BAYESIAN ANALYSIS OF FACTORS INFLUENCING INTENTION NOT TO USE CONTRACEPTIVES AMONG WOMEN IN REPRODUCTIVE AGE IN JIGJIGA CITY, SOMALI REGION ETHIOPIA

MSc. THESIS

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Bayesian Analysis of Factors Influencing Intention Not to Use Contraceptives among Women in Reproductive Age in Jigjiga City, Somali Region Ethiopia

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I hereby certify that I have read and evaluated this thesis entitled "**Bayesian Analysis of Factors Influencing Intention Not to Use Contraceptives among Women in Reproductive Age in Jigjiga City, Somali Region Ethiopia** " prepared under my guidance by Mohamed Ayanle. I recommend that it be submitted as fulfilling the thesis requirement for the degree of Master of Science in Biostatistics.

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STATEMENT OF THE AUTHOR

Mohamed Ayanle hereby declares this MSc. thesis on "Bayesian Analysis of Factors Influencing Intention Not to Use Contraceptives among Women in Reproductive Age in Jigjiga City, Somali Region Ethiopia ". By my signature below, I declare and affirm that this thesis is my own work. I have followed all ethical and technical principles of scholarship in preparation, data collection, data analysis and compilation of this thesis. Any Scholarly matter that is included in the thesis has been given recognition through citation.

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BIOGRAPHICAL SKETCH

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LIST OF ACRONYMS AND ABBREVIATIONS

AIDS	Acquired Immune Deficiency Syndrome
APHC	Asian Pacific Health Corps
CPR	Cardio Pulmonary resuscitation
CSA	Central Statistical Agency
EPHI	Ethiopian Public Health Institute
FDRE	Federal Democratic Republic of Ethiopia
FDREMH	Federal Democratic Republic of Ethiopia Ministry of Health
FP	Family Planning
HIV	Human Immunodeficiency Virus
HSTP	Health Sector Transformation Plan
ICF	Internal Control Framework
MCMC	Markov Chain Monte Carlo
MH	Metropolis-Hastings
OR	Odds Ratio
STD	Sexually Transmitted Infections
UN	United Nations
UNDP	United Nations Development Program
UNICEF	United Nations International Children's Emergency Fund
USAID	United States Agency for International Development
WHO	World Health Organization

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ABSTRACT

Contraception is the prevention of conception intentional through various tools, sexual practices, chemicals, drugs, or surgical procedure. Any kind of tool or actions whose purpose is to prevent a woman from becoming pregnant can be considered contraception. The main objective of this study was to identify factors influencing intention not to use contraceptives among Women in Reproductive Age in Jigjiga City, Somali Region Ethiopia, Bayesian logistic regression approaches were used to meet the objective.

The study used primary data which was collected from sampled respondents across the four sub-cities of Somali regional state capital Jigjiga. Among married women who were in reproductive age (15 – 49) in Jigjiga city, a sample of 352 was taken for this study. Out of the 352 married women in reproductive age, 21 % (74) were contraceptive user, and 79 %(278) were non-users at the time of the data collection. Similarly, among non users, that is 278, about 199(71.6%) had intention not to use modern contraceptive method. Study found that significant association between intention on contraceptive method and the socio-economic and demographic variables: Religion, Living Son(s), Desire to have more children, women's Education Level, Information about Family planning, Known Family planning methods, Past Experience on contraceptives and Access to Family Planning Service.

Bayesian logistic regression procedure were used to make inference, the result of the model parameters, and the model revealed that Protestants (RELIG2) significantly lower odds of intending not to use contraceptives (OR=0.23, 95% CrI: 0.06-0.58), Orthodox Christians (RELIG3) show no statistically significant difference (OR=0.73, 95% CrI:0.30-1.83). The results also show that women who have no desire (DRCH2) for more children have a 91% lower odd of intending not to use contraceptives than the reference (has desire). The result also showed that the odds of not intending to use contraceptive was 4.18 times higher for women who had no past experience than their counter parts. By addressing religious, informational, and behavioral barriers, policymakers and health providers can significantly improve contraceptive uptake and maternal health outcomes.

Keywords*: Married Women, Bayesian Logistic Regression Analysis, Contraceptive, Simulation*

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

Family planning is one of the most important health interventions of the 21^{st} century. It enables women and couples to take control of their fertility, decide the number of children to have, and better space births (APHC, 2018). Family planning was prioritized internationally during the 1970s and 1980s with significant support, which led to an increase in contraceptive prevalence rate with reduced fertility globally (Mwaikambo *et al.,* 2011).

Contraception is the prevention of conception intentional through various tools, sexual practices, chemicals, drugs, or surgical procedure. Any kind of tool or actions whose purpose is to prevent a woman from becoming pregnant can be considered contraception (Jain *et al*., 2021). Modern contraception is a product or procedure medical used intentionally to prevent pregnancy during intercourse with a relatively easier approach than traditional contraception.

Modern contraceptive methods include pills, injections, IUDs, condoms, sterilization, and others (Hubacher *et al*., 2015). Modern contraception proven to reduce maternal mortality and children because modern contraception can prevent unwanted pregnancies desired that leads on unsafe abortion (Prata, 2009). Some methods can even prevent transmission sexually transmitted infection (Apanga, 2015). In a broader context, the use of contraceptives can slow down the rate of population growth and reduce the economic burden of a country (Nonvignon, 2014)

According to United Nations report, among the 1.9 billion women of reproductive age (15-49 years) living in the world in 2019, 1.1 billion have a need for family planning, that is, they are either current users of contraceptives 842 million use modern methods of contraception and 80 million use traditional methods or have an unmet need for family planning190 million women want to avoid pregnancy and do not use any contraceptive method. The proportion of women who have their need for family planning satisfied by modern methods is 76 per cent in 2019 (UN, 2019).

The prevalence of specific contraceptive methods varies widely across the world. In Eastern and South-Eastern Asia, IUD is the most common contraceptive method used (18.6 % of women rely on this method), followed closely by male condom, which is 17%. In Europe and Northern

America, pill and male condom are the most commonly used methods, with 17.8 % and 14.6 % , respectively), while in Latin America and the Caribbean, female sterilization and pill usage is 16% and 14.9 %, respectively(UN,2019).

Similarly, in Oceania, the dominant method is the pill (16.9 %) and in Central and Southern Asia it is female sterilization (21.8 per cent of women rely on this method). In Northern Africa and Western Asia, the two most common methods are the pill (10.5 per cent) and IUD (9.5 per cent).However, Sub-Saharan Africa is the only region in which injectables are the dominant method with a prevalence of 9.6 per cent among women of reproductive age (UN,2019).

The world population had reached 7.7 billion people by mid-2019, up one billion since 2007 and two billion since 1994. The world population is also expected to reach 8.5 billion in 2030, 9.7 billion in 2050, and 10.9 billion in 2100. Sub-Saharan Africa will account for the majority of global population growth in the coming decades, while many other regions will begin to see population decline. The global population between 2019 and 2050, is expected to grow by almost two billion people, with 1.05 billion (52%) of that growth occurring in Sub-Saharan African countries (Ahinkorah *et al.*, 2021).

Fertility rates vary considerably across Sub-Saharan Africa's main regions. According to United Nations, the total fertility rates, around 6.5 births per woman in the early 1960s across all regions, in 2015 range from 2.4 in Southern Africa to 3.1 in Northern Africa, 4.5 in Eastern Africa, and 5.2–5.3 in Western and Middle Africa(UN, 2015)..

Ethiopia is among low income country with poor health service coverage, including family planning, particularly in the emerging regions (Assefa *et al.*, 2020). According to FDRE Ministry of Health report in 2015, the Ethiopian government has made a massive expansion of health facilities and trained human support capacity. Despite their value modern contraceptives are not available across the world. In comparison to women in developing countries, developed-country women have better access to and use of modern contraceptives (Stover *et al., 2017;* Tsui *et al., 2010)*

Ethiopia is the most populous country in Sub-Saharan Africa, with a population of 112 million people and a fertility rate of 4.6 children per woman. As WHO reported in 2014, pregnancy risks are higher in Africa due to a high fertility rate, poor health condition, and a lack of access to medical care. Ethiopia has still one of the highest fertility rates in Africa. Even though, the prevalence of modern contraceptive use by currently married Ethiopian women has tripled over the last fifteen years, jumping from 14% in 2005 to 41% in 2019, but still the use of modern contraception is a common healthcare challenge in the country (EPHI and ICF, 2019)

Regardless of the presence of numerous studies done by adopting Classical or frequentist approaches, to identify the prevalence and the factors which contribute to modern contraceptive use or non use, among women in reproductive age groups (15-49 years old), but it is still unresolved public health issue in Ethiopia (Mulugeta *et al.*, 2022; Gebre et al., 2020; EPHI and ICF, 2021; Tessema et al., 2018).

The current study focused on investigating factors associated with intention that is, not intending to use contraceptive rather than contraceptive use or non use. Since, one needs to comprehend how intention to use contraception influences future use, similarly, not intending to use contraceptives is the immediate cause for not using contraceptives (Ross et al., 2001). According to Ethiopian Public Health Institute and ICF 2021 report, the lowest contraceptive utilization was reported from the Somali region (3%). Therefore, by extracting data from 2019 Ethiopian Mini Demographic and Health Survey, and applying Bayesian approach; this research investigateed Factors Influencing the Intention not to use contraceptives among Women in Reproductive Age at Somali Region, Ethiopia.

1.2. Statement of the problem

Family planning is a procedure that mainly requires a discussion of agreement between a woman and a man. A trained FP service provider focuses on family health and the couple's desires to either limit or space their children (Assefa*et al*., 2020). Contraception methods play a significant role in reducing the complication of child and maternal morbidity and mortality by unintended preventive pregnancies, including social costs (WHO, 2020; FDREMH, 2015).

The health service's Family Health division is in charge of achieving the aims of the Family Planning Program, and several government and non-governmental organizations are aiding Family Health in achieving the government's national and international targets. The primary goal of the Family Planning Program is to increase access to high-quality health care, including FP services, without causing financial hardship (Engelbert *et al*., 2021; Sserwanja*et al.*, 2021).

Ethiopia is among low income country in Africa with poor health service coverage, including family planning (FP), mainly in the emerging regions (Assefa*et al*., 2020).The Ethiopian government has also made a massive expansion of health facilities and trained Family planning service provider(FDREMH, 2015).

The prevalence of any modern contraceptive use by currently married Ethiopian women has tripled over the last fifteen years, jumping from 14% in 2005 to 41% in 2019;but Ethiopia has still one of the highest fertility rates in Africa. However, there was a significant regional variation in CPR among the emerging regions. The lowest contraceptive utilization was reported from the Somali region (3%) and the highest from Amhara (50%) regions of Ethiopia (EPHI and ICF, 2021).

However, as stated in the 2020 report of the Federal Ministry of Health of Ethiopia, the health sector transformation plan (HSTP) I target (55%) of the national contraceptive prevalence rate was not achieved. And all the regions in the country were unable to attain their target set for the year (FMOHE, 2020). These evidences clearly suggest that the modern contraceptive method utilization remains a great public health problem in Ethiopia.

A handful of studies on contraceptive use wereattempted, to identify the prevalence of contraceptive use and related factors in Ethiopia, by applying most frequently classical binary logistic Models(Belachew et al, 2023; Negash *et al. 2023;*Dereje*et al*, 2022;Tesema*et al*, 2022;Asresie*et al*, 2020).Those socio-demographic factors were common in most African countries including Ethiopia, that is, marital status, wealth category, education level, place of residence, number of children, age, religion, and access to a health facility reported in East, South, and West African countries as influencing factors of contraceptive use (Agyemang *et al*., 2019; Bawah *et al*., 2019; Obwoya *et al*., 2018; Makau *et al*., 2018).

Intention to practice contraception is a more valid indicator of the demand for family planning than unmet need (Borda rt al., 2009).However, the intention not to use contraceptives is the direct cause for not using contraceptives, and the major risk factor for unwanted birth, population growth, unwanted pregnancy, un-safe abortion, maternal and child health problems.

Therefore, the present study adopted Bayesian Procedures and determine the influencing factors of intending not to use contraceptives among Women in Reproductive Age in Somali Region, where the prevalence of modern contraceptive usage in the region was reported to be the least (3%) in the country (EPHI and ICF, 2021).

In general, the motivation behind this study was to address the following core research questions:

- What is the proportion of women in reproductive age not intending to use contraceptive in Jigjiga city?
- What are the factors that affect the intention not to use contraceptives among women in reproductive age in Jigjiga city?
- Which predictors have significant effect on the intention not to use contraceptives under Bayesian Approach?

1.3. Objectives of the Study

1.3.1. General Objective

The general objective of the study was investigating Factors Influencing Intention Not to Use Contraceptives among Women in Reproductive Age in Jigjiga City, Somali Region Ethiopia, using Bayesian Logistic Regression Model.

1.3.2. Specific Objectives

The Specific Objectives of the Study are:

- ❖ To determine the prevalence of women in reproductive age not intending to use contraceptive in Jigjiga City, Somali Region Ethiopia.
- ❖ To examine the association between intention towards contraceptives and categorical predictor variables.
- ❖ To identify factors which affect the intention not to use contraceptives using Bayesian logistic regression analysis

1.4. Significance of the Study

The findings of the study may have the following benefits: It is hoped that the study may contribute knowledge to health bureau and stake holders to know factors influencing the intention not to use contraceptives. It may help all office and regional health bureau to identify the strengths and weaknesses of not to use contraceptive to take remedial measures against the challenges to use this knowledge to design targeted interventions.

It may facilitate Policy makers to address reproductive health challenges and promote family planning. Thus, investigating, evaluating and appropriately addressing those underlying factors would better equip the stakeholders with the knowledge and would lead to achievement of better results on behavioral change. Finally, this research is useful for the future Researchers and readers to make any necessary quotations from it.

1.5. Scope of the study

The study used primary data which was collected from November 1 to 21, 2024 across the four sub-cities of Somali regional state capital Jigjiga. For the purpose of this particular study, data corresponding to married women who were in reproductive age (15 – 49), and live in Jigjiga city, was analyzed. Therefore the results and findings of the study were handled accordingly.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Definition and Overview of Family Planning

The definition of family planning is approached in different ways by different authors. These various approaches either overlap or are observable in agreement with one another as what family planning should mean based on the writer's perspective and social context. Family planning is defined as a service which allows individuals and couples to anticipate and attain the desired number of children and spacing and timing of their birth. It is achieved through the use of contraceptive methods and the treatment of involuntarily infertility (WHO, 2015).

Family planning refers to the use of contraception and other methods of birth control to regulate the number, timing, and spacing of human births. Samuel (2010), defined family planning as the practice that helps individuals or married couples to attain certain objectives, such as avoiding unwanted pregnancies, bringing about wanted babies at the right time, regulating the interval between pregnancies, controlling the time at which birth occurs in relation to the ages of parents and determining the number of children in the family. Thus, family planning is a means of reproductive health (Ngwu, 2014).

Family planning helps in empowering the couples living in poverty, through enabling them to have fewer children and reduces the tension of competition of available resources at the household and prevents Sexually Transmitted Infections (STIs) and Human Immunodeficiency Virus (HIV) through the promotion of contraceptives, such as condom thereby preventing unwanted pregnancies among HIV positive married women therefore averting mother to child transmission of the disease.

Planning of the family and implementing the plans is based on mutual understanding and pure voluntary on the part of the couple. Family planning is self-imposed discipline by husband and wife in order to be healthy, wealthy, and happy, and at the same time contributing to social welfare, national progress and world peace at large. High fertility rate can be reduced through the awareness and utilization of family planning. Family planning simply means the propensity or tendency of having intercourse without the result of pregnancy. Thus, one did not abstain from sex, yet nothing like pregnancy for the period of time the couples want. Thus, it is a conscious attempt by couples to space birth to guarantee health of the mother and child or children. Invariably, it results into birth/fertility control (Alana, 2017).

Any action or tool whose purpose is to prevent a woman from becoming pregnant can be considered contraception (Jain et al., 2021). Contraception involves the use of various drugs, devices, agents, sexual practices, or surgical procedures to prevent conception or pregnancy (Koc, 2000).

According to Reshma (2015), contraception is a method of family planning that hinders the survival of infants, as it supports birth control or spacing and reduces high risk pregnancies. This means that, in achieving adequate birth spacing, it could significantly reduce child mortality by 20 percent or more, particularly in developing countries of the world with numerous socioeconomic problems (WHO, 2001).

Somba *et al*., (2014) indicated contraceptive as family planning method which comprises the used of both modern and traditional techniques such as injections, pills, condoms, spermicidal, Intra-Urine Devices (IUD), diaphragm, virginal rings and traditional approaches include things like rhythm, withdrawal, and other methods(EPHI and ICF, 2019)

African population and Health Center reported that, contraceptive use among East African women has increased over the past two decades from 21% in ages 15-44, 1990-94 to 39% in 2010-14. Ethiopia, Kenya, and Rwanda, in particular, have made great strides in terms of access to and use of contraceptives. They were able to accomplish this by implementing health extension workers program, universal health insurance schemes that enhance free access to family planning services, and involving religious leaders in family planning education and counseling to tackle perceived barriers to contraceptive use.

The highest percentage of women who use modern methods is in Kenya (53%) with Uganda recording the lowest use at 26%. Contraceptive discontinuation rate is high among pill users in Ethiopia (70%) and injectable users; where, discontinuation refers to, starting contraceptive use and then stopping for any reason while still at risk of an unintended pregnancy (APHC, 2018).

2.2. Reviews on Factors Related to Contraceptive Practice

Study done in Mexico 86% of female have positive attitude to-wards future use of contraceptives and women who discuss family planning issue with their spouse and having a partner who support use of family planning are more likely to use contraceptive or to have lower risk for unmet need than their counter parts (Barber et al., 2019). A study in India on determinants and differentials of contraceptive use before first pregnancy by women, mentioned that Caste, religion, education, current age, age at marriage, media exposure and zonal classification were found to be significant whereas rural against urban residence was found to be insignificant (Pandey et al., 2015).

A number of researches in Sub-Saharan Africa revealed that there are numerous factors that obstruct the use of the modern contraceptives among the adolescents. Williamson et al., (2009) outline some barriers that could prevent the use of the modern contraceptives among adolescents, these barriers include; poor knowledge on contraceptives, fears and rumors about the side effect and unsupportive or negative impacts on partners and members of the family.
Study from Nigeria shows that 44% of research participants intended to contraceptive after delivery and 59.4% high level of unmet need, though 3% were yet to decide. Advanced age and high parity significantly predicted intention to use postpartum contraceptives. Also high level of respondent's education and family planning counseling by health professional increased the intention to use postpartum contraceptives (Adeyemi et al., 2010).

Ochako et al., 2017 reported that in Kenya, region of residence, marital status, religion, wealth, interaction with a health care provider, fertility preference, number of sexual partners and access to media were all significantly associated with modern contraceptive use among both men and women within the reproductive age. Similar study in Ghana revealed, age, education, work status, knowledge of ovulatory cycle, marital status, and visit to a health facility were significant in influencing contraceptive choice and use (Nyarko, 2015).

In Uganda, study revealed that knowledge of contraceptive methods was almost universal; with 96.2% mentioning at least one method. The most known method was Injectables (85.2%), followed with oral pills, IUD, and male condoms but that of permanent methods was very low

(Anguzu, et al., 2014). This finding was similar with study in Tigray where 99.3% of married women knew at least one contraceptive method (17)

Research evidences obtained from Idowu et al., 2015 and Gebremariam et al., 2014,on intention to use have showed that, maternal age, antenatal care service, prior use of any contraceptive and knowing at least one contraceptive method had been identified as factors associated for intention to use contraceptive.

A study conducted by Deribe *et al.* (2013) indicated that being wealthy, more educated, being employed, having higher number of living children, being in a monogamous relationship, attending community conversation, and being visited by a health worker at home strongly predicted use of modern contraception. While, living in rural areas, older age, being in polygamous relationship, and witnessing one's own child's death were found negatively influence modern contraceptive use.

In Ethiopia studies have shown urban women have better power to make decisions on modern contraceptive use than rural women (Bogale et al., 2011). Level of education, occupation, number of live children, joint fertility related decisions, ownership of a radio or TV, discussion with health care provider (Melka et al., 2015). Similarly, a study conducted in Somali region, Ethiopia by stated that, limited knowledge of contraception and fear of modern health practices negatively influenced contraceptives use (Jalu et al., 2019).

2.3. Empirical Reviews

In Liberia, a study conducted by using binary logistic regression analysis found that women in a union have significantly lower odds of intending to use contraception compared with those who have never been in a union (OR=0.78). Furthermore, with increasing age, the likelihood of intending to use contraception decreased substantially. Specifically, women aged 25–34 (OR= 0.35) and 35–49 (OR= 0.10) years had a lower intent to use contraception than those aged 15–24 years (Yeboah *et al.,* 2023).

A study by Kidayi *et al*. (2020) on Determinants of Modern Contraceptive Use among Women of Reproductive Age in Tanzania, adopting multivariate logistic regression analyses, showed thatthe odds of modern FP utilization among women who perceived that their husbands support the use of modern contraception were more thanthree times higher than those women who do not perceive that their husbands support the use of modern contraceptives. The study also showed that women who had never used modern FP were only 0.018 times less likely to use modern FP methods, compared to those who had ever used modern FP methods.

A community based studyin rural eastern Ethiopia by Mulatu *et al.,* 2020 revealed that, Muslim women and those in higher wealth categories were less likely to intend to use contraception when compared with Christian women and the poorest women, respectively. In addition, the study indicated that women who had prior experience using any method to delay or avoid becoming pregnant were more likely to intend to use contraception in the future than those who had never used any of such methods.

A study on factors associated with non-use of modern contraceptives among sexually active women in Ethiopia using Multivariable Multilevel Logistic regression analysis revealed that husbands with secondary and above educational level (OR= 0.83) had a higher likelihood of being non-users of contraceptives compared to their reference group. As compared to women from poor households, women from middle (OR= 0.66) and rich (OR= 0.74) wealth level had lower probabilities of not using contraception (Mulugeta *et al.*, 2022*).* According to a study conducted by Yeboah et al. (2023) on intention to use contraceptives using logistic regression, contraceptive use increases with increasing number of living children. Women with at least one child displayed a higher likelihood of intending to use contraception compared with those without children.

Based on a study using logistic regression in Tanzania Kidayi *et al*. (2020) justified that better knowledge of modern FP may result in better practice of modern FP methods, that is, the women who know modern FP methods are more likely to use the method consistently and effectively than their counterparts. Similarly, A Cross- sectional study in Aksum town, Tigray region, northern Ethiopia showed that women who were know at least one method of modern contraceptive have 5.17 times higher odds to intention to use modern contraceptive during extended postpartum period compare to their counterparts (Abraha *et al.,* 2018).

A report by Pandey *et al*., 2015 showed that women in towns or urban setups were more likely to use modern contraceptives compared to those in villages. Concerning knowledge that better knowledge of modern FP may result in better practice of modern FP methods, that is, the women who know modern FP methods are more likely to use the method consistently and effectively than their counterparts (Kidayi *et al*., 2020).Similarly, Abraha *et al.*, 2018 reported that women who watched family planning information on TV were less likely to not use contraception (OR= 0.74).

CHAPTER THREE

3. METHODOLOGY

3.1. Description of the Study Area

The Somali Regional State is the second largest Region of the country next to the Oromia Regional State. The Region shares borders with the Afar Region, Oromia Region and Dire Dawa to the West, Djibouti to the North, de facto state Somaliland to the North-East, Somalia from East to South, and Kenya to the South-West. The Region is predominantly inhabited by the Somali ethnic group, but it is ethnically heterogeneous. The capital city of the Somali Regional State is Jijiga divided into four sub-cities these are, Ayardaga, Dulqabow, Dudahide and Qordhere.

3.2. Data Source and Study Population

Target Population

All married women in reproductive age who live in JigJiga city during the study period were the target population.

Data

The survey was cross-sectional which was conducted from November 1 to 21, 2024. And the data was obtained from married women in reproductive age using interviewer administered structured questionnaire. Local enumerators were recruited from each study area among candidates who had completed high school education and who were capable of speaking the local language. Orientation training on proper administration of the questionnaire was given to enumerators. The filled-in-questionnaires were examined on the daily basis to check for completeness and consistency.

Sampling Design and Sampling Procedures

Sampling method is the process of selecting those sampling units which would provide the required estimator with associated margins of uncertainty arising from examining only a part not the whole of the population and to provide various types of statistical information of a qualitative or quantitative nature about the whole by examining a few selected units or samples. The target population for this study was married women in reproductive age.

In this study, stratified random sampling method was adopted as an appropriate sampling design for selecting a representative sample

Sample Size Determination

To determine the adequate sample size for the study, it is important to know some of the factors playing a key role to determine the sample size. Because knowing these factors and their effect helps us to determine the optimum sample size needed. Some of these factors are: the sampling design, statistical analysis, level of precision required, level of confidence and degree of variability(Cochran, 1977 and Al-Subaihi, 2003):.

In spite of the fact that, there are several formulas developed for sample size calculation that conform to different research situations, the sample size determination techniques for this study is based on stratified random sampling techniques. In stratified random sampling, a sample is drawn from each stratum of the population of finite numbers, which is assumed to be divided into subpopulations (or strata) according to a specific characteristic. Then, a simple random sample was taken in each stratum. The sample size determination formula that is adopted in this study is described as follows (Cochran, 1977):

$$n = \frac{\sum_{i=1}^{L} \frac{N_i^{\,2} p(1-p)}{W_i}}{\frac{N^2 d^2}{Z_\alpha^{\,2}} + Np(1-p)}$$

where, n = the sample size needed, N = the total population size, Z_α = Standard normal distribution that correspond to the α level of confidence, p= the probability of not intending to use contraceptive in the stratum (i) , d = the level of precision, L= the total number of strata (sub-cities), N_i = the size of stratum (i), which is the size of the population in each sub-city and the stratum weight, W_i = the estimated proportion of N_i to N.

According to Aradom et al. (2020) 36.1% married women of reproductive age was not intending to use contraceptive in the future in Jigjiga city, Somali Region. Therefore, p=0.0.361 was taken as the probability of not intending to use contraceptive in each stratum. The sampling error is called level of precision in sampling context denoted by d gives the researcher some idea relating to the accuracy of the statistical estimate. The level of precision taken for this study was 3.5% (i.e., d= 0.035). The higher the level of precision is required the greater sample size. The level of confidence is a value which indicates or describes the percentage of instances that test results can be expected to be within a specified range. The level of confidence that is used in this study was 95%. The degree of variability in the attributes being measured equals p (1-p) and has a direct relationship with the sample size. That is, the higher the degree of variability of the distribution of attributes in the population, the larger the sample size is required to obtain a given level of precision.

The study population was stratified into four strata or sub-cities, Ayardaga, Dulqabow , Dudahide and Qordhere. So that the required sample size for the study was determined from each stratum. Hence the divisions /stratifications of a population are:

Stratum 1: married women in reproductive age from Ayardaga sub city with population (house hold) size $\mathbf{N_1}$= 6379and sample size $\mathbf{n_1}$=79.

Stratum 2: married women in reproductive age from Dulqabow sub city with population size $\mathbf{N_2}$= 2526 and sample size $\mathbf{n_2}$=32.

Stratum 3: married women in reproductive age from Dudahide sub city with population size $\mathbf{N_3}$= 9260 and sample size $\mathbf{n_3}$=115.

Stratum 4: married women in reproductive age from Qordhere sub city with population size $\mathbf{N_4}$=10160 and sample size $\mathbf{n_4}$=126.

Let $\mathbf{N}= N_1+ N_2 +N_3 +N_4$ be total number of women in reproductive age across the four sub-cities in Jigjiga, and $n=n_1+n_2 +n3 + n4$ be total sample size of married women age (15 – 49) was used in the study.

Therefore, in this study total population **N**=28325, the level of precision, d=0.05, the probability of not intending to use contraceptive, p=0.36, level of significance, α=0.05 were used as inputs to compute sample size. The sample size in each stratum was determined by using proportional allocation method, and the required total sample size for the study was 352.

3.3. Variables in the Study

3.3.1. Response Variable

The dependent variable (Y) in the study, that is, the intention to use contraceptive is defined as the women who were intending to use any contraceptive methods to avoid pregnancies during the time of data collection. Women who were not intending to use contraceptives are categorized as **1** and those who intend to use categorized as **0**.

$$Y_i = \begin{cases} 1, & if \text{ the } i^{th} \text{ woman is not intending to use contraceptive} \\ 0, otherwise \end{cases}$$

3.3.2. Independent Variables

- Demographic variables and Operational definition
  - **Age of respondent**

It refers to the current age of women in a complete year at the time of the survey. The age of women are classified into three categories: **15** to **24**, **25** to **34** and **35** to **49**.

- **Number of living children (Son and daughter)**

It refers to the total number of living children of the women at the time of the survey. It is categorized into three groups: 0-2 children, 3-5 children and more than 5 children.

- Socio-economic Variables and Operational definition
  - **Religion**

It refers to the religion the women follow during the time of the survey. It is classified into four main classes: Orthodox, Muslim, Protestant, and Others.

- **Educational level of women/husbands**

It refers to the highest level of education in completed years that the woman/husband has attended in the formal education. It is categorized into three levels: no education, Primary, and Secondary and higher.

- **Occupation of women/husband's**

It refers to the activities in which the women/husbands were engaged at the time of conducting the survey. These activities can be categorized into five groups: Day laborer, Government employee, Own business, Non-Government Organization and Housewife (for women)

- **Monthly Income**

It refers to the monthly income of the women; which is categorized into four levels: 1000 -4000, 4000 -7000, 7000 -10000, and 10000 and Above

❖ Awareness and Practice of Contraceptives

- **Knowledge of contraceptive methods**

It refers to knowledge of contraceptive method of a woman at the time of the survey. It is categorized into three (Number of known modern methods): 0-2, 3-5 and more than 5

- **Past Experience on contraceptives**

It refers to women who ever used any contraceptive methods at the time of the survey. It is categorized into two: used modern methods (Yes) and never used (No)

- **Information about Family planning**

It refers to women who had heard about contraceptive information through radio broadcasting /TV in the last months prior to the interview. It is categorized into two: those who heard (Yes) and not (No).

- **Frequency of listening Radio and watching TV**

It refers to women how often used to listening Radio and watching TV.
It is categorized into three: Occasionally, At least once a week and Not at all.

- **Access to Family Planning Service**

It refers to women who had access to family planning service in nearby areas. It is categorized into two: those who had access (Yes) and had no access (No)

- **Visited a health facility in the last 12 months**

It refers to women who had visited a health facility in the last twelve months prior to the survey. It is categorized into two: those who visited and not

3.4. Methods of Data Analysis

3.4.1. Logistic Regression Model

Logistic regression analysis extends the techniques of multiple regression analysis to research situations in which the outcome variable is categorical. Logistic regression allows one to predict a discrete outcome, such as group membership, from a set of predictor variables that may be continuous, discrete, dichotomous, or a mix of any of these (Gellman *et al*., 2007). In general, when the dependent or response variable is dichotomous (binary), such as presence or absence, success or failure etc, binary logistic regression is used. There are two primary reasons for choosing the logistic distribution. First, from a mathematical point of view, it is an extremely flexible and easily used function, and second, it results in a clinically meaningful interpretation (Hosmer *et al*., 1989).

3.4.1.1. Model Description

The response variable in binary logistic regression is dichotomous and we denote the event **Y**=1 when the subject has the characteristic of interest and **Y**= 0 when the subject does not have that characteristic of interest. In logistic regression, a single outcome variable $\mathbf{Y_i}$ (i=1, 2, ..., n) follows a Bernoulli probability function that takes the value 1 with probability of success P_i orthe value 0 with probability of failure 1-P_i. The independent or predictor variables in logistic regression could be discrete, continuous or a mix of both.

The logistic model is defined as follows. Let $\mathbf{Y_{nx1}}$be a dichotomous outcome random vector with categories:**1** (intending not to use contraceptive) and **0** (intending to use). Let $\boldsymbol{X}_{\mathbf{nx(k+1)}}$ denote the set of **k**-predicator (explanatory) variables of **Y** with columns of **1**s. Where,

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \dots & x_{2k} \\ . & . & . & \dots & . \\ . & . & . & \dots & . \\ . & . & . & \dots & . \\ 1 & x_{n1} & x_{n2} & \dots & x_{nk} \end{bmatrix}$$

X is called regression matrix and without the loading column of one, is termed as predictor data matrix. Then, the conditional probability that a woman is intending not to use contraceptive given the set of predictor variables ***X*** is denoted by P (**Y$_i$** =1|***X***) =**P$_i$**.

The expression P_i in logistic regression model can be expressed in the form of:

$$P(x_i) = \frac{e^{\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\ldots+\beta_k X_{ik}}}{1+e^{\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\ldots+\beta_k X_{ik}}} = \frac{e^{X\beta}}{1+e^{X\beta}} = \frac{1}{1+e^{-X\beta}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

And,

P (x_i) = the probability that the ith woman is intending not to use contraceptive given her individual characteristics X_i.

Y_i= response of the ithwoman(intending not to use contraceptive/intending to use).

$\boldsymbol{\beta}$ = is $(k+1)x1$ vector of unknown parameters.

However, since the relationship between the predictors and response variable is not a linear in logistic regression, the logarithmic transformation of $\left(\frac{P(x_i)}{1-P(x_i)}\right)$ results in the linear relationship between the predictor and response variables. Consequently, an alternative form of the logistic regression equation is the logit transformation of **P$_i$** which is given as follows:

$$\log it\left[P(x_i)\right] = \log\left(\frac{P(x_i)}{1-P(x_i)}\right) = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 X_{i1} + \boldsymbol{\beta}_2 X_{i2} + \ldots + \boldsymbol{\beta}_k X_{ik} \ldots\ldots\ldots\ldots\ldots(2)$$

The coefficient can be interpreted as the change in the log-odds associated with the corresponding predictor variable or the odd increases multiplicatively by $e^{\boldsymbol{\beta}}$ for every one unit change increase in ***x*** (continuous variable). As in multiple regression analysis, there are two important stages in the analysis of data. First, estimates for the parameters in the model must be obtained and, second, some determination must be made on how well the model actually fits the observed data.

3.4.1.2. Parameter Estimation for Logistic Regression

To estimate the parameters of logistic regression model, the two estimation methods mostly used are maximum likelihood and non-iterative weighted least squares method (Hosmer et al., 1989; Greene, 1991; Collet, 2003). When the assumption of normality of the predictors does not hold, the non- iterative weighted least squares method is less efficient (Maddala, 1997). In contrast, the maximum likelihood estimation method is appropriate for estimating the logistic model parameters due to this less restrictive nature of the underlying assumptions. Thus in this study the maximum likelihood estimation technique was applied to estimate parameters of the model.

Consider the logistic regression model $P(x_i) = \frac{e^{X_i'\beta}}{1+e^{X_i'\beta}}$. Since observed values of Y say, Y_is (i=1, 2,…., n) are independently distributed as Bernoulli , the maximum likelihood function of Y is given by:

$$L(\beta / y) = \prod_{i=1}^{n} P(y_i \mid X_i') = \prod_{i=1}^{n} \left[\frac{e^{x_i'\beta}}{1+e^{x_i'\beta}} \right]^{y_i} \left[\frac{1}{1+e^{x_i'\beta}} \right]^{(1-y_i)} \quad \text{......... (3)}$$

The objective of ML estimation is to get an estimator $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, ..., \hat{\beta}_k)$ of β which maximizes the likelihood function expressed in equation (3). Since the likelihood equation is non- linear in the parameters, the Newton-Raphson iterative maximum likelihood estimation method that expresses $\hat{\beta}$ at the $(u+1)^{th}$ cycle of the iteration is given as:

$$\hat{\beta}_{u+1} = \hat{\beta}_u + (X'\hat{W}_u)^{-1} XR_u$$

where u=0,1,2,3, …and $\hat{W}$ is a diagonal matrix with its diagonal elements $p\hat{i}(1-p\hat{i})$ i.e. $\hat{W} = diag\left[pi(1 \hat{-} pi) \right] = \text{cov}(y)$. Finally, $\hat{\beta}$ is the maximum likelihood estimator of β with residual $R = p_i - \hat{p}$ (Collet, 2003; Greene, 1991). Newtons method usually converges to the maximum of the log – likelihood in just a few iteration unless the data are especially badly conditioned (Greene, 1991).

3.4.2. Bayesian Logistic Regression

Bayesian logistic regression procedure was adopted to make inference about the parameters of a logistic regression model. The purpose of this method is generating the posterior distribution of the unknown parameters given both the data and some prior density for the unknown parameters. Bayesian Statistics provides much more complete picture of the uncertainty in the estimation of the unknown parameters, especially after the confounding effects of nuisance parameters are removed (Lee, 2003; Draper, 2000; Tanner 1996). The idea on Bayesian statistics is based on Baye's theorem. Assume that we observe a random variable Y and wish to make inferences about another random Variable β, where β is drawn from some distribution p (β).

The posterior probability distribution function of β conditional on y can be written as:

$$P(\boldsymbol{\beta} \mid y) = \frac{P(y \mid \boldsymbol{\beta})P(\boldsymbol{\beta})}{P(y)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

Where, $P(y) = \int \ldots \int P(y \mid \boldsymbol{\beta})P(\boldsymbol{\beta})\, d\beta$ is a normalizing constant

$\beta = (\beta^{(1),}\ \beta^{(2)} \ldots \beta^{(p)}\ )$

3.4.2.1. Bayesian Inference for Logistic Regression Parameters

Bayesian approach provides a very different approach to the problem of unknown model parameters in that the uncertainty about the unknown parameters is quantifiable using probability distributions, so that the unknown parameters are considered as random variables. The basic concepts and procedures that should be considered in analysis of Bayesian inference are the likelihood function of the data, a prior distribution over all unknown parameters and the posterior distribution over all parameters. Bayesian inference for logistic regression models is derived applying a Markov Chain Monte Carlo algorithm to simulate from the joint posterior distribution of the regression and the link parameters.

3.4.2.2. Likelihood Function

The likelihood function used in Bayesian approach is equivalent to that of the classical inference. The joint distribution of n independent Bernoulli trials is the product of each Bernoulli densities, where the sum of independent and identically distributed Bernoulli trials has a Binomial distribution. Specifically, let $y_1, y_2, \ldots y_n$ be independent Bernoulli trials with success probabilities $P_1, P_2, P_3, \ldots, P_n$, that is $y_i = 1$ with probability P_i or $y_i=0$ with probability $1- P_i$, for $i= 1,2,\ldots,n$. Since, the trials are independent, the joint distribution of $y_1, \ldots, y_n$ is the product of n Bernoulli probabilities. The probability of success in logistic regression varies from one subject to another, depending on their covariates. Thus, the likelihood function is illustrated below as product of n Bernoulli trials:

$$L(\beta \mid y) = \prod_{i=1}^{n} \left[P_i^{y_i} (1 - P_i)^{(1-y_i)} \right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where, P_i represents the probability of the event for subject **i** who has covariate vector X_i, $y_i = 1$ indicates the presence and $y_i=0$ the absence of the event for the given subject. The probability of success in logistic regression can be defined as:

$$P_i = \frac{e^{(\beta 0 + \beta 1 x1 + \ldots \beta p x p)}}{1 + e^{\beta o + \beta 1 x1 + \ldots + \beta p x p}}$$

Due to the underlying assumption that each of the subjects are independent of each other, the likelihood function over data set of subjects is written as:

$$L(\beta \mid y) = \prod_{i=1}^{n} \left(\frac{e^{\beta_O + \beta_1 x_1 + \ldots \beta_p x_p}}{1 + e^{\beta_O + \beta_1 x_1 + \ldots \beta_p x_p}} \right)^{y_i} \left(1 - \frac{e^{\beta_O + \beta_1 x_1 + \ldots + \beta_p x_p}}{1 + e^{\beta_O + \beta_1 x_1 + \ldots \beta_p x_p}} \right)^{(1-y_i)} \ldots\ldots\ldots (6)$$

3.4.2.3. Prior Distribution

One of the pre conditions in any Bayesian analysis is the choice of a prior. The main idea here is that when the data have sufficient information, even a bad prior still not greatly influence the posterior. If the posterior is highly dependent on the prior, then the data (likelihood function) may not contain sufficient information. However, if the posterior is relatively stable over a choice of priors, then the data indeed contain significant information. In general, any prior distributions can be used depending on the available prior information. The choice can include informative prior distributions if something is known about the likely values of the unknown parameters $\beta_0, \beta_1, \ldots \beta_p$ or non-informative priors.

Here, the most common priors for logistic regression parameters was used, which are of the form: $\boldsymbol{\beta}_j \sim N\left(\boldsymbol{\mu}_j, \boldsymbol{\sigma}_j^2\right)$. This implies the normal distribution with mean μ_j and with variance σ^2_j. Mathematically:

$$P(\boldsymbol{\beta}_j) = \frac{1}{\sqrt{2\pi\boldsymbol{\sigma}_j^2}} \exp\left\{\frac{-1}{2}\left(\frac{\boldsymbol{\beta}_j - \boldsymbol{\mu}_j}{\boldsymbol{\sigma}_j^2}\right)^2\right\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

The most common choice for prior mean μ_j is 0 for all the coefficients. Prior variance σ is usually chosen to be large enough to be considered as non-informative, common choices being in the range from σ=10 to σ=1000.

3.4.2.4. Posterior Distribution

The posterior distribution is obtained as the product of the prior distribution of the parameters and the likelihood function. Thus, the Posterior distribution is represented as follows:

$$P(\boldsymbol{\beta} \mid y) = \prod_{i=1}^{n}\left[\left(\frac{e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p}}{1+e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p}}\right)^{y_i}\left(1-\frac{e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p}}{1+e^{\beta_0+\beta_1 x_1+\ldots+\beta_p x_p}}\right)^{(1-y_i)}\right] X \prod_{j=0}^{p} \frac{1}{\sqrt{2\pi\boldsymbol{\sigma}_j^2}} \exp\left\{\frac{-1}{2}\left(\frac{\boldsymbol{\beta}_j - \boldsymbol{\mu}_j}{\boldsymbol{\sigma}_j}\right)^2\right\} \ldots (8)$$

Conditioning upon the observed data, the posterior distribution is used to make statements about **β**, which is still a random variable. Computing the estimate of coefficients of the posterior distribution may be mathematically intractable; to overcome this situation, we need to use non numerical integration method such as simulation techniques. The most popular and common method of simulation technique is the Marcov Chain Monte Carlo (MCMC) methods and that was applied in this study.

3.4.2.5. Assessment of Bayesian Logistic Regression Model

Markov Chain Monte Carlo (MCMC)

The main challenge toward applying the Bayesian approaches is that, the posterior distribution often requires the integration of high dimensional functions. MCMC methods attempt to simulate direct draws from some complex distribution of interest. Also, it is used to generate an irreducible Markov chain with stationary probabilities ∏=p (β|y). A popular way of simulating from a general posterior distribution is by using MCMC methods. Markov chain Monte Carlo techniques enabled quantitative researchers to use highly complicated models and estimate the corresponding posterior distributions with accuracy.

As a result, MCMC methods have greatly contributed to the development and propagation of Bayesian theory. In quantitative sciences, the problem of evaluation of integrals of the type given below is often necessary.

$$H = \int_x g(x)dx$$

where $g(x)$ is high-dimensional density function and difficult to approximate the integral numerically.

One of the solutions is based on generating random samples and then obtaining the integral shown above by its statistical unbiased estimate, the sample mean. Hence let us assume that the density function *f(x)* of a random variable enables us to easily generate random values. This can be expressed as

$$\text{H} = \int_x \left[\frac{g(x)}{f(x)}\right] f(x)dx = \int_x g^*(x) f(x)dx,$$

where *g* (x)* = g(x)/f(x). Hence the integral *H* can be efficiently estimated by:

1. Generating $x^{(1)}, x^{(2)}, \ldots, x^{(T)}$ from the target distribution with probability density function (p.d.f.) *f(x).*

2. calculating the sample mean $\hat{\text{H}} = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{g(x^{(t)})}{f(x^{(t)})}\right]$ Ritter *et. al*., 1992.

The idea was known from the early days of the electronic computers and was originally adopted by the research team of Metropolis in Los Alamos (Anderson, 2007; Metropolis *et. al.*,2001). The main advantage of this approach is its simplicity. Even if integrals are tractable, nowadays it is much easier to generate samples than calculate high-dimensional integrals. The method described above is directly applicable to many problems in Bayesian inference. Hence for every function of the parameter of interest *P (*ß|y*)*, we can calculate the posterior mean and variance by:

1. Generating a sample $\beta^{(1)}, \beta^{(2)}, \ldots, \beta^{(T)}$ from the posterior distribution P (ß|y).
2. Calculating the sample mean of *P(*ß|y*)* by simply calculating the quantity

$$\hat{\mathrm{H}} = \frac{1}{T}\sum_{t=1}^{T} P(\beta^{(t)} \mid y)$$

Simulation can also be used to estimate and visualize the posterior distribution of *P (*β|y*)* itself.

The main problem in the above mentioned procedure is how to generate random samples from the posterior density *P*(***ß|y***).

The Gibbs Sampling Algorithm

The aim of Gibbs sampling is to find estimates for the parameters of interest in order to determine how well the observable data fits the model of interest. This sampling procedure requires an initial starting point for the parameters. Then, one at a time, a value for each parameter of interest is sampled given values for the other parameters and data. Once all of the parameters of interest have been sampled, the nuisance parameters are sampled given the parameters of interest and the observed data.

Although Gibbs sampling is a special case of Metropolis-Hasting algorithm, it is usually cited as a separate simulation technique because of its popularity and convenience. One advantage of the Gibbs sampler is that, in each step, random values must be generated from univariate distributions for which a wide variety of computational tools exist (Gilks, 2002). Usually, these conditional distributions have a known form and thus, random numbers can be easily simulated using standard functions in statistical and computing software.

Here, we used the Gibbs sampler implementing by Win BUGS or R to solve approximate properties of the marginal posterior distributions for each parameter. Gibbs sampler algorithm is one attractive method for constructing MCMC algorithms and very widely applicable to a broad class of Bayesian problems and has sparked a major increase in the applications of Bayesian analysis. Gibbs sampling is always moving to new values and does not require specification of proposal distributions. On the other hand, it can be ineffective when the parameter space is complicated or the parameters are highly correlated. Suppose that we partition the parameter vectors of the interest into the p-components, $\beta' = (\beta_1, \beta_2, \beta_3 \ldots \beta p)$. The Gibbs sampler algorithm was implemented by sampling in turn from the P-conditional posterior distributions defined below:

$$\Pi(\beta_1 \mid \beta_2, \beta_3, \ldots, \beta_p), \Pi(\beta_2 \mid \beta_1, \beta_3, \ldots, \beta_p), \Pi(\beta_3 \mid \beta_1, \beta_2, \beta_4, \ldots, \beta_p), \ldots, \Pi(\beta_p \mid \beta_1, \beta_2, \ldots, \beta_{p-1}) \ldots\ldots(6)$$

Gibbs sampler Algorithm was stated as follows:

1. Start with an initial value β^o satisfying, $\beta^0 = (\beta_1^{\,o}, \beta_2^{\,o}, \ldots., \beta_p^{\,o})$

2. Repeat for i= 1, 2... n

Generate $\beta_1^{(i+1)}$ from $\Pi\left(\beta_1 \mid \beta_2^{(i)}, \beta_3^{(i)}, \ldots, \beta_p^{(i)}\right)$

Generate $\beta_2^{(i+1)}$ from $\Pi\left(\beta_2 \mid \beta_1^{(i)}, \beta_3^{(i)}, \ldots, \beta_p^{(i)}\right)$

.

.

Generate $\beta_p^{(i+1)}$ from $\Pi\left(\beta_p \mid \beta_1^{(i+1)}, \beta_2^{(i+1)}, \ldots, \beta_{p-1}^{(i+1)}\right)$

3. Return the values $\left\{\beta^{(1)}, \beta^{(2)}, \ldots., \beta^{(n)}\right\}$

Convergence of the Algorithm

The empirical results from a given MCMC analysis are not deemed reliable until the chain has reached its stationary distribution. On account of this, the term convergenceof an MCMC algorithm refers to whether the algorithm has reached its equilibrium (target) distribution. If this is true, then the generated sample comes from the correct target distribution. Hence, monitoring the convergence of the algorithm is essential for producing results from the posterior distribution of interest. Convergence diagnosis was adopted to answer the question of how to determine whether the sample has reached its stationary distribution (Albert, 2008).

Visualized Tests for Convergence

Generally, it is unclear how many times we must run an algorithm to obtain samples from the correct target distributions. Several diagnostic tests have been developed to monitor the convergence of the algorithm. There are basically three approaches to determining convergence for Markov chains: assessing the theoretical and mathematical properties of particular Markov chain, diagnosing summary statistics from in- progress models, and avoiding the issue altogether with perfect sampling, which uses the idea of "coupling from the past" to produce a sample from the exact stationary distribution (Prop *et. al.,* 2005). Here we provide details on the second approach.

The second convergence assessment methodology involves monitoring the performance of the chain as part of the estimation process and making an often subjective determination about when to stop the chain. Among several ways, the most popular and straight forward convergence assessment methods are discussed here.

I. **Autocorrelation:** High correlation between the parameters of a chain tends to give slow convergence, where as high autocorrelation within a single parameter chain leads to slow mixing and possibly individual non convergence to the limiting distribution because the chain was tend to explore less space in finite time. That is, low or high values indicate fast or slow convergence, respectively. In analyzing Markov chain autocorrelation, it is helpful to identify lags in the series in order to calculate the longer- run trends in correlation, and in particular whether they decrease with increasing lags. Diagnostically, though, it is not necessary to look beyond 30 to 50 lags (Merkle et al., 2005; Gill, 2004).

II. **Time series plots**: Iteration numbers on x-axis and parameter value on y-axis are commonly used to assess convergence (Merkle et al., 2005; Gill, 2004).If the plot looks like a horizontal band, with no long upward or down ward trends, then we have evidence that the chain has converged.

III. **Gelman-Rubin statistic**: for a given parameter, this statistic assesses the variability within parallel chains as compared to variability between parallel chains (Merkle et al., 2005;Gill, 2004). The model is judged to have converged if the ratio of between to within variability is close to one.

IV. **Density plot**: This is another technique for identifying convergence and a classic sign of non convergence is multimodality of the density estimate (Merkle et al., 2005;Gill, 2004). A poor choice of starting values and/or proposal distribution can greatly increase the required burn-in time (trending section).

Monte Carlo Error (MC-Error)

The Bayesian procedures have several statistical diagnostic tests that use to examine Markov chain convergence. In addition, the MC error (SEM) values used to know how much uncertainty there is about the true posterior mean via the sampled mean. As a rule of thumb, the Markov Chain Monte Carlo simulation should be run until the Monte Carlo error for each parameter of interest is less than about 5% of the sample standard deviation. Then, all parameter estimates with Monte Carlo error (MC-error) less than 5% of standard deviation, would be used for inferential purpose (Christensen*et al*., 2011).

CHAPTER FOUR

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

The study used primary data which was collected from November 1 to 21, 2024 across the four sub-cities of Somali regional state capital Jigjiga. Among married women who were in reproductive age (15 – 49) in Jigjiga city,a sample of 352 was taken for this study.The results displayed in Table 4.1 shows percentages and counts of women along with their socio-economic and demographic characteristics. Out of the 352 married women in reproductive age, 21 %(74) were contraceptive user, and 79 %(278) were non-users at the time of the data collection. Similarly, among non users, that is 278, about 199(71.6%) had intention not to use modern contraceptive method.

Table 4.1 Socio-Economic and Demographic characteristics of women in reproductive age in Jijiga city (November 2024)

Variable	Category	Frequency	Percent
Age	25-34	107	30.4
	35-44	208	59.1
	45-49	37	10.5
Religion	Muslim	243	69.0
	Protestant	26	7.4
	Orthodox	83	23.6
Living Son(s)	0 - 2	43	12.2
	3 - 5	190	54.0
	> 5	119	33.8
Living Daughter(s)	0 - 2	254	72.2
	3 - 5	77	21.9
	> 5	21	6.0
Desire to a child	Yes	308	87.5
	No	44	12.5
Education Level	Primary school	162	46.0
	Secondary school	141	40.1
	University Degree or Higher	49	13.9
Visit health facility	Yes	136	38.6
	No	216	61.4

Variable	Category	Frequency	Percent
Husband's Education Level	Primary school	150	42.6
	Secondary school	164	46.6
	University Degree or Higher	38	10.8
Occupation	Day laborer	22	6.3
	Government employee	80	22.7
	Own business	156	44.3
	Non-Government Organization	36	10.2
	Housewife	58	16.5
Monthly Income	1000 -4000	26	7.4
	4000 -7000	178	50.6
	7000 -10000	115	32.7
	10000 and Above	33	9.4
Husband's Occupation	Day laborer	188	53.4
	Government employee	72	20.5
	Own business	81	23.0
	Non-Government Organization	11	3.1
Listening Radio	Almost every day	29	8.2
	Occasionally	91	25.9
	At least once a week	59	16.8
	Not at all	173	49.1
Watching TV	Almost every day	97	27.6
	Occasionally	156	44.3
	At least once a week	78	22.2
	Not at all	21	6.0
Information about Family planning	Yes	105	29.8
	No	247	70.2
Known Family planning methods	0 - 2	267	75.9
	3 - 5	67	19.0
	> 5	18	5.1
Past Experience on contraceptives	Yes	78	22.2
	No	274	77.8
Access to Family Planning Service	Yes	247	70.2
	No	105	29.8
Contraceptive use	Yes	74	21.0
	No	278	79.0

The results are displayed in Table 4.1 above revealed that; the sampled households are predominantly middle-aged, with the majority falling within the 35–44 age range. This suggests that the population is in a life stage where family planning and child-rearing decisions are highly relevant.

With respect to age distribution, the majorities 208 (59.1%) of respondents are aged 35-44, followed by 30.4% in the 25-34 range, and only 10.5% are 45-49. Muslim households dominate 243(69%), followed by Orthodox (23.6%) and Protestant (7.4%).Education levels among both women and their husbands are relatively low, with most having only primary or secondary schooling, and few have attained higher education.

Accordingly, Education level, about 46% of women and 42.6% of husbands have only primary education. Few 13.9% of women, 10.8% of husbands hold university degrees. The occupational distribution shows that, 44.3% of women run their own businesses, while 53.4% of husbands are day laborers. Only 22.7% of women are government employees. Income levels are moderate for most households, with very few falling into the highest category, 50.6% earn 4000–7000 units/month, while only 9.4% earn >10,000.

The data shows a distinct pattern in the number of children, particularly sons and daughters. Households have more sons than daughters, which are 54% of households have 3–5 living sons, while 72.2% have 0–2 living daughters.

A remarkable majority of respondents expressed a desire for more children, with only a small fraction indicating no further interest in expanding their families, which are 308(87.5%) want more children, while only 12.5% do not.

Family Planning Awareness and Access are considered in study; about 247(70.2%) of the respondents lack information about family planning, and 75.9% know 0–2 methods, thus, low awareness likely exacerbate the intention not to use contraceptive. Meanwhile, 70.2% have access to family planning services, but 61.4% not visited health facility in the past 12 months.

Media habits provide additional insights into potential channels for disseminating family planning information. While radio listenership is low, television viewership is more common, making TV a viable medium for awareness campaigns. However, the media exposure in the study displays that 49.1% never listen to the radio, but 44.3% watch TV occasionally, and past on contraceptive Use, 77.8% have no experience with contraceptives.

4.2 Bivariate Analysis Results

This section reports the association between the intention not to use contraceptive and each of the socio-demographic variables using chi-square and likelihood ratio tests. Also, frequency distributions of each category of socio-demographic variables were included. The results are displayed in Table 4.2. Accordingly among 278 non users, about 199(71.6%) had intention not to use modern contraceptive method

From Table 4.2 we can see that a significant association was found between intention on contraceptive method and the socio-economic and demographic variables: Religion, Living Son(s), Desire to have more children, women's Education Level, Information about Family planning, Known Family planning methods, past experience on contraceptives and Access to Family Planning Service. However, no association was found between women's intention on contraceptive.

Table 4.2 Socio-Economic and Demographic characteristics of women in reproductive age in Jijiga city (November 2024)

Variable	Chi-Square Value	P-Value
Age	0.952	0.621
Religion	21.134	**0.000***
Living Son(s)	6.258	**0.044***
Living Daughter(s)	5.675	0.059
Desire to a child	36.415	**0.000***
Education Level	7.611	**0.022***
Husband's Education Level	1.674	0.433
Occupation	2.320	0.677
Monthly Income	1.233	0.745
Husband's Occupation	0.204	0.977
Visit to health facility	2.982	0.084
Listening Radio	5.874	0.118
Watching TV	5.395	0.145
Information about Family planning	39.186	**0.000***
Known Family planning methods	73.680	**0.000***
Past Experience on contraceptives	16.044	**0.000***
Access to Family Planning Service	5.710	**0.017***

4.3 Bayesian Logistic Regression Analysis

Bayesian logistic regression procedure were used to make inference, the result of the model parameters in this study are computed by MCMC techniques, specially using Gibbs sampler algorithm methods using R software. The Gibbs sampler algorithm was implemented with 2500 iterations in three different chains, 500 burn-in terms discarded, so that the 2000 iteration are sampled from the full posterior distribution. The Gibbs sampler algorithm with three simultaneous chain running provided 6000 posterior samples. There are different ways of checking the convergence of Bayesian analysis using Gibbs sampler algorithm and Model Accuracy, The convergence of the chain can be initially checked visually using trace plots , Density plot, and MC error in comparison to its posterior standard errors (Vehtari et al. 2021).

Density plot

This is another technique for identifying convergence. The plots for all predicator variables indicated the coefficient has unimodal density, and hence the simulated parameter values were converged to known target distribution.

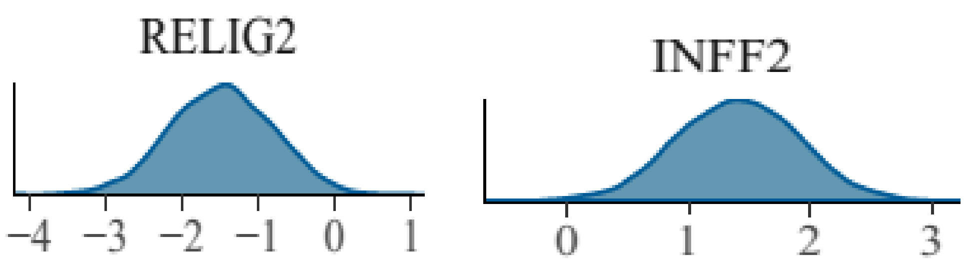

Figure 4.1: Convergence for Density Plot of the Parameter's for Religion: Protestant (**RELIG2**), and Information about family planning (**INFF2**)

Time series plot

The chain was run with a burn-in of 500 iterations with 2,000 retained draws. It indicates the sample value taken from the full conditional posterior distribution of each parameter in the model after burn–in point which is assumed as values taken from marginal posterior distribution of each parameter. The values on the Y-axis are the posterior parameter values and the value on the X-axis is the number of iteration made to sample the corresponding values from their posterior parameter. The time series plot below indicates a good convergence; since three independently generated chains are mixed together in a good ways.

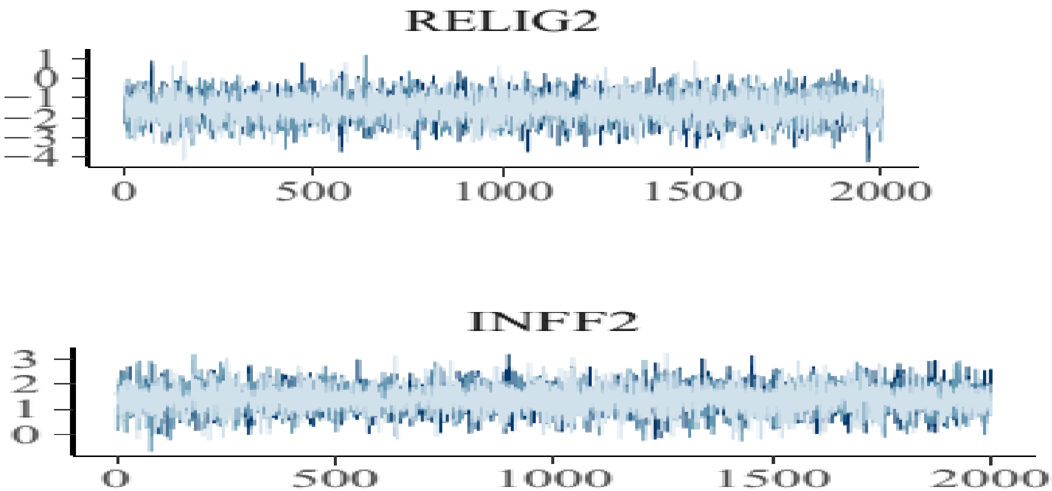

Figure 4.2: Convergence for Time series Plot of the Parameter's for Religion: Protestant (**RELIG2**), and Information about family planning (**INFF2**)

4.5 Assessing Accuracy of Bayesian Logistic Regression Model

The Monte Carlo error for each parameter of interest is less than 5% of its posterior standard error and **Rhat** values are **< 1.01** or equal to **1.000** which indicates perfect convergence (Gelman et al. 2013) table 4.3, and hence evidence for accuracy of posterior estimates in Bayesian logistic regression accomplished. In this study MC error for each significant predictor was found to be less than 5% of its posterior standard error. This implies convergence and accuracy of posterior estimates of the Bayesian simulation were attained. In addition, the mean posterior predictive value (0.715) in table 4.3, closely matches observed data's proportion of "intention not to use contraceptives" (event=1). This suggests your model is accurately capturing the overall outcome distribution, and also the narrow standard deviation (0.028) used to assess predictive performance of the model, the value (0.028) indicates stable predictions(Vehtari et al. 2021)

The results of Bayesian logistic regression analysis are given in Table 4.3. The results revealed that Religion , Desire for more child, Information about family planning, Number of known contraceptive Methods and Past experience on contraceptive contribute significantly to intention to contraceptives.

Table 4.3 Estimation of the Posterior Distribution Parameters of Binary Logistic Regression Model

Predictors	Category	Mean	SE	MCSE	Rhat	OR	95% CrI for OR 2.5%	97.5%
(Intercept)	------------	-0.566	0.974	0.011	1.000	0.57	0.12	1.50
Religion	Protestant (RELIG2)	**-1.490**	0.682	0.008	1.000	0.23	0.06	0.58
	Orthodox(RELIG3)	-0.309	0.461	0.005	1.000	0.73	0.30	1.83
Living Son(s)	3 – 5 (NLS2)	0.466	0.632	0.008	1.000	1.59	0.46	5.57
	> 5 (NLS3)	-0.993	0.649	0.009	1.000	0.37	0.10	1.31
Desire to child	No(DRCH2)	**-2.361**	0.525	0.006	1.000	0.09	0.03	0.26
Education Level	S.School(EDUL2)	0.498	0.391	0.004	1.000	1.65	0.77	3.56
	Degree.Higher (EDUL3)	0.793	0.670	0.008	1.000	2.21	0.59	8.31
Info. Family planning	No (INFF2)	**1.403**	0.521	0.006	1.000	4.07	1.47	11.29
Known Family planning m.	3- 5 (NFPM2)	**-2.915**	0.532	0.006	1.000	0.05	0.02	0.15
	>5(NFPM3)	-1.743	1.126	0.012	1.000	0.18	0.02	1.58
P. Experie. on contraceptives	No(PECU2)	**1.429**	0.813	0.009	1.000	4.18	1.85	20.56
Acce. Family P. Service	No(ACCE2)	0.398	0.409	0.004	1.000	1.49	0.67	3.33

Posterior Predictive Check (PPD) Results:
mean_PPD = 0.715 (**sd**=0.028, 95% **CrI**: 0.672-0.760)

The results in Table 4.3 show above, Religious differences matter, compared to Muslims (reference): Protestants (RELIG2) show significantly lower odds of intending *not* to use contraceptives (OR=0.23, 95% CrI: 0.06-0.58), Orthodox Christians (RELIG3) show no statistically significant difference (OR=0.73, 95% CrI: 0.30 -1.83). The results also show that women who have no desire (DRCH2) for more children have a 91% lower odd of intending not to use contraceptives than the reference (has desire).

The relationship between information about family planning and intention to contraceptive was also found statistically significant. The odds ratio shows that women who had no information about family planning are 4.07 times more likely to intend not to use contraceptive compare to those who had information about contraceptive.

Another variable which was found statistically significant was the number of known family planning methods by the respondent (woman). Comparing the odds of not intending to use of the women based the number of methods they know, women who know 3 to 5 different methods are 0.05 times less likely intending not to use contraceptives than women who know 0 to2 methods.
In addition, the relationship between women's past experience on contraceptive methods and intention to contraceptive was statistically significant, the result shows that the odds of not intending to use contraceptive was 4.18 times higher for women who had no past experience than their counter parts.

4.6 Discussion

This study attempted to identify factors that affect women's intention towards contraceptive methods in Somali regional state capital city Jigjiga. The results of the study showed that, out of a sample of 352 sampled women in reproductive age, about 199(71.6%) had intention not to use contraceptive method.

Religious Differences in Contraceptive Intentions**, t**he significantly lower odds of intention not to use contraceptives among Protestants (OR = 0.23) compared to Muslims corroborates findings **by** Ahmed et al. (2018) in similar settings, who attributed this to denominational teachings on family planning. However, the non-significant result for Orthodox Christians (OR = 0.73) contrasts with Tesfaye et al. (2020**)**, who reported stronger religious effects across all groups. This discrepancy may reflect regional variations in doctrinal interpretations or sample characteristics. Our tighter credible intervals for Protestants (95% CrI: 0.06–0.58) strengthen confidence in this association**.**

Fertility Desires and Contraceptive Use**,** the 91% lower odds among women with no desire for more children (DRCH2) aligns robustly with the theory of planned behavior (Ajzen, 1991), supporting the universality of fertility goals as a predictor of contraceptive intentions. This mirrors findings by Bankole et al. (2022**)** across 12 sub-Saharan African countries, where fertility desires were the strongest predictor of contraceptive uptake.

Information and Knowledge Gapsthe fourfold higher odds of non-use intention among women lacking family planning information (INFF2: OR = 4.07) echoes Sedgh & Hussain's(2014) meta-analysis linking information access to contraceptive adoption. However, the magnitude of effect here is larger than their pooled estimate (OR ≈ 2.5), suggesting localized information deficits. The dramatic reduction in non-use intention among women knowing 3–5 methods (NFPM2: OR = 0.05) extends Kavanaugh et al.'s (2021) work, highlighting method-specific knowledge as a critical lever a nuance often overlooked in awareness campaigns.

Past Experience and Behavioral Intentions**,** the elevated odds among women without prior contraceptive experience (PECU2: OR = 4.18) supports Rogers' (2003) diffusion of innovations theory, where familiarity predicts adoption. However, the wide credible interval (0.85–20.56) implies heterogeneity in this effect, possibly due to varied prior experiences (e.g., side effects). This aligns with Castle et al. (2021)**,** who found past negative experiences moderated intention shifts.

While our religious findings partially align with Gonsalves et al. (2022)**,** their study reported Orthodox Christian effects (unlike ours), possibly due to differing religiosity measures. Similarly, the stronger information-effect here versus WHO (2020**)** benchmarks may reflect our focus on intentions rather than *use*, capturing earlier decision-making stages.

CHAPTER FIVE

5. CONCLUSIONS AND RECOMMENDATIONS

5.1.Conclusions

The purpose of this study was to explore factors influencing intention not to use contraceptives among Women in Reproductive Age in Jigjiga City, Somali Region Ethiopia, by employing Bayesian logistic regression approaches.

Out of the 352 married women in reproductive age, 21 %(74) were contraceptive user, and 79 %(278) were non-users at the time of the data collection. Similarly, among non users, that is 278, about 199(71.6%) had intention not to use modern contraceptive method, and significant bivariate association was found between intention on contraceptive method and the socio-economic and demographic variables: Religion, Living Son(s), Desire to have more children, women's Education Level, Information about Family planning, Known Family planning methods, Past Experience on contraceptives and Access to Family Planning Service.

Bayesian logistic regression procedure were used to make statistical inference, the result of the model parameters in this study are computed by MCMC techniques, specially using Gibbs sampler algorithm methods using R software. The Gibbs sampler algorithm was implemented with 2500 iterations in three different chains, 500 burn-in terms discarded, so that the 2000 iteration are sampled from the full posterior distribution. The Gibbs sampler algorithm with three simultaneous chain running provided 6000 posterior samples

The study found that Religion as a significant predictor, compared to Muslims (reference), Protestants (RELIG2) show significantly lower odds of intending not to use contraceptives (OR=0.23, 95% CrI: 0.06-0.58), Orthodox Christians (RELIG3) show no statistically significant difference (OR=0.73, 95% CrI:0.30-1.83). The results also have shown that women who have no desire (DRCH2) for more children have a 91% lower odd of intending not to use contraceptives than the reference (has desire).

The relationship between information about family planning and intention to contraceptive was also found statistically significant. The odds ratio reveals that women who had no information about family planning are 4.07 times more likely to intend not to use contraceptive compare to those who had information about contraceptive.

Similarly, the relationship between women's past experience on contraceptive methods and intention to contraceptive was statistically significant, the result indicates that the odds of not intending to use contraceptive was 4.18 times higher for women who had no past experience than their counter parts.

5.2 Recommendations

Based on the findings of this study, the following interventions are recommended to improve contraceptive uptake:

- Collaborate with Protestant religious leaders to leverage their influence in promoting contraceptive use, given their adherents' lower resistance.
- Engage Orthodox Christian communities in dialogue to address potential misconceptions, as their contraceptive intentions did not differ significantly from Muslims.
- Improve information dissemination through community health workers, mobile clinics, and media campaigns to reduce misinformation.
- Focus on teaching 3–5 contraceptive methods rather than general awareness, as method-specific knowledge had the strongest protective effect.
- Integrate fertility goal assessments into family planning programs to tailor counseling for women who want to delay or stop childbearing.
- Promote long-acting reversible contraceptives (LARCs) for women who desire no more children, given their high efficacy
- Further Research Longitudinal studies to assess causal relationships between religious affiliation, knowledge, and contraceptive behavior, and Qualitative research to explore why Orthodox Christian women's intentions did not differ significantly from Muslims, despite doctrinal differences.

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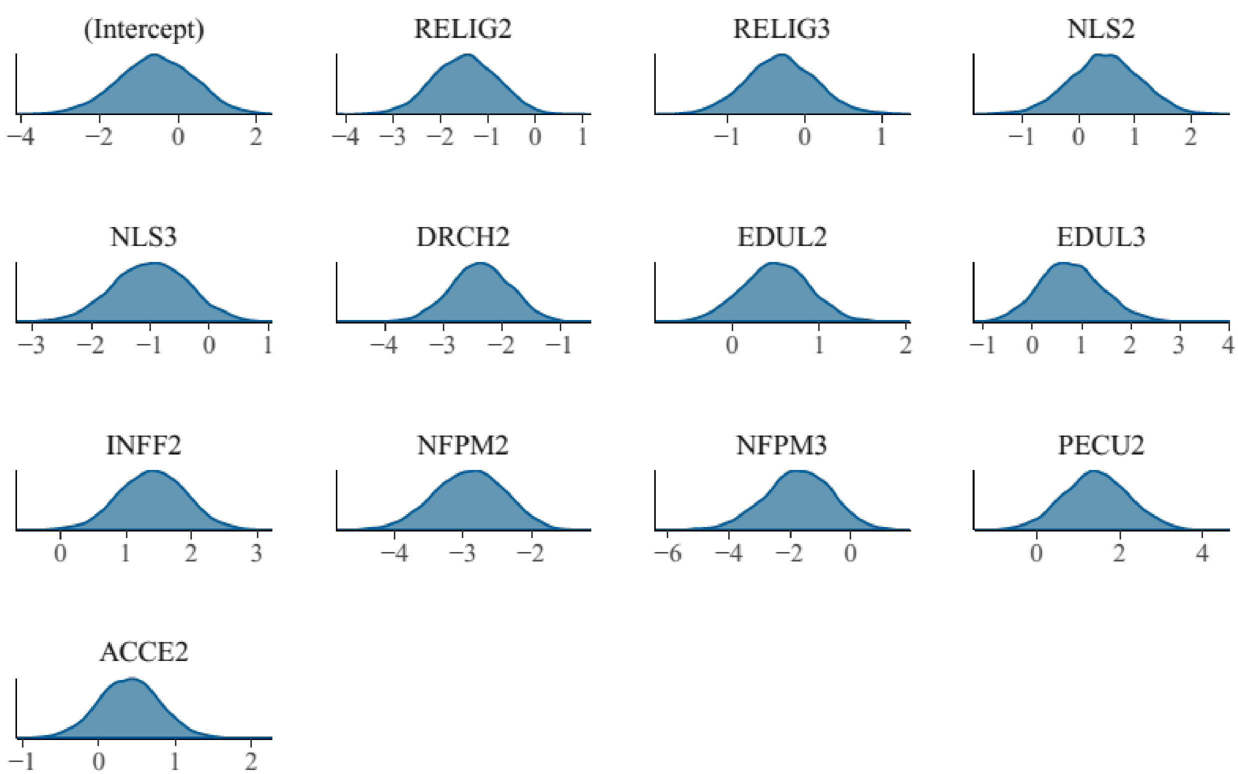
5. APPENDICES

Figure A: Density Plots for the Simulations of Posterior Distribution of the Model Parameters.



Appendix:Figures

Figure B: Time Series Plots of the Simulations of Posterior Distribution of the Model Parameters.

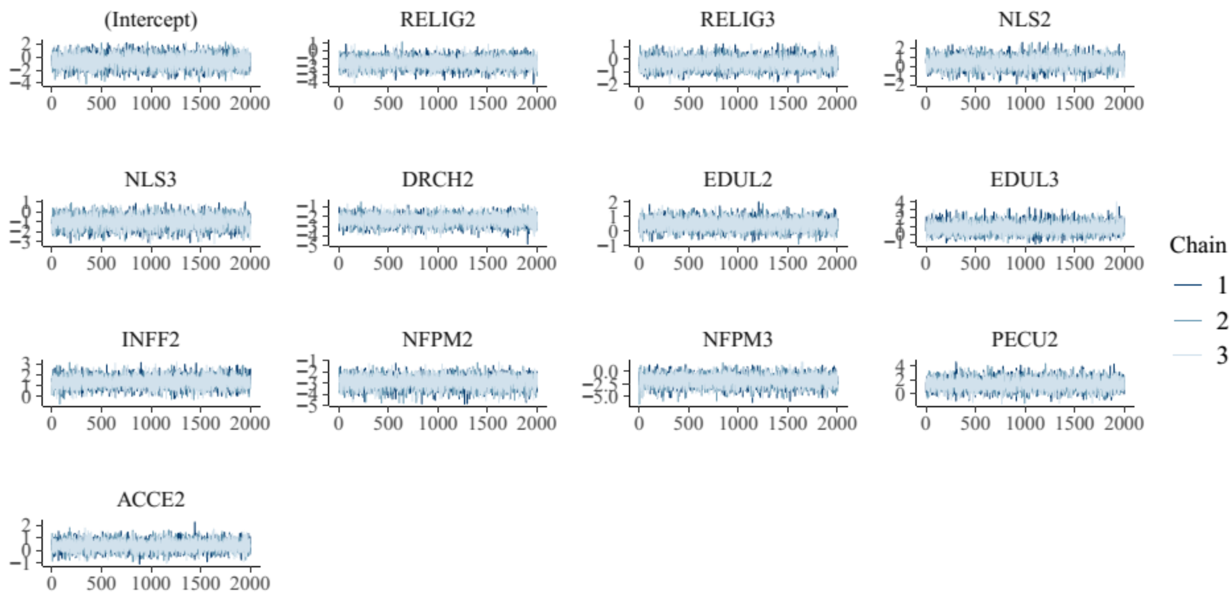
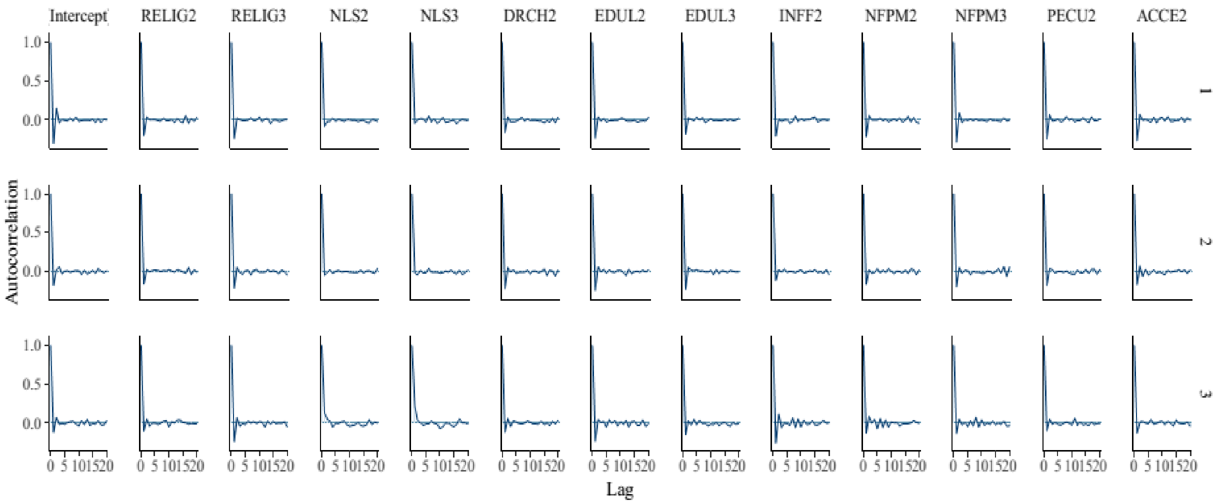


Figure C: Autocorrelation Plots of the Simulations of Posterior Distribution of the Model Parameters.


Intercept
RELIG2
RELIG3
NLS2
NLS3
DRCH2
EDUL2
EDUL3
INFF2
NFPM2
NFPM3
PECU2
ACCE2
Autocorrelation
1.0
0.5
0.0
1
2
3
0 5 10 15 20
Lag