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Article

Leveraging principal component analysis of crime trends to drive innovation in industry, policy, and society

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Abstract: Given the multifaceted nature of crime trends shaped by a range of social, economic, and demographic variables, grasping the fundamental drivers behind crime patterns is pivotal for crafting effective crime deterrence methodologies. This investigation adopted a systematic literature review technique to distill thirty key factors from a corpus of one hundred scholarly articles. Utilizing the Principal Component Analysis (PCA) for diminishing dimensionality facilitated a nuanced understanding of the determinants deemed essential in influencing crime trends. The findings highlight the necessity of tackling issues such as inequality, educational deficits, poverty, unemployment, insufficient parental guidance, and peer influence in the realm of crime prevention efforts. Such knowledge empowers policymakers and law enforcement bodies to optimize resource allocation and roll out interventions grounded in empirical evidence, thereby fostering a safer and more secure societal environment.

Keywords: crime trends; Principal Component Analysis; crime rate; poverty rate; inequality

1. Introduction

Crime is a major worry for countries worldwide, profoundly affecting public safety and well-being (Clear and Montagnet, 2022). Understanding the elements influencing crime patterns is critical for developing successful crime prevention and intervention measures. Traditional techniques for analyzing crime trends have often concentrated on individual variables or small subsets of data, frequently disregarding the complex interplay of several causes (De Nadai et al., 2020). However, developments in statistical approaches, such as Principal Component Analysis (PCA), provide new options to examine crime data thoroughly and discover the underlying contributing elements.

PCA is a multivariate statistical technique for reducing high-dimensional data to a smaller number of uncorrelated variables known as principal components (Salem and Hussein, 2019). These primary components capture the most variance in the original data, revealing the underlying structure and relationships between variables. It can discover the fundamental elements that drive crime patterns and evaluate their relative relevance by using PCA to crime data and a variety of probable contributing factors.

Studies have shown that crime trends are influenced by a myriad of factors, including socioeconomic indicators, demographic characteristics, environmental conditions, and law enforcement efforts (Jones and Pridemore, 2019). However, traditional methods of crime trend analysis often fail to capture the complex interplay of these factors. PCA offers a data-driven approach to address this challenge by transforming the original data into a set of uncorrelated principal components that capture the most significant variance in the dataset. This dimensionality reduction allows researchers to examine the underlying structure of crime data and identify the primary factors contributing to crime trends.

The application of PCA in crime analysis has been widely recognized for its ability to reveal latent patterns and relationships among various contributing factors (Rabin et al., 2021). Through PCA, researchers can determine which factors have the most substantial impact on crime rates and explore how these factors interact to shape crime patterns. Moreover, PCA enables the identification of potential outliers and patterns that may not be evident through traditional analysis methods, thereby enriching the understanding of crime trends.

This study aims to investigate the underlying factors driving crime trends and apply Principal Component Analysis (PCA) to crime data. Various potential contributing factors, including socioeconomic indicators, demographic characteristics, and environmental variables, are collected through the gathering of relevant crime data, such as recorded crimes categorized by type, location, and time. The objective is to identify the primary factors that explain the variations in crime trends by analysing this data using PCA and to examine their significance in influencing crime rates.

The findings of this study will contribute to evidence-based decision-making in crime prevention and law enforcement and provide valuable insights into the complex nature of crime trends. Armed with knowledge about the key contributing variables to crime trends, policymakers, and law enforcement agencies can develop targeted interventions and allocate resources more efficiently to address the root causes of crime. The goal is to enhance community safety and well-being by gaining a deeper understanding of the factors impacting crime trends.

The following sections of this paper will be organized as follows: Section 2 will review relevant literature on crime trend analysis and the application of PCA in this context. Section 3 will describe the materials and methods employed in the study, including data collection and PCA implementation. Section 4 will present the results of the PCA analysis and the identified contributing factors to crime trends. Section 5 will discuss the findings in detail, exploring the implications and potential policy implications. Section 6 will conclude the research, summarizing the key insights gained from the PCA analysis and its significance for crime trend analysis.

2. Related works

Crime rates have been calculated using a variety of methods. Analysis of official crime statistics acquired from law enforcement organizations is one method that is frequently used (Bowling and Phillips, 2020). These statistics give academics quantifiable information on reported crimes so they can spot trends and patterns. In 2019, the South African Police Service emphasised that official crime statistics may not fully capture the extent of criminal activity, as underreporting and other biases can significantly distort the data.

In addition to official crime statistics, victimization surveys have emerged as a valuable tool for crime rate analysis. With the help of these surveys, which directly interview crime victims, we can learn more about crimes that have gone unreported or undiscovered. One such survey, the South African Victims of Crime Survey (VOCS), is carried out by Statistics South Africa and collects data on the frequency and kind of crime victimization. This study by the South African Statistics is an addition to official statistics and aids in locating the “dark figure” of crime.

Spatial analysis methods, particularly Geographic Information Systems (GIS), have gained prominence in analysing crime rates. These methods enable researchers to map crime incidents, identify high-crime areas, and understand spatial patterns of criminal activities. The study conducted by (Hassan et al., 2020) highlighted the utility of GIS in mapping crime incidents and identifying crime hotspots, which facilitates the development of targeted interventions and resource allocation strategies. In addition, the process of urbanization and spatial factors have also been linked to high crime rates. Arnold (2021) investigated the spatial determinants of crime and found that urban areas, particularly informal settlements, had higher crime rates compared to rural regions. This highlights the importance of considering the spatial context when analysing crime patterns.

The relationship between urban sprawl and crime rates was explored by (Contreras and Hipp, 2020), who found a positive correlation between the two variables. This suggests that the expansion of urban areas may contribute to increased crime rates. Understanding these spatial factors is crucial for effective crime prevention strategies. Moreover, Hotspot mapping, a spatial analysis technique, has been utilized by researchers such as (Roest et al., 2023) and (Singh et al., 2021) to identify crime hotspots and gain insights into spatial patterns of criminal activities. By identifying areas with a high concentration of crime incidents, law enforcement agencies and policymakers can focus their efforts on these specific locations.

Researchers have also integrated GIS technology with socio-demographic variables to gain a comprehensive understanding of crime-prone areas. Bako et al. (2021) utilized GIS to combine crime data with socio-demographic factors, enabling a more nuanced analysis of the underlying social and economic dynamics contributing to high crime rates.

A study conducted by Matzopoulos et al., (2020) focused on a high-crime area in South Africa and utilized GIS analysis to investigate the spatial relationship between crime and environmental factors. They specifically examined proximity to liquor outlets and public spaces as potential contributors to crime in the area. By employing GIS analysis, the researchers were able to gain insights into the spatial dynamics of crime and its association with specific environmental factors (Aroba and Ramchander 2024).

Moreover, GIS analysis has gained prominence in understanding spatial patterns and crime hotspots throughout the world Researchers have utilized GIS to map crime incidents, demographic data, and socio-economic factors, allowing for the identification of high-crime areas and their associated characteristics. For instance, (Leitner and Ristea, 2020) conducted a study using GIS analysis to explore the relationship between urbanization and crime rates in various municipalities. This enabled them to identify spatial patterns and uncover the influence of urbanization on crime rates in different regions.

Similarly, geographical Information Systems (GIS) technology has been utilized by researchers like (Dunlop et al., 2022) to integrate crime data with socio-demographic variables. This integration facilitates a comprehensive understanding of the spatial relationship between crime and various socio-demographic factors. By analysing this combined information, researchers can identify crime-prone areas and gain insights into the underlying social and economic dynamics that contribute to high crime rates. In addition, Marais et al. (2022) emphasizes the significance of time series analysis in understanding crime rates, as it enables researchers to identify long-term trends, and inform policy decisions, and resource allocation. This approach allows for the identification of temporal patterns in crime, such as higher rates during specific seasons or periods, which can guide targeted interventions.

Lisowska-Kierepka (2022) presents an innovative Criminal Risk Index designed for spatial crime analysis, utilizing street-level data organized within a grid system. Tested in Wrocław, Poland, this approach applies Tobler's First Law of Geography to estimate crime probabilities based on historical patterns. The study reviews established spatial crime analysis techniques, such as crime mapping, hotspot analysis, and spatial regression, and evaluates the index's performance through autocorrelation analysis. The findings highlight the index's effectiveness in pinpointing high-risk areas, providing valuable insights for crime prevention strategies. Moreover, the results align with theoretical frameworks on urban crime distribution, reinforcing its applicability in real-world scenarios.

Sikorski et al. (2024) explore the relationship between crime rates and a range of socioeconomic, demographic, and spatial characteristics in Wrocław, Poland. By applying principal component analysis and correlation analysis to 43 variables across 48 residential districts, the study identifies statistically significant links between elevated crime rates and factors such as high-density housing, concentrated economic activity (particularly in the service sector), and specific land-use patterns. The authors emphasize that the choice of observational units and statistical variables plays a crucial role in shaping the findings. Ultimately, the study concludes that crime is not exclusively driven by social factors but is also profoundly influenced by the spatial characteristics of urban environments.

Longitudinal studies provide a comprehensive understanding of crime rates by tracking changes over time and evaluating the impact of various interventions. These studies are crucial for identifying the effectiveness of policy measures and addressing the dynamic nature of crime. Adugna and Italemahu (2019) conducted a notable longitudinal study that analysed crime trends in South Africa before and after the implementation of community policing initiatives. Such studies enable researchers to assess the outcomes of specific interventions and make informed recommendations for policy improvements.

Moreover, Makondo et al. (2021) conducted a longitudinal analysis to explore the relationship between police strategies, economic conditions, and crime rates in major cities. These studies help identify patterns and shifts in crime rates and assess the impact of policy interventions. They provide valuable insights into the complex relationship between socioeconomic factors, policy measures, and crime rates over time.

The link between socioeconomic factors and crime rates in South Africa has been extensively studied. Mulamba (2021) investigated the relationship between unemployment, income inequality, and crime rates in South African provinces. Their findings indicated a positive correlation between unemployment and crime, emphasizing the role of economic deprivation in fostering criminal behaviour (Mulamba 2021). However, Garidzirai (2021) conducted a study in Gauteng province, revealing a significant association between income inequality and violent crime rates. These studies highlight the importance of addressing socio-economic disparities to reduce crime rates in South Africa.

Gangs and organized crime have been recognized as significant contributors to crime rates in South Africa. Dziewanski (2020) investigated the role of gangs in contributing to violent crime in Cape Town. Their study highlighted the territorial control exerted by these groups and their involvement in drug-related activities as key factors driving violent crime. In addition, Adekoye and Fafore (2019) analysed the impact of organized crime on crime rates in South Africa, emphasizing the involvement of criminal networks in activities such as human trafficking and illegal firearm trade. These findings underscore the importance of targeted interventions to address underlying factors such as gang-related crime and organized criminal networks, which can indirectly contribute to car accident severity through behaviors like reckless driving, high-speed pursuits, or impaired judgment caused by criminal activities (Adeliyi et al., 2023; Aroba et al., 2023; Aworinde et al., 2024).

Analysing the elements that contribute to South Africa's high crime rates necessitates a multifaceted approach. Researchers have made tremendous progress in understanding the complex elements related to crime in South Africa by using quantitative analysis, qualitative methodologies, GIS analysis, and longitudinal investigations. The combination of these methodologies offers policymakers will full understanding of the socioeconomic, cultural, and geographic aspects that contribute to crime rates, allowing them to build evidence-based crime prevention and reduction policies.

The literature study demonstrates the varied range of methodologies used to analyse the factors leading to South Africa's high crime rates. Socioeconomic issues, urbanization and spatial factors, gangs and organized crime, and demographic traits have all been highlighted as major contributors to the country's crime problem. These research findings can help policymakers and practitioners develop focused crime prevention initiatives, address fundamental causes of crime, and build a safer environment for all South Africans. To guarantee that crime rate analysis remains a dynamic and evolving subject, ongoing efforts are required to refine the methodology, resolve data restrictions, and address data limitations.

3. Methodology

A search of the literature yielded all published material on crime trends and analyses of crime rates. PRISMA technique was used to identify relevant research, screen, and select those studies, and complete the eligibility and inclusion stages.

3.1. Identification

The Web of Science database (300) and SCOPUS (350) databases were used to choose scientific articles that addressed the significant factors that cause the high crime rate and the crime trends in South Africa. The search term used to search the database is (factors OR influence* OR cause*) AND (crime OR "crime trend" OR "crime rate"). Furthermore, articles preceding January 2011 to 2023 were excluded. The exclusion criteria were limited to journal articles written in the English language, in the fields of criminology and computer science.

3.2. Screening

A review of publications relevant to major elements that contribute to high crime rates, as well as crime trends in South Africa, was conducted. The articles were vetted by analysing the abstracts. The duplicated articles that did not fit the purpose of this study were eliminated.

3.3. Eligibility

To pick acceptable publications, eligible criteria must be used [100]. As a result, as indicated in **Table 1**, articles are filtered depending on inclusion and exclusion criteria. Only publications that meet the requirements are chosen, as shown in **Table 1**; chapter books, brief reports, articles, non-English papers, and works published before 2014 are all omitted. In this case, 209 things were removed because they did not match the requirements, and 100 articles remain.

Table 1. Inclusion and exclusion criteria.

Inclusion Criteria	
IC1	Article published in English
IC2	Paper in Criminology and Computer Science
IC3	Paper relating that addressed the significant factors that cause high crime rate and the crime trends in South Africa
IC4	Journals and articles only
IC5	Papers between 2014 to 2023
Exclusion Criteria	
EC1	Papers that abstract and conclusion explain the method used
EC2	Duplicate records
EC3	Reviews and Methods papers
EC4	Papers not applying PCA or Factor Analysis or Dimensions
EC5	Papers not written in the English language
EC6	Papers not relevant to factors that cause high crime rates and crime trends

Out of the initial pool, 103 articles were identified as aligning with the inclusion criteria. From these, a targeted review of 100 papers was conducted to extract relevant insights for the study. This involved a detailed examination of each document to glean and synthesize vital information, which will be instrumental in this research. The systematic approach to the database search, depicted in **Figure 1** through the PRISMA framework, outlines this meticulous process. From the comprehensive review of 100 scholarly articles, 30 distinct factors were identified as significant contributors to this phenomenon. These factors have been tabulated and presented in binary form in **Table 2** to delineate the attributes of the identified components, setting the stage for in-depth analysis and further exploration.

Table 2. Sources of crime-influencing factors for principal component analysis (PCA).

F1	Poverty	(Adolphe et al. 2019), (Anser et al., 2020), (Dong et al., 2020), (Francke et al., 2023), (Kassem et al., 2019), (Kujala et al., 2019), (Mandalapu et al., 2023), (McCrea et al., 2019), (Zulkiflee et al., 2022)	F17	Population density	(Adeyemi et al., 2021), (Kassem et al., 2019), (Kayaoglu, 2022), (Vakhitova et al., 2022)
F2	Inequality	(Anser et al., 2020), (Buonanno and Vargas, 2019), (Dong et al., 2020), (Kujala et al., 2019), (McCrea et al., 2019), (Rowhani-Rahbar et al., 2019), (Ruiter and van Ruitenburg, 2023)	F18	Psychological	(Hornsveld and Kraaimaat, 2022), (Krahé, 2020)
F3	Lack of education	(Fuller et al., 2023), (McCrea et al., 2019), (Pina-Sanchez et al., 2022)	F19	Demographic Factors	(Johnson and Nikolovska 2022), (Kassem et al., 2019), (Vakhitova et al., 2022), (Wang et al., 2019)
F4	Unemployment	(Adeyemi et al., 2021), (Anser et al., 2020), (Chen et al., 2022), (Francke et al., 2023), (Jonathan et al., 2021), (Kassem et al., 2019)	F20	Access to Firearms	(Hink et al., 2019), (Kivisto et al., 2019)
F5	Violence	(Blumstein and Wallman, 2020), (Campbell et al., 2021), (Chen et al., 2022), (Fuller et al., 2023), (Garritsen et al., 2022), (Hawkins and Zimring, 2020), (Haylock et al., 2020), (Rıos, 2019)	F21	Social and Cultural	(Britt, 2019), (Guedes et al., 2022), (Hawkins and Zimring, 2020)
F6	Drug and substance abuse	(Adolphe et al., 2019), (Campbell et al., 2021), (Cho et al., 2019), (Kiss and Szigeti 2023)	F22	Inadequate Policing	(Brunson and Wade, 2019), (Holmes et al., 2019), (Rosenfeld and Wallman, 2019)
F7	Poor living conditions	(Cho et al. 2019), (Campedelli et al. 2020), (Desmond 2022), (Davidson 2019)	F23	Social Disintegration	(Rowhani-Rahbar et al., 2019), (Wilkinson, 2020)
F8	Lack of Parental Discipline	(Agnew and Brezina, 2019), (Farrington, 2020), (Kirk et al., 2023), (Kroese et al., 2021), (Haylock et al., 2020)	F24	Lack of urban planning	(Jarah et al., 2019), (Zavadskas et al., 2019)
F9	Peer Pressure	(Bui and Deakin, 2021), (Gonggrijp et al., 2023), (Kahan, 2019), (Kroese et al., 2021), (Lenkens et al., 2023), (McGloin and Thomas 2019)	F25	Corruption	(Arbolino and Boffardi, 2023), (Calderoni et al., 2022), (Jiahong, 2019), (Kemp et al., 2020)
F10	Political instability	(Anser et al., 2020), (Chainey et al., 2021)	F26	Availability of illicit drugs and arms trafficking	(Falode, 2021), (Opara et al., 2020), (Semenza et al., 2022)
F11	Unfair judicial system	(Eckhouse, 2019), (Lopez and Rosenfeld, 2020), (Pollock and Rossmo, 2019), (Thompson, 2019)	F27	lack of trust in law enforcement	(Brunson and Wade, 2019), (Capellan et al., 2020), (Rosenfeld and Wallman, 2019)
F12	Religion	(Inglehart, 2020), (Wortmann, 2020)	F28	Criminal justice system and Racial profiling	(Bacchini and Lorusso, 2019), (Dragomir and Tadros, 2020)
F13	Deprivation	(De Courson and Nettle, 2021), (Dong et al., 2020), (Knopov et al., 2019)	F29	Weak border controls	(John, 2019), (Mantzaris and Ngcamu, 2019)
F14	Immigration and refugee influx	(Kayaoglu, 2022), (Mercan et al., 2022), (Piatkowska et al., 2020), (Vakhitova et al. 2022)	F30	Wealth disparity	(Wilkinson, 2020)
F15	Truancy	(Farrall et al., 2020), (Gerth, 2022)			

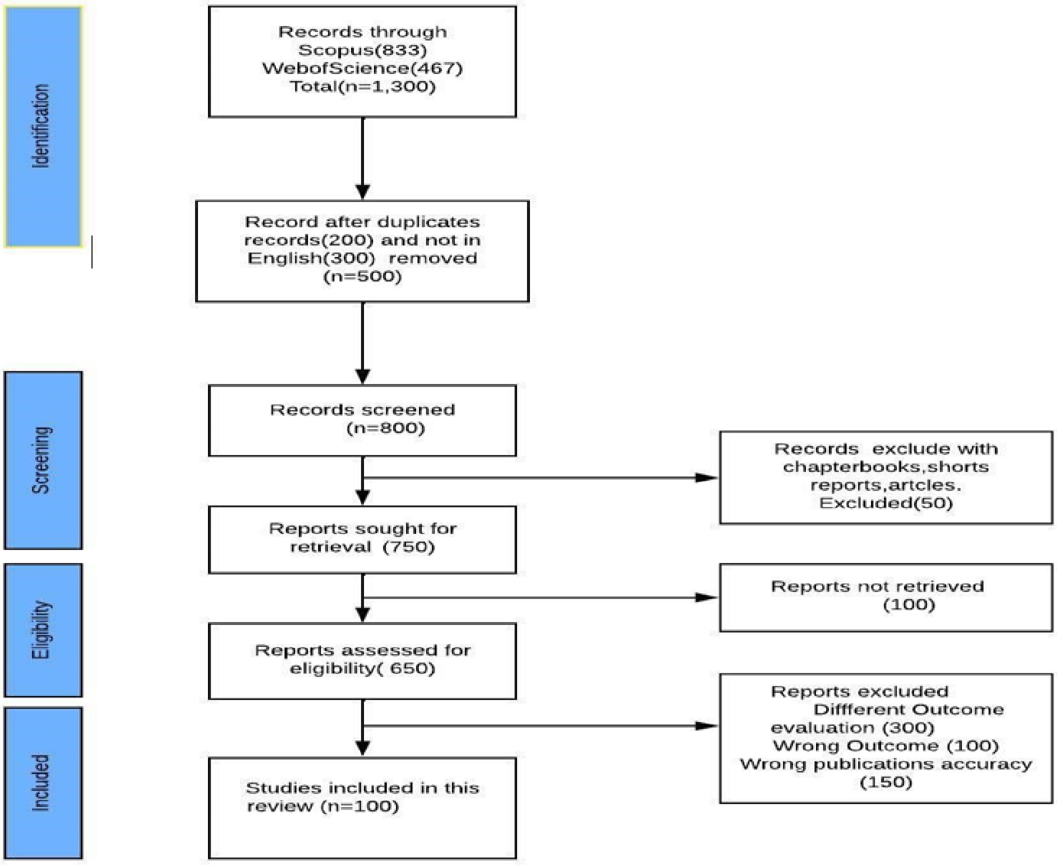

Figure 1. Flow diagram of database search using PRISMA.

3.4. Principal Component Analysis (PCA)

A statistical strategy that uses an orthogonal transformation to convert correlated variables into linearly uncorrelated variables (Salem and Hussein, 2019). PCA was applied to R-studio using the built-in R stats package function. Some of these linear combinations of the original variables can describe these variables' variance-covariance structure. PCA generates an uncorrelated set of variables (principal components), the top few of which maintain most of the variation found in all the original variables. Unlike its relative Factor Analysis counterpart, PCA always yields the same answer from the same data (apart from arbitrary sign fluctuations). The use of PCA to analyse crime trends can have a significant impact on industry, policy, and society by providing deep insights into the underlying patterns and factors driving criminal activity. This data-driven approach allows for more targeted and effective interventions, ultimately contributing to a safer and more secure environment for all.

3.5. Scaling

Scaling is the term used to describe the process of normalizing PCA data. An equation is used to change the dataset in this case. This means that the mean of the attributes is zero, and the resulting distribution has a unit standard deviation. When transforming a vector of p random variables, such as X, the goal is to discover a limited number of derived variables that retain most of the information offered by the p random variables' variance. The following data was standardized (Pursan et al., 2023).

$$Xil = \frac{(Xil - Xn)}{\sigma}$$

where i = 1, 2, 3, 4, …, 103 (number of articles) and l = 1,2,3,4…, 30 (number of factors) indicate the original values of the ith research rating of the lth factor. Xn represents the mean and the deviation of the series created by the values of the ith research for all 30 factors (Too et al., 2021). The R-studio function scale was used to normalize the data. The numeric matrix is entered as input, and then the columns are scaled.

Table 3 presents a 5-factor loading ranking of qualities that have been identified as major contributors to South Africa's crime rate. From an initial pool of 103 factors, this table includes the top 19 factors ranked based on their contribution to the identified 5 factors. Each row in the table represents a specific factor's ranking, and the attributes associated with that factor are listed along with their respective contributions.

Table 3. A 5-factor loading ranking of the qualities.

Ranked	Attributes	Contribution
0.887	1	0.483F9 + 0.483F8 + 0.392F7 + 0.355F3 + 0.272F13…
0.7814	2	0.437F26 + 0.423F20 + 0.358 F17 − 0.302F1 − 0.268F2…
0.6967	3	0.544F21 + 0.544F23 − 0.321F6 − 0.32F5 + 0.239F26…
0.6233	4	−0.505 F16 − 0.491F25 + 0.337F5 + 0.331F6 + 0.221F26…
0.5549	5	−0.422F6 − 0.413F5 − 0.332 F16 − 0.331F25 − 0.289F21…
0.4914	6	−0.344F1 − 0.335F25 − 0.325 F16 + 0.321F11 + 0.314F14
0.4312	7	−0.535F11 + 0.488F14 − 0.432F28 + 0.343F29 − 0.278F2…
0.3848	8	0.39 F22 + 0.39 F12 − 0.37F28 − 0.319F4 + 0.255F24…
0.3403	9	0.447F2 + 0.381F29 + 0.324F13 − 0.314F22 − 0.314F12…
0.2995	10	−0.707F12 + 0.707F22 − 0F24 + 0F29 + 0F2…
0.259	11	−0.902F24 + 0.305F12 + 0.305F22 + 0.015F29 + 0.008F2…
0.221	12	−0.784F10 + 0.323F13 + 0.223F1 + 0.217F2 − 0.18F9…
0.1891	13	0.682F13 + 0.352F4 − 0.333F7 − 0.319F29 − 0.246F1…
0.1577	14	0.683F29 − 0.372F14 + 0.288F13 + 0.269F28 + 0.21 F4
0.1285	15	−0.651F3 + 0.423 F17 + 0.372F7 − 0.302F20 − 0.203F26…
0.1016	16	−0.599 F17 + 0.443F7 − 0.366F3 + 0.35 F20 − 0.168F29…
0.0768	17	0.438F4 − 0.424F28 + 0.365F11 − 0.317 F17 − 0.297F3…
0.0572	18	0.566F11 − 0.406F28 − 0.314F2 + 0.287F7 + 0.269F10…
0.042	19	−0.553F1 + 0.347F7 − 0.294F6 − 0.279F14 − 0.272F26…

The analysis reveals the relative importance of each attribute in influencing the identified factors. For instance, the top-ranked factor, with a contribution of 0.887, is primarily determined by a combination of attributes such as F9, F8, F7, F3, F13, and others. Similarly, the second-ranked factor, with a contribution of 0.7814, is influenced by attributes like F26, F20, F17, F1, F2, and so on.

The negative values in the contributions indicate that certain attributes have an inverse relationship with the identified factors, meaning they contribute to decreasing the impact of those factors on South Africa's crime rate. **Table 2** provides valuable insights into the factors that play a significant role in shaping the crime rate in South Africa. By understanding the contribution of each attribute to the identified factors, policymakers and researchers can gain valuable knowledge to address and mitigate the factors contributing to crime in the country.

4. Result and analysis

A scree plot serves as a useful tool for assessing the effectiveness of Principal Component Analysis (PCA) on a dataset. It helps determine the extent to which the principal components capture the variability in the data. PC1 captures the most variability, followed by PC2, and so forth. While the number of primary components in PCA is equal to the number of attributes or qualities in the data, each component provides valuable information about the dataset. It is essential to retain all relevant principal components to avoid losing crucial information. The scree plot visually represents the relationship between the number of principal components (xaxis) and their corresponding eigenvalues (y-axis), clearly illustrating the variability explained by each component. **Figure 2** displays this scree plot, giving insight into the significance of the principal components in the data analysis process.

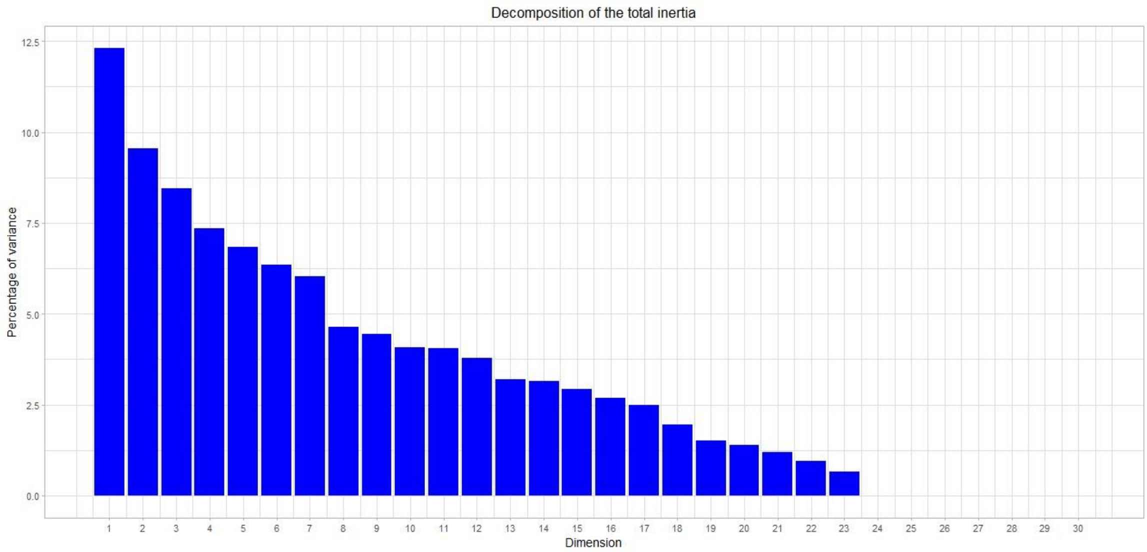

Figure 2. Scree plot of the principal components.

Table 4 provides a comparison of the principal component analysis (PCA) results for two different software tools, RStudio and WEKA. The table displays the principal components (PC1 to PC30) for both analyses, along with their respective eigenvalues, percentage of variance explained, and cumulative percentage of variance.

For the PCA conducted in RStudio, 30 principal components were obtained. The eigenvalues represent the amount of variance explained by each component, with PC1 having the highest eigenvalue of 3.08, indicating that it accounts for 12.30% of the total variance in the dataset. As we move down the table, the eigenvalues gradually decrease, with each subsequent component explaining a decreasing percentage of variance. The cumulative percentage of variance column shows the accumulated contribution of each component to the total variance. At PC30, the cumulative percentage of variance reaches 100%, indicating that all 30 components collectively explain the entire variance in the data.

On the other hand, the PCA conducted in WEKA resulted in 19 principal components. Interestingly, the eigenvalues for both PC1 and PC2 are remarkably close to the values obtained in RStudio, indicating a similar level of variance. However, the cumulative percentage of variance for PC2 in WEKA is already at 21.86%, while in RStudio, it is not until PC3 that the cumulative percentage of variance reaches a similar value. This suggests that the number of principal components and their respective variance contributions differ slightly between the two software tools.

Table 4. Comparative results pcs of the factors for WEKA and RStudio.

30 PCA for RStudio				**19 PCA for WEKA**			
Principal Components	**Eigenvalue**	**% of variance**	**Cumulative % of variance**	**Principal Components**	**Proportion**	**% of variance**	**Cumulative % of variance**
PC1	3.08	12.30	12.30	PC1	3.07565	0.12303	0.12303
PC2	2.39	9.56	21.86	PC2	2.3902	0.09561	0.21863
PC3	2.12	8.46	30.33	PC3	2.11573	0.08463	0.30326
PC4	1.84	7.34	37.67	PC4	1.83519	0.07341	0.37667
PC5	1.71	6.84	44.51	PC5	1.71053	0.06842	0.44509
PC6	1.59	6.35	50.86	PC6	1.58778	0.06351	0.5086
PC7	1.51	6.02	56.88	PC7	1.50548	0.06022	0.56882
PC8	1.16	4.64	61.52	PC8	1.15892	0.04636	0.61518
PC9	1.11	4.45	65.97	PC9	1.11356	0.04454	0.6597
PC10	1.02	4.08	70.05	PC10	1.02062	0.04082	0.70055
PC11	1.01	4.05	74.10	PC11	1.01221	0.04049	0.74103
PC12	0.95	3.80	77.90	PC12	0.94881	0.03795	0.77899
PC13	0.80	3.19	81.09	PC13	0.79668	0.03187	0.81085
PC14	0.79	3.14	84.23	PC14	0.78519	0.03141	0.84226
PC15	0.73	2.92	87.15	PC15	0.7303	0.02921	0.87147
PC16	0.67	2.69	89.84	PC16	0.67347	0.02694	0.89841
PC17	0.62	2.48	92.32	PC17	0.62	0.0248	0.92321
PC18	0.49	1.96	94.28	PC18	0.48973	0.01959	0.9428
PC19	0.38	1.52	95.80	PC19	0.38069	0.01523	0.95803
PC20	0.35	1.39	97.20				
PC21	0.30	1.20	98.40				
PC22	0.24	0.95	99.34				
PC23	0.16	0.66	100.00				
PC24	0.00	0.00	100.00				
PC25	0.00	0.00	100.00				
PC26	0.00	0.00	100.00				
PC27	0.00	0.00	100.00				
PC28	0.00	0.00	100.00				
PC29	0.00	0.00	100.00				
PC30	0.00	0.00	100.00				

The **Table 5** provides insights into the contribution of 10 factors to identify distinct groups for the 6 principal components (PCs). Each PC is represented as a linear combination of the 10 factors, denoted as F1, F2, F3, …, and F29, with specific weights or coefficients. The principal component, PC1, is significantly influenced by multiple factors, notably F9, F8, F7, F3, F13, F4, F20, F1, F26, and F17, among others that might not be explicitly listed. The primary contributing factor to PC1 is F9, with a weight of 0.483. However, F8, F7, F3, and F13 also play crucial roles in determining the behaviour of this component.

Table 5. Depicts the contribution of 10 factors identifying the different groups for the 6 pcs.

PC	Contribution
PC1	0.483F9 + 0.483F8 + 0.392F7 + 0.355F3 + 0.272F13 + 0.176F4 − 0.172F20 + 0.166F10.161F26 − 0.147 F17…
PC2	0.437F26 + 0.423F20 + 0.358F17 − 0.302F1 − 0.268F2 − 0.265F210.265F23 + 0.218F8 + 0.218F9 − 0.157F5…
PC3	0.544F21 + 0.544F23 − 0.321F6 − 0.32F5 + 0.239F26 + 0.21 F20 + 0.192 F17 + 0.192F20.095F4 + 0.093F1…
PC4	−0.505F16 − 0.491F25 + 0.337F5 + 0.331F6 + 0.221F26 − 0.216F14 + 0.214F20 + 0.157 F17 + 0.157F1 − 0.135F11
PC5	−0.422F6 − 0.413F5 − 0.332F16 − 0.331F25 − 0.289F21 − 0.289F23 + 0.239F10 + 0.209F2 + 0.181F1 + 0.177F4…
PC6	−0.344F1 − 0.335F25 − 0.325F16 + 0.321F11 + 0.314F14 − 0.313F4 + 0.304F28 + 0.243F29 − 0.195F10 − 0.144F26…

Figure 3 illustrates the PCA graph showcasing the correlation between the variables in the dataset. The graph reveals that a correlation is present when two variables align in the same direction, absent when they form a 90-degree angle, and negative when they point in opposite directions. In the graph, Dimension 1 plays a significant role in distinguishing individuals based on their coordinates. Those situated to the right, such as individual 25, have strongly positive coordinates on the axis, while individuals like 46, 48, 49, 50, 51, 52, 44, 47, and 53 are found on the left side with strongly negative coordinates. The group to which individual 25 belongs, marked by positive coordinates, shares certain characteristics. They exhibit high values for variables like Inequality, Lack of Education, Poverty, and Unemployment, sorted in descending order of strength. Conversely, this group demonstrates low values for variables like Violence and Drug and substance Abuse, sorted in ascending order of weakness.

On the other hand, the group comprising individuals 46, 48, 49, 50, 51, 52, 44, 47, and 53, who occupy negative coordinates, displays different traits. They tend to have high values for variables like Drug and substance Abuse and Violence, sorted from the strongest. Conversely, this group exhibits low values for variables like Poverty and Inequality, sorted from the weakest. Additionally, there is a group labelled Group 3, characterized by negative coordinates on the axis. This group is distinguished by having low values for the variable Poverty. It is important to note that the variables Lack of Parental Discipline, Peer Pressure, Truancy, and Psychological strongly correlate with Dimension 1, with correlation values of “Inf”. Therefore, these variables themselves serve as summaries of Dimension 1.

Dimension 2 in the graph represents a contrasting opposition between individuals positioned at the top and those at the bottom. Individuals like 25 are located at the top with strongly positive coordinates, while individuals like 46, 48, 49, 50, 51, 52, 44, 47, 53, and 42 are situated at the bottom with strongly negative coordinates.

The first group, characterized by a positive coordinate on the axis, shares certain characteristics. They have high values for the variable Poverty and low values for Violence and Drug and substance Abuse, ranked in descending order of strength. The group to which individual 25 belongs, also characterized by a positive coordinate on the axis, exhibits distinct characteristics. They have high values for variables like Inequality, Lack of Education, Poverty, and Unemployment, ranked in ascending order of strength. Conversely, this group displays low values for Violence and Drug and substance Abuse, ranked from weakest to strongest.

The group consisting of individuals 46, 48, 49, 50, 51, 52, 44, 47, and 53, positioned at the negative end of the axis, shares certain traits. They demonstrate high values for variables like Drug and substance Abuse and Violence, ranked in descending order of strength. Conversely, this group has low values for variables like Poverty and Inequality, ranked from weakest to strongest. Lastly, the group comprising individuals 42, 43, and 45, also located at the negative end of the axis, exhibits specific characteristics. This group shows high values for variables like Drug and substance Abuse and Violence, ranked in descending order of strength.

It is noteworthy that the variables Peer Pressure and Psychological are highly correlated with Dimension 2, indicated by an infinite correlation value. As a result, these variables may serve as concise summaries of Dimension 2.

Moving on to Dimension 3, it distinguishes individuals 67 and 66, who have strongly positive coordinates on the axis. Individual 66 belongs to a group characterized by a positive coordinate on the axis and shares high values for the variable De-policing. On the other hand, individual 67 also belongs to a group with a positive coordinate on the axis, but this group shares high values for the variables Corruption and De-policing, with the variables sorted in descending order of strength. Notably, Lack of Parental Discipline, Peer Pressure, Truancy, and Demographic Factors show high correlations with Dimension 3. Lack of Parental Discipline, Peer Pressure, and Truancy exhibit an infinite correlation (Inf).

Lastly, Dimension 4 serves as a differentiating factor between individuals. The graph associated with this dimension shows a strong positive coordinate on the axis for one group and a strong negative coordinate for another group. The first group, positioned towards the top, includes individuals such as 21, 35, 83, 68, 57, and 58 with positive coordinates. They share common characteristics, such as high values for variables like Unfair Judicial System and Inequality, and low values for the variable Immigration and Refugee Influx. The second group, situated at the bottom, comprises individuals such as 37, 32, 95, 99, 55, and 56 with negative coordinates. This group exhibits contrasting characteristics, including high values for variables like Weak Border Controls and Availability of Illicit Drugs and Arms Trafficking. They are also affected by the variable Immigration and Refugee Influx. Individual 68, on the other hand, belongs to a group with a positive coordinate on the axis, sharing high values for the variable Criminal Justice System and Racial Profiling.

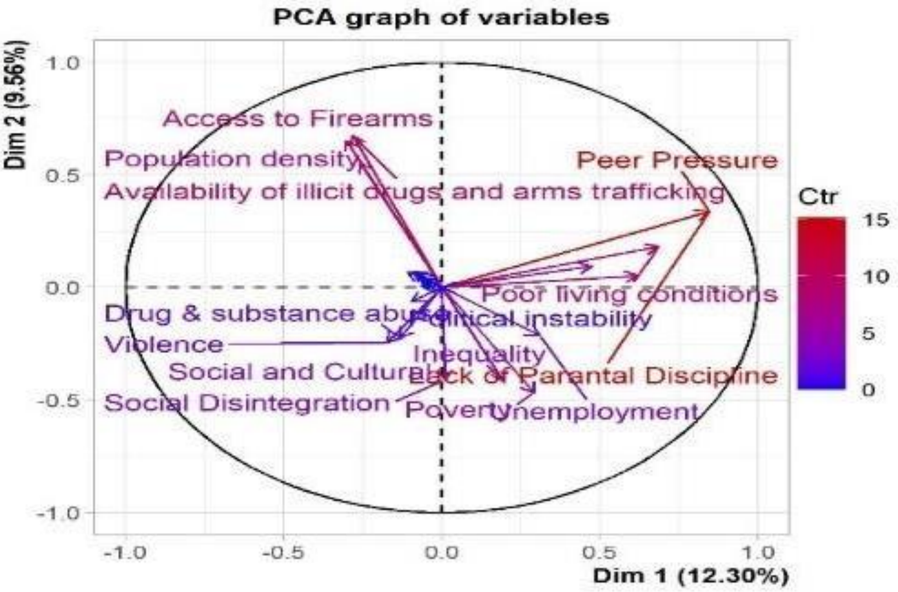

Figure 3. Contribution of each variable.

5. Discussion

Crime is a multifaceted social issue that is influenced by numerous factors. Among the top five factors associated with crime are inequality, lack of education, poverty, unemployment, and lack of parental discipline and peer pressure. Research has consistently shown that inequality in society is linked to higher crime rates. When there is a significant gap between the rich and the poor, feelings of resentment and frustration can arise, leading some individuals to resort to criminal activities as a means of expressing their grievances or seeking economic opportunities. A study conducted by Pickett and Wilkinson (2009) found that countries with higher levels of income inequality tend to have higher rates of violent crimes and property offenses.

Lack of education and limited access to quality education are also contributing factors to crime. Research conducted by (Kassem et al., 2019) revealed a strong negative correlation between crime rates and educational attainment. Individuals with higher levels of education are more likely to have stable employment and income, reducing their likelihood of engaging in criminal behaviour. Poverty and unemployment are closely interconnected with crime as well. The absence of economic opportunities can push individuals towards criminal activities to meet their basic needs. A study by (Fone et al., 2019) showed that an increase in unemployment rates is associated with a rise in property crimes. Additionally, the lack of parental discipline and influence, coupled with peer pressure, can lead adolescents and young adults to engage in delinquent behaviours. The absence of strong parental guidance and positive role models can make individuals more susceptible to negative influences from peers, fostering a criminal environment. Addressing these underlying factors through comprehensive social policies, educational reforms, and community support can be crucial in tackling crime and promoting safer communities.

6. Conclusion

This study underscores the importance of understanding the complex interplay of social, economic, and demographic factors in shaping crime trends. By employing a systematic literature review to identify thirty key determinants and utilizing Principal Component Analysis (PCA) for dimensionality reduction, the investigation provided a clearer perspective on the key factors of crime. From the original set of 30 factors considered for evaluating crime rate contributors, the study identified the 25 most significant ones. The low variances observed in the first five primary components indicated that the most important KSFs significantly enriched the diversity of the pool, with eigenvalues of 3.08, 2.39, 2.12, 1.84, and 1.71. These findings contribute significantly to our comprehension of KSFs for Crime analyses. This study underscores the importance of understanding the complex interplay of social, economic, and demographic factors in shaping crime trends. By employing a systematic literature review to identify thirty key determinants and utilizing Principal Component Analysis (PCA) for dimensionality reduction, the investigation provided a clearer perspective on the primary drivers of crime.

The top five key socio-economic factors (KSFs) responsible for contributing to crime are Inequality, Lack of Education, Poverty, Unemployment, and Lack of Parental Discipline and Peer Pressure. To gain deeper insights and simplify the data, Principal Component Analysis (PCA) was employed, resulting in three principal components that captured a substantial portion of the original dataset's variance. This reduction in the number of variables while retaining the essence of the KSFs facilitated a clearer understanding of their impact on crime rates. Specifically, the study's results highlight the interconnected nature of these factors, with Peer Pressure, Unemployment Rate, and Lack of Parental Discipline playing significant roles in different principal components, namely PC2, PC3, and PC1, respectively.

Furthermore, the research delved into various morphological taxonomies of the KSFs, leading to the development of a diverse model that reinforces the significance of these findings. By focusing on morphological traits and effectively utilizing PCA, this study enhances our comprehension of the socioeconomic factors influencing crime analyses. The identified KSFs not only contribute to a more nuanced understanding of crime patterns but also offer valuable insights for policymakers and researchers in addressing the underlying issues related to crime prevention and intervention strategies.

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