from the union of overconfidence

and loss aversion is a particularity that affects overconfident investors. Their overestimation regarding the skills they possess to interpret information from the market, estimate the price of an asset in the future and value their capacity to choose investments that are profitable in general is carried at the time of investing [7, 25]. As a result, they take more

risks than average; they concentrate their assets in few of their preferences and operate more than average. In a growing market, any of the behaviors of the companies where they invested favors the overconfidence, making them value that the results they are obtaining are due to their talent and ability and not to the favorable evolution of the market. The distortion of the reality leads them to underestimate the risk that the market decreases and to have a higher level of speculation.

The next bias, loss aversion, is particularly dangerous during the bear market. It prevents the investor from taking losses or admitting mistakes for his investments. An investor tends to hold fast to depreciating assets even when value-informing news is presented to him with false hopes of “recovering” the losses. It creates a behavioral trap because they become overconfident in their decisions and are making wrong investment choices and loss aversion prevents them from taking any action. As a result, they become victims of portfolio inertia and keep the failing investment. Instead of selling off unprofitable shares and admitting someone that the market is doing poorly, both Wolves are bearers of two biases. The two described biases promote the disposition effect and provide a perfect opportunity to understand how cognitive and emotional biases contribute to the ration withdrawal from one’s investment during the bear market.

Loss Aversion × Anchoring

Loss aversion and anchoring vindicates the idea of emotion and cognition being mutually supportive and powerful in terms of investment behaviour. Anchoring is wherein market participants give disproportionate weight to reference points (3). These reference points may be the price of the asset, past highs in indices or particular stocks, or current or past value of a portfolio, and so on, with these reference points factoring in assessment of

future pathway. Reference point here takes a psychological, as opposed to economic, valuation, with regards to absolute and relative gain and loss. The market events are gauged with respect to these anchors even if these had no further economic value.

Two other theories, which are closely related to the loss aversion theory, in a way strengthen the anchor effect, and are associated with emotional capital with the difference between the current state and the benchmark [4]. So, if the market price of the asset is falling compared to the purchase price, or lower than the previous maximum, then the investor feels a sense of loss. From an emotional point of view, our country feels that it has lost the market value of the asset in the range from the current state to expectations and previous dynamics on the market. Loss aversion theory states that we perceive loss as such, and re-evaluation of the asset - intrinsic and actual value vs. market price - becomes psychologically unpleasant to deal with. Therefore, we consider the loss of the asset to be profitable, with the hope that over time the market will return to anchor and compensate for the loss of value. The anchor effect strengthens the propensity to distance itself from the sale of the asset, even if the asset does not show positive dynamics. Loss aversion reduces market dynamics and the inertia of re-evaluation. In case of cravings phenomenon, the combination of loss aversion and the anchoring effect increases recovery periods. Investors refuse to change the perception of the market, the value of the asset from the old one to the new one [22, 23].

Loss Aversion × Herd Behavior

Similar economic forces responsible for herding behavior can also be explained through loss aversion as it deals with emotion-based human tendencies. Loss aversion had the investor experience to demonstrate the sensitivity to financial losses and uncertainty in even more another market asset drops than

market asset rises [4]. The most common emotion affecting investor behavior in a distressed market is fear so the investors are more likely to implicitly conform to the behavior of their peers to a much more less degree openly [6]. This does not prevent them from making independent decisions, but a lack of uncertainty makes them more vulnerable to a herd.

Herd behaviour [5] is another behaviour that is linked with the fear inducing shocks in the financial market. Long-term selling by investors results into panic selling and when panic is incorporate among other investors this seeing other side as the owners of the 'information' also and immediately following-down. Panic behaviour across the investors affects herd behaviour as in certain situations people are 'forced' to sell down off their holdings out of panic. It is the panic behaviour in shocks especially during major shocks impacting herding whereby there is the feeling the 'outbreak' of shock events are seen as triggers for panic buying and selling where panic is fly around. Herding shows evidence of behaviours that led to the buying conducted during the panic behaviour events and how the herding presented itself and influence this situations to debauch the accurate market behaviours to be the case as were the starting influences during the Global Financial Crisis and the COVID-Indicate behaviour collapse which lead were financial contagion runaway behaviour . It is this behaviour seen that necessitated the severe socio aspect of market executions have also been explained by the emotional elements that impaction herd during market breaking caused by the economic crisis [20-25].

Overconfidence × Anchoring

The overconfidence bias and anchoring bias are two misperception related cognitive biases that can induce a wrong perception of the data by the investor. The overconfidence bias makes the investor excessively confident in his

judgment and predictions. The anchoring bias makes the investor "anchored" to the first guesses of the price and other anchors [3, 7]. These cognitive biases may create a belief-based thinking - where the investor believes in any guess related to the increase or rise of the asset value, market perspective and general economic situation.

For the investors who are affected by both these biases, the process of information adaptation incorporates loss of anchors as well forecasting problems. Therefore, they tend to defer information adaptation. When the market is deteriorating, they prefer to cling to an overstated forecast despite worsened conditions in a decaying market. The combination of the two biases defers information trading, mispricing and overstatement. In a bullish market, overconfidence and anchoring biases strengthen each other, leading to the violation of a falsification mechanism, with investors treating positives as confirming and negatives as disconfirmatory evidence [22, 23]. The above cognitive rigidity increases the risks of damaging and stressful financial losses and price corrections.

Overconfidence × Herd Behavior

Another effect that overconfidence has impacting herd behavior is seemingly-habitually which contradicts the definition of herd behavior as an obvious consequence of confidence is the lack of independent thinking from the confident investor. Herd behavior stems from social validation of overconfidence by inflated self-perception of one's skills and talents in the financial markets, this causes the confident investor to believe that their ability to decide what is best for the market is better than anyone else but despite this superiority the other-honest, overconfident investor reinforces their decisions based off of the social-factor [7]. Being influenced by social validation, the investor believes they have discovered the most profitable opportunities

from the market which reinforces the now-confident decision from the investor. Overall, herd behavior and confidence creates a synergistic effect rather than adverse effects from the finance market.

Additionally, this phenomenon is accentuated in speculative periods in which the rise in prices and collective participation can lead to an illusion of consensus among participants. In such situations, it functions as a source of 'confirmation' of existing 'beliefs' for investors by observing the behavior of other participants and further reinforcing their conviction and encouraging participation. This generates a feedback mechanism that stimulates excessive optimism, speculation, and bubbles [20-24]. The current example of such effects are hype cycles with currencies like crypto currency, the rise in memes shares, and tech adventure bubbles, where collective enthusiasm strengthens investors' confidence in risky decisions. In this regard, the interaction demonstrates that social influence can amplify cognitive biases that destabilize the market.

Anchoring × Herd Behavior

The group behavior accounts for the non-empirical considering of the expectations set of the agent as groupings change only resulting state in the market. The anchoring bias signals how the validators center on the references points that are constant for all the units that are used by the traders on the floor previously to the communicate on the market [3, 5]. The grouping behavior bias arranging pulses the traders on the marketing company floor in their pegging reference point. All media units of communication, agencies, platforms and other mediators enters in the parties on the market and floor and in the insure unit are signals for anticipated company cost or promising market signal.

Finally, the functioning of herding allows to maintain the collective anchors, when they have been created, by reproducing the

tendency to conform and absence of desire to analyze the situation independently. The actors of the market are afraid to break with standard usually accepted because it brings them cognitive dissonance and social pressure. This is why the investors based on misleading or irrelevant but nevertheless preserved reference points through transformations of financial or non-financial context. The interaction between the functioning of collective anchors and herding practices makes it possible to maintain overprizing, postponement of adjustment and refusal of innovators to accept new evidence [22, 23]. Based on these findings, the author concluded that inefficiency of markets is not relevant to cognitive error of private investors but on social interaction of collective errors of cognition.

Analysis of Three-Way Behavioral Interactions

Loss

Aversion × Overconfidence × Anchoring

The second factor that is driving confidence bias is anchoring in uncertainty conditions. In most situations, overconfident market players are highly certain in their future expectations of the market general tendency and the value of their securities [7, 25]. These expectations are usually anchored on a reference point that may be initial price, expected profitability, or historical maximum market value [3]. If the market is showing price movement consistent with the investor's beliefs, the positive return in this case is perceived as a signal confirming the investor's ability to successfully predict the market, which reinforces his confidence in tendency and expectations.

All the behavioral influences of the loss aversion during a bearish market merely amplify the importance of deviations from these anchors, while investors are blind to their losses and to the opportunity to revise expectations [4]. Rather than keeping an adaptive portfolio that would communicate the information to the investor, the denial options

available from their primary reference points prevail, and they wait for prices to revert to their anchors. Consequently, a holding bias for their losing assets emerges, portfolio rebalancing is postponed and the continuation of malfunctioning investments is encouraged. The compound effect of emotional idleness, cognitive lock-in and over-optimism fully justifies the existence of the disposition effect and illustrates the mechanisms through which various biases conspired to undermine rationality during the downswings in the stock market.

Loss Aversion × Overconfidence × Herd Behavior

The phenomenon of speculative market cycles can be explained by loss aversion, overconfidence, and herd behavior. Overconfidence plays an important role in the rising phases of the business cycle since naturally people underestimate risk and overestimate expected returns [7]. Herd behavior contributes to the optimistic expectation at the market level, which gives additional social validation for participants to take further risks and invest [5]. Finally, the growing market participation reinforces the confidence of market participants, exciting new entrants to invest contributing raise in assets prices.

Sometimes it becomes a herd panic while memory behavior states, that when it turns to bear mode, the emotion of bearish sentiment is fear, which makes the loss to be aversive [4]. What a bubble investor thinks of, one who was overconfident with his investments. The only thing that will be in his mind is how to stop his funded capital from losing more. According to loss aversion nature, this makes the fear spread to his herd. The sentiment goes from "I am losing" to "we are losing", and the boom degenerates into a bust, the market goes from overconfidence to over worry in no time. This drives the volatility in the financial market, and at the end, it drives the financial system

into instability. From this perspective, we can see the connectivity between emotion theories, which led to cognitive theory, which led to social theory, all deepening at the same time their penetration in the financial market.

Loss Aversion × Anchoring × Herd Behavior

Notably, the stock market volatility associated with disasters can also be explained through loss aversion alongside herding and anchoring [3]. Loss aversion affected the financial market, forcing investors to stick to their target values set before the disaster and 'herd' along the entire irrational market, influenced by herding behavior. Therefore, anchoring made them hold their expectations and prices, and the market could not find the weakness behind the stable status quo. It could be too obvious for everyone to realize that the underlying is not as expected, but the market lacks the will to move either away from its expectations or toward accepting losses.

During this process, herding behavior takes the tasks away - an agreement is struck as to what the expectations of the starting point should be [5]. An investor who sees that other investors are not leaving the position takes their actions as a sign that it is best not to leave the position and continue with their forecast and also remains in the position longer than he or she otherwise would. This also applies to entire classes of investors who remain longer than they would have left at the wrong price. This in turn amplifies the effects of a drawn-out recovery, inefficient pricing and inertia in adjusting to the new economic realities after the shock. Overall, the research shows that the recovery process is in many cases driven by emotional attachment, cognitive inertia and herding more than by the economic reality.

Overconfidence × Anchoring × Herd Behavior

Overconfidence, anchoring and herding are arguably the most significant driver in the

formation of speculative bubbles. The signal overconfidence is the investor believes that their intuition of the market opportunities could surpass other participants'; anchoring is based on a specific expectation, valuation, or narrative [3, 7]. With positive market performance, the investor becomes increasingly confident that this would persist, augmenting their sense of optimism and risk-taking behavior.

Then, bubbles in prices could be amplified through collective mechanisms. There are collective steps by numerous participants which herd the same expectations across the markets [5]. Validations are done through collective action and this reinforces cognitive confidence and anchors. There are constructive expectation-holding mechanisms with positive expectations, leading more investors to the values and changes that diverge from fundamental readings. A few examples of the evidences are the Dot-Com Bubble, housing bubble that generated the Global Financial Crises and the bursting of various cryptocurrency bubbles. Cognitive confidence, anchors, and herd validation allow the markets to develop a positive bias initially towards the speculation and mispricing and then the corrections.

Four-way Interaction and Behavioral Systems Theory

The contribution of this study is that it established that the four-way interaction of the loss aversion, overconfidence, anchoring and related herd behavior had effect on investor behavior. These effects as explained previously interact on decision-making process of retail investors on two-way and three-way depictions. Nevertheless, the

complex systems model has effect on four-way and higher-order interaction since it is an integrated effect of emotional, cognitive and social. In this model, the investors value overconfidence (herd behavior), faith in the course of the market path (overconfidence), stable expectations (anchoring) and the positive influence of social interactions on flocking animals on the increase of over-confidence and expectations [3, 5, 7]. This model operates under positive feedback and away from the fundamental value of price because of the position of flocks in the market.

Unrealized losses associated to loss adventures and bad news on one or more of the co-movements investments markets [4]. The former bias is the one used to trigger evidence that the investment market is bad after previous assessments and the overall news idea from other markets that the investor refuses to accept. Pain of loss increases versus sums, social consensus and cognitive anchors help to guide making decisions regarding realizing a loss. The herd effect that brought the optimism consensus during previous euphoric stages gives rode to disbelief and negative effects that make radiate and enhance the new losses. Co-moving variables have play in the same exercise a recurrent feedback dynamic such that the confidence, expectations, social behavior and emotional response reinforce each other in each round of the cyclical process. The emerging conclusion from their arguments is that the underlying and explanatory variable of these phenomena is not the individual investor irrationality but systemic one, based on common effects. Figure 2 illustrates the full Behavioral Systems Theory Model.

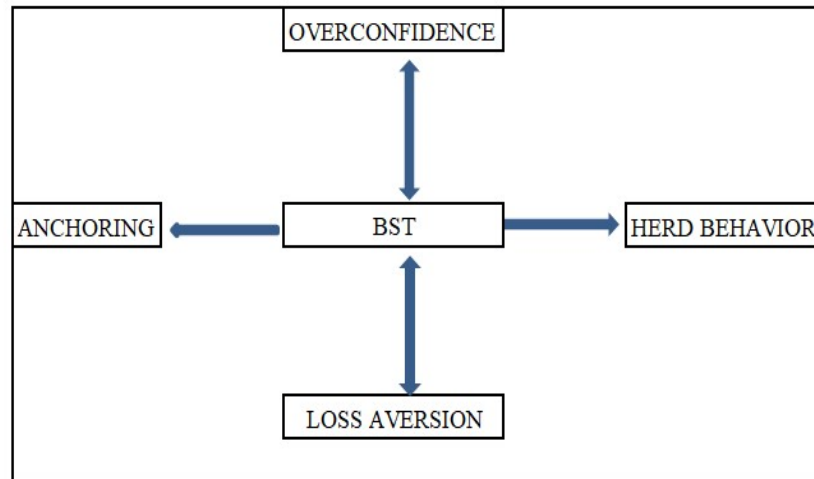


Figure 2. Full Behavioral Systems Theory Model

Source: Developed by the Author

Within this four-way relationship, Behavioral Systems Theory (BST) portrays itself as a novel and unified behavioral framework wherein the investors' behavior in condition of uncertainties and crises bears the implication of BST. The general premise of the theory assumes that financial decision-making is shaped by three key dimensions which correspond to on-field financial psychology, that is 1) emotional dimension based on the loss aversion at the core of the fear and greed systems, 2) cognitive dimension linked to overconfidence and anchoring biases, and 3) social dimension associated with herd behavior. Instead of being treated as individual components, each of these dimensions interacts with one another via feedback loops that allow the emergence of undesired behavioral outcomes. Therefore, speculative bubbles, panic selling, time in the black, excessive volatility and financial contagion along with many other phenomena might be the outcome of a behavioral system at play.

Theoretical contribution of the model - BST contributes as a theoretical framework by positioning itself in contrast to common behavioral finance models. It is acknowledged that previous research has demonstrated the impact on financial decisions due to specific behavioral biases. However, no systematic investigation exists that focused on it in detail.

Understanding that a financial crisis usually does not occur due to only one behavioral bias but because several biases interact among themselves and with other ones. BST architecture in behavioral finance offers a multidimensional explanation for market failure since it understands investor behavior occurs due to influencing dynamic interactions between emotional factor, cognitive factor, and social factor. It rises to an increased understanding of mechanisms and their synergetic implications in the financial market in the light of behavioral finance within a systems approach.

Contributions

This study contributes to behavioral finance literature in several important ways.

1. It develops a Behavioral Systems Theory integrating cognitive, emotional, and social biases.
2. It extends behavioral finance beyond isolated-bias analysis.
3. It applies combination theory to multidimensional behavioral interactions.
4. It integrates narrative finance and complexity theory into behavioral finance research.

Practical Implications

The findings provide practical implications for investors, regulators, financial institutions, and policymakers.

Investors should recognize that irrational decision-making often emerges from interacting biases rather than isolated psychological distortions. Financial institutions may incorporate behavioral risk monitoring into portfolio management systems. Regulators may use behavioral systems analysis to anticipate speculative bubbles, panic selling, and crisis contagion.

The study also suggests that digital investment platforms should consider implementing behavioral safeguards capable of reducing emotional contagion and speculative amplification.

Conclusions and Recommendations

The analysis done in this article showcases how irrational behaviour of investors during the crisis timeline can be best holistically explained by the multidimensional behavioural model which is interconnected through the feedback system of loss aversion, overconfidence, anchoring and herd effect. None of the behavioural bias works in isolation rather they all interconnect and interplay with each other through the emotional, cognitive and social feedback systems.

It justifies as well that modern-day digitalized finance has made collective behavior from traders' activities in online-social media, hype-communities, and algorithm-driven information systems and has caused the collective behavior whereby fluctuations in the market and emotions circulate among the financial system.

The study recommends that future research:

1. Empirically test the Behavioral Systems Theory using SEM and longitudinal data.

2. Examine cross-country variations in multidimensional behavioral interactions.
3. Develop behavioral intervention mechanisms capable of reducing crisis-driven irrationality.
4. Expand behavioral systems analysis to institutional and corporate investment behavior.

Data Availability

No new datasets were generated or analyzed during this study. The research is based entirely on qualitative narrative synthesis of publicly available secondary sources, including peer-reviewed journal articles, scholarly books, institutional reports, and documented historical accounts of major financial crises such as the Dot-Com Bubble, the Global Financial Crisis (2008), the COVID-19 market crash, and post-pandemic market developments. All sources used in the preparation of this manuscript are cited in the reference list.

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Ethical Approval

The study relies exclusively on secondary literature and publicly available crisis narratives. Ethical approval was therefore not required.

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Conflict of Interest

The author declares no conflict of interest.

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Reproducible Multistage Mixed-Methods Sampling Methodology for Studying the Mental Health and Psychosocial Support (MHPSS) Workforce in Complex Humanitarian Settings: A Methodological Framework from Gambella, Ethiopia

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Abstract Evidence on the Mental Health and Psychosocial Support (MHPSS) workforce in refugee settings remains limited due to workforce diversity, staff mobility, multiple organizations, geographically dispersed services, and incomplete personnel records. This study developed and implemented a rigorous mixed-methods sampling protocol to assess the MHPSS-related workforce in Ethiopia's Gambella Region. A convergent mixed-methods design combined multistage stratified probability sampling for the quantitative component with purposive sampling for the qualitative inquiry. The sampling frame was developed using the June 2026 5Ws matrix and organizational staffing records, then verified with focal persons. Sample size was calculated using Cochran's formula with finite population correction, plus 10% for non-response. Proportional allocation across organizations was used with intentional oversampling of smaller professional cadres. The verified sampling frame included 1,336 eligible personnel from 12 organizations. After finite population correction, the required sample was 299 participants, with a final target of 332 after accounting for non-response. Systematic random sampling was conducted within final strata, supported by reserve lists and replacement procedures. Sampling weights were specified to account for unequal selection probabilities. This protocol provides a transparent, reproducible, and practical approach for studying heterogeneous humanitarian MHPSS workforces, informing workforce planning, capacity development, and service improvement in refugee-hosting settings.

Keywords Humanitarian Settings, MHPSS, Mixed-Methods, Refugees, Workforce.

Introduction

Mental Health and Psychosocial Support (MHPSS) is essential to humanitarian response because armed conflict, forced displacement, disease outbreaks, natural disasters, and other emergencies can have profound psychological and social consequences [1]. People affected by crises face increased risks of depression, anxiety, post-traumatic stress disorder (PTSD), prolonged grief, substance use disorders, severe mental illness, and psychosocial distress [2, 3]. In response, humanitarian agencies have increasingly integrated MHPSS into health, protection, gender-based violence (GBV), child protection, nutrition, and education programs to promote well-being and strengthen community resilience [1, 4].

Problem to be Solved

The effectiveness of MHPSS services depends largely on the availability of a competent, well-distributed workforce [5]. This workforce includes psychiatrists, psychologists, psychiatric nurses, social workers, counselors, community psychosocial workers, GBV case managers, GBV Response Officers, GBV Prevention Officers, General Practitioners, Nurses, Health Officers, Midwives, refugee incentive workers, program managers, supervisors, and personnel working with Refugee-Led Organizations (RLOs), Local NGOs, National NGOs, and International NGOs in the Health and GBV sectors [6]. Despite their important role, humanitarian settings continue to face workforce shortages, uneven geographic distribution, limited training opportunities, high staff turnover, and inadequate supervision [7]. These challenges can affect both service quality and people's access to services [8, 9].

Reliable information on the barriers and drivers of MHPSS workforces, as well as their characteristics, capacity, and distribution, is essential for effective workforce planning, policy development, and evidence-informed programming [10, 11]. However, collecting

representative workforce data in humanitarian settings is challenging. Populations and services are often geographically dispersed, organizational structures can change rapidly, personnel may move between locations or organizations, and comprehensive workforce registries are frequently unavailable [12, 13]. These factors make it difficult to develop accurate sampling frames and to implement probability-based sampling approaches [13, 14].

Existing Solutions and Their Limitations

Previous studies have employed various sampling approaches to study humanitarian workforces. Some have used convenience sampling, which is practical but introduces selection bias and limits generalizability [13]. Others have attempted probability sampling using organizational staff lists, but these lists are often incomplete, outdated, or not consolidated across multiple agencies [14]. Simple random sampling, while statistically robust in theory, is difficult to implement when the workforce is distributed across different organizations, sectors, and geographic locations with no single comprehensive registry [36]. Stratified sampling has been used in some contexts, but often without adequate representation of smaller professional cadres, limiting subgroup analysis [37].

Purposive sampling has been widely used in qualitative MHPSS research, providing rich contextual data on workforce experiences and organizational practices [14, 15]. However, qualitative findings alone cannot provide population-level estimates of workforce characteristics, distribution, or the prevalence of workforce challenges [16]. Mixed-methods approaches have been recommended for MHPSS research, but few studies have documented a systematic, reproducible protocol that integrates probability sampling for quantitative components with purposive sampling for qualitative components in complex humanitarian settings [14, 17].

Best Approach: Mixed-Methods Multistage Stratified Sampling

The most appropriate approach for studying the MHPSS workforce in complex humanitarian settings is a convergent mixed-methods design that combines multistage stratified probability sampling for the quantitative component with purposive sampling for the qualitative component [14]. This approach offers several advantages. First, stratified sampling ensures representation across key organizational, geographic, sectoral, and professional characteristics, improving the precision of estimates and enabling subgroup analysis [37]. Second, multistage sampling accommodates the hierarchical and dispersed nature of humanitarian service delivery [13]. Third, probability sampling enables valid statistical inference and population-level estimation [36]. Fourth, purposive qualitative sampling provides contextual depth and explanatory power that survey data alone cannot provide [16]. Fifth, integrating quantitative and qualitative evidence strengthens the credibility and comprehensiveness of the findings [14].

Limitations of Existing Approaches

Despite the advantages of mixed-methods approaches, several limitations persist in current practice. First, sampling frames are often incomplete due to staff mobility, multiple organizations, and lack of centralized workforce registries [12, 13]. Second, proportional allocation may underrepresent small but strategically important professional cadres, limiting the ability to conduct meaningful subgroup analysis [37]. Third, non-response is common in humanitarian settings due to competing operational demands, staff turnover, and mobility, yet replacement procedures are often not systematically

documented [36]. Fourth, sampling weights are frequently not specified when disproportionate sampling is used, limiting the ability to generate population-level estimates [38]. Fifth, the integration of quantitative and qualitative components is often not clearly described, reducing the reproducibility of the methodology [14].

Achievements of this Protocol

This protocol addresses these limitations through several key achievements. First, it establishes a verified sampling frame by consolidating multiple organizational records and verifying eligibility with designated focal persons [36]. Second, it uses proportionate allocation across organizations with intentional oversampling of smaller professional cadres to improve analytical representativeness while specifying sampling weights for population-level inference [38]. Third, it implements systematic random sampling within strata with reserve lists and documented replacement procedures to address non-response [39]. Fourth, it integrates quantitative and qualitative components within a convergent mixed-methods design, with clear documentation of sampling procedures for reproducibility [14]. Fifth, the protocol is implemented in a complex humanitarian setting with multiple organizations, dispersed service delivery sites, and diverse professional cadres, demonstrating operational feasibility [13, 14].

Conceptual Framework

Figure 1 illustrates the conceptual framework guiding this study. The framework depicts the sequential process of developing the sampling frame, applying multistage stratification, selecting participants through probability and purposive sampling, and integrating quantitative and qualitative data for comprehensive workforce assessment.

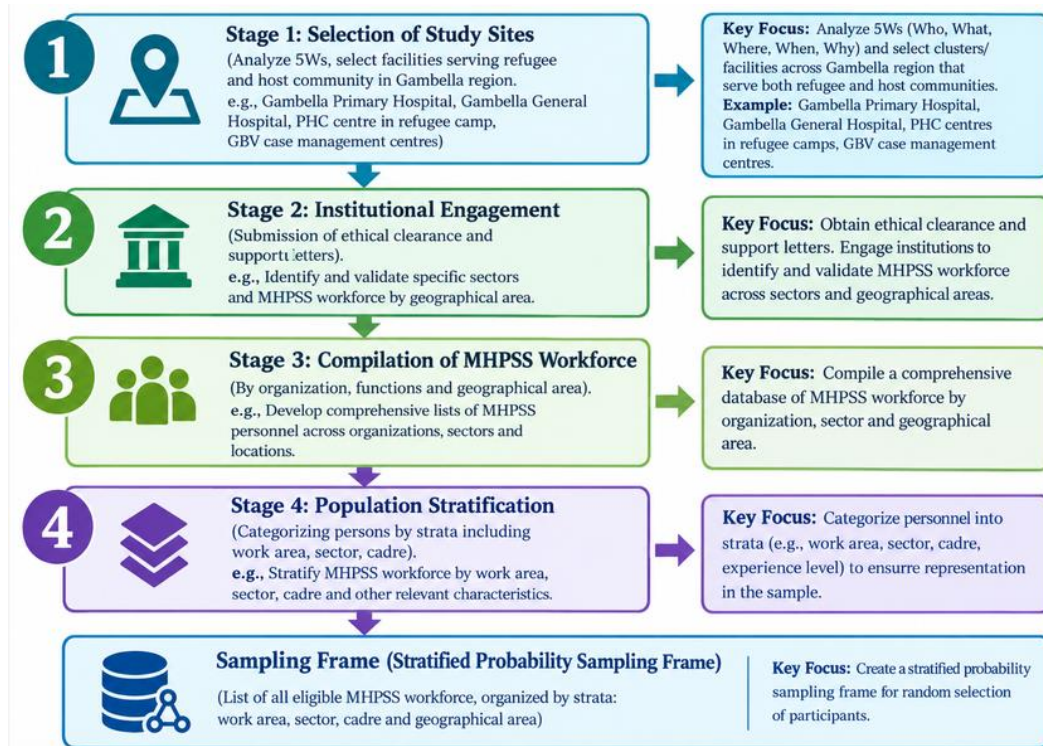


Figure 1. Conceptual Framework of the Multistage Mixed-Methods Sampling Protocol

Source: Original work of the author

Study Objectives

The overall objective of this study was to develop and implement a rigorous mixed-methods sampling protocol to assess the MHPSS-related workforce in the Gambella Region, Ethiopia. Specific objectives were to:

1. Develop a verified sampling frame of eligible MHPSS personnel across organizations, sectors, and professional cadres in the Gambella refugee response
2. Determine an appropriate quantitative sample size using finite population correction and account for anticipated non-response
3. Allocate the sample proportionally across organizations with intentional oversampling of smaller professional cadres
4. Implement systematic random sampling within strata with documented replacement procedures
5. Specify sampling weights to account for unequal selection probabilities

6. Recruit information-rich participants for qualitative inquiry using purposive sampling
7. Document the sampling procedures to ensure transparency and reproducibility

Novelty of the Work

This protocol makes several novel contributions to humanitarian workforce research. First, it provides a transparent, step-by-step framework for constructing a verified sampling frame in a setting with multiple organizations, dispersed service delivery, and incomplete personnel records—a common challenge in humanitarian contexts that is rarely addressed in methodological literature [13, 14]. Second, it demonstrates how to balance population representativeness with analytical representativeness through intentional oversampling of smaller professional cadres while specifying sampling weights to enable population-level inference [38]. Third, it provides a practical example of implementing systematic random sampling with reserve lists

and replacement procedures in a complex humanitarian setting, addressing non-response in a way that maintains probability-based selection [39]. Fourth, it integrates quantitative and qualitative sampling within a convergent mixed-methods design, with clear documentation of procedures to support reproducibility in other humanitarian settings [14]. Fifth, it applies these methods specifically to the MHPSS workforce, a critical yet understudied area in humanitarian response [10, 11]. This protocol contributes to the methodological literature on sampling in complex settings and provides a practical tool for researchers, program managers, and policymakers seeking to generate evidence on humanitarian workforces.

Materials and Methods

Study Setting

The study was conducted in the Gambella Region of western Ethiopia from July 15 to August 15, 2026, a major refugee-hosting area with a longstanding humanitarian response to displacement from South Sudan [18]. The response involves government institutions, United Nations agencies, International NGOs, National NGOs, and Local NGOs, including refugee-led organizations [19]. MHPSS services are delivered through refugee camps, health facilities, community platforms, schools, and protection programs, reflecting the multisectoral and inter-agency nature of humanitarian MHPSS programming [1].

Population

The study population included health and GBV sector personnel involved in planning, coordinating, managing, supervising, and delivering MHPSS services within the Gambella refugee response [20]. This included personnel from the Regional Health Bureau, INGOs, NNGOs, and local NGOs/refugee-led organizations [21]. Eligible personnel may be involved in program management, technical coordination, clinical and psychosocial

services, protection, GBV, community outreach, and supervision in the health and GBV sectors [22].

The target population included individuals who meet the predefined eligibility criteria and are actively involved in MHPSS implementation during the study period [23]. The source population comprised eligible personnel identified through verified organizational records, including human resources databases [24]. These sources were coded by cadre category and consolidated to establish the quantitative sampling frame [25].

Unit of Analysis and Eligibility Criteria

The primary unit of analysis for the quantitative component was individual humanitarian staff in the health and GBV sectors whose direct role involves providing MHPSS to people in need [26]. This aligns with research on mental health, psychosocial well-being, burnout, and work-related experiences among humanitarian personnel [27, 28]. For the qualitative component, the units of analysis included individual key informants, focus-group participants, and organizational representatives in the health and GBV sectors [29]. This approach reflects the multisectoral nature of MHPSS programming, in which responsibilities and knowledge are distributed among mental health professionals, psychosocial workers, primary health care staff, GBV prevention and response staff, program managers, coordinators, and other humanitarian actors, including refugee-led organizations [1, 30].

Participants were eligible if they were 18 years or older, employed or formally engaged by a humanitarian organization operating in Gambella, had at least one month of MHPSS-related experience prior to data collection, were directly involved in MHPSS planning, coordination, supervision, implementation, or support, were available during the data-collection period, and provided written informed consent [31]. These criteria align with

previous MHPSS research involving adult practitioners and humanitarian personnel actively engaged in MHPSS or humanitarian activities [32, 33]. Given the current global funding crisis, many front-line staff cannot work for more than six months. Therefore, the practical experience threshold was one month.

Individuals were excluded if they had less than one month of relevant experience, were on extended leave during the data-collection period, performed only administrative or logistical duties unrelated to MHPSS, or were unable or unwilling to provide informed consent [34]. The study obtained written informed consent before participation, in accordance with ethical requirements for research involving human participants [27, 35].

Sampling Frame Development

The research team developed a verified sampling frame of eligible MHPSS personnel through a systematic process of organizational engagement, compilation, screening, data cleaning, and verification. Following institutional approval and organizational authorization, updated personnel records, including the number and categories of personnel by duty station, were obtained from participating organizations and coded according to organization, duty station, professional cadre, and programme sector [36]. Duplicate records and individuals who did not meet the study eligibility criteria were removed. The resulting sampling frame included a unique identification number for each eligible participant, organization, duty station, professional cadre, programme sector, employment status, and duration of service [37].

The compiled staffing lists were double-checked against human-resource and programme records at facility level to confirm eligibility, employment status, professional role, duty station, and programme assignment [38]. Any discrepancies, duplicate records, or incomplete information were discussed and

resolved with the designated organizational focal person before the sampling frame was finalized. This verification process strengthened the accuracy and completeness of the sampling frame and ensured that each eligible individual was represented only once.

The Principal Investigator reviewed and approved the finalized sampling frame before participant selection commenced. Verification and double-checking were particularly important for establishing a valid probability-sampling frame in which each eligible individual had a known, non-zero probability of selection. Where a selected participant could not be located at the assigned workplace during data collection because of unforeseen circumstances, replacement was made from a pre-established reserve list generated using the same stratification and random-selection procedures. This approach minimized disruption to fieldwork while preserving the methodological integrity and representativeness of the sampling procedure.

Sampling Stratification and Coverage Control

To improve representativeness and reduce sampling error, the quantitative sample was stratified by study site (Jewi, Kule, Tierkidi, Nguenyiel, Luakdong, Akula, Pugnido I, Pugnido II, and Gambella Town), organization type (government, INGOs, NNGOs, and local NGOs/RLOs), program sector (health and GBV), and professional cadre. The professional cadres included program managers, coordinators and supervisors; mental health professionals, including psychologists, psychiatric nurses, general nurses, general practitioners, and midwives; health officers/clinical officers; GBV prevention and response officers; social workers; counselors; community psychosocial workers; case managers; and refugee incentive workers, including community health workers and GBV outreach workers.

To reduce coverage errors, the team compared staffing records from organizational, site, and facility-level sources before finalizing the sampling frame. This process helped identify and address duplicate records, missing personnel, staff transfers, recruits, resignations, and other inconsistencies. The study obtained access to personnel records, including the type and number of cadres at each facility, through written institutional authorization. The study collaborated with agency and facility heads, as well as cadre supervisors, to support random participant selection. The study did not use identifiable information, and participants were encouraged to participate freely and voluntarily without providing unique identifiers, such as their name, email, or phone number.

The study used a convergent mixed-methods design, combining probability sampling for the

quantitative survey with purposive sampling for the qualitative component. The study collected quantitative and qualitative data concurrently and analyzed them separately before integrating them during interpretation. The quantitative component described the characteristics and distribution of the MHPSS workforce and the status of professional quality, organizational support, and job satisfaction. In contrast, the qualitative component provided a deeper understanding of contextual experiences, organizational practices, implementation challenges, and priorities for strengthening the workforce. Bringing the two components together provided complementary perspectives and contributed to a more comprehensive and credible understanding of the MHPSS workforce. The convergent mixed-methods design is summarized in Figure 2 [39-41].

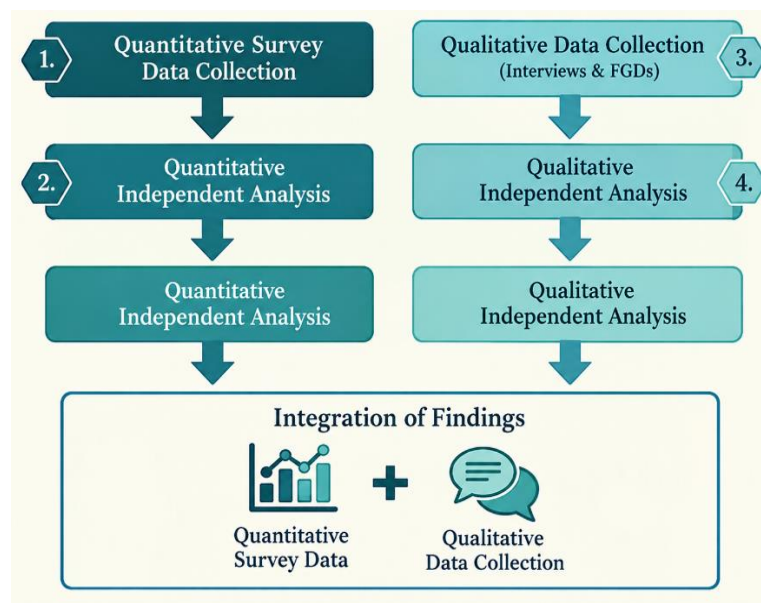


Figure 2. Convergent Mixed-Methods Design

Sampling Approach

The study used multistage proportionate stratified random sampling for the quantitative component and purposive sampling for the qualitative component. For the quantitative component, the study included all eligible MHPSS service locations, including refugee camps and designated health facilities, to capture the workforce's geographic and

organizational diversity. The study then identified eligible organizations and stratified participants by location, organization type, program sector, and professional cadre. Participants were allocated proportionally across strata and selected through systematic sampling. This approach ensured that each eligible individual had a known and equal probability of selection within their stratum [13, 14].

For the qualitative component, participants were purposively selected based on their relevant knowledge and experience in MHPSS leadership, programming, and service delivery, primarily from INGOs, NGOs, RLOs/CBOs/LNGOs, RHB, and hospitals. This approach helped identify information-rich participants who could provide detailed insights into the contextual and operational aspects of MHPSS implementation, including primary health care, hospitals, GBV case management facilities, women's and girls' safe spaces, and community-based activities [14, 16].

Proportionate Stratified Sampling

The quantitative component of the study used proportionate stratified random sampling. The eligible workforce population was first divided into relevant, mutually exclusive strata, and the number of participants selected from each stratum was proportional to that stratum's size within the total eligible workforce population. Proportionate allocation is an established stratified sampling approach in which the sample size assigned to each stratum reflects the stratum's proportion of the total population. The proportional allocation formula is:

$$n_h = (N_h / N) * n$$

Where:

n_h = Sample allocated to stratum h

N_h = Population size of stratum h

N = Total eligible population

n = Total sample size

After verifying the sampling frame, each eligible participant was assigned a unique identification number and entered into a secure spreadsheet for randomization. Participants were then ordered according to the resulting random sequence and selected within each stratum until the required sample size was reached. A reserve list was generated from the same random sequence to replace non-respondents or participants who became ineligible, while maintaining the original probability-based selection process. All

sampling and randomization procedures were documented to promote transparency and reproducibility, in line with established principles of stratified random sampling.

For the qualitative component, purposive sampling identified information-rich participants based on professional expertise, leadership responsibilities, humanitarian experience, program involvement, and knowledge of MHPSS planning and service delivery in the health and GBV sectors, primarily from RHB, Hospitals, INGOs, NNGOs, and CBOs/LNGOs. This approach suits qualitative inquiry because it intentionally selects participants whose experiences and knowledge provide detailed information relevant to the research questions.

Qualitative Sampling: Key Informant Interviews and FGDs

Key informant interviews (KIIs) purposively recruited focal persons from the health and GBV sectors in RHB, hospitals, INGOs, NNGOs, and CBOs/LNGOs involved in MHPSS programming, implementation, and supervision. Focus group discussions (FGDs) included frontline workers such as counselors, psychosocial workers, psychiatric nurses, social workers, refugee incentive workers, community health workers, GBV outreach workers, GBV case managers, the GBV Prevention Officer, and response officers.

Each FGD included approximately 6-10 participants with broadly similar professional roles to encourage open discussion and reduce potential power imbalances. The qualitative sample was expected to include approximately 8-12 program managers, 8-10 technical specialists, 6-10 RLOs, and 10-15 participants across 4-6 FGDs with frontline workers. However, the final qualitative sample size was guided by thematic saturation rather than determined solely by the initial estimates [14, 16].

Results

Identification of the Eligible Workforce

A review of the June 2026 Who is doing what, Where, When, and for Whom (5Ws) matrix, jointly compiled by the United Nations High Commissioner for Refugees (UNHCR), the Refugees and Returnees Service (RRS), and implementing partners, identified 12 organizations providing Health and/or Gender-Based Violence (GBV) services with MHPSS-related components in the Gambella refugee response. These organizations formed the organizational sampling frame.

Subsequent verification with designated organizational focal persons identified an eligible MHPSS-related workforce of 1,336 personnel across the health and GBV sectors. The workforce included medical doctors, nurses, midwives, Health Officers, MHPSS professionals, community health workers (CHWs), GBV prevention and protection officers, GBV response officers, GBV managers/supervisors, and GBV outreach agents/social workers. CHWs constituted the largest professional group (613; 45.9%),

followed by nurses (263; 19.7%) and social workers (256; 19.2%). MHPSS professionals represented the smallest group (14; 1.0%), followed by protection officers (22; 1.6%) and response officers (35; 2.6%).

Sampling Frame and Workforce Distribution

The team developed the final sampling frame by consolidating organizational staffing records and verifying participant eligibility with designated organizational focal persons. The team removed duplicate, inactive, and ineligible records and cross-checked information on organization, program sector, professional cadre, and duty station before sampling began.

The resulting workforce comprised 1,336 eligible personnel across the Health and GBV programs. DPO reported the largest workforce (n = 495), followed by GGH (n = 184), GPH (n = 147), PI (n = 124), Goal (n = 89), IRC (n = 79), RLOs (n = 74), CUAMM (n = 61), FRC (n = 46), DCA (n = 24), ASDEPO (n = 7), and RADO (n = 6) (Table 1).

Table 1. Distribution of Eligible MHPSS-Related Workforce by Professional Cadre

Professional Cadre	Population (N)	Proportion (%)
Community Health Workers	613	45.9
Nurses	263	19.7
Social Workers	256	19.2
Medical Doctors	46	3.4
Health Officers	45	3.4
Midwives	42	3.1
Response Officers	35	2.6
Protection Officers	22	1.6
MHPSS Professionals	14	1.0
Total	1,336	100.0

Determination of the Quantitative Sample Size

We determined the quantitative sample size using Cochran's formula for estimating a single

population proportion. In the absence of prior estimates of the distribution of the principal workforce characteristics in Gambella, we assumed a conservative 50% prevalence. We

specified a 95% confidence level and a 5% margin of error. The initial sample size was:

$$n_0 = (z^2 \times p \times q) / d^2$$

where $Z = 1.96$, $p = 0.50$, $q = 0.50$, and $d = 0.05$. This yielded an initial sample of 384.16 participants.

Because the eligible workforce was finite ($N = 1,336$), the finite population correction was applied:

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

The corrected sample size was approximately 298.6 participants. Allowing for an anticipated 10% non-response rate:

$$n_{adj} = 332$$

The final quantitative sample was therefore 332 participants (Table 2).

Table 2. Summary of Quantitative Sample-Size Determination using Cochran's Formula with Finite Population Correction

Parameter	Value
Eligible workforce (N)	1,336
Initial Cochran sample (n_0)	384.16
Finite population-corrected sample	298.6
Anticipated non-response	10%
Final sample size	332

Proportional Allocation Across Organizations

The final sample of 332 participants was initially allocated proportionally across the 12 organizations according to their representation in the eligible workforce. The allocation was calculated as:

$$n_h = (N_h / N) * n$$

where n_h represents the sample allocated to stratum h , N_h represents the eligible workforce in that stratum, N represents the total eligible workforce (1,336), and n represents the total sample (332).

The largest allocation was assigned to DPO (123 participants), reflecting its comparatively large workforce, followed by GGH (46), GPH (37), PI (31), Goal (22), IRC (20), RLOs (17), CUAMM (15), FRC (11), DCA (6), ASDEPO (2), and RADO (2) (Table 3).

Table 3. Initial Proportional Allocation of the Quantitative Sample Across Organizations, Calculated as $(N_h/N) \times n$, Before Applying Oversampling to Small Professional Cadres

Organization	Workforce (N)	Proportion (%)	Sample (n)
DPO	495	37.05	123
IRC	79	5.91	20
PI	124	9.28	31
Goal	89	6.66	22
CUAMM	61	4.57	15
ASDEPO	7	0.52	2
RADO	6	0.45	2
DCA	24	1.80	6
FRC	46	3.44	11
GPH	147	11.00	37
GGH	184	13.77	46

RLOs	74	5.54	17
Total	1,336	100.00	332

Multistage Stratification and Participant Selection

The final sampling procedure combined geographic, organizational, sectoral, and professional stratification before selecting individual participants. We retained all identified refugee camps and referral health facilities in the sampling frame, then stratified eligible personnel by organization, program sector, and professional cadre.

Within each final stratum, we selected participants using systematic random sampling. The sampling interval was calculated as:

$$k = \frac{N_h}{n_h}$$

where N_h was the number of eligible personnel in the stratum and n_h was the required sample size. We generated a random starting point between 1 and k , then selected every k th eligible individual until we reached the required allocation.

This procedure ensured that selection remained probability-based while accommodating the geographically dispersed and organizationally heterogeneous nature of the humanitarian workforce. We used a reserve list generated using the same randomization procedure when selected participants declined participation, were subsequently found

ineligible, or could not be contacted after three documented attempts. Replacement was restricted to the same relevant sampling stratum to preserve the intended sampling structure.

Representation of Small Professional Cadres

The workforce distribution demonstrated substantial imbalance across professional cadres. Under strict proportional allocation, the large CHW workforce would account for approximately 152 of the 332 participants, whereas only approximately 3 MHPSS professionals, 5 protection officers, and 9 response officers would be selected. Although proportional allocation accurately reflects the underlying workforce composition, such small subgroup samples would substantially limit the precision of cadre-specific analyses.

Accordingly, the sampling design incorporated disproportionate allocation of selected smaller professional cadres to improve their analytical representation. The MHPSS professional group was included through a census approach (14 of 14 personnel), while protection officers, response officers, medical doctors, health officers, and midwives received higher allocations than strict proportional sampling would allow. The remaining sample was distributed among the larger professional groups (Table 4).

Table 4. Final Sample Allocation by Professional Cadre, with Oversampling of Small Professional Groups to Improve Analytical Representativeness

Professional Cadre	Population (N)	Final Sample (n)	Sampling Fraction (%)
MHPSS Professionals	14	14	100.0
Protection Officers	22	20	90.9
Response Officers	35	30	85.7
Medical Doctors	46	30	65.2
Health Officers	45	30	66.7
Midwives	42	30	71.4
Social Workers	256	40	15.6

Nurses	263	40	15.2
Community Health Workers	613	98	16.0
Total	1,336	98	16.0

Because selection probabilities differed across professional cadres, we specified sampling weights for subsequent quantitative analysis. The stratum-specific weight was calculated as:

$$w_h = \frac{(N_h|N)}{(n_h|n)}$$

This weighting procedure allows population-level estimates to reflect the underlying workforce distribution despite the deliberate oversampling of smaller professional groups.

Discussion

This protocol demonstrates how a multistage mixed-methods sampling strategy can be adapted to a diverse and changing humanitarian MHPSS workforce. Its main methodological contribution is combining a verified organizational sampling frame, probability-based quantitative sampling, purposive qualitative recruitment, and deliberate representation of smaller professional cadres. Unlike a conventional workforce confined to a single geographic or organizational setting, humanitarian MHPSS personnel are distributed across different organizations, sectors, professional groups, and refugee-hosting locations. A simple random sampling approach would therefore be difficult to implement and could underrepresent professionally or strategically important cadres [13, 14].

The sampling frame identified 1,336 eligible personnel across 12 organizations, with considerable variation in workforce composition. Community health workers accounted for 45.9% of the workforce, while MHPSS professionals represented only 1.0%; nurses and GBV Outreach agents/social workers were also major workforce groups. This distribution highlights that MHPSS delivery extends beyond specialist mental

health professionals and reflects the multisectoral, layered, and task-sharing nature of humanitarian MHPSS programming [1, 4, 30]. Limiting the sampling frame to formally designated mental health professionals would therefore exclude many personnel who contribute to MHPSS services. At the same time, treating the workforce as a single homogeneous group would overlook important differences in roles, training, supervision, and responsibilities.

Using organizational records on staffing by cadre, along with the June 2026 5Ws UpToDate matrix, to construct the sampling frame was an important strength of the protocol. Humanitarian personnel may be distributed across multiple agencies, facilities, and program databases and may frequently transfer between locations, join organizations, or leave their positions. Relying on a single data source could therefore result in missing or duplicate records. Consolidating multiple sources and verifying eligibility with organizational focal persons improved the sampling frame's completeness and provided a practical foundation for probability-based sampling [36].

The sample-size calculation was appropriate for a defined population of 1,336 personnel. The conservative Cochran assumption of 50% prevalence provided a maximum-variance estimate, while the finite population correction reduced the required sample to approximately 299 participants. Adding 10% to account for anticipated non-response resulted in a final target of 332 participants. This approach is transparent and can be reproduced in other humanitarian settings by using the locally verified workforce population and relevant assumptions.

Proportional allocation across organizations aligned with workforce size and resulted in the largest allocations to DPO, GGH, GPH, PI,

Goal, IRC, RLOs, CUAMM, FRC, DCA, ASDEPO, and RADO. However, strict proportional allocation would have produced very small numbers for some professionally important cadres. For example, approximately 152 participants would have been selected from the large CHW group, while only about three MHPSS professionals would have been included. The protocol therefore used disproportionate allocation, included all 14 MHPSS professionals, and ensured substantial representation of other small cadres. This approach distinguishes population representativeness from analytical representativeness: proportional sampling reflects the actual workforce composition, whereas oversampling improves the ability to examine smaller but important groups.

Because disproportionate sampling creates unequal selection probabilities, appropriate sampling weights are needed to produce population-level estimates [36]. The final allocation included all 14 MHPSS professionals, 20 of the 22 GBV prevention officers, and 30 of the 35 GBV response officers, while also adequately representing other cadres. This strengthens subgroup analysis without preventing population-level inference, provided that the selection probabilities are accurately documented and incorporated into the analysis.

Random selection within the final strata and the use of a reserve list further strengthened the sampling procedures. A randomly determined starting point and sampling interval reduced the possibility of discretionary participant selection, while reserve participants were drawn from the same probability-based sequence and relevant stratum. This reduced the risk that field teams would substitute convenient participants and helped prevent non-response from turning the probability sample into a convenience sample [36]. Such procedures are particularly important in humanitarian settings, where staff mobility, leave, turnover, competing operational

demands, and unexpected disruptions can affect participant availability.

The qualitative component followed a different but complementary sampling logic. Purposive sampling recruited information-rich participants with relevant leadership, technical, frontline, community, and organizational experience. This complements the quantitative component by providing contextual explanations of workforce capacity, organizational practices, barriers, supervision, and service-delivery experiences that survey data cannot fully capture [14]. Separating frontline focus groups from senior managerial or technical groups may also reduce power-related constraints and create a more comfortable environment for discussing workload, supervision, organizational support, and resource limitations.

Including refugee-led organizations, incentive workers, and other community-level personnel is particularly important because MHPSS delivery depends not only on formally trained professionals but also on locally embedded and non-specialist actors. Their perspectives can highlight operational realities that may not appear in administrative workforce records and align with the community-based and multisectoral orientation of MHPSS [1, 30].

The one-month experience criterion provides a practical threshold to ensure participants have had sufficient exposure to MHPSS-related activities to comment meaningfully on workforce capacity and operational challenges. However, this criterion is study-specific rather than a universal standard and may need adaptation to workforce composition, staff turnover, and research objectives in other settings [32].

The convergent mixed-methods design strengthens the study by combining population-level estimates with contextual explanations. Quantitative findings can identify patterns in workforce composition, distribution, and experiences, while qualitative evidence can help explain the organizational and operational

factors underlying those patterns. Integrating the two components during interpretation allows the study to identify areas of convergence as well as differences between the two strands of evidence [14].

Several limitations should also be considered. The quantitative sample depends on the completeness and accuracy of organizational records and may not capture informal, temporary, newly recruited, or recently departed personnel. The workforce definition is also limited to personnel involved in Health and GBV programs with MHPSS-related components. It may not capture all actors contributing to MHPSS through sectors such as education, child protection, nutrition, livelihood, or community protection. Oversampling improves representation of smaller subgroups but requires appropriate weighting for population-level estimates. Similarly, purposive qualitative sampling provides contextual depth but is not intended to achieve statistical representativeness. Finally, because humanitarian workforces can change rapidly, the sampling frame represents the workforce at a particular point in time rather than a permanent or fixed structure.

Despite these limitations, the protocol provides a transferable framework for humanitarian workforce research. The approach involves defining and verifying the workforce, consolidating multiple administrative sources, establishing clear eligibility criteria, stratifying participants according to analytically relevant characteristics, determining and allocating the sample transparently, oversampling important small groups when justified, documenting unequal selection probabilities, and integrating quantitative and qualitative evidence. Overall, the protocol demonstrates that methodological rigor and operational feasibility can be achieved together in complex humanitarian settings.

Conclusion

This protocol provides a rigorous and operationally feasible framework for sampling the MHPSS-related workforce in a complex humanitarian setting. Using the June 2026 5Ws matrix and organizational verification, it established a sampling frame of 1,336 eligible personnel across 12 organizations and a quantitative sample of 332 participants based on a finite population-adjusted sample-size calculation and an allowance for anticipated non-response.

A key strength of the protocol is its balance between population-level representativeness and adequate representation of smaller but strategically important professional cadres. Proportional allocation across organizations reflects the overall workforce structure, while disproportionate sampling and census inclusion of small specialist groups support meaningful subgroup analysis. Sampling weights can then support population-level inference despite unequal selection probabilities.

The qualitative component complements the survey by purposively recruiting management, technical, frontline, community, refugee-led, health, and GBV-related personnel. Together, the two approaches provide both quantitative estimates and contextual understanding of workforce capacity, drivers, barriers, supervision, job satisfaction, professional quality of life, organizational practices, and service-delivery realities.

The protocol also addresses major threats to sampling validity, including incomplete records, duplicate entries, staff mobility, non-response, organizational heterogeneity, and geographically dispersed service delivery. Although developed for Gambella, its methodological structure can be adapted to other refugee-hosting and humanitarian settings by modifying workforce definitions, eligibility criteria, sampling strata, sample-size assumptions, and sectoral scope. Its broader contribution is a reproducible approach for generating workforce evidence that can inform

MHPSS planning, capacity development, supervision, recruitment, and resource allocation.

Conflict of Interest

The authors declare no conflicts of interest.

Acknowledgements

The authors gratefully acknowledge the support and cooperation of all participating organizations, including UNHCR, RRS, RHB, Gambella region hospitals and health centres, and the implementing partners in the Gambella Region, including INGOs, NGOS and RLOs/CBOs. We thank the organisational focal persons who facilitated access to personnel records and verified workforce data. We also express our appreciation to the humanitarian staff who participated in this study for their time and valuable insights.

Ethical Approval

Ethical approval for this study was obtained from the Institutional Review Board of Texila American University (Reference Number: 2026/TIMM-UCN/2/00026). The study also received administrative clearance from the relevant regional authorities (RHB and RRS-77/131/2018) and organizational leadership. Written informed consent was obtained from all participants prior to their involvement in the

study. The study was conducted in accordance with the Declaration of Helsinki and relevant Ethiopian national guidelines for research involving human participants.

Data Availability

The anonymized dataset generated from the sampling frame is available from the corresponding author upon reasonable request. The 5Ws matrix used to identify organizations is publicly available through RRS and UNHCR coordination channels. Due to privacy and confidentiality considerations, detailed organizational staffing records are not publicly accessible.

Author Contributions

AM: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Project administration. GA: Supervision, Validation, Methodology, Writing – review & editing. Both authors read and approved the final manuscript.

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