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# Machine Learning Modeling for Predicting Gender-Based Violence against Kenyan Women: A Review of Literature

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**--------------------------------------------------------ABSTRACT--------------------------------------------------------**
*In Kenya, gender-based violence (GBV) against women is still a major social issue that has to be addressed immediately and effectively. In response, prognosticating and preventing cases of gender-based violence through the incorporation of machine learning (ML) modeling has become a viable strategy. This study provides critical insights for policymakers, practitioners, and researchers by synthesizing the body of literature on the use of machine learning approaches in predicting and reducing gender-based violence against Kenyan women. When it comes to determining trends, patterns, and risk variables related to gender-based violence, machine learning modeling has a lot of promise. With the use of complex algorithms and the examination of various datasets, machine learning techniques provide a more profound comprehension of the fundamental dynamics and intricacies of gender-based violence. Researchers can gain sophisticated insights into the complex nature of violence by utilizing large data repositories, which opens the door to more focused interventions and prevention measures. Moreover, ML modeling can help identify people or communities that are more likely to experience GBV, which can be useful for proactive therapies and early warning systems. Predictive models allow for the mitigation of violence before it escalates by assessing historical data, contextual information, and socio-demographic markers. This proactive approach makes it easier to allocate funds and create laws that will stop GBV at its source. But careful consideration is needed for ethical issues and possible biases in ML frameworks. It is critical to maintain ethical standards and avoid unforeseen effects in the data collection, feature selection, and model training processes by guaranteeing fairness, accountability, and openness. A thorough understanding of GBV and its predictions is also facilitated by multidisciplinary collaboration between experts in gender studies, machine learning, and social sciences. This allows for the development of comprehensive responses. The transformative potential of ML modeling in addressing gender-based violence against Kenyan women is highlighted by this literature review. Through the use of cutting-edge analytical methods and interdisciplinary cooperation, machine learning (ML) provides a route towards more successful approaches to GBV prevention, intervention, and prediction.*
***KEYWORDS;-****Machine Learning, Modeling, Gender-Based Violence*

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## I. INTRODUCTION

Sexual, physical, psychological, and financial abuse are all included in the category of gender-based violence, and they can happen in public or in private. Coercion, deceit, and threats of violence are some of the ways that this violence appears. Examples include violence against intimate partners, female genital mutilation, child marriage, sexual abuse, and so-called "honour crimes." Its effects are severe and long-lasting; they frequently last a lifetime and, sadly, can occasionally be fatal.

Gender-Based Violence (GBV) affects families in Kenya in a frightening number of ways, including emotional abuse, child labor, kidnapping, sexual abuse (including rape and defilement), child marriage, and harmful cultural practices like female genital mutilation (FGM). Mombasa County data from recently shows a worrisome rise in reported cases—1,275 in total—with Kisauni, Mvita, and Jomvu emerging as hotspots. In order to handle the spike in cases during the COVID-19 pandemic, the Mombasa County administration developed a GBV situation center in cooperation with community-based organizations (CBOs), Kisauni and Mvita were designated as the GBV Hotspots in Mombasa in 2023.

Nearly one-third of women worldwide may have experienced physical or sexual abuse at the hands of an intimate partner at some point in their lives, according to research conducted by the World Health Organization (WHO). Over 41 percent of Kenyan women report that they have experienced physical or sexual violence at the hands of their spouses, according to recent research [1]. This situation was made worse by the COVID-19 pandemic, as a rise in GBV cases was caused by insufficient government actions [2]. Such violence has long-lasting effects on women's physical, psychological, and emotional health and constitutes a serious violation of their fundamental human rights.

GBV has significant negative societal and familial repercussions that include financial hardships, detrimental consequences on one's physical and mental well-being, and more. Victims frequently experience both short-term and long-term effects, such as anxiety and depression as well as increased susceptibility to future abuse, especially if they had a history of sexual abuse as children. Furthermore, children who witness gender-based violence suffer grave consequences for their mental health [3]. Due to insufficient support services for survivors, gender-based violence was made worse in Kenya as a result of the COVID-19 reaction. Their vulnerability is further increased by the government's refusal to offer victims comprehensive mental health care, medical attention, financial assistance, or legal recourse.

Innovative strategies, such machine learning, are being used to create risk assessment models for victim recidivism in an effort to address this epidemic. These models attempt to predict the probability of reoffending by utilizing structured data from cases of intimate partner abuse against women. This allows for more focused interventions. A multimodal strategy for monitoring and reducing gender-based violence is highlighted by the National Police Service's cooperation with groups such as GBV SHOFCO Coast Region, as well as with government agencies and civil society [4].

Effective responses to gender-based violence are hampered by operational misunderstandings and implementation gaps, which persist despite gains in policy frameworks. The goal of attempts to create machine learning models for predictive analysis is to close this knowledge gap by giving institutions and organizations precise and timely information to inform preventive actions. By using supervised machine learning techniques, these models aim to improve decision-making and encourage proactive actions to prevent GBV.

To put it briefly, the creation and utilization of machine learning models present viable approaches to tackling the widespread problem of gender-based violence in Kenya, in addition to more extensive initiatives meant to promote a community devoid of such crimes.

**Research Questions**

a) What are the main characteristics or predictors of gender-based violence (GBV) among women in Kenya that show a lot of promise for use in predictive modeling?
b) Which techniques or methods work best for assessing the efficacy and precision of GBV prediction models in Kenyan women?

Effective preventive and intervention measures for gender-based violence (GBV) against Kenyan women depend on an understanding of the predictive features and an assessment of the efficacy of machine learning models. Through the identification of the most significant variables linked to the occurrence of GBV, predictive modeling can offer important insights into risk assessment and potential for early intervention. In addition, strong assessment techniques are necessary to evaluate the precision and dependability of these predictive models, guaranteeing their usefulness in practical settings. In order to shed light on the state of machine learning modeling for GBV prediction in the Kenyan setting, this review of the literature attempts to consolidate the findings of previous research on predictive features and evaluation techniques.

## II. METHODOLOGY

**Search Strategy**

A methodical and thorough strategy was taken in the process of finding relevant literature sources for our study, incorporating a number of essential elements. First, important scientific databases that are well-known for their extensive coverage—PubMed, Scopus, Web of Science, and Google Scholar—were carefully chosen. This choice was made with the intention of guaranteeing that our review framework would contain a wide range of pertinent materials. Then, a carefully selected list of search terms that were closely related to teenage pregnancies and machine learning was created. This was a very carefully constructed list that included important phrases like "supervised learning," "machine learning," "predictive modeling," "GBV," and "logistic regression." The careful selection of these terms had a crucial role in making it easier to retrieve research resources that closely matched our study's goals.

Making our way through the maze of databases required careful attention to selecting the appropriate keywords related to our field of study. Our review was made more comprehensive and in-depth by the wealth of scholarly insights that could be accessed through each of the keywords we chose. The careful selection of keywords played a crucial role in optimizing the search procedure, guaranteeing that our study explored the complex nuances of teenage pregnancies and machine learning applications. This clever combination of relevant keywords improved the accuracy and pertinence of the material that was found while also streamlining the search process.

Essentially, the foundation of our literature search approach is the methodical combination of extensive databases and well-chosen search terms. Through the careful integration of these fundamental elements, we attempted to sweep a broad swath across the academic terrain, guaranteeing the capture of a variety of viewpoints and factual data relevant to our investigation. In the context of gender-based violence prediction, this methodological rigor highlights our dedication to carrying out a thorough and complete review, thereby promoting a nuanced understanding of the interaction between adolescent pregnancies and machine learning.

**Data Extraction and Synthesis**

Although they necessitate the extraction of data that is frequently hidden within textual articles and journals and are a labor-intensive process in and of itself, systematic reviews are essential for obtaining accurate estimations of diagnostic test accuracy [5]. Against the backdrop of relevant literature on Gender-Based Violence (GBV), a painstaking effort was made to extract and synthesize data from earlier studies in order to obtain crucial information about different study designs, sample sizes, variables under consideration, supervised learning techniques relevant to machine models, and important findings. In order to extract data, each study was carefully examined, with special attention paid to relevant variables like age, educational attainment, history of intimate partner violence, economic stability, cultural norms, and social support networks. This all-encompassing method sought to provide a logical representation of machine learning.

The amalgamation of extracted data highlighted the difficulties faced by machine learning models, particularly the dependence on a single research design, which is mostly associated with cross-sectional studies, and the use of logistic regression as the primary learning technique for GBV dataset analysis. However, the results clarified the possible applicability of machine learning models in anticipating GBV incidents, highlighting their usefulness in tackling this widespread social problem. The work provides valuable insights into the application of machine learning approaches for predictive purposes in the field of gender-based violence. Its ramifications for researchers, humanitarian groups, legislators, and law enforcement bodies are noteworthy.

Important information on GBV predictors was carefully extracted from a subset of studies, together with extensive information about study designs, sample sizes, demographic factors taken into account, and supervised learning techniques used. The synthesis data were rigorously analyzed to discover recurrent themes and trends within the literature. Special attention was given to the impact that socioeconomic and demographic characteristics have in predicting cases of GBV against women. This all-encompassing method makes it easier to comprehend how complex GBV prediction is, and it emphasizes how crucial it is to take into account a range of contextual aspects while doing predictive modeling in this field.

## III. CRITICAL ANALYSIS AND SYNTHESIS OF THE STUDIES

**Methodological Approaches**

Most of the research designs used in these studies are cross-sectional, which makes it easier to gather and analyze large amounts of data and show how Gender-Based Violence (GBV) is complex and affects different populations and periods of time. The research' strong statistical power is highlighted by their diverse sample sizes, which range from 1,000 to 69,000 individuals. This allows for the important correlations between factors and GBV cases to be identified.

Numerous sociodemographic characteristics, such as age, education, economic stability (income), cultural norms, history of intimate partner violence (IPV), and social support, repeatedly show up as critical determinants throughout the research. The careful examination of these factors highlights the complex relationship between social dynamics and the incidence of GBV, requiring a thorough comprehension of their impact in attempts to use predictive models.

The research consistently employs supervised learning approaches, particularly logistic regression, which facilitates the creation of prediction models customized to predict GBV cases based on characteristics that have been found. By using these approaches, researchers can anticipate and address possible GBV cases in advance, which support focused intervention plans and preventive actions.

Age and education are important markers of gender-based violence (GBV), and this is shown by several consistent outcomes that hold true despite differences in study designs and sample sizes. Furthermore, it becomes clear that cultural norms and socioeconomic factors like social support and economic security (income) interact intricately to determine the prevalence of GBV. Furthermore, the noteworthy prognostic value of a past history of intimate partner violence (IPV) highlights the increased susceptibility of those who have experienced such abuse to additional cases of GBV.

The rigorous methodology used in all of these researches emphasizes how important it is to use trustworthy statistical methods and account for a wide range of sociodemographic characteristics. By doing this, researchers are better able to predict and understand the intricate dynamics of GBV, which helps to guide evidence-based interventions and policy frameworks that are intended to address this widespread problem in society.

**Predictive Factors**

Numerous sociodemographic characteristics have been identified in multiple researches as predictive factors for gender-based violence (GBV). Age was found to be a major predictor by Volpe et al. (2013) [6], who also highlighted the increased risk that young women face when they are in relationships with partners who are much older than them. These dynamic highlights power imbalances in relationships, as partners who are older than each other may be able to impose more control because of advantages in terms of experience and money. The results highlight the need for age-appropriate interventions and support networks in order to successfully reduce GBV.

Lawoko et al. (2007) [7] noted that while higher education among women can reduce this risk, there is a correlation between lower levels of education and increased vulnerability to GBV. Paradoxically, though, women who have greater levels of education and employment may still be victims of GBV, maybe as a result of partner fears or inferiority complexes. The significance of educational attainment in comprehending and tackling gender-based violence is highlighted, underscoring the necessity of all-encompassing educational programs and awareness campaigns.

Moreover, social factors—in particular, income levels—have a major impact on GBV. Lower income has been linked to intimate partner violence in studies by Dalal (2011) [8], which highlights the aggravating impact of socioeconomic disparities on the occurrence of GBV. Furthermore, Bows, H., & Fileborn, B. (2020) [9] research shows that those with a history of intimate partner violence and little social support networks are more vulnerable. These results highlight the intricate interactions between sociodemographic variables in the prediction of GBV and highlight the need of incorporating these variables into policy and programmatic initiatives targeted at lowering the prevalence of GBV.

**Model Performance and Accuracy**

Many research have used supervised learning approaches, namely Logistic Regression, to analyze predictive models for Gender-Based Violence (GBV). This method is preferred because it can manage intricate datasets and identify trends among the factors taken into account. Interestingly, these models show remarkable predictive power for intimate partner violence across a range of research methods and sample sizes. For example, using logistic regression, Study 1 Bows, H., & Fileborn, B. (2020) [9] finds that among partners with recurring histories of intimate partner violence (IPV), a lack of social support and familial estrangement are important predictors of GBV. These results highlight the model's ability to accurately identify critical parameters driving GBV rates.

The models' conclusions gain credibility when they are consistent across several studies. Both age and education are strong indicators of GBV and have been shown to be significant in a number of studies [7];[8]. Additionally, albeit less consistently, several research demonstrate that variables including ethnicity and cultural norms have significant predictive value [6];[8]. These results imply that the models effectively capture the subtleties of sociodemographic factors affecting the prevalence of GBV.

Although the models are predictively accurate, there are still biases and issues with interpretability. Prejudices that prefer some factors over others might provide inaccurate forecasts or reinforce preconceived notions. Furthermore, models with no explanatory power present interpretability challenges that impede decision-makers in the healthcare and policy domains from understanding and reacting appropriately.

To address these problems and strengthen the models' cross-context applicability, more research is required. This could include reducing biases, improving interpretability, and compiling thorough data on underrepresented topics. Developing more accurate GBV prediction models could help guide focused actions and policy, which could lead to a significant reduction in GBV incidence.

Several sociodemographic traits have been identified in multiple studies as predicting variables for GBV. Notably, Volpe et al. (2013) [6] found that age was a significant predictor, emphasizing the increased vulnerability of young women in partnerships with significantly older males. This discrepancy highlights power dynamics mismatches, as elder partners may have more clout because of their wealth and expertise. To effectively mitigate GBV, addressing this calls for specialized interventions and age-sensitive support networks.

Lawoko et al. (2007) [7] also draw attention to the nuanced connection between education and the risk of GBV. While women who have completed more education are generally less vulnerable, those who have not completed as much school are more susceptible. Ironically, GBV can still affect women who have advanced degrees and jobs. This could be because of partner concerns or feelings of inferiority. These results highlight how important educational programs are to effectively addressing GBV.

Furthermore, socioeconomic variables—in particular, income levels—have a big impact on the occurrence of GBV. Dalal (2011) [6] highlights the compounding effect of socioeconomic differences by establishing a relationship between lower income and increased chances of intimate partner violence. Fedima et al. (2022) further highlight the susceptibility of those with poor social support networks and a history of intimate partner abuse. These results highlight the complex interactions between sociodemographic factors and GBV prediction, supporting the inclusion of these factors in focused policy and programmatic measures meant to reduce the prevalence of GBV.

**Challenges and Limitations**

A potentially useful method for forecasting gender-based violence (GBV) against Kenyan women is the use of logistic regression models. But in spite of their potential, these models have a number of issues and restrictions that should be taken into account:

First, there is a big problem with the accuracy and comprehensiveness of the data sources that are currently available. The National Police Service and Community-Based Organizations (CBOs) are two common sources of data used in these models; the accuracy and comprehensiveness of each dataset varies. For this reason, the validity of these data sources is a determining factor in the predictive power of logistic regression models—a feature outside the researchers directs control [16].

Furthermore, there is another challenge due to the dynamic nature of GBV. Gradual alterations in cultural standards, legal structures, and more exogenous factors contribute to the dynamic terrain of gender-based violence. The usefulness of logistic regression models in accurately projecting GBV patterns may be diminished due to their possible inability to adjust to these changes.

Furthermore, logistic regression models have a great deal of difficulty due to the complexity of GBV dynamics. Numerous sociodemographic, cultural, and economic factors all have an impact on GBV, which adds to its complex nature. The complex relationships between these variables may be difficult for logistic regression models to capture, resulting in overly simplistic representations of GBV dynamics. As a result, the models might not be able to offer complex insights into the underlying mechanisms and causes of GBV occurrences.

Although logistic regression models are a promising tool for predicting gender-based violence against Kenyan women, there are a number of issues and constraints with them. In order to resolve these problems, a concentrated effort must be made to improve data quality, modify models to reflect shifting societal dynamics, and create more advanced analytical techniques that can faithfully capture the intricacy of GBV dynamics. Predictive modeling can only make a significant contribution to the reduction and prevention of GBV in Kenya through such initiatives.

**Recommendations for Future Research**

Several important approaches can be taken to improve the effectiveness and usability of machine learning models for forecasting gender-based violence (GBV) against women in Kenya. First and foremost, it's critical to improve model interpretability. The utilization of explainable AI methodologies, such as feature importance analysis and model visualization, can provide insight into the fundamental elements that influence GBV predictions. A deeper understanding of the factors influencing model outcomes would help stakeholders trust and understand these models' predictive power, which will support well-informed decision-making.

Second, creating accurate and trustworthy prediction models requires verifying the quality of the incoming data. Improving data cleaning methods, investigating data augmentation techniques, and putting in place reliable data standards procedures should be the top priorities for future research projects. Researchers can improve the accuracy and completeness of input data, minimize biases, and lower mistakes by improving data quality, all of which will improve the performance of GBV prediction models.

Thirdly, cooperative efforts and data exchange programs are needed to increase the generalizability of machine learning models. Encouraging cooperation between various academic institutions, research centers, and data sharing networks can help to curate extensive datasets for model training and validation. Machine learning models can capture a wider range of GBV dynamics when they have access to diverse and large-scale datasets, which improves their generalizability across a variety of contexts and populations.

Consequently, in order to further machine learning modeling for predicting GBV against Kenyan women, a multimodal approach is needed. Scientists can produce more accurate, dependable, and practical prediction models by emphasizing model interpretability, enhancing data quality, and extending generalizability. These programs could provide valuable insights for targeted interventions, policies, and support systems aimed at reducing GBV and improving the safety and well-being of Kenyan women.

## IV. DISCUSSION

The results of the literature review are summarized and critically analyzed in the discussion chapter, which also offers recommendations for future research on the prediction of gender-based violence (GBV) against women in Kenya. It does this by highlighting methodological approaches, predictive factors, model performance and accuracy, challenges, limitations, and recommendations.

Strong statistical power is demonstrated by the methodological approaches used in the examined research, which primarily use cross-sectional designs with a range of sample sizes. Critical factors of gender-based violence (GBV) are frequently identified as sociodemographic traits such age, education, economic stability, cultural norms, history of intimate partner violence (IPV), and social support. Because logistic regression can handle large and complicated datasets and recognize patterns, it is the supervised learning method of choice for developing prediction models.

The literature has discovered several predicting factors, such as age, education, economic level, and social support. These factors underscore the complex nature of gender-based violence and the significance of incorporating diverse sociodemographic variables in predictive models. However, the efficacy of logistic regression models is constrained by issues including data accuracy, the dynamic nature of GBV, and the complexity of GBV dynamics.

Future research is advised to address these issues by promoting collaborative efforts and data exchange programs to increase model generalizability, enhancing data quality through data cleaning and augmentation techniques, and improving model interpretability through explainable AI methodologies. To advance machine learning modeling for predicting GBV against Kenyan women, a multimodal strategy emphasizing model interpretability, data quality, and generalizability is necessary. Even though logistic regression models have the potential to predict GBV, overcoming obstacles and putting suggestions for further study into practice are essential for enhancing the predictive models' usefulness and efficacy and, eventually, lowering the incidence of GBV in Kenya.

## V. CONCLUSION

In conclusion, gender-based violence (GBV) has terrible effects on people individually, in families, and in communities. It is still a widespread and deeply ingrained problem in Kenyan society. The results of this review highlight the complexity of GBV and the intricate interactions between sociodemographic variables that influence its prevalence. Many predictors, ranging from financial status and cultural norms to age and education, have been found via thorough investigation and analysis. These indicators provide important insights for the creation of predictive models targeted at early intervention and prevention in addition to aiding in the study of the dynamics of GBV.

Significant obstacles and restrictions still exist in the use of machine learning approaches for GBV prediction, despite recent advancements. Predictive models' performance is hampered by problems with data quality, model interpretability, and the dynamic nature of GBV dynamics. Improving data gathering techniques, enhancing model interpretability, and encouraging stakeholder engagement are all necessary to address these difficulties. Through the use of a multimodal strategy that prioritizes openness, data quality, and cooperation, scientists may create prediction models that are more precise and dependable, with applications for interventions and policy choices.

Furthermore, a comprehensive grasp of the predictive characteristics of GBV and the effectiveness of machine learning models is crucial for the execution of successful preventive and therapeutic strategies. Evidence-based methods that address the underlying issues leading to GBV can be informed by researchers by identifying crucial variables and assessing the performance of predictive models. In addition, continuous research and cooperation are necessary to ensure that predictive models are relevant and applicable in a variety of contexts by validating and improving them.

In order to effectively combat gender-based violence in Kenya, a thorough, multidisciplinary strategy incorporating knowledge from practice, policy, and research is needed. Through the utilization of machine learning and data-driven methodologies, stakeholders can collaborate to create focused initiatives, supportive networks, and legislative frameworks that advance gender parity and forestall gender-based violence. We can work toward a time where GBV is not a constant danger to women's safety and wellbeing in Kenya by working together and making consistent investments in research and innovation.

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