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Healthy Families, Thriving Communities: Assessing the Transformative Role of Women in Health Improvement

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Abstract: This paper employs a novel approach by integrating machine learning techniques to quantitatively assess the impact of women's roles on family health outcomes. Through the analysis of data from 284 families, encompassing both urban and rural settings, this study highlights the pivotal role of women in healthcare decision-making processes and their significant contribution to promoting healthier family lifestyles. Key findings from the exploratory data analysis reveal that families with women holding Bachelor's degrees or higher exhibit markedly better health outcomes, underscoring the critical link between women's education and family health. Furthermore, the study identifies a positive correlation between women's participation in health-related discussions and the family's overall satisfaction with healthcare services. Most notably, the analysis demonstrates that women's influence in healthcare decisions significantly correlates with a lower incidence of chronic diseases within families. Machine learning analysis further substantiates these observations, pinpointing critical factors such as the educational attainment of women, their engagement in health discussions, and their active participation in managing the family's health budget as significant predictors of improved health outcomes. These findings underscore the substantial role of women in family health dynamics and advocate for targeted interventions to empower women in their roles as key agents of health within families. The study contributes valuable insights into the intersection of public health, gender studies, and data science, offering evidence-based recommendations for policy formulation and health interventions focused on leveraging the role of women to enhance family health outcomes.

Keywords: *Machine Learning, Social Science Research, Women Empowerment, Exploratory Data Analysis, Comparative Analysis, Feature Selection, Machine Learning Classifiers.*

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I. INTRODUCTION

Women, traditionally seen as primary caregivers, significantly influence health outcomes through decision-making processes related to nutrition, hygiene, and healthcare access. This research is driven by the desire to quantitatively validate and explore the depth of this role using advanced machine learning techniques, aiming to uncover patterns and insights that can inform targeted interventions for enhancing family health outcomes. The motivation is further fueled by the potential for these findings to contribute to the broader goals of gender equality and public health improvement, showcasing how empowering women directly benefits broader societal health.

However, this innovative approach is not without its challenges. One of the primary hurdles is the complexity of accurately capturing and quantifying the multifaceted roles of women within the dataset. The nuanced nature of women's contributions to family health, encompassing both direct actions and indirect influences, requires sophisticated data collection and preprocessing strategies to ensure meaningful analysis. Additionally, the application of machine learning algorithms to social science data presents methodological challenges, including addressing biases within the data, choosing appropriate models that can handle the complexity of human behavior, and interpreting results in a manner that is actionable for policy and intervention design.

Moreover, the interdisciplinary nature of this research, bridging public health, gender studies, and data science, demands a broad skill set and deep understanding of each field. Ensuring that the analysis remains sensitive to the socio-cultural context and grounded in public health realities adds another layer of complexity. Despite these challenges, the potential impact of illuminating the role of women in family health through machine learning analysis motivates this research endeavor. By overcoming these obstacles, this research aims to offer significant contributions to our understanding of gender dynamics in health, providing

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evidence-based recommendations to empower women and improve family health outcomes.

Research questions are foundational to any academic study, serving as the guiding compass that shapes the direction, scope, and focus of the research. The research questions of the study are given below.

➢ *How Does the Level of Educational Attainment among Women within Families Affect Overall Health Outcomes?*

- *Clarification:*

This question seeks to explore the association between women's education levels, specifically those with a Bachelor's degree or higher, and the health outcomes observed in their families. It aims to understand the mechanisms through which education may empower women to make informed health decisions and practices that benefit family health.

➢ *What is the Relationship Between Women's Participation in Health-Related Discussions and Decisions and the Family's Satisfaction with Healthcare Services?*

- *Clarification:*

This question aims to investigate how women's active involvement in health-related conversations and decision-making processes within the family correlates with the family's perceptions and satisfaction regarding the healthcare services they receive. It seeks to quantify the impact of women's voices and choices on the perceived quality and effectiveness of healthcare.

➢ *Does Women's Influence on Healthcare Decisions within the Family Correlate with a Reduction in the Incidence of Chronic Diseases among Family Members?*

- *Clarification:*

This question focuses on examining the potential causal relationship between women's authority and influence over healthcare decisions in the household and the prevalence of chronic diseases among family members. It looks to identify whether women's decision-making roles serve as a protective factor against chronic health conditions.

➢ *What Barriers and Facilitators Affect Women's Ability to Influence Health Outcomes and Decisions Within their Families?*

- *Clarification:*

Beyond examining the direct correlations, this question delves into the broader context affecting women's empowerment in healthcare settings. It seeks to uncover the challenges and supports that condition women's capacity to positively impact family health, providing a deeper understanding of the socio-cultural, economic, and systemic factors at play.

➢ *How do Differences in Women's Roles and Participation in Healthcare Vary Across Families with Different Socio-Economic and Cultural Backgrounds?*

- *Clarification:*

This question broadens the scope of the study to consider the diversity of family structures, socio-economic statuses, and cultural contexts. It aims to assess how these variables modulate the relationship between women's roles in health improvement and family health outcomes, offering insights into tailored approaches for different communities.

➢ *Based on the Research Questions of the Study, the Following three Hypotheses have Been Formulated.*

- *Hypothesis 1:*

Families where women have a higher level of educational attainment (Bachelor's degree or above) exhibit better overall health outcomes compared to families where women have lower levels of education.

- *Hypothesis 2:*

Women's participation in health-related discussions and decisions is positively correlated with the family's average satisfaction with healthcare services.

- *Hypothesis 3:*

Women's influence in healthcare decisions within the family leads to a lower incidence of chronic diseases among family members.

The study utilized advanced machine learning algorithms to process and analyze data related to women's health behaviors, decision-making processes, and their impact on family health outcomes. This involves developing predictive models that can identify key factors where women's involvement has a significant positive effect on the health status of family members. The scope includes exploring a range of machine learning techniques, from regression analyses to more complex algorithms like random forests and neural networks, to determine the most effective approaches for this unique interdisciplinary challenge.

Central to this study is the exploration of women's empowerment as a critical determinant of family health. This includes examining how women's autonomy, access to resources, and participation in health-related decision-making correlate with improved health metrics such as reduced child and maternal mortality rates, enhanced nutritional status, and increased utilization of healthcare services. The study aims to quantify these relationships, providing empirical evidence to support initiatives aimed at empowering women within households.

The research also considered the socio-cultural and economic factors that influence women's roles in family health, acknowledging that empowerment and health outcomes are shaped by broader societal dynamics. This includes analyzing the impact of education, income, and societal norms on women's ability to effect change in family health practices. A significant portion of the study's scope is dedicated to translating findings into actionable insights for policy-making and health interventions. By identifying specific areas where women's roles have the most substantial impact on health outcomes, the study aims to inform targeted

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strategies that can empower women and improve family health at a community or even national level.

II. LITERATURE REVIEW

Historically, women have been central to maintaining and improving family health, serving in roles that span from caregivers to decision-makers in health-related matters. Their contributions include managing nutrition, facilitating access to healthcare services, and influencing health behaviors and lifestyle choices within the household. Research has consistently shown that women's education and empowerment are directly correlated with positive health outcomes in children and families, including lower mortality rates, improved nutritional status, and increased utilization of healthcare services. Despite their critical role, gender disparities often limit women's access to resources, decision-making authority, and opportunities for empowerment, directly impacting their ability to effect change within their families and communities.

The advent of machine learning (ML) has revolutionized the ability to analyze complex datasets, uncover patterns, and predict outcomes in various fields, including healthcare. ML algorithms can process vast amounts of data to identify risk factors, predict disease outbreaks, personalize treatment plans, and improve healthcare delivery. In the context of public health, ML offers an innovative tool to analyze the impact of socio-economic, behavioral, and environmental factors on health outcomes, providing insights that can inform targeted interventions.

Combining machine learning with an investigation into women's role in family health presents a novel approach to addressing public health challenges. This interdisciplinary research leverages the analytical power of ML to quantify and model the contributions of women to family health dynamics. By analyzing data from diverse sources, including healthcare records, surveys, and socio-economic datasets, ML algorithms can illuminate the complex relationships between women's empowerment and health outcomes. This analysis not only contributes to the academic understanding of these dynamics but also offers practical insights for policymakers, healthcare providers, and communities seeking to enhance family health through women's empowerment.

This background underscores the critical need to explore and harness women's potential in improving family health outcomes. Despite considerable progress in gender equality and healthcare access, significant gaps remain, particularly in low- and middle-income countries. Machine learning analysis provides a powerful means to bridge these gaps, offering evidence- based strategies to empower women and enhance their role in family health. The findings from such research have the potential to inform scalable interventions, shape public health policies, and advocate for gender-equitable practices in healthcare and beyond.

Several studies underscore the critical role of women's empowerment in improving health outcomes, particularly in maternal and child health [1]. Portela et al. (2003) [10] introduced the “Making Pregnancy Safer” initiative, which emphasized empowerment through a health promotion framework. Rather than merely focusing on interventions, it prioritized empowering communities and ensuring quality in both processes and outcomes. However, the study lacked empirical evidence of implementation effectiveness across diverse contexts.

Grown et al. (2005) [5] highlighted global improvements in women’s health such as increased life expectancy and lower fertility rates. Yet, maternal mortality and the growing burden of HIV/AIDS—especially among young women—remain pressing issues. The study’s limitation lies in its superficial treatment of the structural causes behind these health challenges and the absence of targeted recommendations. Currie et al. (2010) [14] proposed a sociocultural tool to understand women's health-seeking behavior, offering a feminist lens that connects personal behavior with broader gender equity goals. While conceptually strong, the practical application and effectiveness of the tool remain unexplored.

Chonody et al. (2012) [8] evaluated a Family Health Advocacy program in rural America, showing knowledge improvements on safe sex and prenatal care, though not always translating into behavior change. It stressed the necessity for educational efforts coupled with systemic support to achieve behavioral outcomes. Nerker et al. (2013) [4] explored tribal perceptions in India, linking watershed management with health and empowerment. Although it effectively identified water scarcity as a barrier to health and development, its qualitative nature limits generalizability, calling for quantitative validation.

Kar et al. (2013) [12] critiqued traditional development strategies, advocating for community-level indicators that assess both individual and societal health promotion efforts. While conceptually innovative, the framework awaits empirical application and validation. Amirrood et al. (2013) [7] assessed an empowerment-based dietary intervention among obese Iranian women, finding notable behavioral improvements. However, the study’s short duration and narrow focus on diet reduce its generalizability to broader obesity management. Sado et al. (2014) [6] linked women’s empowerment in Albanian households to increased maternal healthcare utilization. It established a strong statistical association, though it lacked exploration of the mechanisms and sustainability behind these behaviors.

Narasimha et al. (2016) [3] examined SHGs in Bangalore, finding economic and social gains but minimal health behavior improvements. This gap suggests a need for integrating focused health education within empowerment frameworks. Calvi et al. (2018) [13] used legal inheritance changes as a proxy for empowerment in India, finding improved family health outcomes. Still, it lacked exploration of the qualitative dynamics of how resource control leads to health gains. Karlina (2019) [9] studied the P2WKSS Program in Indonesia, showing strong economic impact but weaker effects in health and education, indicating a need for holistic empowerment strategies. Heckert et al. (2019) [11] revealed

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that women's empowerment, especially in spousal communication, reduced child wasting in Burkina Faso but didn't improve hemoglobin levels. This highlighted the need for multifactorial interventions. Finally, Kate et al. (2021) [2] found that while asset transfers and training programs improved women's empowerment in Uganda, they did not translate into better child welfare outcomes, emphasizing that empowerment alone may not directly improve broader family well-being without systemic support.

III. MATERIALS

➢ *Dataset Generation and Considered Features*

The dataset was generated through a comprehensive survey designed to capture detailed information about family dynamics, healthcare decision-making roles, and access to healthcare services among families. Respondents were asked to provide information ranging from basic demographic details to nuanced insights into healthcare preferences and satisfaction levels. The survey was structured to ensure a balanced representation of different family sizes, residential areas, and educational backgrounds, aiming to reflect the diverse experiences and perspectives within the targeted population. Considered features in this study are:

- *Demographic Information:*

Features include roll number (anonymized identifier), total number of family members, number of adults (age 18 and above), and number of children (below age 18), providing a foundational understanding of the family structure.

- *Residential Area:*

Categorized into different types of primary residence areas, this feature offers insights into the geographical and possibly socio-economic context of the respondents.

- *Educational Background:*

The highest degree of women in the family is documented, highlighting the role of educational attainment in healthcare decision-making and access.

- *Healthcare Decision-Making:*

Several features capture the role of women in healthcare decisions, their participation in health-related discussions, and their influence in choosing family physicians, underscoring the gender dynamics within healthcare choices.

- *Dietary and Lifestyle Choices:*

Information on the number of fast-food meals per week and participation in planning nutritional aspects of meals provides a glimpse into lifestyle choices that may impact family health.

- *Healthcare Access and Satisfaction:*

Features related to the ease of access to primary healthcare facilities, health insurance coverage, waiting times for healthcare appointments, and satisfaction with the quality of healthcare received offer valuable perspectives on the healthcare system's efficiency and effectiveness as perceived by the families.

- *Quantitative and Categorical Data:*

The dataset includes both quantitative (e.g., number of family members) and categorical data (e.g., satisfaction levels, healthcare access), suitable for various statistical and machine learning analyses.

This dataset, with its rich and multifaceted features, is poised for an in-depth analysis of healthcare decision-making dynamics, access to healthcare services, and the impact of lifestyle choices on health within families. The thoughtful selection of variables ensures that the dataset can support a wide range of analyses, from exploring the influence of women's education on healthcare decisions to assessing the satisfaction with healthcare services across different residential areas. Through machine learning models and statistical tests, this dataset offers a fertile ground for uncovering insights that could inform policy-making, healthcare service improvement, and targeted interventions aimed at enhancing family health outcomes.

➢ *Data Collection Process*

The data collection process for this research involved a strategic and digitally-enabled approach to gather comprehensive information from a diverse set of participants, ensuring a robust dataset reflective of various family dynamics and healthcare decision-making processes. Utilizing Google Forms as the primary tool for survey distribution, the research capitalized on the platform's accessibility and ease of use to facilitate the collection of data from 284 families. The creation of the survey entailed a meticulous design phase, where questions were formulated to capture detailed insights into demographic information, healthcare decision- making roles within families, access to healthcare services, dietary and lifestyle choices, and satisfaction with healthcare services. The survey was structured to be intuitive and user- friendly, encouraging participants to provide accurate and thoughtful responses.

To reach a broad audience, the survey link was disseminated through multiple channels, including social media platforms, email newsletters, and community forums, targeting a wide demographic to ensure diversity in the responses. This strategy aimed to include families from different socio-economic backgrounds, residential areas, and educational levels, enriching the dataset with varied perspectives on healthcare accessibility and decision-making. Participants were briefed on the purpose of the research and assured of their anonymity and the confidentiality of their responses, fostering a trust-based environment that encouraged honest and comprehensive feedback. The digital nature of the survey allowed for real-time data collection, with responses being automatically recorded and stored securely, facilitating efficient data management and analysis.

Upon closing the survey, a total of 284 samples were collected, each representing a unique family unit. This sample size was deemed sufficient to provide statistical significance for the analysis while being manageable for in-depth qualitative and quantitative evaluation. The dataset was then subjected to preliminary cleaning to address any

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inconsistencies or missing values, preparing it for the subsequent phases of the research.

➢ *Raw Dataset Characteristics*

The raw dataset, integral to this research, encompasses a rich compilation of 284 samples, each meticulously representing diverse family units across varied demographic regions. This dataset, characterized by its multidimensional nature, includes a wide array of both categorical and continuous variables, capturing intricate details pertaining to family dynamics, healthcare decision-making, lifestyle choices, and access to healthcare services. Key characteristics of the dataset are:

- *Diverse Variables:*

The dataset is comprised of 28 distinct features, ranging from basic demographic information such as family size and residential area to more nuanced data regarding healthcare expenditure, dietary habits, and the presence of chronic diseases within family members. This variety allows for a comprehensive analysis of factors influencing health outcomes.

- *Categorical and Continuous Data:*

It features a balanced mix of categorical (e.g., type of residential area, presence of chronic diseases) and continuous variables (e.g., number of family members, healthcare expenditure), enabling the application of a broad spectrum of statistical and machine learning techniques.

- *High-Quality Responses:*

Despite the initial presence of inconsistencies such as string values for numerical data and duplicate entries, meticulous preprocessing ensured the dataset's high quality, with such issues resolved to maintain data integrity.

- *No Missing Values:*

The dataset's completeness is noteworthy, with no missing values across all features, indicating thorough and reliable data collection efforts. This completeness significantly enhances the dataset's utility for analysis.

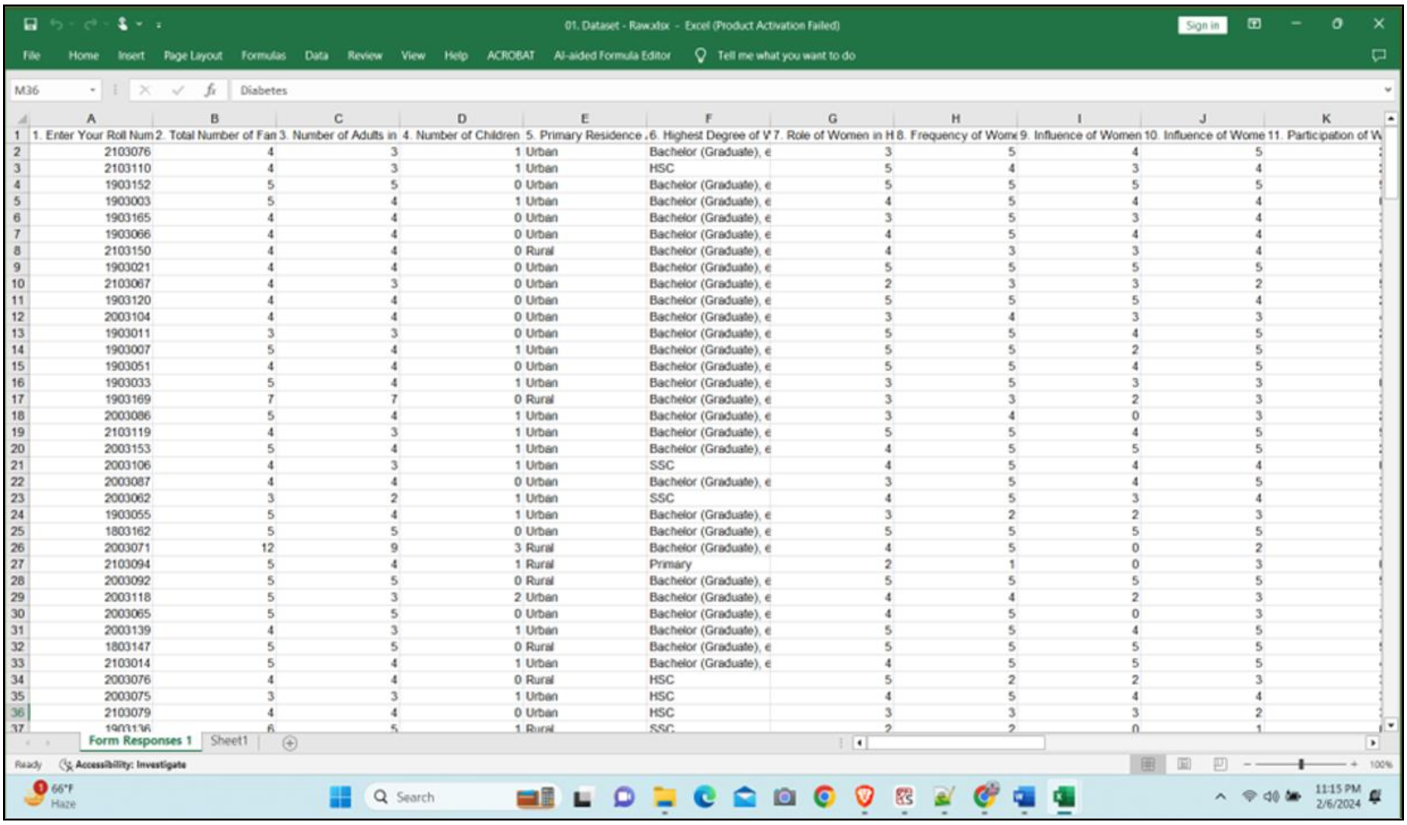
- *Target Variable for Binary Classification:*

The dataset's target variable has been clearly defined based on the presence of chronic diseases in family members, facilitating its direct application in binary classification tasks. This clear definition enables focused research into predicting health-related outcomes based on a variety of predictors.

- *Prepared for Advanced Analysis:*

Following preprocessing, including the conversion of categorical string values to numerical categories, the dataset is primed for advanced analytical techniques. This preparation extends its utility beyond basic statistical analysis to more complex machine learning models.

The raw dataset's characteristics make it exceptionally suited for exploring the intricate relationships between lifestyle choices, demographic factors, and health outcomes. Its rich composition allows for the examination of hypotheses regarding the impact of socioeconomic status, education, and healthcare access on family health, providing a solid foundation for generating actionable insights. Figure 1 showcases a snapshot of the raw dataset.



	A	B	C	D	E	F	G	H	I	J	K
1	1. Enter Your Roll Num	2. Total Number of Fan	3. Number of Adults in	4. Number of Children	5. Primary Residence .	6. Highest Degree of V	7. Role of Women in H	8. Frequency of Wome	9. Influence of Women	10. Influence of Wome	11. Participation of W
2	2103076	4	3	1	Urban	Bachelor (Graduate), e	3	5	4	5	
3	2103110	4	3	1	Urban	HSC	5	4	3	4	
4	1903152	5	5	0	Urban	Bachelor (Graduate), e	5	5	5	5	
5	1903003	5	4	1	Urban	Bachelor (Graduate), e	4	5	4	4	
6	1903165	4	4	0	Urban	Bachelor (Graduate), e	3	5	3	4	
7	1903066	4	4	0	Urban	Bachelor (Graduate), e	4	5	4	4	
8	2103150	4	4	0	Rural	Bachelor (Graduate), e	4	3	3	4	
9	1903021	4	4	0	Urban	Bachelor (Graduate), e	5	5	5	5	
10	2103067	4	3	0	Urban	Bachelor (Graduate), e	2	3	3	2	
11	1903120	4	4	0	Urban	Bachelor (Graduate), e	5	5	5	4	
12	2003104	4	4	0	Urban	Bachelor (Graduate), e	3	4	3	3	
13	1903011	3	3	0	Urban	Bachelor (Graduate), e	5	5	4	5	
14	1903007	5	4	1	Urban	Bachelor (Graduate), e	5	5	2	5	
15	1903051	4	4	0	Urban	Bachelor (Graduate), e	5	5	4	5	
16	1903033	5	4	1	Urban	Bachelor (Graduate), e	3	5	3	3	
17	1903169	7	7	0	Rural	Bachelor (Graduate), e	3	3	2	3	
18	2003086	5	4	1	Urban	Bachelor (Graduate), e	3	4	0	3	
19	2103119	4	3	1	Urban	Bachelor (Graduate), e	5	5	4	5	
20	2003153	5	4	1	Urban	Bachelor (Graduate), e	4	5	5	5	
21	2003106	4	3	1	Urban	SSC	4	5	4	4	
22	2003087	4	4	0	Urban	Bachelor (Graduate), e	3	5	4	5	
23	2003062	3	2	1	Urban	SSC	4	5	3	4	
24	1903055	5	4	1	Urban	Bachelor (Graduate), e	3	2	2	3	
25	1803162	5	5	0	Urban	Bachelor (Graduate), e	5	5	5	5	
26	2003071	12	9	3	Rural	Bachelor (Graduate), e	4	5	0	2	
27	2103094	5	4	1	Rural	Primary	2	1	0	3	
28	2003092	5	5	0	Rural	Bachelor (Graduate), e	5	5	5	5	
29	2003118	5	3	2	Urban	Bachelor (Graduate), e	4	4	2	3	
30	2003065	5	5	0	Urban	Bachelor (Graduate), e	4	5	0	3	
31	2003139	4	3	1	Urban	Bachelor (Graduate), e	5	5	4	5	
32	1803147	5	5	0	Rural	Bachelor (Graduate), e	5	5	5	5	
33	2103014	5	4	1	Urban	Bachelor (Graduate), e	4	5	5	5	
34	2003076	4	4	0	Rural	HSC	5	2	2	3	
35	2003075	3	3	1	Urban	HSC	4	5	4	4	
36	2103079	4	4	0	Urban	HSC	3	3	3	2	
37	1903136	6	5	1	Rural	SSC	2	2	0	1	

Fig 1 Snapshot of the Raw Dataset.

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➢ *Dataset Pre-Processing*

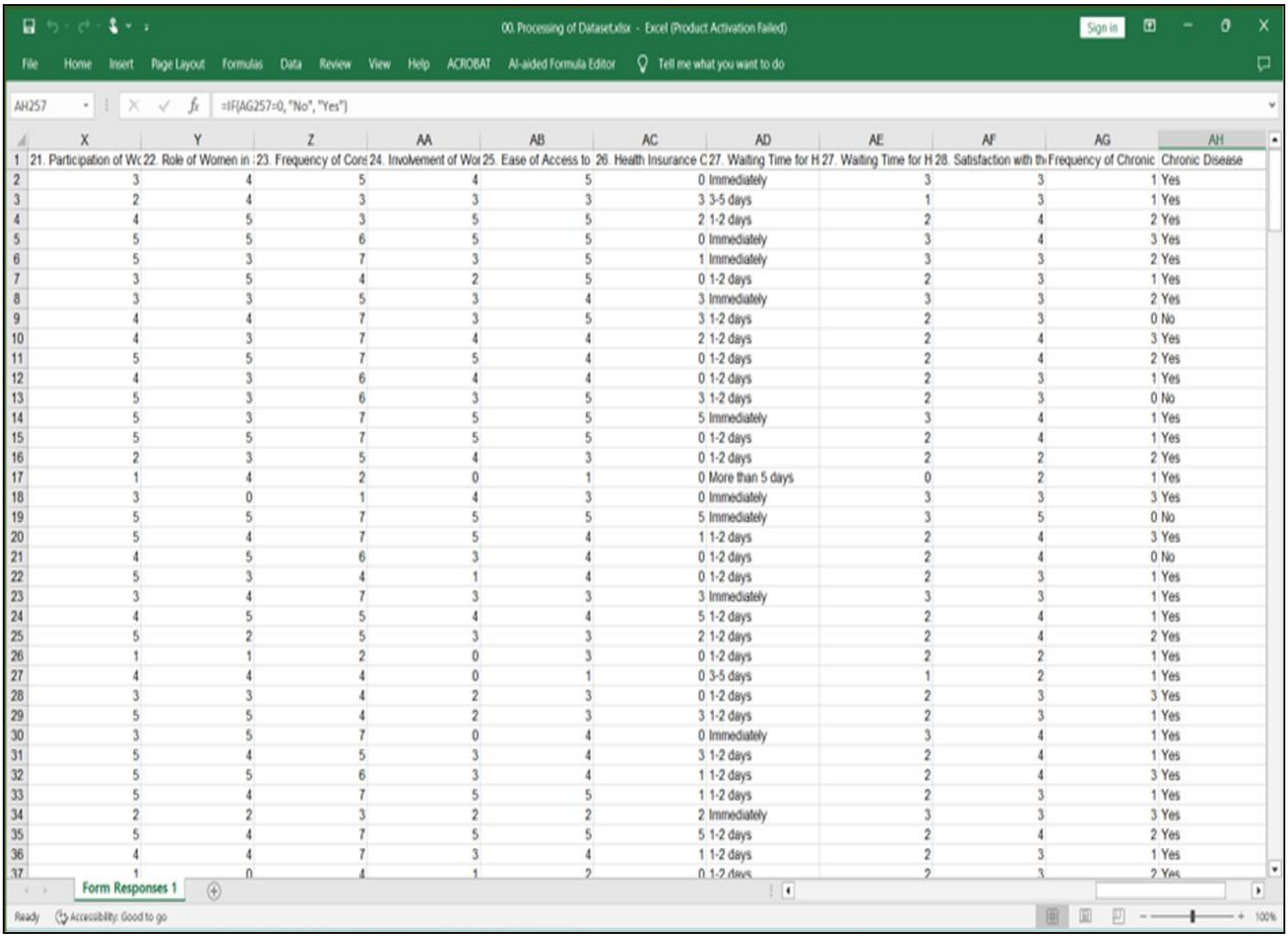
Upon gathering the raw dataset, certain inconsistencies were identified and subsequently addressed through a series of data preprocessing steps, outlined as follows:

- Information pertaining to the submitter was excluded from the analysis due to its lack of correlation with other variables in the dataset, ensuring that the focus remained on features directly relevant to the study's objectives.

- The dataset included features with monetary values related to healthcare expenditures, where some responses were provided in textual formats such as "40K" or "56K." These entries were standardized by converting them into numerical values, facilitating quantitative analysis.

- An examination for missing data revealed no absent values, indicating comprehensive responses across the dataset. However, the presence of duplicate entries was noted. To maintain data integrity, these duplicates were identified and removed, ensuring that each sample uniquely represented a distinct family unit.

- The definition of the target class was established based on the presence of chronic diseases within family members. Families with at least one member suffering from a chronic condition were categorized under the "Yes" class for the target variable, while those without were assigned to the "No" class. This classification enabled a focused investigation into the factors influencing chronic disease prevalence among families.



	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH
1	21. Participation of Wo	22. Role of Women in	23. Frequency of Cons	24. Involvement of Wo	25. Ease of Access to	26. Health Insurance C	27. Waiting Time for H	27. Waiting Time for H	28. Satisfaction with th	Frequency of Chronic	Chronic Disease
2	3	4	5	4	5	0	Immediately	3	3	1	Yes
3	2	4	3	3	3	3	3-5 days	1	3	1	Yes
4	4	5	3	5	5	2	1-2 days	2	4	2	Yes
5	5	5	6	5	5	0	Immediately	3	4	3	Yes
6	5	3	7	3	5	1	Immediately	3	3	2	Yes
7	3	5	4	2	5	0	1-2 days	2	3	1	Yes
8	3	3	5	3	4	3	Immediately	3	3	2	Yes
9	4	4	7	3	5	3	1-2 days	2	3	0	No
10	4	3	7	4	4	2	1-2 days	2	4	3	Yes
11	5	5	7	5	4	0	1-2 days	2	4	2	Yes
12	4	3	6	4	4	0	1-2 days	2	3	1	Yes
13	5	3	6	3	5	3	1-2 days	2	3	0	No
14	5	3	7	5	5	5	Immediately	3	4	1	Yes
15	5	5	7	5	5	0	1-2 days	2	4	1	Yes
16	2	3	5	4	3	0	1-2 days	2	2	2	Yes
17	1	4	2	0	1	0	More than 5 days	0	2	1	Yes
18	3	0	1	4	3	0	Immediately	3	3	3	Yes
19	5	5	7	5	5	5	Immediately	3	5	0	No
20	5	4	7	5	4	1	1-2 days	2	4	3	Yes
21	4	5	6	3	4	0	1-2 days	2	4	0	No
22	5	3	4	1	4	0	1-2 days	2	3	1	Yes
23	3	4	7	3	3	3	Immediately	3	3	1	Yes
24	4	5	5	4	4	5	1-2 days	2	4	1	Yes
25	5	2	5	3	3	2	1-2 days	2	4	2	Yes
26	1	1	2	0	3	0	1-2 days	2	2	1	Yes
27	4	4	4	0	1	0	3-5 days	1	2	1	Yes
28	3	3	4	2	3	0	1-2 days	2	3	3	Yes
29	5	5	4	2	3	3	1-2 days	2	3	1	Yes
30	3	5	7	0	4	0	Immediately	3	4	1	Yes
31	5	4	5	3	4	3	1-2 days	2	4	1	Yes
32	5	5	6	3	4	1	1-2 days	2	4	3	Yes
33	5	4	7	5	5	1	1-2 days	2	3	1	Yes
34	2	2	3	2	2	2	Immediately	3	3	3	Yes
35	5	4	7	5	5	5	1-2 days	2	4	2	Yes
36	4	4	7	3	4	1	1-2 days	2	3	1	Yes
37	1	0	4	1	2	0	1-2 days	2	3	2	Yes

Fig 2 Class Feature Values for Some Samples of the Dataset

The data collection process culminated in the accumulation of 284 samples, each representing a unique family from diverse demographic backgrounds. This comprehensive dataset, after undergoing the aforementioned preprocessing steps, was poised for in-depth analysis. To illustrate the distribution of the target class across the collected samples, Figure 2 provides a visual representation of the class feature values for selected entries, offering an initial glimpse into the dataset's structure and the prevalence of chronic diseases among the surveyed families.

➢ *Final Dataset Preparation*

To facilitate the application of feature selection algorithms and machine learning classifiers, it was imperative to transform categorical string values into numerical categorical values. This conversion process was a critical step in the preparation of the final dataset, ensuring compatibility with the algorithms that require numerical input. The transformations were meticulously carried out, aligning the dataset with the prerequisites of the analytical methods to be employed. As a result, the dataset was primed for in-depth

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analysis, with its variables suitably encoded to reflect their categorical nature numerically. Figure 3 presents the prepared dataset, now fully ready for the subsequent application of feature selection techniques and machine learning models, illustrating the readiness of the data for comprehensive exploration and analysis.

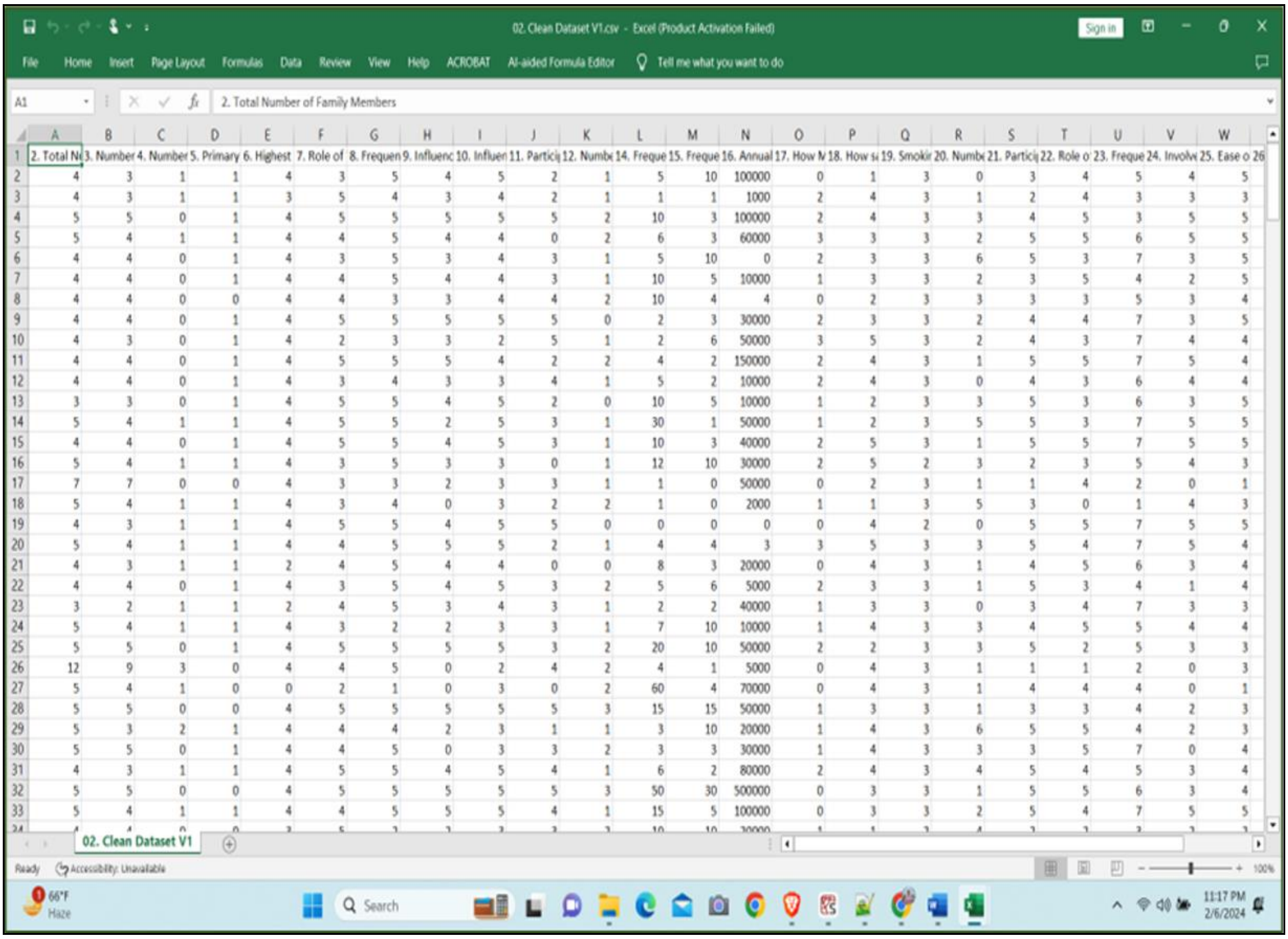

Fig 3 Snapshot of the Final Dataset

➢ *Train-Test Split*

The process of dividing the dataset into training and testing subsets is a crucial step in the development and evaluation of machine learning models. For this work, the dataset was partitioned following a 70:30 ratio, where 70% of the data was allocated for training the models, and the remaining 30% was reserved for testing their performance. This approach ensures that a substantial portion of the dataset is used to train the models, allowing them to learn effectively from a wide range of examples and capture the underlying patterns in the data. Meanwhile, setting aside 30% of the data for testing purposes provides a sufficiently large, independent subset to evaluate the models' generalization capabilities accurately.

The train-test split was executed with careful consideration to maintain the distribution of key variables and the balance of classes across both subsets. This is vital to ensure that the training and testing data are representative of the entire dataset, thereby preventing bias in the model evaluation process. By adhering to this division, the study aims to strike a balance between maximizing the learning potential from the training data and ensuring a robust evaluation of the models' predictive power on unseen data.

Implementing the 70:30 train-test split not only aligns with common practices in machine learning but also addresses the specific needs of this research by providing a solid foundation for developing reliable and valid predictive models. This methodological choice underpins the study's commitment to rigor and precision in assessing the effectiveness of the machine learning classifiers employed, ultimately contributing to the credibility and scientific validity of the research findings.

IV. PROPOSED METHODOLOGIES

In this section, first the considered feature selection approaches have been mentioned that have been utilized for dimensionality reduction. The later sub-section describes the considered machine learning approaches.

➢ *Considered Feature Selection Approaches*

For this research the considered feature selection approaches are Chi-Square Test, Fisher's Exact Test, Student's T-Test, and Kruskal Wallis Test. These tests are described below.

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- *Chi-Square Test:*

The Chi-square test, denoted as $\chi 2$ test, is a statistical tool used to assess the differences between categorical variables, making it a cornerstone in the field of statistics for hypothesis testing. It's particularly useful for evaluating whether there's a significant association between two categorical variables or if observed frequencies differ from expected frequencies in one categorical variable. The $\chi 2$ test is based on the comparison between observed frequencies (O) and expected frequencies (E) across different categories of variables. The core principle lies in quantifying how much the observed frequencies deviate from the expected frequencies, assuming the null hypothesis of no association or no difference is true [15].

- *Fisher's Exact Test:*

The Fisher's Exact Test is a statistical significance test used to determine if there are nonrandom associations between two categorical variables, particularly in 2 × 2 contingency tables. Unlike the Chi-square test, which approximates significance, Fisher's Exact Test calculates the exact probability of observing the data given the null hypothesis of no association. This makes it particularly useful for small sample sizes where the assumptions of the Chi-square test do not hold. Fisher's Exact Test is based on the hypergeometric distribution, which models the probability of observing a given set of frequencies in a 2 × 2 contingency table under the assumption of fixed row and column totals. The test examines every possible arrangement of the observed data that could occur under the null hypothesis and calculates the probability of each arrangement [16].

- *Student's T-Test:*

The Student's t-test is a statistical method used to determine if there is a significant difference between the means of two groups, which may be related in certain features or measurements. It is one of the most commonly used hypotheses testing techniques in statistical analysis for comparing means. The t-test comes in three main variants: the one-sample t-test, the independent two-sample t-test, and the paired sample t-test, each serving different experimental designs and hypotheses [17].

- *Kruskal Wallis Test:*

The Kruskal-Wallis H test is a non-parametric statistical test that extends the Mann-Whitney U test for comparing medians among three or more independent groups. Unlike the ANOVA, which assumes the data to be normally distributed and homogeneity of variances across groups, the Kruskal-Wallis test does not require these assumptions, making it particularly useful for ordinal data or continuous data that does not meet the criteria for parametric testing. The test is grounded on the ranks of data rather than their raw values, providing a comparison of the distributions across groups. The null hypothesis ($H0$) for the Kruskal-Wallis test states that the medians of all groups are equal, while the alternative hypothesis ($H1$) suggests that at least one group's median differs from the others [18].

➢ *Considered Machine Learning Classifiers*

In this research the machine learning classifiers utilized are k-Nearest Neighbors (k- NN), Naïve Bayes, Logistic Regression, Decision Trees, Random Forest, and Support Vector Machines (SVM). These classifiers have been described below.

- *k-Nearest Neighbor:*

The k-Nearest Neighbor (k-NN) algorithm is a simple, yet powerful non-parametric technique used for classification and regression. In classification, it assigns a class label to a new observation based on the majority vote of its k nearest neighbors in the feature space. For regression, it predicts the value for a new observation based on the average of the values of its k nearest neighbors. $\mathrm{k-NN}$ is grounded in the intuitive premise that similar things exist in close proximity [19].

- *Naïve Bayes:*

The Naïve Bayes classifier is a probabilistic machine learning model used for classification tasks, which is based on Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable. Despite its simplicity, Naïve Bayes can outperform more sophisticated classification methods and is especially known for its effectiveness in text classification tasks such as spam detection or sentiment analysis. Naïve Bayes classifier calculates the posterior probability of a class, based on the prior probability of the class and the likelihood of the observed data given the class. The model is "naive" because it assumes that the features are conditionally independent given the class. This assumption simplifies the computation, making the algorithm efficient and scalable [20].

- *Logistic Regression:*

Logistic Regression is a statistical method for analyzing datasets in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable (in which there are only two possible outcomes). It is used extensively in various fields, including machine learning, most commonly for binary classification problems. Unlike linear regression, which predicts a continuous outcome, logistic regression predicts the probability of the outcome occurring, which lies between 0 and 1. This is achieved by using the logistic function, also known as the sigmoid function, which maps any real-valued number into the range 0,1, making it suitable for probability estimation [21].

- *Decision Tree:*

Decision Trees are a non-parametric supervised learning method used for classification and regression tasks. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. A decision tree is essentially a hierarchical structure consisting of nodes and branches, where each internal node represents a "test" on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label (in classification) or a continuous value (in regression) [22].

- *Random Forest:*

Random Forest is an ensemble learning method for classification, regression, and other tasks that operates by constructing a multitude of decision trees at training time and

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outputting the class that is the majority vote (for classification tasks) or mean prediction (for regression tasks) of the individual trees. Random Forests correct for decision trees' habit of overfitting to their training set, providing a more robust and accurate prediction by aggregating the results of multiple trees [23].

- *Support Vector Machine:*

Support Vector Machine (SVM) is a powerful and versatile supervised machine learning algorithm used for both classification and regression tasks. However, it is most commonly used in classification problems. The SVM algorithm seeks to find the hyperplane that best separates different classes in the feature space by maximizing the margin between the closest points of the classes, which are known as support vectors. The main idea behind SVM is to draw a hyperplane that best divides a dataset into classes. The best hyperplane for an SVM means the one with the largest margin between the two classes. The margin is defined as the distance between the hyperplane and the nearest points from each class. These nearest points are called support vectors [24].

V. EXPERIMENTAL ANALYSIS

➢ *Exploratory Data Analysis Based on Specific Features*

For each of the features exploratory data analysis has been made. For the features with categorical values bar plots have been presented and for other features data insights have been presented. With each of the plots, brief description of the plots has been presented also. In the next subsections the exploratory data analysis of the features has been presented one by one. Table 1 showcases the frequency table for each of the features.

Table 1 Frequency Table for Each of the Features

Feature Name	Feature Label	Frequency
Primary Residence Area	Rural	98
	Urban	186
Highest Degree of Women in Your Family	Bachelor	188
	HSC	44
	SSC	25
	Secondary	9
	Primary	18
Role of Women in Healthcare Decisions	0	12
	1	21
	2	24
	3	66
	4	74
	5	87
Frequency of Women's Participation in Health-Related Decisions	0	11
	1	17
	2	30
	3	47
	4	46
	5	133
Influence of Women in Choosing Family Physicians	0	33
	1	20
	2	42
	3	64
	4	56
	5	69
Influence of Women in Health Emergency Decisions	0	15
	1	23
	2	38
	3	54
	4	68
	5	86
Participation of Women in Managing Family Health Budget	0	35
	1	30
	2	39
	3	66
	4	57
	5	57
How satisfied is your family members with the Average Hours of Sleep per Night	0	2
	1	10
	2	20

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	3 4 5	85 92 75
Smoking and Alcohol Consumption in the Family	Both None Smoking	1 227 56
Number of Fast-Food Meals per Week (For the Family)	0 1 2 3 4 5 6 7	52 77 63 44 24 10 6 8
Participation of Women in Planning Nutritional Aspects of Meals	0 1 2 3 4 5	18 21 21 39 71 114
Role of Women in Selecting and Purchasing Groceries	0 1 2 3 4 5	13 23 19 55 74 100
Frequency of Consumption of Fresh Fruits and Vegetables per Week (For the Family)	0 1 2 3 4 5 6 7	4 7 13 26 42 65 54 73
Involvement of Women in Planning Preparing Means with Specific Dietary Requirements (e.g., low-sodium, diabetic-friendly, high-fiber)	0 1 2 3 4 5	18 21 41 66 59 79
Ease of Access to Primary Healthcare Facilities	1 2 3 4 5	22 21 67 94 80
Health Insurance Coverage for Family Members	0 1 2 3 4 5	159 27 20 41 21 16
Waiting Time for Healthcare Appointments (Average in Days)	1-2 days 3-5 days Immediately > 5 days	149 30 80 25
Satisfaction with the Quality of Healthcare Received	1 2 3 4 5	18 39 120 79 28

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➢ *Correlation Analysis*

Figure 3 shows the correlation analysis of the features utilized in this research. The correlation matrix has been regenerated with the features renamed from 1 to 28 for simplicity. This heatmap displays the correlation coefficients between these renamed variables. This visualization aids in quickly identifying which pairs of features have significant relationships, guiding further analysis and hypothesis testing.

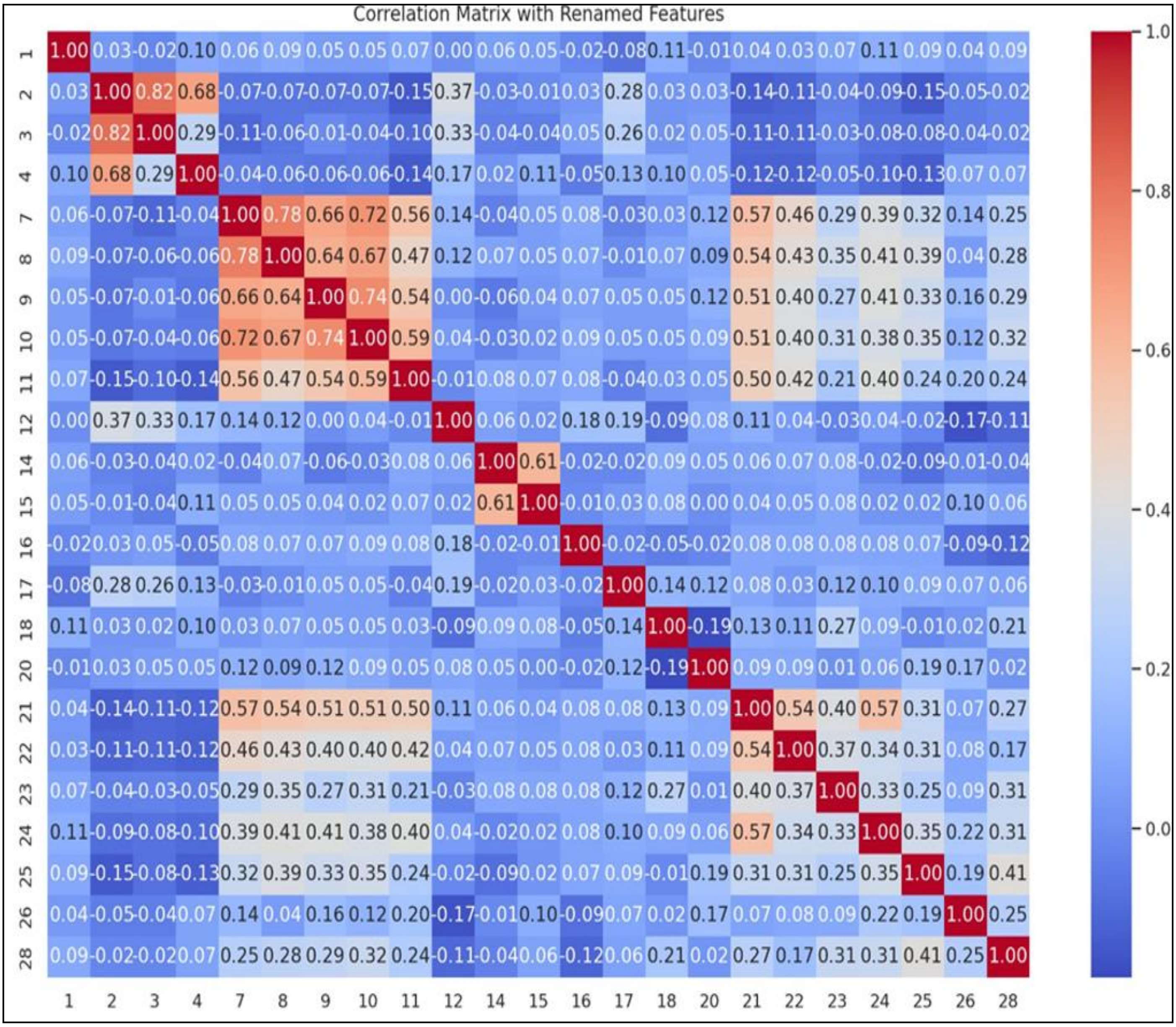

Fig 4 Correlation Analysis of the Features

➢ *Comparative Analysis*

Comparative analysis is a research methodology used to identify, analyze, and compare the similarities and differences between two or more items, subjects, phenomena, or case studies. This analytical approach can be applied across various fields such as literature, sociology, history, political science, economics, and business, among others. The primary goal of comparative analysis is to understand the underlying principles, processes, or outcomes that distinguish the subjects under examination, thereby gaining insights into their unique and shared characteristics. In conducting a comparative analysis, researchers start by selecting a basis or criteria for comparison, which depends on the research question or objective. This framework guides the analysis, helping to focus on specific aspects that are relevant to the study. For instance, in comparing two political systems, one might examine aspects such as governance structures, electoral processes, and policy outcomes. In business studies, companies might be compared based on criteria like market share, product innovation, and customer satisfaction. From Figure 5-10, comparative analysis has been shown.

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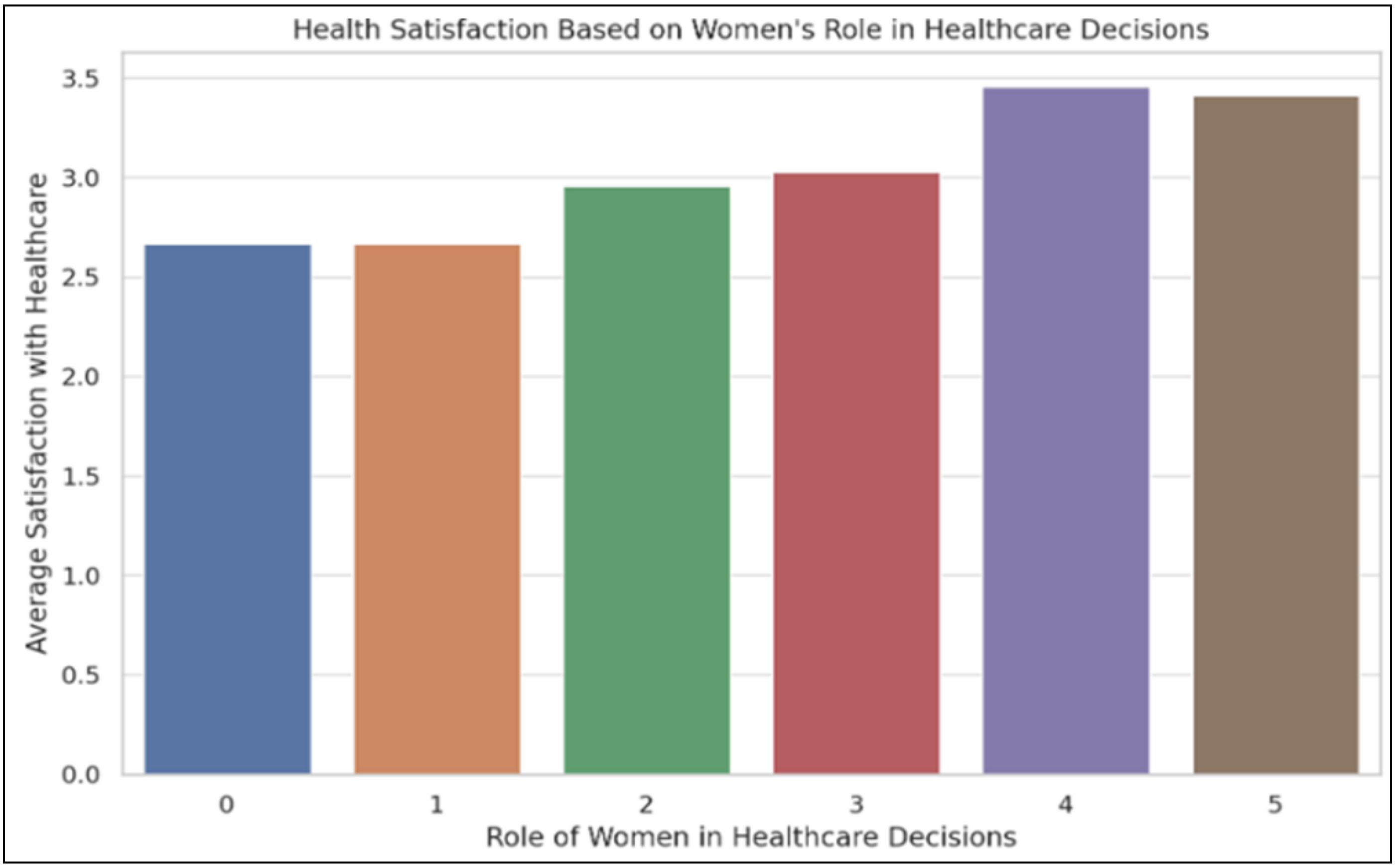

Fig 5 Comparative Analysis: Average Satisfaction with Healthcare vs. Role of Women in Healthcare Decisions

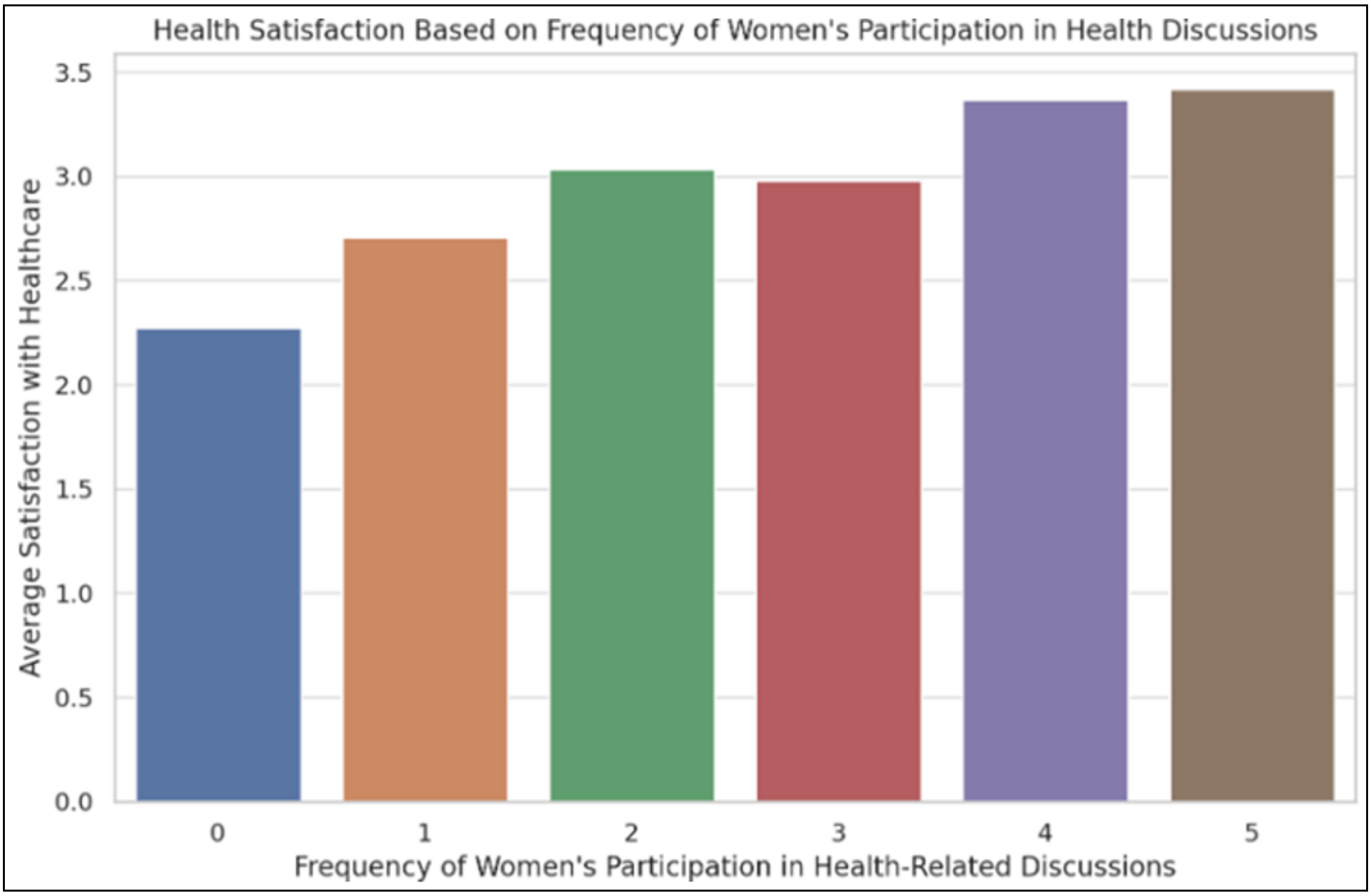

Fig 6 Comparative Analysis: Average Satisfaction with Healthcare vs. Frequency of Women's Participation in Health-Related Discussions

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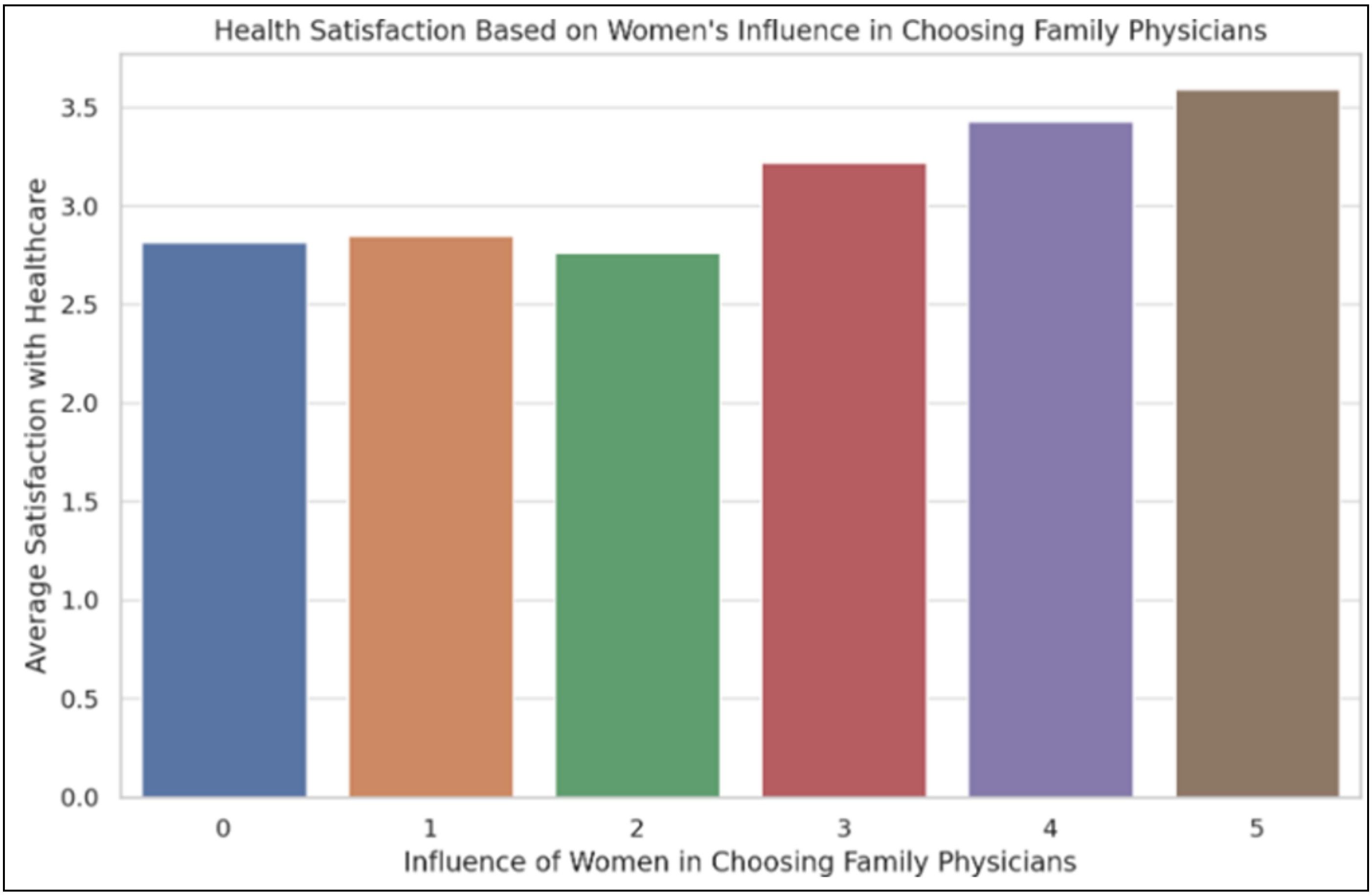

Fig 7 Comparative Analysis: Average Satisfaction with Healthcare vs. Influence of Women in Choosing Family Physicians

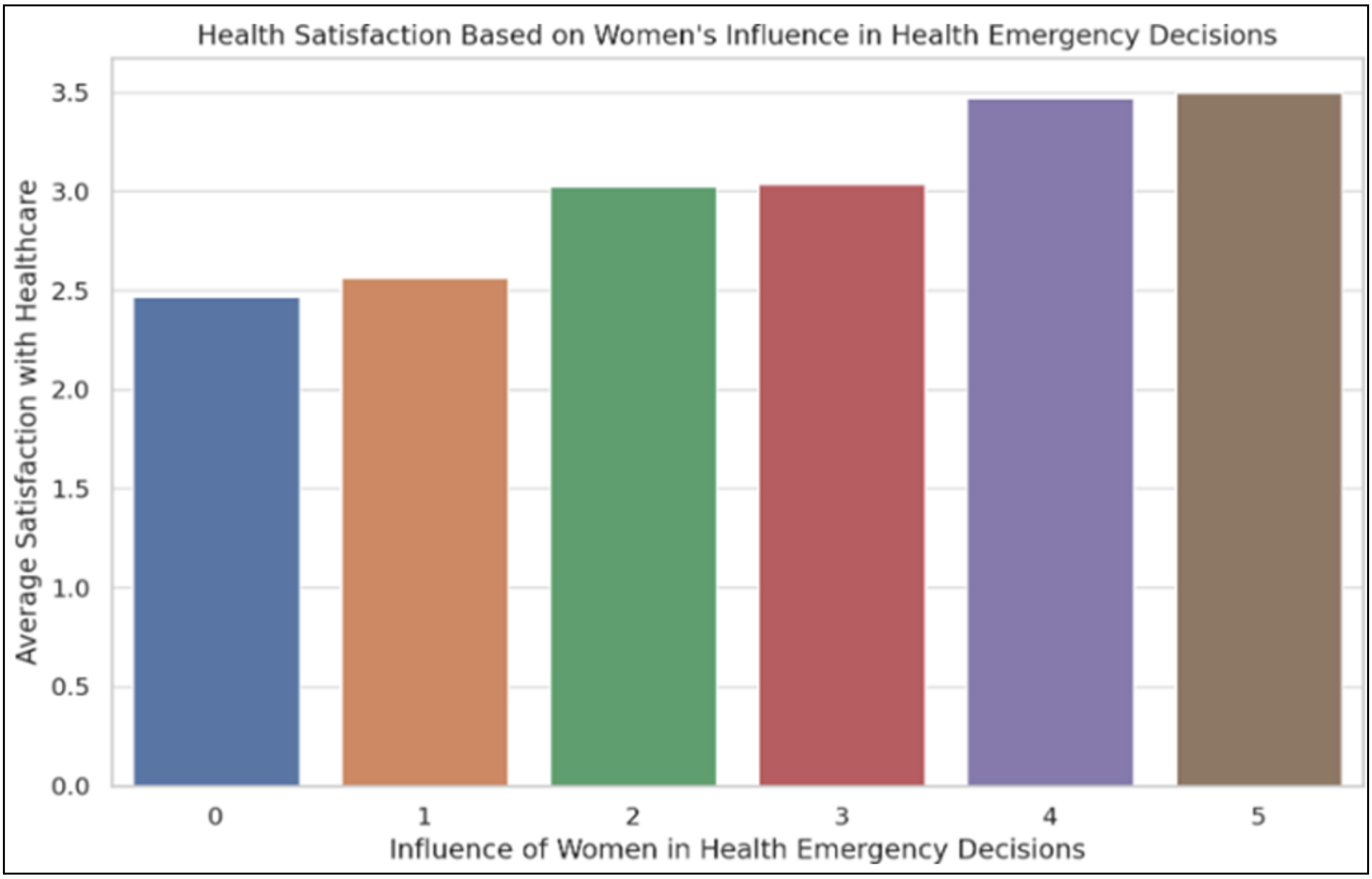

Fig 8 Comparative Analysis: Average Satisfaction with Healthcare vs. Influence of Women in Health Emergency Decisions

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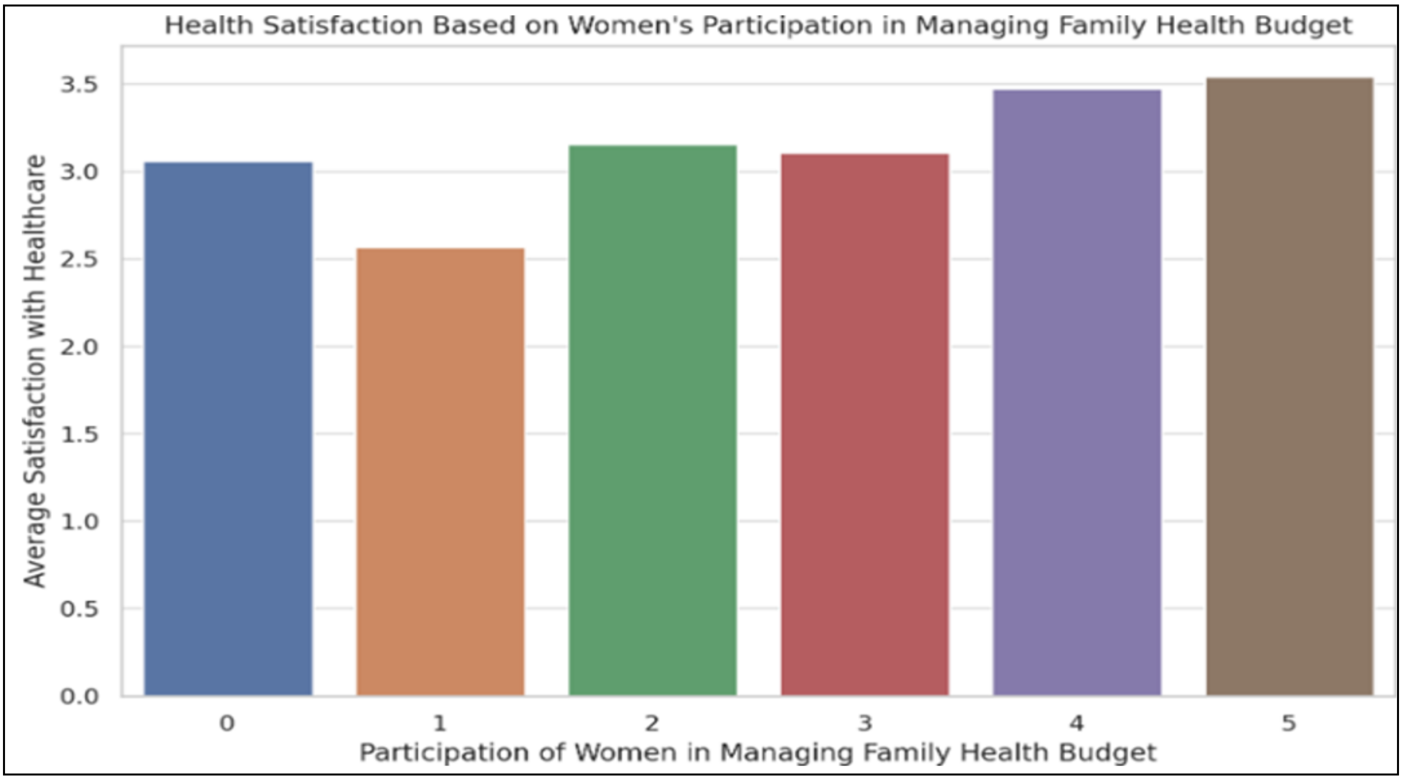

Fig 9 Comparative Analysis: Average Satisfaction with Healthcare vs. Participation of Women in Managing Family Health Budget

The comparative analysis conducted in this study has shed light on the profound influence of women's involvement in healthcare decisions and practices on family health satisfaction. Through the careful examination of various aspects, including women's roles in healthcare decisions, their participation in health-related discussions, and their contribution to nutritional and dietary planning, we have uncovered significant correlations that emphasize the importance of women's active engagement in health management. The findings highlight how the degree of women's involvement can directly impact the satisfaction levels regarding healthcare services, indicating a clear link between empowered decision-making roles for women and positive health outcomes for families.

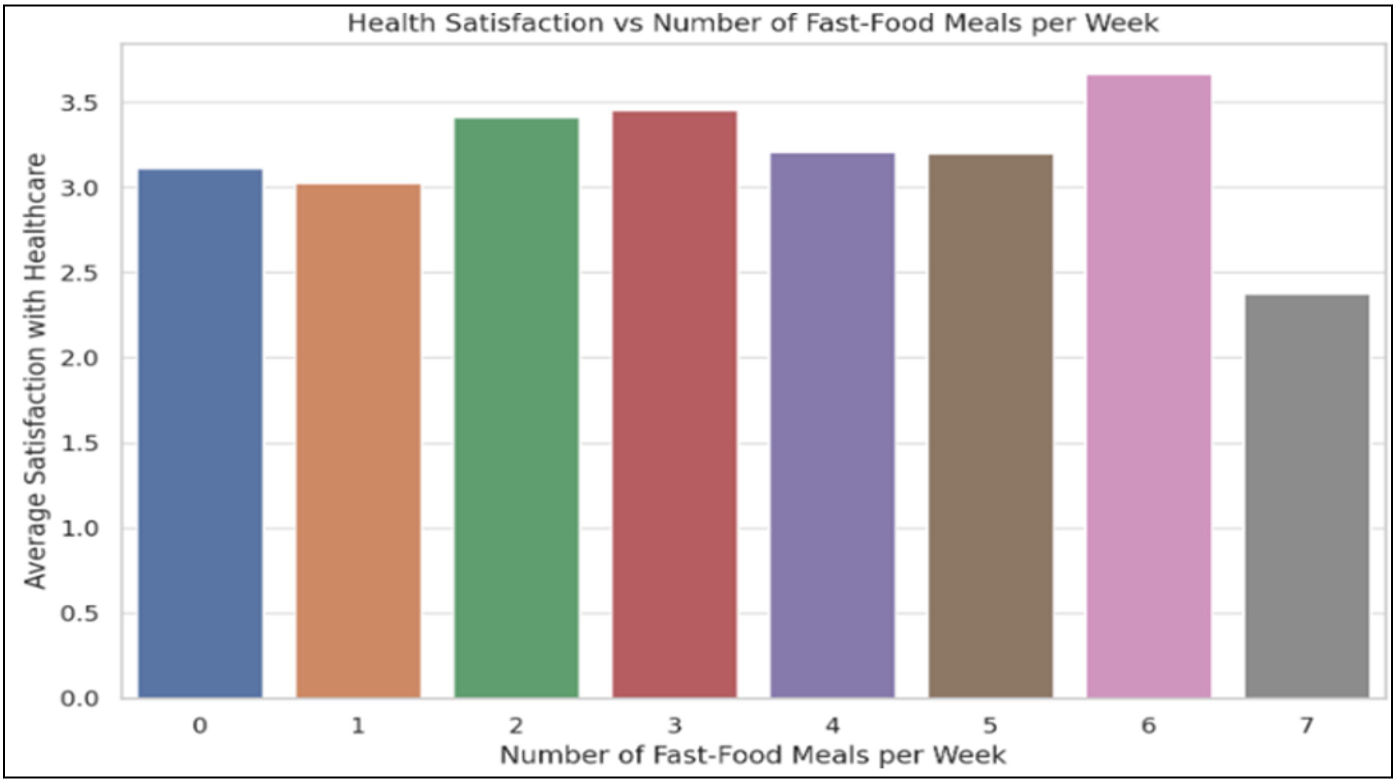

Fig 10 Comparative Analysis: Average Satisfaction with Healthcare vs. Number of Fast- Food Meals Per Week (For the Family)

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➢ *Feature Selection Results*

After applying the feature selection algorithms, the following 20 features have been selected. The features are:

- Number of Family Members with Chronic Illnesses
- Annual Expenditure on Healthcare (For all family members combined)
- Frequency of General Doctor Visits per Year (For all family members combined)
- Frequency of Specialist Doctor Visits per Year (For all family members combined)
- Highest Degree of Women in Your Family
- Satisfaction with the Quality of Healthcare Received
- Total Number of Family Members
- How satisfied is your family members with the Average Hours of Sleep per Night
- Number of Children in the Family (Below Age 18)
- Frequency of Women's Participation in Health-Related Discussions
- Frequency of Consumption of Fresh Fruits and Vegetables per Week (For the Family)
- Participation of Women in Managing Family Health Budget
- Influence of Women in Choosing Family Physicians
- Number of Adults in the Family (Age 18 and above)
- Participation of Women in Planning Nutritional Aspects of Meals
- Health Insurance Coverage for Family Members
- Role of Women in Selecting and Purchasing Groceries
- Ease of Access to Primary Healthcare Facilities
- Number of Fast-Food Meals per Week (For the Family). If your family consume any fast-food item in a day count as one (therefore, the highest count can be 7 and lowest can be 0)
- Role of Women in Healthcare Decisions

➢ *Machine Learning Classifiers Results*

The performance of the classifiers has been mentioned in Table 2.

Table 2 Performance Metrices of Different Classifiers

Class	Accuracy	Precision	Recall	F1-Score
k-Nearest Neighbor				
No	26.32	29.41	26.32	27.78
Yes	82.09	79.71	82.09	80.88
Overall	69.77	54.56	54.20	54.33
Naïve Bayes				
No	89.47	68.00	89.47	77.27
Yes	88.06	96.72	88.06	92.19
Overall	88.37	82.36	88.77	84.73
Logistic Regression				
No	73.68	60.87	73.68	66.67
Yes	86.57	92.06	86.57	89.23
Overall	83.72	76.47	80.13	77.95
Decision Tree				
No	84.21	69.57	84.21	76.19
Yes	89.55	95.23	89.55	92.31
Overall	88.37	82.40	86.88	84.25
Random Forest				
No	100.00	67.86	100.00	80.85
Yes	86.57	100.00	86.57	92.80
Overall	89.53	83.93	93.28	86.83
Support Vector Machine				
No	100.00	67.86	100.00	80.85
Yes	86.57	100.00	86.57	92.80
Overall	89.53	83.93	93.28	86.83

From Table 2, it can be seen that Random Forest and Support Vector Machine have achieved highest accuracy. For both classifiers the confusion matrices are the same which has been shown in Figures 11 and 12.

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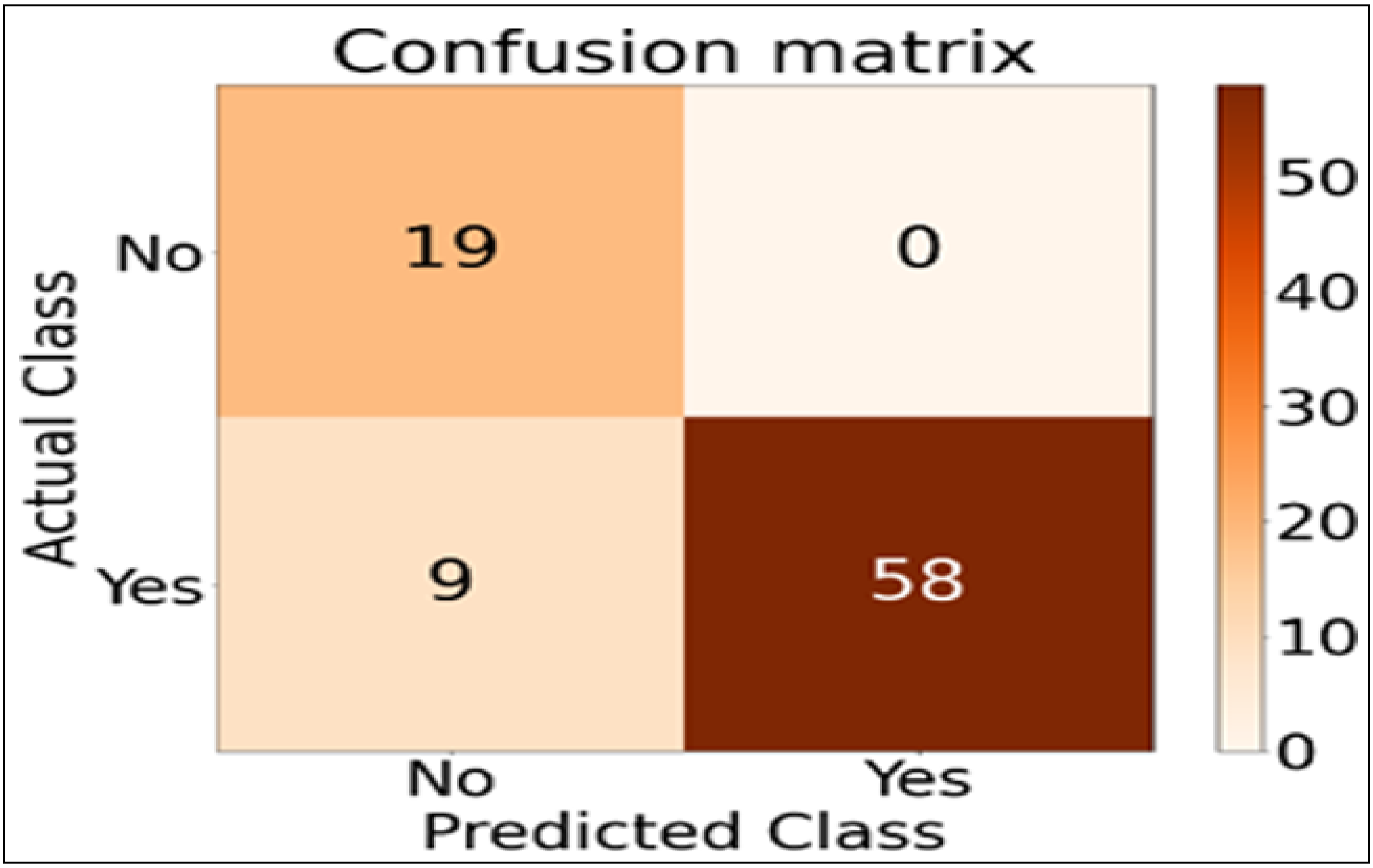

Fig 11 Confusion Matrix of Random Forest

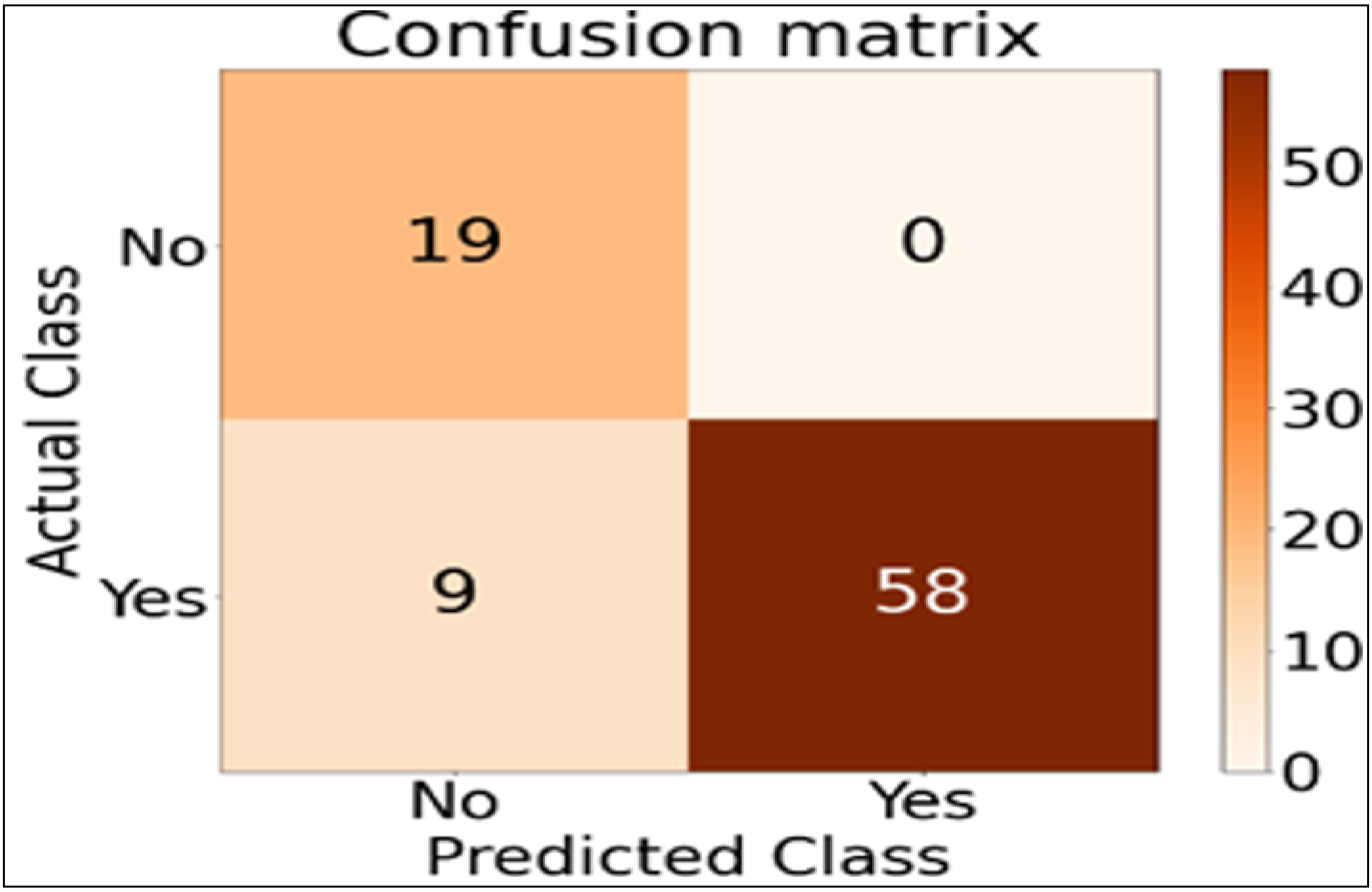

Fig 12 Confusion Matrix of Support Vector Machine

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➢ *Decisions and Discussions*

This research undertakes a comprehensive investigation through three analytical dimensions: exploratory data analysis integrated with correlation analysis, a comparative analysis to uncover relationships and differences, and a factor analysis aimed at selecting critical features supported by machine learning classifiers. These collective methodologies converge to produce a rich, multidimensional understanding of the underlying dynamics of family healthcare, especially the role women play in influencing health-related outcomes.

The exploratory data analysis provided several significant findings regarding demographic distribution and behavioral patterns across 284 families, both from urban and rural settings. Notably, 188 families reported that women held at least a Bachelor's degree, reflecting a relatively high level of female educational attainment within the dataset. This educational background appears to support a broader trend of women exerting considerable influence over healthcare decisions in the household. The analysis found a consistent agreement across families about the importance of women in healthcare decision-making, emphasizing their central role in shaping the family's health outcomes.

Women's participation in health-related discussions was also perceived as both valuable and necessary, reflecting the trust placed in their health knowledge and perspective. Their role in selecting family physicians was widely acknowledged, indicating that their judgment is often relied upon in making critical medical choices. Further, their active management of the family's health-related finances—such as setting budgets for medical expenses—demonstrated both responsibility and influence over economic aspects of healthcare. Families also expressed general satisfaction with the average hours of sleep reported per night, suggesting an environment conducive to well-being.

The data further revealed predominantly healthy lifestyle choices within the surveyed households. There was a widespread absence of smoking and alcohol consumption, and most families reported limiting fast-food consumption to no more than two days per week. These patterns reflect a health-conscious outlook. The role of women in planning and managing family nutrition stood out, with strong involvement in meal preparation, planning for dietary restrictions, and the selection and purchase of groceries. Fresh fruit and vegetable consumption was regular, with most families reporting intake five to seven days a week. Overall, these habits point to a generally high standard of nutritional awareness, largely shaped by women's choices and efforts. However, despite these positive trends, concerns emerged regarding health insurance coverage—most families lacked sufficient coverage—and satisfaction with the quality of healthcare services was typically neutral, suggesting that systemic improvements may still be needed.

The comparative analysis provided further clarity on how specific actions and roles impact satisfaction with healthcare services. It revealed that when women actively participate in healthcare decision-making, satisfaction with services tends to increase. Similarly, their involvement in health-related discussions, selection of physicians, and decisions made during health emergencies were all associated with higher satisfaction ratings. Their control over the health budget and contributions to planning meals with specific dietary considerations also enhanced healthcare satisfaction.

Interestingly, the frequency of fast-food consumption was not significantly linked to changes in satisfaction, possibly indicating that occasional indulgence does not necessarily offset positive perceptions if other healthy behaviors are present. What did matter, however, was the regular involvement of women in selecting and purchasing groceries and in planning nutritionally balanced meals, both of which positively influenced overall satisfaction. Another influential factor was the presence of health insurance—families with insurance coverage reported greater satisfaction, likely due to improved access and reduced financial strain.

In the final phase of analysis, machine learning models were used to predict the presence of chronic diseases within families, and these models helped identify the most influential features for prediction. The findings emphasized the substantial role women play in shaping family health dynamics, especially through their educational background and behavioral involvement. The level of education attained by women emerged as a key predictor, reinforcing the idea that better-educated women are more likely to make informed health decisions that reduce disease risk.

The extent to which women engaged in health-related discussions, managed the health budget, selected physicians, and planned meals were all significant indicators. Additionally, grocery selection and the frequency of fast-food consumption provided useful signals for dietary patterns that might correlate with chronic disease risk. Importantly, women's role in making broader healthcare decisions also surfaced as a critical determinant in disease prediction. These features were not only statistically significant but were validated through rigorous feature selection techniques and performance metrics from the machine learning classifiers, confirming their reliability and relevance.

Collectively, these insights reflect a consistent and compelling narrative: women serve as the backbone of health-related decision-making within families. Their educational attainment, financial engagement, nutritional planning, and strategic involvement in healthcare choices all contribute directly to family health outcomes and satisfaction with services. While the dataset and methods used offer a rich perspective, the findings also point to areas for future improvement. Enhancing women's access to health education, ensuring wider health insurance coverage, and addressing quality gaps in healthcare services could further amplify the positive influence women already have in this domain.

This research thus not only sheds light on patterns of behavior and decision-making in the context of family health but also underscores the need for policies and interventions that recognize, support, and empower women in their pivotal roles. By reinforcing women's capacity as health advocates within households, broader goals related to public health,

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chronic disease prevention, and healthcare satisfaction can be more effectively achieved.

Therefore, the three hypotheses can be proved from the three analyses.

- *"Hypothesis 1:*
  Families where women have a higher level of educational attainment (Bachelor's degree or above) exhibit better overall health outcomes compared to families where women have lower levels of education." – can be proved via exploratory data analysis and feature selection approaches.

- *"Hypothesis 2:*
  Women's participation in health-related discussions and decisions is positively correlated with the family's average satisfaction with healthcare services." – can be proved with the help of comparative analysis.

- *"Hypothesis 3:*
  Women's influence in healthcare decisions within the family leads to a lower incidence of chronic diseases among family members." – can be proved with the help of machine learning classifiers and validated by cluster analysis.

VI. CONCLUSION

This research has illuminated the significant impact of women on family health improvement, presenting a nuanced analysis that bridges exploratory data, comparative insights, and machine learning findings. Through the lens of 284 families, it has underscored the importance of women's educational levels, their engagement in health discussions, and their roles in healthcare and nutritional decision-making as pivotal to enhancing healthcare satisfaction and mitigating chronic disease prevalence. Despite facing methodological and scope limitations, the study charts a path for future research, emphasizing the need for longitudinal studies, broader sample diversity, and qualitative insights. It advocates for policies and interventions that bolster women's roles in health-related domains, highlighting their indispensable contribution to family health dynamics. In conclusion, this research not only enriches the academic discourse on family health but also offers actionable insights for policymakers, healthcare providers, and families, aiming to foster healthier communities through the empowerment of women.

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