

African Journal of Gender, Society and Development
Published consistently since 2012
ISSN: 2634-3614 E-ISSN: 2634-3622

Accredited by DHET (the South African regulator of Higher Education) and Indexed by IBSS, EBSCO, COPERNICUS, ProQuest, ERIH PLUS, SABINET and J-Gate.

Volume 14 Number 3 September, 2025
Pp 5-24

Determinants of Gender-Equitable Attitudes (GEA) in Zimbabwe: A Machine Learning Approach

DOI: <https://doi.org/10.31920/2634-3622/2025/v14n3a1>

Abieyuwa Ohonba

*School of Economics
University of Johannesburg
aohonba@uj.ac.za*

Abstract

This study seeks to identify the determinants of GEA among Zimbabweans using the World Values Survey dataset wave 7 (2017-2022) and a machine learning approach. Except for tangential references, there has not been an outstanding empirical work that took Zimbabwe into account on this matter. Our findings indicate that secondary and tertiary education, income equality, and urban residency contribute decisively to GEA. On the other hand, masculinity, political interest, freedom, trust, and having children inhibit GEA. Age, marital status, employment status, religion, and household financial situation do not predict GEA in Zimbabwe. These findings suggest that education remains critical for women and youth empowerment in the political, economic, and social spheres. However, they face access constraints to the empowerment benefits. These access issues stem primarily from the country's human rights-infringing-conservative political ideology. This ideology not only promotes masculine behaviour but also obstructs the transfer of empowerment benefits to future generations.

Keywords: *Binary logistic regression; Gender Equity Attitudes; Machine Learning; Sustainable Development Goal (SDG) 5; Zimbabwe.*

JEL: *C83; E66; J16.*

1. Introduction

Exploring the determinants of GEA is apparent for three main reasons. First, the Sustainable Development Goal (SDG) 5 of achieving gender equality by empowering marginalized girls and women by 2030 is yet to be met. Second, to remain relevant and integrated with new developments in an ever-changing economic, political, and social environment, gender-inclusive policies must be continuously assessed and reviewed. Third, gender equity ensures sustainable economic development. According to the African Development Bank (AfDB) report on the Gender Equality Index (GEI) in 2015, while African women contribute significantly to the continent's economic growth and development through farming and entrepreneurship, they are held back from fulfilling their potential by many constraints, whether as leaders in public life, in the boardroom, or in growing their businesses. In Zimbabwe, women and girls make up the majority of the population (52%) (Zimbabwe National Statistics Agency (ZIMSTAT), 2020), implying that sustainable development goals and other economic targets are frequently unattainable if half of a country's population is hampered by limited opportunities (World Economic Forum, 2021).

GEI is widely used to track progress toward gender equity (AfDB, 2015; World Economic Forum, 2021). This index measures gender disparities in four key areas: "economic participation and opportunity," "educational attainment," "health and survival," and "political empowerment" on a scale of 0 (gender inequality) to 1 (perfect gender equality) (World Economic Forum, 2021). According to the World Economic Forum's Global Gender Gap Report 2021, Zimbabwe's GEI was 73.2% in 2021, ranking the country 47th globally and 6th in Africa in terms of gender equality. The report shows that the gender gap in health (98%) and educational attainment (97.7%) were relatively close. Political empowerment (21%) had the largest gap, followed by economic participation and the opportunity dimension (76.3%). Similarly, ZIMSTAT (2020) and the National Gender Policy (2013) acknowledge that women's representation in Zimbabwe's political and economic spheres is relatively low. These statistics show that Zimbabwe has yet to embrace gender inclusivity in the political and economic spheres. Furthermore, the gender gap of 21% in the political empowerment dimension indicates that the country subscribes to a conservative political ideology with compromised human rights and institutional quality (Casey

et al., 2020). As stated by AfDB (2015), this can constrain the potential of the country's economy. Drawing from the components of GEI and literature (see, Casey *et al.*, 2020), GEA is defined in this study as behaviours that support gender parity in political, economic, and social spheres in both private and public sectors. Hence, the study is interested in political, economic, and social predictors of GEA.

While the GEI provides a quantitative measure of gender parity to inform gender mainstream policies, the current study is also important for informing policies on the factors that support and discourage gender equitable attitudes based on current data. This study is, to the best of our knowledge, a novel in Zimbabwe. In general, empirical research on this subject is still scarce, typical in the African context. Perhaps researchers were constrained by recent data, and it has been hardly possible to conduct primary research since 2020 due to COVID-19 pandemic restrictions. The current study makes use of the readily available Word Values Survey (WVS) dataset wave 7 (2017-2022) (WVS, 2022).

This paper is divided into five sections. The literature on GEA is reviewed after this introductory section. Section three discusses the empirical strategy. Section four presents and discusses the findings. Section five concludes the study.

2. Gender Equitable or Inequitable Attitudes

According to the United States Agency for International Development (USAID) (n.d), gender attitudes refers to “views held by individuals regarding the roles that men and women and boys and girls should play in society”. Similarly, Landry *et al.* (2020: 95) define gender attitudes “as an individual's perceptions, beliefs, or support of gender norms”, and they defined gender norms “as culturally shared expectations about the characteristics that men and women should possess and how they should behave.” Rogers *et al* (2023: 2) also defined gender norms as “a subset of social norms, reflecting a shared understanding of how women, compared with men, are expected to behave”. All of these definitions take into account the socially acceptable norms regarding the roles, qualities, status, and power that are connected to masculinity and femininity in a given culture.

Depending on the gender norm, gender attitudes can be equitable or inequitable. Endorsement of stereotypical gender norms that foster male dominance is linked to inequitable gender attitudes such as substance

use, violence and criminality, less male participation in caregiving and domestic chores, inappropriate sexual conduct, and perpetration of domestic violence by partners (Landry *et al.*, 2020). According to Hill *et al.* (2021: 523), gender inequitable attitudes “include individually- and societally-held beliefs about the norms in which people of certain genders should adhere to” and “are associated with violence perpetration and poor sexual health”. Gender inequitable attitudes in Africa are frequently the result of social, cultural, and religious patriarchal factors integrating to influence the development of traditional masculinity (Sikweyiya *et al.*, 2020; Rogers *et al.*, 2023).

Several studies indicate that GEA frequently develops during adolescence, making this an essential stage for transforming gender perceptions (see, for example, Amin *et al.*, 2018; Casey *et al.*, 2023; Hill *et al.*, 2021; Landry *et al.*, 2020; Palermo *et al.*, 2020; Rogers *et al.*, 2023). These studies show that adolescent boys support masculinity norms such as physical resilience, independence, sentimental prowess, and heterosexual prowess. Furthermore, in Africa, adolescent boys tend to support unequal gender norms more than girls, and Amin *et al.* (2018) provide three main reasons to support this assertion. First, in many contexts, norms that favour men are accepted as "normal," so boys might not feel the need to criticize them. Second, boys may be less inclined to challenge the privileges bestowed upon them by society as they approach puberty because they enjoy more relative freedom and power than girls do. Finally, boys face more social barriers (such as peer ridicule, labelling, and stigmatization from society) than girls when they try to adopt more equitable attitudes, such as helping with domestic chores that society associates with girls

Palermo *et al.* (2020), Rogers *et al.* (2023), and Sikweyiya *et al.* (2020) assert that young adolescents' gender socialization varies depending on the societal context, community, and family, and is influenced by various levels of the socio-ecological framework. Macro-level influences include political, social, and patriarchal structures as well as socioeconomic circumstances. Agents of influence at the meso level include the neighbourhood, social institutions like the school and religious organizations, peers, and social networks. Individual-level factors that impact how a person internalizes their gender identity and is treated by others include sex, ethnicity, cognitive and motivational processes, physical and sexual maturation, and personality.

While several factors influence young adolescents' gender socialization, Amin *et al.* (2018) contend that there is especially compelling evidence regarding the crucial roles that parents and peers play. Through direct and indirect communication, parents play a role in the gender socialization of their children by establishing different rules, sanctions, and expectations for boys and girls. Nevertheless, the review lacks clarity regarding how this influence is mediated—that is, whether it is influenced by parents' endorsement of stereotypical or GEA, the division of labour in the home, the nature of the family structure (two-parent versus single-parent homes), or the attitudes of the mothers or fathers.

Peers appear to be particularly important in forming and upholding masculinity norms as boys enter adolescence. Male peers who engage in risk-taking behaviours, such as drug and alcohol abuse and unsafe sexual behaviour, or who physically and verbally challenge one another, support the dominant norms of masculinity. They also challenge one another to demonstrate their masculinity by seducing girls at a young age. Any transgression of the expectations of masculinity, such as bullying and homophobic remarks, is met with mockery. Additionally, there is some evidence that early adolescent gender attitudes are shaped in schools through teacher communication and, in certain cases, the provision of comprehensive sexuality education. Du, Xiao, and Zhao (2020) investigated how education shapes people's attitudes toward gender roles and discovered that more egalitarian gender role attitudes are the result of additional schooling brought about by the reform of compulsory education. Nonetheless, the influence of education on gender-equal conduct is considerably less pronounced than that of attitude.

Palermo *et al.* (2020) and Rogers *et al.* (2023) state that structural forms of gender inequality disproportionately affect girls and women in Africa, as evidenced by outcomes related to education, livelihoods, property rights and asset ownership, political participation, health, violence, and child marriage. While existing empirics on GEA focused primarily on physiological aspects, this study adds to the literature from a development economics perspective. Women outnumber men in the world as a whole, and especially in the majority of developing countries, making them critical agents of economic development. As a result, depriving them of the political, social, and economic spheres can stifle economic development. This study is pertinent to SDG 5 and adds to the limited empirical evidence on the subjects in Zimbabwe. The empirical strategy is presented in the following section.

3. Machine Learning

The estimations of this study are based on machine learning. Jiang *et al.* (2020: 678) define machine learning as a “branch of computer science that aims to learn patterns from data to improve performance at various tasks.” Machine learning provides researchers with tools for producing research outputs from any form of data for which traditional statistical techniques are not well suited (see, for example, Bi, Goodman, Kaminsky & Lessler, 2019; Bonaccorso, 2018; Jiang *et al.*, 2020). Despite its superior performance in any type of data, machine learning is still underutilized, typically in economic research. To the best of our knowledge, this is the first study to employ machine learning to investigate the determinants of gender-equitable attitudes among Zimbabweans.

Machine learning is broadly divided into two categories: supervised and unsupervised learning (Bonaccorso, 2018). The former is similar to model fitting in that the outcome variable for each observation is known, whereas the latter attempts to infer natural structure within the data without reference to any outcome variable (Bi *et al.*, 2019). Thus, whereas supervised machine learning works with labelled input and output data, unsupervised machine learning works with raw or unlabeled data. Since prior knowledge about the outcome variable (GEA) is known in the current study, we use supervised machine learning algorithms. Supervised machine learning algorithms are well suited to problems involving regression and classification. Classification problems predict discrete or categorical outcomes, whereas regression problems predict real values or continuous outcomes. Among the most common supervised machine learning algorithms are logistic regression, random forest, support vector machine, extreme gradient boosting, and decision trees (Uddin *et al.*, 2019).

The decision tree is a popular, earliest, and versatile non-parametric supervised machine learning algorithm that can be used to solve both regression and classification problems (Jiang *et al.*, 2020). It predicts an outcome in general by developing a series of decision logics based on categorical and/or continuous predictor variables. The classification and regression tree (CART) algorithm is used to generate the decision tree. Random forest, also known as the ensemble method, predicts an outcome based on a collection of many decision trees from various samples and uses their majority vote for classification and average for regression (Venkatesh *et al.*, 2020). This algorithm employs bagging and

feature randomness when constructing each tree in an attempt to produce an uncorrelated forest of trees whose forecast by the committee is more accurate than that of any individual tree. Extreme gradient boosting is another tree-based algorithm (Ma, Meng, Yan, Yan, Chai & Song, 2020; Venkatesh *et al.*, 2020). The trees, however, are not based on the actual class labels but rather the residuals. Regression trees rather than classification trees are used as the algorithm's basis estimators since residuals are continuous rather than discrete. The support vector machine is primarily intended for binary classification across a large number of explanatory variables (Uddin *et al.*, 2019). The algorithm can classify both linear and nonlinear data and is effective at detecting outliers. Finally, logistic regression is an extension of ordinary linear regression that is designed to model dichotomized outcome variables with a set of regressors. Although the nature of our outcome variable suggests that logistic regression should be used, we used a training and testing procedure to select the best machine-learning algorithm for our dataset. The logistic regression algorithm performed well in both training and testing, as expected (see, Table 3).

3.1 Logistic Regression

The logistic regression algorithm is derived from the sigmoid function¹, and its mathematical function (Equation (1)) is decomposed like the linear function. The key difference is that the dependent or outcome variable y is probabilistic, dichotomized, and takes binary values (0 or 1), as opposed to linear regression, which takes any numerical value (see, for example, Brownlee, 2016; Pennsylvania State University, 2018; Zabor, Reddy, Tendulkar & Patil, 2021).

$$y = \frac{e^{(\alpha + \beta_1 x_1 + \dots + \beta_p x_p)}}{1 + e^{(\alpha + \beta_1 x_1 + \dots + \beta_p x_p)}} \quad (1)$$

where α is the intercept, x is a proxy for the regressors, and β is the estimated coefficient associated with x .

The outcome variable, y , in the binary logistic regression, is a "success probability" (Gasso, 2021; Pennsylvania State University, 2018). This

¹ It's an S-shaped function that can map any real-valued number to a value between 0 and 1, but never exactly between those limits. $Y = \frac{1}{1 + e^{-x}}$

implies that if the probability of a regressor x ($P(x)$) belongs to the default class ($y = 1$), then

$$P(x) = P(y = \frac{1}{x}) \tag{2}$$

As a result, Equation (1) can also be written as:

$$P(x) = \frac{e^{(\alpha + \beta_1 x_1 + \dots + \beta_p x_p)}}{(1 + e^{(\alpha + \beta_1 x_1 + \dots + \beta_p x_p)})} \tag{3}$$

Taking natural logs on both sides to eliminate the exponentials ($e^{(\cdot)}$) and make Equation (3) linear converts the equation to:

$$\ln\left(\frac{P(x)}{1-P(x)}\right) = \alpha + \beta_1 x_1 + \dots + \beta_p x_p \tag{4}$$

where $\ln\left(\frac{P(x)}{1-P(x)}\right)$ is the odds² of the default class and thus, Equation (4) can be specified in log odds as:

$$\ln(odds) = \alpha + \beta_1 x_1 + \dots + \beta_p x_p \tag{5}$$

Equation (5) is the logit transformation of the “success probability” (y) (Pennsylvania State University, 2018). In the current study, for example, the likelihood that the sampled respondents support gender-equitable attitudes. This study's estimations are based on Equation (5), and the variables are described in Table 1 below.

Table 1: Variables description and data source

| Variable | Description | Question No. |
|--------------------------------------|--|--------------|
| Outcome variable - GEA Index: | | |
| | Justifiable: For a man to beat his wife | 189 |
| | Pre-school child suffers from working mother | 28 |
| | Men make better political leaders than women do | 29 |
| | University is more important for a boy than for a girl | 30 |
| | Men make better business executives than women do | 31 |
| | Being a housewife is just as fulfilling | 32 |
| | Jobs scarce: Men should have more rights to a job than women | 33 |
| | Problem if women have more income than their husband | 35 |

² In horse racing, they use odds instead of probabilities. For example, if there is a 90% chance that a certain horse will win, then the odds are $0.9/(1-0.9) = 9$, or 9:1.

| | | |
|--------------------------------|--|-----|
| | Degree of agreement: On the whole, women are less corrupt than men | 119 |
| Explanatory variables: | | |
| Age | Age | 262 |
| Sex | Sex | 260 |
| Marital status | Marital status | 273 |
| Education level | Highest education level | 275 |
| Employment status | Employment status | 279 |
| Religiosity | Independently of whether you attend religious services or not | 173 |
| Freedom and Equality | Freedom and Equality - Which is more important? | 149 |
| Have children | How many children do you have? | 274 |
| Political interest | Interest in politics | 199 |
| Importance of Religion in life | Indicate how important is religion in your life | 6 |
| Household financial situation | Satisfaction with the financial situation of the household | 50 |
| Trust | Would you trust or need to be careful when dealing with people? | 57 |
| Income Equality | Income equality vs larger income differences | 106 |
| Residency | Urban-Rural | H |

Source: Authors' compilation using (2017-2022) World Values Survey wave 7 Master survey questionnaire and F00010847-WVS_Wave_7_Zimbabwe_Excel_v2.0 (WVS, 2022).

The GEA index was dichotomized using the median (21) threshold, with 'Yes' for *GEA Score* > 21 indicating support for gender inequitable attitudes and 'No' for *GEA Score* < 21 indicating support for gender equitable attitudes (see, Table 1 for the variables that comprise the GEA index, as well as the Likert scale in the master survey questionnaire).

4. Results

The results are presented in four stages. We begin with descriptive statistics. Second, we run training and testing procedures to help us decide which machine learning algorithm is best suited for our dataset. Accordingly, the third step is to run the regression using the algorithm of

choice and perform diagnostic tests to validate the results. Finally, we discuss the results.

Table 2: Descriptive Statistics

| Variables | | Number respondents (N) = 1215 | of | | Overall p- value |
|-----------------------------|------------------|-------------------------------------|--------------------------|----------------|---------------------|
| | | | By GEA Index No = 638 | Yes = 537 | |
| GEA Index: | No | 638(54.3%) | | | |
| | Yes | 537(45.7%) | | | |
| Age: | <18 | 4 (0.33%) | 2 (50.0%) | 2 (50.0%) | 0.958 |
| | 18-34 | 568 (46.7%) | 302 (54.6%) | 251 (45.4%) | |
| | 35-54 | 418 (34.4%) | 214 (53.4%) | 187 (46.6%) | |
| | 55+ | 225 (18.5%) | 120 (55.3%) | 97 (44.7%) | |
| Sex: | Female | 615 (50.6%) | 290 (48.7%) | 305 (51.3%) | 0.001*** |
| | Male | 600 (49.4%) | 348 (60.0%) | 232 (40.0%) | |
| Marital Status: | Married | 760 (62.6%) | 405 (54.8%) | 334 (45.2%) | 0.529 |
| | Divorced | 76 (6.26%) | 35 (47.9%) | 38 (52.1%) | |
| | Never married | 379 (31.2%) | 198 (54.5%) | 165 (45.5%) | |
| Education Level: | Primary | 195 (16.9%) | 113 (60.8%) | 73 (39.2%) | 0.016*** |
| | Secondary | 911 (78.9%) | 469 (53.1%) | 414 (46.9%) | |
| | Tertiary | 48 (4.16%) | 18 (38.3%) | 29 (61.7%) | |
| Employment Status: | Employed | 555 (45.7%) | 301 (55.9%) | 237 (44.1%) | 0.325 |
| | Unemploy ed | 660 (54.3%) | 337 (52.9%) | 300 (47.1%) | |
| Religiosity: | Religious | 1167 (96.3%) | 619 (54.7%) | 512 (45.3%) | 0.591 |
| | Not Religious | 43 (3.55%) | 18 (46.2%) | 21 (53.8%) | |
| Freedom and Equality: | Atheist | 2 (0.17%) | 1 (50.0%) | 1 (50.0%) | 0.141 |
| | Equality | 249 (20.5%) | 116 (49.8%) | 117 (50.2%) | |
| | Freedom | 966 (79.5%) | 522 (55.4%) | 420 (44.6%) | |
| Have children: | No | 289 (23.8%) | 146 (52.1%) | 134 (47.9%) | 0.447 |

| | | | | | |
|--------------------------------|---------------|--------------|-------------|-------------|----------|
| | Yes | 926 (76.2%) | 492 (55.0%) | 403 (45.0%) | |
| Political Interest: | No | 633 (52.1%) | 295 (48.8%) | 310 (51.2%) | 0.001*** |
| | | | 343 | | |
| Importance of Religion in life | Yes | 582 (47.9%) | 8 (60.2%) | 10 (39.8%) | |
| | No | 18 (1.48%) | 630 (44.4%) | 426 (55.6%) | 0.544 |
| Household financial situation: | Yes | 1197 (98.5%) | 494 (54.5%) | 527 (45.5%) | |
| | Not Satisfied | 945 (77.8%) | 144 (53.7%) | 111 (46.3%) | 0.474 |
| | Satisfied | 270 (22.2%) | 619 (56.5%) | 531 (43.5%) | |
| Trust: | No | 1189 (97.9%) | 19 (53.8%) | 6 (46.2%) | 0.046** |
| | Yes | 26 (2.14%) | 401 (76.0%) | 309 (24.0%) | |
| Income equality: | No | 737 (60.7%) | 237 (56.5%) | 228 (43.5%) | 0.073* |
| | Yes | 478 (39.3%) | 455 (51.0%) | 342 (49.0%) | |
| Residency: | Rural | 820 (67.5%) | 183 (57.1%) | 195 (42.9%) | 0.006*** |
| | Urban | 395 (32.5%) | 269 (48.4%) | 195 (51.6%) | |

Note: ***, **, and * significance at 1%, 5%, and 10%, respectively.

Source: Authors' computation using R

Table 2 shows that only gender, education level, political interest, trust, income equality, and residency can help predict gender equitable or inequitable attitudes among Zimbabweans. Although more than half of the sampled respondents (54.3%) appear to support gender-equitable attitudes, the opposing group remains sizable (45.7%), reflecting the effort required to achieve gender parity in the country. The following is a summary of the training and testing results. The training and testing datasets were split into 70-30 splits.

Table 3: Training and Testing Results

| Accuracy Metric | MACHINE LEARNING ALGORITHMS | | | | |
|-----------------|-----------------------------|---------------|-------------------------------|---------------------------------|----------------|
| | Logistic Regression | Random Forest | Support Vector Machines (SVM) | Extreme Gradient Boosting (EGB) | Decision Trees |
| F1 | 0.545 | 0.503 | 0.513 | 0.491 | 0.491 |

Note: The best ML algorithm is the one with the highest F1 score.

Source: Authors' computation using R

According to the results in Table 3, logistic regression is the best algorithm for this study. Hence, Table 4 displays the main results obtained through logistic regression (Equation (5)).

Table 4: Logistic Regression Results

| Dependent Variable: Gender Equitable Attitudes (GEA) Index | | |
|---|-----------|----------------------|
| Sex: | Male | -0.651*** (0.139) |
| Education Level: | Secondary | 0.417*** (0.183) |
| | Tertiary | 1.170*** (0.356) |
| Freedom and Equality: | Freedom | -0.263* (0.156) |
| Have children: | Yes | -0.572*** (0.234) |
| Political Interest: | Yes | -0.310*** (0.127) |
| Trust: | Yes | -1.187*** (0.529) |
| Income equality: | Yes | 0.254*** (0.128) |
| Residency: | Urban | 0.276*** (0.135) |
| AIC | | 1509.9 |
| Null deviance | | 1536.1 (df = 1112) |
| Residual deviance | | 1469.9 (df = 1039) |
| Number of Fisher Scoring iterations | | 11 |
| Log-likelihood | | -734.959 (df = 20) |
| Chi-Square | | 66.221 (df = 19) |
| P-value | | < 0.001 |

Notes: Dispersion parameter for binomial family taken to be 1. ***, **, and * significance at 1%, 5%, and 10%, respectively.

Source: Authors' computation using R.

Table 4 shows the statistically significant predictors of GEA³. The results were as predicted by the descriptive statistics, except for freedom, which was not statistically significant. According to our findings, secondary and tertiary education, income equality, and urban residency support gender equality attitudes, whereas boys and men, freedom, political interest, trust, and having children endorse gender inequality attitudes. Surprisingly, age, marital status, employment status, religion, and household financial situation do not help predict gender equitable attitudes in Zimbabwe, although they are the most discussed factors, particularly in the media. These results have been tested for robustness in terms of model fitness, multicollinearity, and outliers, as shown below.

4.1. Diagnostic Tests

4.1.1. Model Fitness

Table 4 shows that the model fits significantly well, as indicated by the Chi-square of 66.221 with 19 degrees of freedom and an associated p-value < 0.001 calculated from the fitness indices (null and residual deviance).

4.1.2. Test for Multicollinearity

Table 5: Multicollinearity Results

| Variables | GVIF | Df | GVIF^{1/(2*Df)} |
|--------------------------------|-------------|-----------|--------------------------------|
| Age | 1.610 | 3 | 1.083 |
| Sex | 1.259 | 1 | 1.122 |
| Marital Status | 2.131 | 2 | 1.208 |
| Education Level | 1.212 | 2 | 1.049 |
| Employment Status | 1.153 | 1 | 1.073 |
| Religiosity | 1.060 | 2 | 1.015 |
| Freedom and Equality | 1.026 | 1 | 1.013 |
| Have children | 2.661 | 1 | 1.631 |
| Political Interest | 1.052 | 1 | 1.026 |
| Importance of Religion in life | 1.031 | 1 | 1.016 |

³ Statistically insignificant variables were not reported; however, the whole output can be made available upon request.

| | | | |
|-------------------------------|-------|---|-------|
| Household financial situation | 1.062 | 1 | 1.031 |
| Trust | 1.027 | 1 | 1.013 |
| Income equality | 1.027 | 1 | 1.013 |
| Residency | 1.062 | 1 | 1.031 |

Note: A DVIF value > 5 generally indicates collinearity

Source: Authors' computation using R

Table 5 demonstrates that there is no collinearity among the predictors because all of them have DVIF values well below 5.

4.1.3. Outliers

Although not all outliers are influential observations, they have the potential to degrade the quality of the logistic regression model. Figure 1 detects outliers by displaying Cook's distance values, whereas Figure 2 checks potentially influential observations by inspecting absolute standardized residuals.

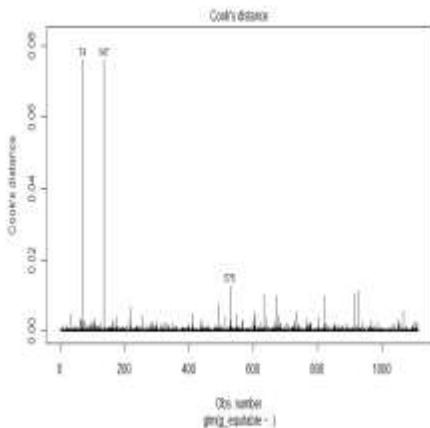


Figure 1: Cook's distance

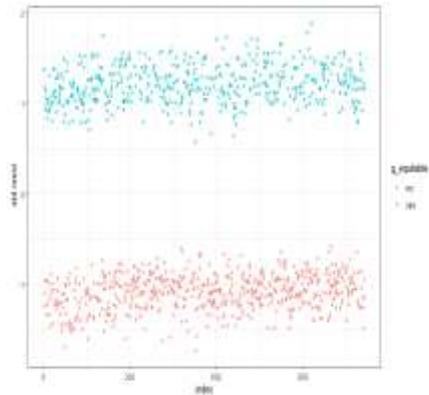


Figure 2: Absolute Standard Residuals

Note: Only the top 3 outliers are labelled

Note: $\text{std.resid} < 3$ generally indicates no potentially influential outliers

Source: Authors' computation using R

Figure 2 shows that there are no data points with absolute standardized residuals greater than 3, indicating that the dataset contains no potentially influential observations. The subscript *g_equitable* represents the GEA index dichotomized into 'yes' and 'no'. As stated before, a 'yes' indicates

support for gender-inequitable attitudes, while a 'no' indicates support for gender-equitable attitudes.

4.2 Discussion of the Main Findings

Our findings suggest that traditional masculinity beliefs persist among Zimbabwean men and boys. According to Casey *et al.* (2020; 2023), endorsing the masculinity concept is associated with supporting gender inequitable attitudes. Casey *et al.* (2020) also support estimated results for education and having children variables. Their analysis shows that 18(10) out of 21(11) studies found a significantly positive (negative) association between GEA and education (having children). Thus, as noted in ZIMSTAT (2020), Zimbabweans who complete secondary and tertiary education tend to be economically, politically, and socially empowered. Furthermore, a high level of education increases bargaining power for competitive salaries. This explains why secondary and tertiary education, as well as income equality, promote gender equity.

However, education, according to AfDB (2015), can significantly support gender equity if the empowering benefits are passed down to future generations (both men and women). As evidenced by a GEI of 21% in the political empowerment dimension (World Economic Forum, 2021), the political sphere in Zimbabwe is dominated by a few autocratic elites, the majority of whom are elderly men. The benefits are rarely passed on to the younger generation (both men and women), exacerbating the marginalization of youth and women. This human rights-violating-conservative political ideology supports inequitable attitudes (Casey *et al.*, 2020). Precisely, the political ideology fosters corruption and discourages women and youths from participating in business and politics.

Women, according to Kimmel (2019), trust less than men, and they are easily discouraged from engaging in business, politics, and social spaces in an environment of high corruption and human rights abuse. Corruption also fosters an environment in which politicians and business elites can exploit resources for their gain at the expense of the poor majority (the majority of whom are women and youths), widening the inequality gap. Furthermore, in a corrupt environment, basic service delivery dwindles dramatically, and the majority of those affected are women, who are frequently sought out for domestic chores (AfDB, 2015). Freedom of expression and opinion can be politicized in a human

rights-violating-conservative political ideology to the point where those who voice their opinions are viewed as a threat to the government and punished. Furthermore, men in positions of power and cultural norms use freedom of expression to discourage women and youths. (United Nations, 2021).

In her investigation of why having children supports gender inequitable attitudes, DeRose (2019) discovered that both men and women behave traditionally if they have children at home. In essence, women care for children far more than men do. In terms of urban residency, although ZIMSTAT (2020) found that most (53%) of the urban population are females, our findings suggest that urbanization can be linked to transformation, which provides opportunities that can foster GEA.

5. Conclusion

This study used a binary logistic regression machine learning algorithm in the World Values Survey dataset wave 7 (2017–2022) to investigate the determinants of GEA among Zimbabweans. The study's scope is premised on political, economic, and social predictors of GEA. We found that, while secondary and tertiary education, income equality, and urban residency support gender-equitable attitudes, the opposite applies to masculinity, political interest, freedom, having children, and trust. These findings suggest that educated women and youth have a better chance of political, economic, and social empowerment, as well as bargaining power for a competitive salary. They do, however, face access issues to the empowerment benefits. These findings expose the country's human rights-violating-conservative political ideology in the country, which appears to support masculine behaviour in politics and economic participation and opportunities while abusing freedom of speech and expression. This political ideology encourages corruption (in both economic and political arenas), making women and young people sceptical to participate in business and politics. According to these findings, women and youths are discouraged from participating in economic, political, and social spheres due to the masculinity of those in power. This subsequently impedes economic growth and development potential. Another pertinent derivation is that urbanization supports GEA. This study explored the predictors of GEA among Zimbabweans in general, without taking into account provincial heterogeneities. As a

result, future studies can examine this aspect using a geospatial approach to identify provinces where efforts to promote gender equity in the country are needed.

References

- AfDB. (2015), “*African Gender Equality Index 2015*”, Available at: https://www.afdb.org/fileadmin/uploads/afdb/Documents/Publications/African_Gender_Equality_Index_2015-EN.pdf. (Accessed: 05 July 2022).
- Amin, A., Kågesten, A., Adebayo, E., & Chandra-Mouli, V. (2018), “Addressing Gender Socialization and Masculinity Norms among Adolescent Boys: Policy and Programmatic Implications”, *Journal of Adolescent Health*, 62, S3-S5. <https://doi.org/10.1016/j.jadohealth.2017.06.022>
- Bi, Q., Goodman, K. E., Kaminsky, J., & Lessler, J. (2019), “What Is Machine Learning: a Primer for the Epidemiologist”, *American Journal of Epidemiology*, 188(12), 2222-2239. <https://doi.org/10.1093/aje/kwz189>
- Bonaccorso, G. (2018), *Machine Learning Algorithms: Popular algorithms for data science and machine* (2nd Edition), Packt Publishing Ltd, Birmingham.
- Brownlee, J. (2016), “*Logistic Regression for Machine Learning*”, Available at: <https://machinelearningmastery.com/logistic-regression-for-machine-learning/>. (Accessed: 14 July 2022).
- Casey, E. A., Ihrig, A., Roman, M., Hoxmeier, J. C., Carlson, J., & Greer, K. (2020), “Life Course and Socioecological Influences on Gender-Equitable Attitudes among Men: A Scoping Review”, *Trauma, Violence, & Abuse*, XX(X), 1-14. <https://doi.org/10.1177/1524838020977140>
- Casey, E. A., Willey-Sthapit, C., Hoxmeier, J. C., & Carlson, J. (2023), “Patterns of Gender Equitable Attitudes and Behaviors among Young Men: Relationships with violence perpetration and

- masculinity ideologies”, *Violence Against Women*, 0(0). <https://doi.org/10.1177/10778012231153359>
- DeRose, L. (2019), “Gender equality at home takes a hit when children arrive”, *The Conversation: Academic rigour, journalistic flair*, 8 August, Available at: <https://theconversation.com/gender-equality-at-home-takes-a-hit-when-children-arrive-118420>. (Accessed: 01 July 2022).
- Du, H., Xiao, Y., & Zhao, L. (2020), “Education and gender role attitudes”, *Journal of Population Economics*, 34, 475-513. <https://doi.org/10.1007/s00148-020-00793-3>
- Gasso, G. (2021), “*Logistic regression*”. INSA Rouen - ITI Department Laboratory LITIS, Available at: https://moodle.insa-rouen.fr/pluginfile.php/7984/mod_resource/content/7/Parties_1_et_3_DM/RegLog_Eng.pdf. (Accessed: 10 July 2022).
- Hill, A.L., Miller, E., Switzer, G.E. *et al.* (2021), “Gender Equitable Attitudes among Adolescents: A Validation Study and Associations with Sexual Health Behaviors”, *Adolescent Research Review*, 7, 523-536. <https://doi.org/10.1007/s40894-021-00171-4>
- Jiang, T., Gradus, J. T., & Rosellini, A. J. (2020). Supervised machine learning: A brief primer. *Behaviour Therapy*, 55(5): 675-687. <https://doi.org/10.1016/j.beth.2020.05.002>
- Kimmel, L. (2019), “Business Should Mind the Gender Trust Gap”, *Edelman*, 1 May. Available at: <https://www.edelman.com/research/business-should-mind-gender-trust-gap>. (Accessed: 01 July, 2022).
- Landry, M., Vyas, A., Malhotra, G., & Nagaraj, N. (2020), “Adolescents’ development of gender equity attitudes in India”, *International Journal of Adolescence and Youth*, 25(1), 94-103. <https://doi.org/10.1080/02673843.2019.1590852>
- Ma, B., Meng, F., Yan, G., Yan, H., Chai, B., & Song, F. (2020), “Diagnostic classification of cancers using extreme gradient boosting algorithm and multi-omics data”, *Computers in Biology and Medicine*, 121. <https://doi.org/10.1016/j.compbiomed.2020.103761>
- Palermo, T., Chzhen, Y., Balvin, N. *et al.* (2020), “Examining determinants of gender attitudes: evidence among Tanzanian

- adolescents”, *BMC Women's Health*, 20: 195. <https://doi.org/10.1186/s12905-020-01057-8>
- Pennsylvania State University. (2018), “*Logistic Regression | STAT 462*”, Available at: <https://online.stat.psu.edu/stat462/node/207/>. (Accessed on 14 July 2022).
- Rogers, K., Ranganathan, M., Kajula, L. *et al.* (2023), “The influence of gender-equitable attitudes on sexual behaviour among unmarried adolescents in rural Tanzania: a longitudinal study”, *Sexual and Reproductive Health Matters*, 31(1), 1-20. <https://doi.org/10.1080/26410397.2023.2260169>
- Sikweyiya, Y., Addo-Lartey, A.A., Alangea, D.O. *et al.* (2020), “Patriarchy and gender-inequitable attitudes as drivers of intimate partner violence against women in the central region of Ghana”, *BMC Public Health*, 20, 682. <https://doi.org/10.1186/s12889-020-08825-z>
- The National Gender Policy. (2013), “*The Republic of Zimbabwe National Gender Policy (2013-2017)*”, UNDP, Available: <http://catalogue.safaid.net/sites/default/files/publications/2013%20national%20gender%20policy%20-%20final%20april%2020th.pdf>. (Accessed: 14 July 2022).
- Uddin, S., Khan, A., Hossain, M. E., & Moni, M. A. (2019), “Comparing different supervised machine learning algorithms for disease prediction”, *BMC Medical Informatics and Decision Making*, 19(289), 1-16. <https://doi.org/10.1186/s12911-019-1004-8>
- United Nations. (2021), “*Gender equality in freedom of expression remains a distant goal -UN expert*”, Available at: <https://www.ohchr.org/en/press-releases/2021/10/gender-equality-freedom-expression-remains-distant-goal-un-expert>. (Accessed: 14 July 2022).
- USAID. (n.d), “*Equitable Gender Attitudes*” Available at: <https://www.advancingnutrition.org/resources/caregiver-toolkit/equitable-gender-attitudes#:~:text=Zimbabwe%2014%20items-,Gender%20attitudes%20refers%20to%20views%20held%20by%20individuals%20regarding%20the,girls%20should%20play%20in%20society.&text=To%20measure%20attitudes%20toward%20gender,subscales%3A%20equitable%20and%20inequitable%20norms.> (Accessed: 12 November 2023).

- Venkatesh, K. K., Strauss, R. A., Grotegut, C. A., Heine, R. P., Chescheir, N. C., Stringer, J. S. A., Stamilio, D. M., Menard, K. M., & Jelovsek, J. E. (2020), "Machine Learning and Statistical Models to Predict Postpartum Hemorrhage", *Obstetrics & Gynecology*, 135(4), 935-944. <https://doi.org/10.1097/AOG.0000000000003759>
- World Economic Forum. (2021), "Global Gender Gap Report 2021", Available at: https://www3.weforum.org/docs/WEF_GGGR_2021.pdf. (Accessed: 05 July 2022).
- Word Values Survey. (2022), "WVS Wave 7 (2017-2022)" Available at: <https://www.worldvaluessurvey.org/WVSDocumentationWV7.jsp>. (Accessed: 02 June 2022).
- Zabor, E. C., Reddy, C. A., Tendulkar, R. D., & Patil, S. (2021), "Logistic Regression in Clinical Studies", *International Journal of Radiation Oncology Biology Physics*, 112(2), 271-277. <https://doi.org/10.1016/j.ijrobp.2021.08.007>
- ZIMSTAT. (2020), "Understanding Gender Equality in Zimbabwe: Women and Men in Zimbabwe Report 2019", UN Women Office Publishing, Zimbabwe. Available at: <https://www.zimstat.co.zw/wp-content/uploads/publications/Social/Gender/Women-and-Men-Report-2019.pdf>. (Accessed: 05 July 2022).