Modeling Violence against Women in Palestinian Society

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Abstract

This paper aimed to develop a framework for analyzing various forms of violent incidents against women in the Palestinian society in the context of finding a good statistical model that can describe this phenomenon and to find the most important risk factors with the highest effects on the prevalence level of violence against women. The paper is based on an analysis of survey data on domestic violence and includes many socioeconomic, political, and cultural explanatory variables and focuses on violence of various forms against women in the Palestinian territories. The results were that the multinomial logistic regression proved to be a good model and achieved all the goals of this study. The paper concluded that the most important risk factors associated with violence against women are not only directly related to women but also related to the status of their intimate partners and kids. Thus, family development should be the core of any policy program to end violence against women in the society.

Key Words: Classification, multinomial logistic regression, odds ratio, risk factors, ROC curve

1. Introduction

Violence against women is a global phenomenon that is increasingly prevalent all over the globe. The World Health Organization (2012) studied this phenomenon using data on more than 24,000 women from 10 different countries and indicated that violence against women is practiced on a large scale. Moreover, the Human Development Report published by the United Nations Development Program Regional Office for Arab States (2009) confirmed that women in the Arab world are exposed to various forms of dramatic violence. Lately, violent incidents against women are an increasingly prevalent phenomenon in Palestine, perhaps due to the deteriorating economic status and rapidly growing unemployment rates. Although violence against women is a global phenomenon, there seem to be very few studies based on a thorough analysis of the phenomenon to investigate the causes of the problem. Therefore, it is useful to investigate this phenomenon in order to propose policy actions toward reducing the prevalence rates. The research issue of this study is how to model various forms of violent incidents against women in Palestine and how to investigate their associated risk factors in order to help formulate policy programs that can reduce the prevalence rates of this phenomenon. Despite the fact that many data sets are available on the phenomenon, only a few have been analyzed using a statistical model that can classify and predict different types and sources of violent incidents or identify the most important risk factors associated with violence against women in Palestine.

The main objective of this study is to explore the applicability, importance, assumptions, and advantages of a statistical model that can be used when the response variable is categorical and that can identify the most important risk factors associated with various forms of violence against woman in the Palestinian society. In particular, the study aims to identify and build a model for describing the relationship between various forms of violence against women as a response variable and some important influencing factors as independent variables. The goal is to identify the most important risk factors associated with violent incidents against women and to draw some conclusions that can decrease the prevalence level of violence against women in Palestine. To achieve this goal, we analyzed survey data provided by the Palestinian Central Bureau of Statistics (PCBS) and built a statistical model that can identify the important risk factors on violence against women in Palestine.

The Woman's Affairs Center conducted two studies in 2005 and 2009 on violence against women in the Gaza Strip in order to diagnose this phenomenon and to identify the priorities to be addressed under the special circumstances of the Gaza Strip and within a feminist vision that suggests that the phenomenon of violence is a product of unbalanced power in relationships in the society. The first study found that one out of every five women in the Gaza Strip is exposed to physical violence, and one of every three women is exposed to verbal humiliation, and one out of every 10 is exposed to sexual abuse. Although the study did not seek to compare the magnitude of the phenomenon in the Gaza Strip with other regions, the incoming indicators were alarming. In the second study, the researchers got insight (directly or indirectly) on the causes of problems and consequential results through detailed presentation of the problem tree and presentation of women's rights violations. The conclusions reflected priority issues as to women's and men's desires according to information sources included in the study, as follows. Those issues are the denial of women's inheritance and the seizure of their money, the stereotype of women in the media, the impact of internal Palestinian instability on women, the vulnerability of women to psychological abuse from neighbors, and the impact of women's problems on the psycho-social situation.

Statistical models can describe the relationship between the outcome as a dependent variable and the set of causes affecting the outcome as independent variables. Linear models are often applied in social sciences, but they require that the dependent and independent variables be numeric variables. Moreover, they also require meeting some assumptions, such as the normal distribution of the error terms. However, the outcome variables obtained in social sciences are typically categorical and cannot be studied within the linear model context. Accordingly, appropriate statistical methods for categorical or nominal outcome variables should be used. Salih (2005) conducted a study on the use of objective manner path analysis as a new method for the analysis of disaggregated data by building models of causation to propose and determine the relative importance between the variables specified in the models.

Another study by Al-Sabbah (2009) aimed to investigate the health expense of some biomarkers on births, deaths, and illnesses of children over a two-year period of time (2004–2006) and constructed a model for establishing a health rate through the application of statistical models and investigated performance using a logistic regression model. A study by Pai (2009) aimed to determine the efficiency of mathematical programming classification models, or more specifically, linear programming (LP) methods vis-à-vis statistical approaches such as discriminant analysis and logistic regression, neural networks, and a non-parametric technique (e.g., k-nearest neighborhood, or k-NN, for four-group classification problems). Furthermore, the study extended an existing two-group LP model (BAL et al., 2006) based on the work of Lam and Moy (1996) and applied it to four-group classification problems.

Manzoor, et al. (2013) investigated violence against women in the Pakistani Punjab. Using related socioeconomic, political and cultural indicators, they found that women have to face multiple forms of violence in patriarchal societies similar to Palestinian society. This study provided a simple but brief overall scenario of violence against women in Pakistan. UN Women Pacific (2011) found that too many Pacific women and girls experience violence in their lives. The report acknowledged the availability of qualitative, comprehensive, and comparable data and strong and alarming evidence of the high prevalence and severity of violence committed against women by their partners and by strangers. The study identified high rates and severe consequences of violence against women in Samoa, the Solomon Islands, and Kiribati.

Lee (2010) proposed a method for multi-way classification of problems using ensembles of multinomial logistic regression models as base classifiers. The multinomial logit model showed that it can be applied to each mutually exclusive subset of the feature space without variable selection. By combining multiple models, a huge database could be handled with the proposed method without the parametric constraint needed for analyzing high-dimensional data, and the prediction accuracy could be improved by the random partition through reducing the correlation among base classifiers. The proposed method was implemented using R statistical software, and the performance measures included overall prediction accuracy, sensitivity, and specificity for each category, which were evaluated on real data sets. To investigate the quality of prediction in terms of sensitivity and specificity, the area under the ROC curve was also examined. The performance of the proposed model was compared to a single multinomial logit model and another ensemble method combining multinomial logit models using the algorithm of Random Forest.

The focus of this paper is to discuss the use of a multinomial logistic regression (MLR) as a classification model and assessment technique and to apply this model on the classification of cases of violence against women by all sources in the Palestinian society. The classification was based on different socioeconomic and demographic indicators. Further, we look at the effects of these indicators on the status of violence against Palestinian women and on the source of violence.

2. The Data

In this paper, we analyzed different types of violence against women in Palestinian society. The study is based on a 2011 survey provided by the PCBS titled "Violence Survey in the Palestinian Society." The aim of the survey was to study all types of violence in Palestinian society. This survey is the second of its kind to be executed nationwide. The survey data has been obtained through direct communication with the PCBS officials for the purpose of academic research. The target population of this study consisted of currently and previously married women aged 15 years old and above residing in the Palestinian territories. The sampling frame was composed of all existing 300 enumeration areas in the Palestinian territories established by the 1997 Population, Housing and Establishment Census. The enumeration areas were close in geographical size and number of households. The sample of the survey was a statistical two-staged, clustered strata sample composed of 5,811 households located in all the 300 enumeration areas in the Palestinian territories. The survey was distributed to 3,891 households in the West Bank and 1,920 in the Gaza Strip. The data was collected according to the procedures, rules, and methodology established by the PCBS (compatible with international data collection standards) to achieve the highest data quality. Results are described in the PCBS user guide (PCBS, 2003).

Thus, the PCBC's survey was collected in order to provide information on all types of violence faced by all individuals in Palestinian society. The study population of the survey is composed of all individuals in the population in the following categories:

1. Currently or previously married women.
2. Unmarried young people (males and females) in the 18–64 age group and over.
3. Children in the 12–17 age group.
4. The elderly (65 years old and over).
5. Husbands.

Since we are only interested in violence against currently or previously married women in the society, we used only one section of the survey covering that category. However, the different types of violence against women and their source in the survey are listed below:

1. Violence by husband: This subsection in the survey involves 30 questions and is divided into three types of violence (psychological violence, physical violence, and sexual violence). The percentage of women in Palestinian society who suffered from all types of violence by husband is 62.2%.
2. Violence by others: This subsection involves 21 questions on the same three types of violence. The percentage of women in Palestinian society who suffered from all types of violence by others at home is 21.8%.
3. Violence in other places: This is another subsection that involves eight questions on the same three types of violence. The percentage of women in Palestinian society who suffered from all types of violence in other places is 13.0%.

From the above three sources, we established a new response (dependent) variable, which is our main focus in this paper. It is called "violence status" (violence against women from all sources) and has four categories. They include the three forms of violence faced from any of the above three sources, and the fourth category is the case where women have never faced any form of violence. Therefore, the response variable that we focused on in our analysis was restricted only to the violence status from all sources, represented by four categories: no violence, psychological violence, physical violence, and sexual violence.

3. The Model

Suppose that we have a categorical response variable Y of interest that has k = 4 categories representing the violence status of Palestinian women and q explanatory variables, $X_1, X_2, \ldots\ldots\ldots, X_q$, representing the q socioeconomic and demographic characteristics of the women.

Suppose also that we have n independent observations of the q variables x_{ij} (i = 1,2,.....,n, j = 1,2,.....,q) and that the corresponding values of the dependent variable Y takes the values y_i (i = 1,2,.....,n) such that:

$y_i = 1$ if the woman has been exposed to physical violence,
$y_i = 2$ if the woman has been exposed to psychological violence,
$y_i = 3$ if the woman has been exposed to sexual violence, and
$y_i = 0$ if the woman has never been exposed to violence of any of the above types.

Similar situations with a similar response variable can be found in many areas of social research, including economic and business cases. In such situations, where there are many explanatory variables of different types, including continuous, discrete, and binary variables, the multinomial logistic regression (MLR) model can be applied. The basic concept was generalized from binary logistic regression, and only one response variable can be used, as discussed in Menard (2002). Can (2013) applied the multinomial probit model in a similar case for the estimation of travel mode choices for domestic tourists to Nha Trang. Habib (2012) used the same model for modeling commuter mode choices jointly with work start time and work duration. Omidvar et al. (2011) used an MLR model to analyze online customers' interactions with a company's website. The results offered the company an unprecedented understanding of the needs and wants of its audience and of website performance relative to customer experience, allowing the company to determine whether business objectives were being met. The MLR model can be used effectively when the response variable is composed of more than two levels or categories. The MLR model may be used to predict a response variable on the basis of continuous and/or categorical explanatory variables to determine the percent of variation in the response variable explained by the explanatory variables and to determine the effect of covariate control variables, as the model allows the simultaneous comparison of more than one contrasting variable; that is, the log odds of three or more contrasting variables are estimated simultaneously (Garson, 2010).

Let p_j denote the probability of any observation $\boldsymbol{i}$ falling into the j[th] category: $p_j = P(Y_i = j), i = 1,2,\ldots,n;\ j = 1,2,3,4$. To find the relationship between this probability and the q explanatory variables, X_1, X_2 ,........., X_q, we may construct the logits in the multinomial case, considering the last category in which the woman has never been exposed to violence ($y_i = 0$) as the base level, and all the logits are constructed relative to it. The multiple logistic regression model is then can be written as:

$$log\left[\frac{p_j}{1-p_j}\right] = \beta_{j0} + \beta_{j1}x_1 + \beta_{j2}\, x_2 + \ldots + \beta_{jq}\, x_q \quad \ldots\ldots(1)$$

If we take the exponentiation of both sides and solve for the probabilities, we get:

$$p_j = P(Y_i = j) = \frac{e^{-(\beta_{j0} + \beta_{j1}\, x_1 + \beta_{j2}\, x_2 + \ldots + \beta_{jq}\, x_q)}}{1 + e^{-(\beta_{j0} + \beta_{j1}\, x_1 + \beta_{j2}\, x_2 + \ldots + \beta_{jq}\, x_q)}} = \frac{\exp\left(-\sum_{i=0}^{q} \beta_{ji} \cdot x_i\right)}{1 + \exp\left(-\sum_{i=0}^{q} \beta_{ji} \cdot x_i\right)} \quad \ldots\ldots(2)$$

for i = 1, 2, …... , n , j = 1, 2, …... , (k-1) and $\sum_{j=1}^{k} p_j = 1, k = 4$ (Train, 2009). Therefore, we can use this to find the probabilities of each observation falling into the category j = 1,2,3 as:

$$p_1 = P(Y_i = 1) = \frac{\exp\left(-\sum_{i=0}^{q} \beta_{1i} \cdot x_i\right)}{1 + \exp\left(-\sum_{i=0}^{q} \beta_{1i} \cdot x_i\right)} \quad \ldots\ldots(3)$$

$$p_2 = P(Y_i = 2) = \frac{\exp\left(-\sum_{i=0}^{q} \beta_{2i} \cdot x_i\right)}{1 + \exp\left(-\sum_{i=0}^{q} \beta_{2i} \cdot x_i\right)} \quad \ldots\ldots(4)$$

$$p_3 = P(Y_i = 3) = \frac{\exp\left(-\sum_{i=0}^{q} \beta_{3,i} \cdot x_i\right)}{1 + \exp\left(-\sum_{i=0}^{q} \beta_{3,i} \cdot x_i\right)} \quad \ldots\ldots(5)$$

and $p_4 = 1 - p_1 - p_2 - p_3$.

Multinomial logistic regression (MLR) is used to predict categorical placement in a category or the probability of category membership of a specific observation based on multiple explanatory variables. The explanatory variables can be either dichotomous (i.e., binary) or continuous (i.e., interval or ratio in scale). MLR does necessitate careful consideration of the sample size and examination for outlying cases. Like other data analysis procedures, initial data analysis should be thorough and include careful univariate, bivariate, and multivariate assessment. Specifically, multicollinearity should be evaluated with simple correlations among the independent variables. Also, multivariate diagnostics techniques can be used to assess multivariate outliers and for the exclusion of outliers or influential cases. Sample size guidelines for multinomial logistic regression indicate a minimum of 10 cases per independent variable (Schwab, 2002).

Odds ratios are often used for comparing two categories of an independent variable after controlling for the other variables in the model (Moorman & Carr, 2008). For example, an odds ratio for comparing two categories of the variable X_1 is

$$\hat{O}R_{X_1=1 vs X_1=0} = \frac{\hat{O}dds(Y=1 \mid X_1=1, X_2, ..., X_k)}{\hat{O}dds(Y=1 \mid X_1=0, X_2, ..., X_k)}$$

$$= \frac{e^{\hat{\beta}_{10}+\hat{\beta}_{11}+\hat{\beta}_{12}X_{12}+...\hat{\beta}_{1k},X_k}}{e^{\hat{\beta}_{10}+\hat{\beta}_{12}X_{12}+...\hat{\beta}_{1k}X_k}} = e^{\hat{\beta}_{11}} \quad .... (6)$$

MLR is often considered an attractive analysis because it does not assume normality, linearity, or homoscedasticity. A more powerful alternative to multinomial logistic regression is discriminant function analysis, which requires that these assumptions are met. Indeed, multinomial logistic regression is used more frequently than discriminant function analysis because the analysis does not have such assumptions. MLR has very few assumptions, including the assumption of independence among the dependent variable choices. This assumption states that the choice of or membership in one category is not related to the choice or membership of another category. The assumption of independence can be tested with the Hausman-McFadden test. Furthermore, MLR also assumes non-perfect separation. If the groups of the outcome variable are perfectly separated by the predictor(s), then unrealistic coefficients will be estimated and effect sizes will be greatly exaggerated (Starkweather and Moske, 2011, 2013).

There are different parameter estimation techniques based on the inferential goals of multinomial logistic regression analysis. One might think of these as ways of applying MLR when strata or clusters are apparent in the data (Starkweather & Moske, 2011). The wide use of the MLR model, particularly in the fields of medicine, psychology, mathematical finance, and engineering (Bayaga, 2010), is because it has a number of major advantages, including:

1) It is more robust to violations of assumptions of multivariate normality and equal variance-covariance matrices across groups than other classification techniques.
2) Its interpretation is similar to that of linear regression and has more easily interpretable diagnostic statistics.
3) Most importantly, MLR does not assume a linear relationship between the dependent variable and each independent variable.
4) Independent variables need not to be continuous or quantitative to apply the MLR model.
5) The MLR model does not require that the independent variables be unbounded.
6) Normally distributed error terms are not assumed, and the independent variables need not be on an interval level (Schüppert, 2009).

4. Assessment of the Model's Accuracy

The goodness of fit or calibration of a model tests whether the model adequately describes the variations in the response variable (women's violence status). Assessing goodness of fit involves investigating how close values predicted by the model are to the observed values. The Hosmer-Lemshow test evaluates the goodness of fit by creating 10 ordered groups of subjects and compares the number actually in each group (observed values) to the number predicted by the logistic regression model (predicted values). Thus, the test statistic is a chi-square statistic with a desirable outcome of non-significance, indicating that model prediction does not significantly differ from the observed (Hosmer et al., 2000; Hosmer & Lemshow, 2013).

The classification table, also called a confusion table, is a table in which the rows are the observed categories of the dependent variable and the columns are the predicted categories. When prediction is perfect, all cases will lie on the diagonal. The percentage of cases on the diagonal is the percentage of correct classifications. The receiver operating characteristic (ROC) curve graph is a technique for visualizing, organizing, improving, and selecting classifiers based on their performance. The area under the ROC curve is often used as a measure of quality of a probabilistic classifier. It is close to the perception of classification quality that most people have. A random classifier has an area under curve of 0.5, while a perfect classifier has 1. Classifiers used in practice should therefore be somewhere in between, preferably close to 1.

There are several equivalent approaches to construct an ROC curve, each resulting in different area under the ROC curve measurements (Vuk & Curk, 2006). To compute the classification accuracy, we need to know the ratio of positively : negatively assigned cases. Knowing this, we can find a point on the graph with optimal classification accuracy (Fawcett, 2003). Another important aspect of ROC performance analysis is the ability to assign weights to positive and negative errors. Weights influence just the angle of the tangential line and thus influence the selection of the optimal binary classifier (Vuk & Curk, 2006). The area under the ROC curve (AUC) has become a standard performance evaluation criterion in two-class pattern recognition problems, used to compare different classification algorithms.

Hand and Till (2001) extended the AUC to the multiclass case, creating the volume under the ROC hypersurface (VUS). They derived a simplified VUS measure that ignores specific intraclass dimensions and regards interclass performances only. Zweig and Campbell (1993) investigated the clinical performance of a laboratory in terms of diagnostic accuracy, or the ability to correctly classify subjects into clinically relevant subgroups through the ROC curve plots. This is because “ROC plots provide a pure index of accuracy by demonstrating the limits of a classifier's ability to discriminate between alternative states of health over the complete spectrum of operating conditions” (Zweig & Campbell, 1993). Ferri et al. (2003) studied the generalized VUS and provided calculations/estimations of the performance bounds of the VUS as a function of an increasing number of classes (C). This involved comparing performance between perfect (separable) classifiers and random classifiers (random performance). The study provided an important step in understanding the VUS performance measure. A related paper was presented by Edwards et al. (2004) and argued that since the VUS of a random classifier approaches that of a perfect classifier as C increases, the VUS may not in fact be a very useful performance measure.

Unfortunately, most previous works have not gone into detail as to how the VUS can practically be applied to an arbitrary set of classifiers in realistic cases. Edwards et al. (2004) considered the practical implementation of the VUS applied to a simplified case in which the overall class performances were considered, ignoring specific intraclass and interclass errors. This type of simplification restricts the VUS analysis, but nevertheless may be suitable for some problems, for example, where we are still interested in all operating points in terms of overall class performance, but the class to which an erroneous object is assigned is arbitrary. This simplification ensures that good classifiers tend to result in higher VUS scores than poorer ones resulting in an alternative measure. Hand and Till (2001), however, proposed a simple generalization of the ROC curve for multiple class classification problems through averaging pairwise comparisons. This measure reduces to the standard form in the two class case, and it is useful in many situations similar to ours, where it is impossible to give costs for the different kinds of misclassification.

5. Analysis of the Violence against Women Data

The violence survey data of 2011 conducted by PCBS and described in Section 2 has been used for the analysis of violence against women phenomenon in Palestine using the MLR model. The response variable that we focus on in our analysis is restricted to the violence status from all sources represented by four categories (no violence, psychological violence, physical violence, and sexual violence). Moreover, some 50 socioeconomic independent variables, such as region (the West Bank and the Gaza Strip), governorate, type of location (urban, rural, or camp), and economic status, were selected to be included in the analysis. The number of applicable women in the sample was 4,372. Among those, only 33% of the women had never faced any type of violence from any source, 34.8% of them suffered from psychological violence, 17.6% suffered from physical violence, and (14.6%) suffered from sexual violence. Figure 1 illustrates the above percentages. These results indicate that psychological violence is the most prominent type of violence against women from all sources in Palestinian society.

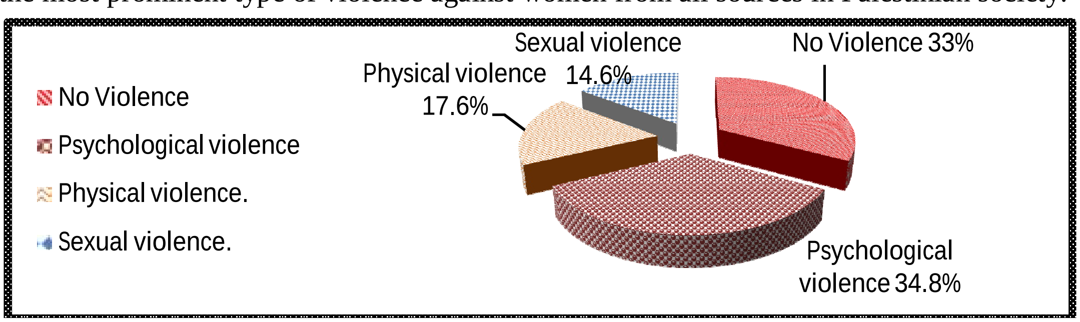

Figure 1. Frequencies of Types of Violence for All Sources

Now, we analyze the violence status of women as a categorical response variable that involves four categories (no violence, psychological violence, physical violence, and sexual violence). Some 50 independent variables had been included in the model as influential independent variables and possible candidates to be strong risk factors on the violence status of women. The multinomial logistic regression model that has been described in Section 3 above was constructed for this response variable using all the available independent variables. The result was that many coefficients in the fitted model were not significantly different from zero, indicating that the underlying independent variables should be removed from the fitted full model. For this purpose, a stepwise selection procedure was applied on the full model to select the best subset of independent variables that have statistically significant effects on the response variable. The results of the final model were then fully described.

First, all significant independent variables in the final model that manifest to be strong risk factors on violence against women in the Palestinian society are shown in Table 1. The values of the chi-squared test statistics for the significance of the variables and their degrees of freedom, as well as their p-values, are shown in the table. The result is that there are 27 significant risk factors related to this phenomenon. In testing the goodness of fit of the final model, the p-value of the deviance goodness-of-fit test was 0.0672654, indicating that the result was not significant and the model provided a good fit to the data.

Table 1. Significant Explanatory Variables in the Final Model, the Values of the Chi-Squared Test Statistics, and their p-Values

LR	Variable	Chisq	Df	Pr(>Chisq)	Signif.
Reg	Region: West Bank or Gaza Strip	159.870	3	< 2.2e-16	***
HC05	Number of rooms at home	6.368	3	0.0950158	.
HC06	Number of bedrooms in residence	13.470	3	0.0037238	**
HC09_1	Family owns a private car	6.062	3	0.1086450	
HC09_11	Family owns a library at home	8.482	3	0.0370391	*
HC09_14	Family owns an Internet line	6.604	3	0.0856456	.
Loctype	Type of locality: urban	10.676	3	0.0136129	*
HR05A	Age of woman	26.757	3	6.621e-06	***
HR06	Refugee status	14.865	3	0.0019353	**
HR08	Educational status of woman	13.064	3	0.0044995	**
HR10	Relation to the labor force of woman	13.638	3	0.0034423	**
WB01B	Husband has had troubles at work within the last 12 months	11.261	3	0.0103975	*
WB11B	Increased troubles with husband within last 12 months	194.508	3	< 2.2e-16	***
WB14B	Own child has been involved in illegal social issues in the last year	22.917	3	4.203e-05	***
WZ02	Husband has tried to limit wife's connections with her family or (female) friends	16.829	3	0.0007662	***
WZ03	Husband has insisted on being told about whom wife talks to and where she is always	36.916	3	4.795e-08	***
WZ04	Husband conceals information about the family income even if she ask him	21.302	3	9.111e-05	***
WZ06	Husband tries to control what wife usually wears	24.663	3	1.816e-05	***
WZ07	Husband is careless about wife	43.032	3	2.423e-09	***
WZ08	Husband prohibits wife from travelling abroad	25.233	3	1.380e-05	***
WZ10	Husband prohibits wife from freedom of expression	38.231	3	2.526e-08	***
WL01	Wife shares decision making in buying a family car	8.332	3	0.0396326	*
WL04	Wife shares decision making in internal family affairs, e.g., kitchen or house renovation	8.297	3	0.0402524	*
WL05	Wife shares decision making in buying or building a new house	22.293	3	5.668e-05	***
WL06	Wife works at job other than household work	14.946	3	0.0018630	**
WL10	Wife visits her husband's relatives or friends	7.638	3	0.0541123	.
WL13	Wife manages her own properties	9.508	3	0.0232460	*

Note: Signif. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The examination of the values of odds ratios (OR) for binary independent variables as risk factors can easily be interpreted. However, since many of the available independent variables are either continuous numeric or multiclass categorical variables, they are not easily interpretable. The OR's of a few binary risk factors can easily be interpreted since they are binary variables. Those include Reg (region: the West Bank or the Gaza Strip), WB11B (increased troubles with husband within the last 12 months), and many other variables, including WB14B (own child has been involved in illegal social issues in the last year). Region is the first variable in the model with high odds ratios that equal 2.9, 4.1, and 3.4, respectively, which means that a woman in the Gaza Strip suffers from psychological violence and sexual violence approximately three times as much as a woman in the West Bank, and a woman in the Gaza Strip suffers from physical violence approximately four times as much as a woman in the West Bank. The second significant variable in the model with high ORs is WB11B (increased troubles with husband within the last 12 months). The odds ratios for this variable equal 2.61, 5.51, and 4.62, respectively, which means that a woman with a husband who has faced increased troubles within the last year suffers from psychological violence approximately 2.6 times, physical violence approximately 5.5 times, and sexual violence approximately 4.6 times as much as a woman whose husband did not face any troubles in the last year. Other risk factors have approximately similar values of ORs ranging between 1.2 and 2.0 and have a similar interpretation.

The initial model (with no independent variables included) can predict violence against women with an overall percentage of accuracy of 34.8%. The table below shows the classification results of applying the final model of multinomial logistic regression.

Table 2. Classification Table for Multinomial Logistic Regression with the Explanatory Variables

Observed	Predicted				
	No Violence	Psychological Violence	Physical Violence	Sexual Violence	Percent Correct
No Violence	1,083	300	30	30	75.1%
Psychological Violence	421	911	120	69	59.9%
Physical Violence	119	289	270	94	35.0%
Sexual Violence	85	219	102	232	36.4%
Overall Percentage	39.0%	39.3%	11.9%	9.7%	57.1%

The figures from Table 3 indicate that the model can correctly classify the first category (no violence) with a percentage accuracy of 75.1%, the second category (psychological violence) with a percentage accuracy of 59.9%, the third category (physical violence) with a percentage accuracy of 35%, and the fourth category (sexual violence) with a percentage accuracy of 36.4%. The overall correct classification rate of the final model to classify cases of violence against women is 57.1%. The apparent low rate of correct classification, particularly in the last two categories, is due to the fact that the number of elements in those two categories is so small; this means that there are still other risk factors that were not accounted for, and no data on them exist in the PCBS survey.

The ROC curve illustrates the performance of a classifier, as its threshold is varied. As described in Section 5, the ROC curves have been drawn and exhibited in Figure 2, and the area under the curve measurements have been computed for different categories of the response variable in Table 3. As the ROC curve has been designed for the binary classifiers, observations in each category were considered separately as positive values if they were true, and all other values were considered negative if they fell in any other category. Table 3 shows that the area under the curve of the first category (no violence) equals 85.2%, the second category (psychological violence) equals 73.1%, the third category (physical violence) equals 79.3%, and the fourth category (sexual violence) equals 82.4%. Finally, The area under curve of the MLR model (multi-class area under the curve) equals 73.94%. This result indicates that the MLR model performed well as it produced very good classification with reasonably good, correct classification rates for all categories of the dependent variable.

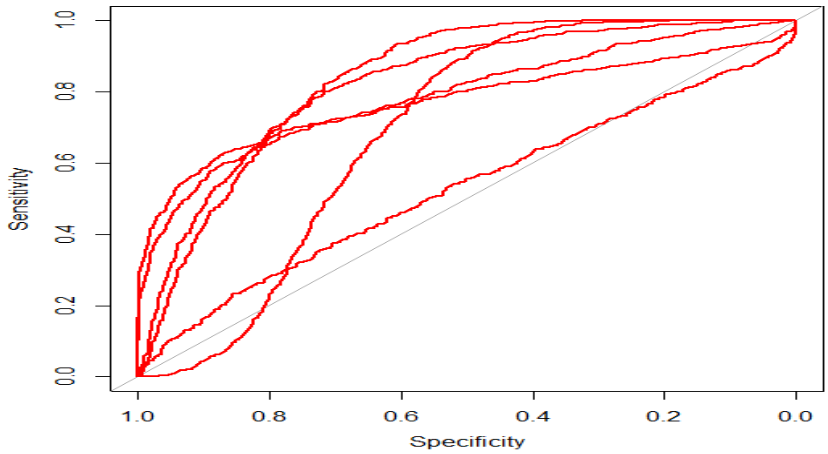

Figure 2. Multiclass ROC Curve of Multinomial Logistic Regression

Table 3. The Area Under the ROC Curves	
No violence	0.852
Psychological violence	0.731
Physical violence	0.793
Sexual violence	0.824
The area under the curve:	0.7394

Now, the MLR model takes the form given in Eq. 2 and in equations 3, 4, and 5, respectively, for the three values 1, 2, and 3 (different forms of violence) of the response variable relative to the fourth value (no violence). The maximum likelihood estimates of the β parameters of the three equations were estimated using data on all significant independent variables and the R statistical software. Estimates of the parameters for the three models for k = 1,2,3 corresponding to the three categories of violence, respectively, are given in Table 4.

Table 4 : Estimates of the Parameters of the Multinomial Logistic Regression Model

k	(Intercept)	Reg	HC05	HC06	HC09_1	HC09_11
1	4.795843	1.074831	0.09742788	-0.1608760	0.008634863	-0.1416740
2	8.614281	1.416215	0.09584390	-0.1892900	0.139113797	-0.3012323
3	8.961823	1.223194	0.08079266	-0.3030618	0.327841303	-0.3899768
k	**HC09_14**	**Loctype**	**HR05A**	**HR06**	**HR08**	**HR10**
1	-0.006844361	0.1215542	-0.00717473	-0.1252216	0.02444486	-0.06210583
2	0.264057387	0.2481825	-0.02137888	-0.1967189	-0.10581195	-0.09984201
3	0.185697772	0.1360528	-0.02708582	-0.1864896	-0.07440314	-0.05189411
k	**WB01B**	**WB11B**	**WB14B**	**WZ02**	**WZ03**	**WZ04**
1	-0.04811904	-0.9597512	-0.1217577	-0.06858006	-0.1273126	-0.1409961
2	-0.10753544	-1.7069590	-0.3096689	-0.18863305	-0.1630755	-0.1446450
3	-0.21825910	-1.5314563	-0.2931302	-0.09991655	-0.1687726	-0.2380682
k	**WZ06**	**WZ07**	**WZ08**	**WZ10**	**WL01**	**WL04**
1	-0.09076652	-0.05326887	-0.1290890	-0.2046732	0.10938193	-0.07887958
2	-0.13829119	-0.22379463	-0.1485212	-0.3185783	0.09705473	-0.13765917
3	-0.19219638	-0.28912537	-0.1510614	-0.4045761	0.03546392	-0.11603516
k	**WL05**	**WL06**	**WL10**	**WL13**		
1	0.1830460	0.09110939	-0.085050625	-0.04218754		
2	0.2326449	0.11253750	-0.113034308	-0.02641094		
3	0.2243208	0.16107970	-0.006581946	0.03143494		

The most important influential independent variables and risk factors in the model are found to be locality type (urban areas, rural areas, and camp), region (the West Bank and the Gaza Strip), the age of the woman, family owns a private car, family owns a library at home, family owns an internet line, refugee status, child involved in illegal social issues in the last year, relation to the labor force, number of rooms in the residence, number of bedrooms in the residence, educational status of the woman, husband tries to limit his wife's connections with her family or (female) friends, husband insists on being told about whom his wife talks to and where she is always, husband prohibits his wife from travelling abroad, husband prohibits his wife from freedom of expression, wife shares decision making in buying a family car, increased troubles with husband within the last 12 months, husband conceals information about the family income even if you ask, husband is careless toward his wife, wife shares decision making in buying or building a new house, and the wife manages her own properties.

6. Conclusion and Recommendations

From the discussion of the previous section, we can conclude that the MLR model provides a good classifier for the violence against women's data in Palestine and can assist in estimating the probability of a woman being exposed to violence of different sources and in classifying women according to their propensity to fall into different categories of women's violence status. In this paper, we estimated the coefficients of the model and tested its goodness of fit. We further examined the accuracy of the fitted model, using the correct classification table and the ROC curves analysis. The fitted model proved to be appropriate for our data set. Most importantly, the fitted model managed to identify the most important risk factors that have the greatest effects on the prevalence of violence against women in Palestine. Other results that may be concluded from the previous sections are as follows:

1. Violence by husband is one of the most common forms of violence that Palestinian women are exposed to.
2. Violence against women by others is not highly prevalent in Palestinian society, where only 21.8% of women in the survey were exposed to at least one type of violence by others.
3. Violence against women in other places is also not highly prevalent in Palestinian society.
4. Violence against women in the Gaza Strip from all types of violence is more prevalent than that of women in the West Bank.
5. Women in rural areas are less exposed to all forms of violence than women in other types of localities in Palestine.
6. Young women have a higher chance than older women of being exposed to all forms of violence from all sources.

Form all those results, we may recommend the following:

We recommend using the MLR models in women’s studies, particularly for violence against women studies, because of the model’s ability to provide good classifications and predictions and to identify the most important risk factors in terms of women's issues.

1. For reducing the prevalence of violence against women, special care should be given to husbands, as they are the primary source of violence against women and a primary source for risk factors leading to violence against women.
2. It is important to give priority to women in the Gaza Strip in any program that aims to limit violence against women, as women in the Gaza Strip suffer more than women in the West Bank from all sources of violence.
3. Multi-disciplinarily approach programs should be established for women in the refugee camps and for poor families in urban areas as a part of any strategy that aims to reduce the level of violence against women.
4. More attention should be given to young woman under 19 years old to limit women's early marriages because young married women have more risk of experiencing violence than older women.
5. Priority should be given to less-educated married women because men are more likely to commit violent acts against less-educated women than against educated women
6. Further research should be conducted that considers the inclusion of additional explanatory variables related to violence against women to achieve a model with a higher rate of correct classifications.

Finally, the results of this study indicated that many risk factors associated with violence against women are not directly related to women but are more related to other family members, particularly their intimate partners and kids, as well as their education, economic status, and housing conditions. This suggests that family and household development should be the main focus of any empowerment programs for women and any policy to end violence against women in Palestinian society.

Acknowledgment

The data used in this study has been provided by the Palestinian Central Bureau of Statistics (PCBS) for the purpose of scientific research. The authors are thus very grateful to the PCBS' president and staff for their efforts and anticipation since without their kind cooperation this work would have been impossible to be conducted.

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