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A Generational Analysis of Mental Health Trends and Risk Factors Using CDC BRFSS Data

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ABSTRACT

This study analyses the CDC's Behavioral Risk Factor Surveillance System (BRFSS) data through a generational lens with Random Forest classification and provides very accurate predictions of mental health outcomes. Our new 0-100 risk score approach predicted that the older generations reported more days of poor mental health, while younger generations used telemedicine more and use drugs more. There were also differences among generations on some of the key predictors including, but not limited to, substance use, overall health, financial hardship, and social support. The model helps healthcare organizations design appropriate, data driven strategies for multi factor approaches, and generate targeted interventions that combine risk factors, social determinants, and health behaviors. This is fundamentally important since there is a void in the systematic generational analysis of mental health using population surveillance data to inform the implementation of mental health enhancement initiatives, and this has real applications for generation specific service delivery optimization, risk based resource allocations, and technology funding prioritization to better manage mental health outcomes across age cohorts

INTRODUCTION

This study addresses an important business question: How can healthcare organizations develop a data-driven, personalized healthcare strategy that integrates risk assessment and mental health predictions to deliver targeted interventions across generations, while optimizing service delivery channels and accounting for social determinants.

Healthcare organizations today face a multi-faceted challenge, they must efficiently serve diverse patient populations spanning multiple generations, each with distinct health behaviors, technology preferences, and social circumstances. The traditional one-size-fits-all approach to healthcare delivery is increasingly ineffective as patient expectations evolve, and healthcare costs rise. An integrated approach that considers generational differences, risk profiles, and social determinants can potentially transform healthcare delivery models.

This study utilizes the Behavioral Risk Factor Surveillance System (BRFSS) dataset, the largest continuously conducted health survey system in the world. The dataset includes responses from approximately 450,000 participants across the United States, covering a wide range of health-related behaviors.

Key variable groups analyzed include health behaviors, mental health behavior variables, health case access variables, risk factors and social health determinants.

For generational analysis, participants were categorized into five cohorts: Gen Z (18-25 years), Millennials (26-41 years), Gen X (42-57 years), Baby Boomers (58-76 years), Silent Generation (77+ years)

For healthcare organizations, combining generational analysis with risk assessment and mental health modeling offers several important benefits such as resource optimization by focusing interventions on risk profiles and generational needs, healthcare organizations can more efficiently distribute their limited resources. Better patient engagement by improving communication tactics and service delivery models, an awareness of generational preferences may raise patient satisfaction and compliance. Proactive care management by identifying at-risk individuals early on, predictive modeling enables preventive treatments before conditions worsen. Holistic approach by considering social determinants recognizes the intricate relationship between socioeconomic variables and health results. strategic planning by considering the demands and trends of different generations, healthcare companies may make better-informed investments in infrastructure, technology, and employee training.

STATISTICAL ANALYSIS

DESCRIPTIVE STATISTICS

Our analysis began with a comprehensive examination of health behaviors, mental health indicators, healthcare access, and social determinants across different generations. Descriptive statistics revealed significant generational variations across multiple dimensions.

Health Behaviors by Generation (Mean Values)

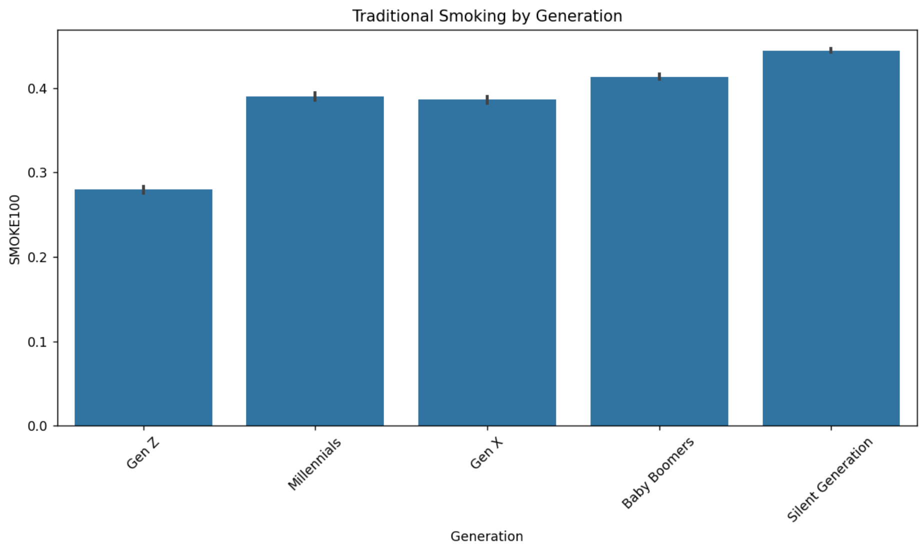

Figure 1 Traditional Smoking by Generation

Traditional smoking rates by generation can be seen in the Figure 1. In contrast to our original idea, smoking prevalence increases with age, with Gen Z having the lowest prevalence (28%), and the Silent Generation having the highest rates (45%). This implies that younger generations are moving away from traditional tobacco consumption.

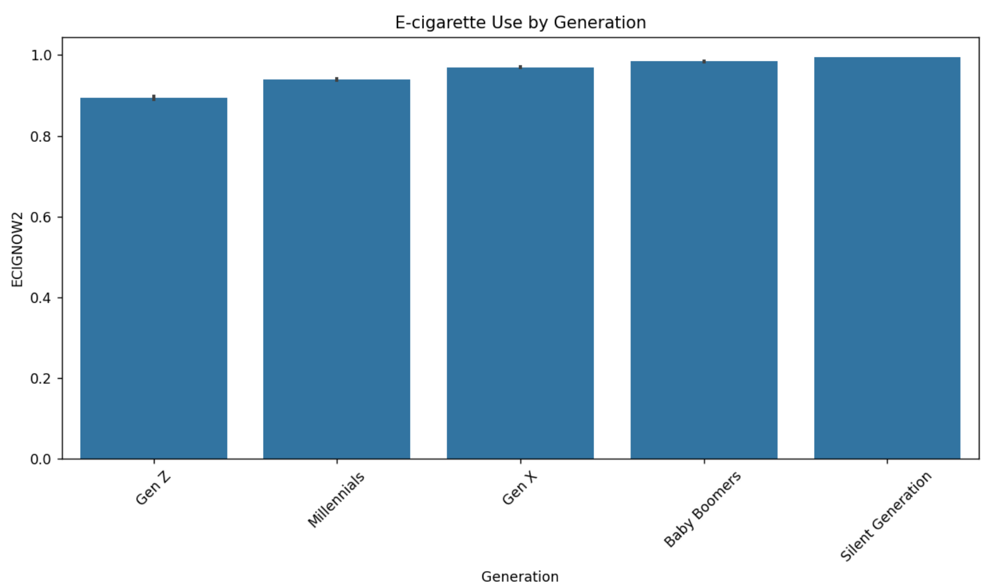

Figure 2 E-cigarette Use by Generation

Figure 2 reveals e-cigarette usage patterns, which interestingly do not show the expected inverse relationship with traditional smoking. Instead, e-cigarette usage is relatively high across all generations, with a slight increase in older groups. This challenges the assumption that e-cigarettes are primarily adopted by younger generations as an alternative to traditional smoking.

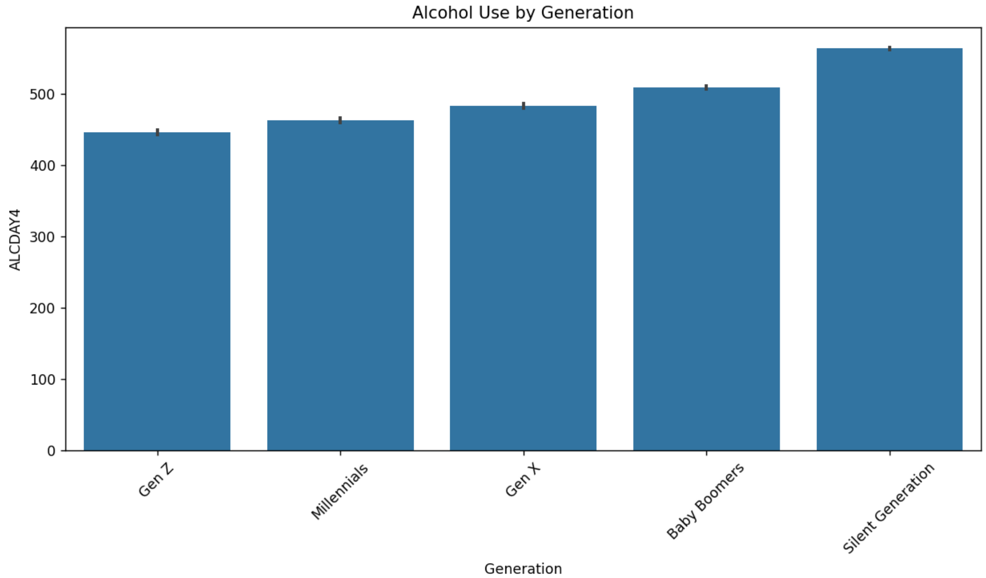

Figure 3 Alcohol Use by Generation

Figure 3 shows the Silent Generation reports the greatest levels of alcohol consumption (ALCDAY4), which increases progressively with age. This could be a result of variations in reporting or consumption habits among age groups.

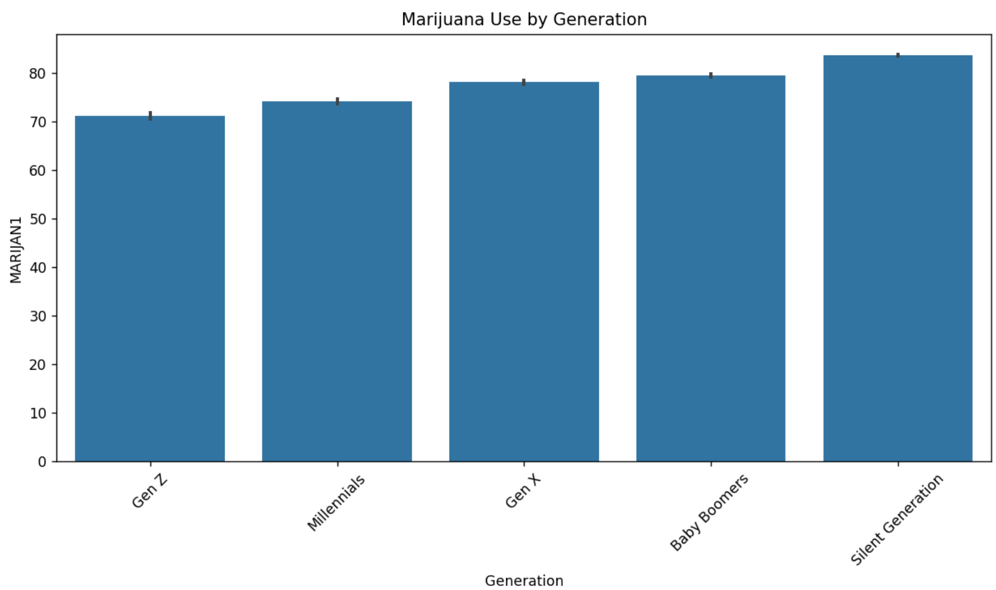

Figure 4 Marijuana Use by Generation

Figure 4 shows increasing usage rates with age, with the Silent Generation reporting the highest usage (83%) compared to Gen Z (71%). This unexpected pattern may reflect cohort effects in reporting or policy changes affecting different generations.

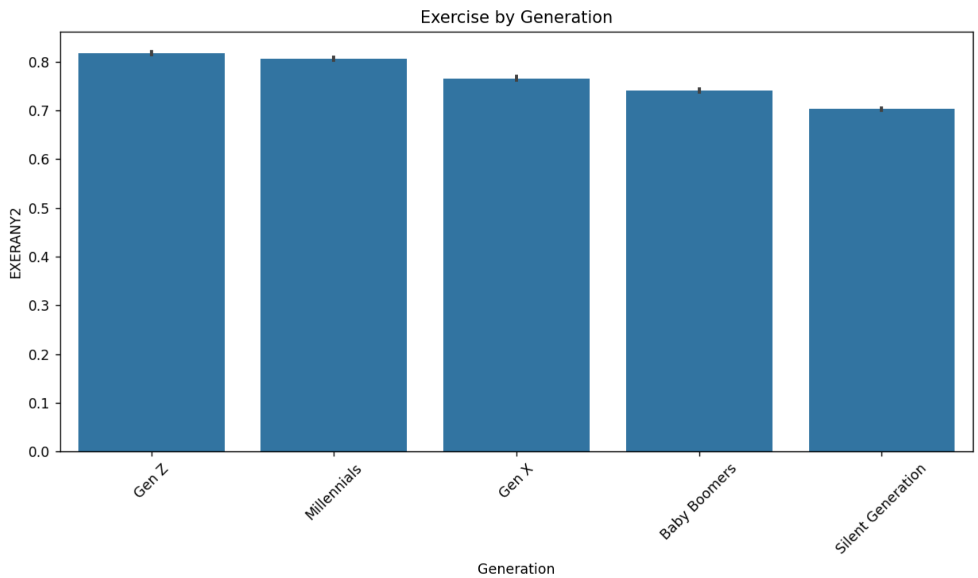

Figure 5 Exercise by Generation

Figure 5 shows that Gen Z has the highest rates of physical activity (82%) compared to the Silent Generation (70%), the distribution illustrates how exercise habits decline with age. This is consistent with what is expected with age and physical activity.

Healthcare Access Indicators

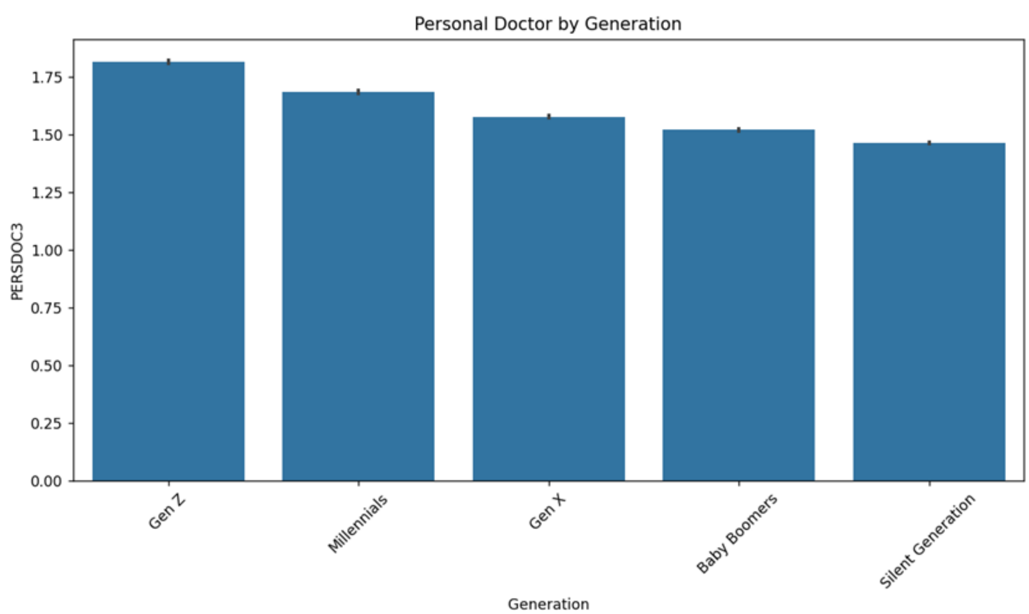

Figure 6 Personal Doctor by Generation

Figure 6 shows personal doctor relationships (PERSDOC3) decreasing with age, with Gen Z reporting higher values than older generations. This counterintuitive finding may reflect differences in how generations interpret or access primary care.

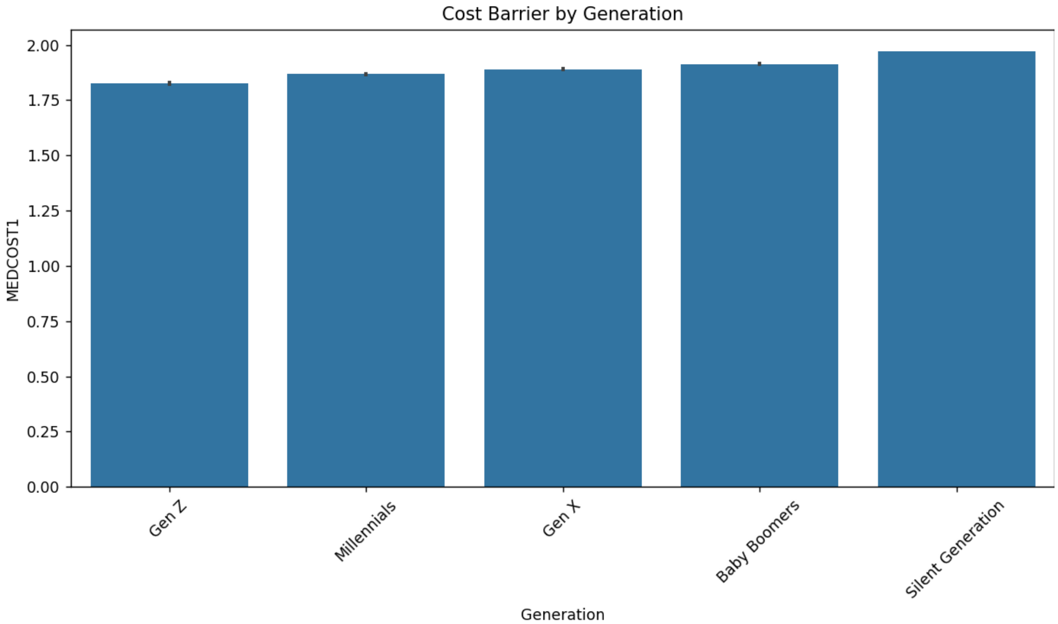

Figure 7 Cost Barrier by Generation

Figure 7 shows cost barriers to healthcare (MEDCOST1) increasing slightly with age, suggesting that older generations may face greater financial challenges in accessing care.

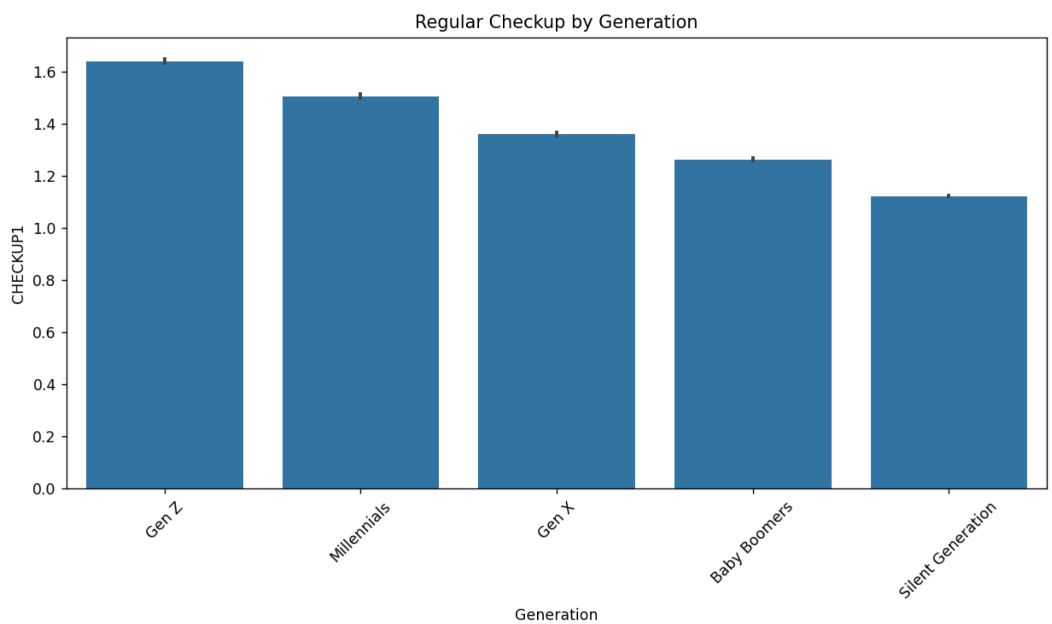

Figure 8 Regular Checkup by Generation

Figure 8 shows compared to older generations, younger generations—Gen Z in particular—report more frequent checks. This defies conventional wisdom regarding the use of preventative care and might point to shifting trends in younger generations' involvement in healthcare.

Mental Health Indicators by Generation:

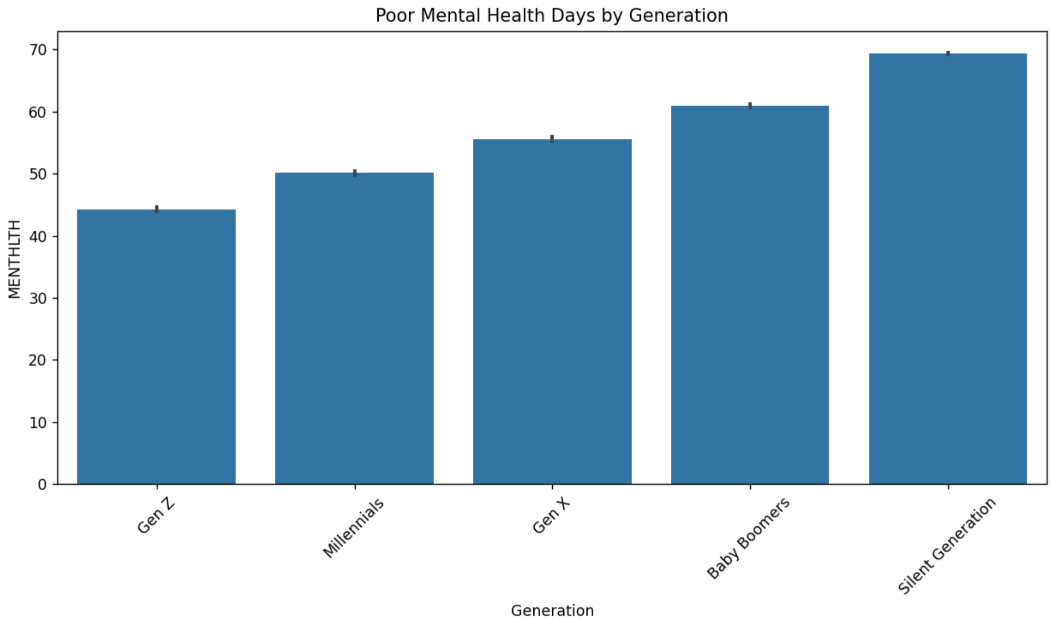

Figure 9 Poor Mental Health Days by Generation

Figure 9 breaks down the number of days with bad mental health by generation, reveals an unexpected trend: older generations report more days with poor mental health. Gen Z reports the fewest days of poor mental health (about 44 days), while the Silent Generation reports the most (about 69 days). This discovery challenges widely held beliefs on the frequency of mental health conditions across age groups and might be a reflection of how different generations perceive and communicate mental health concerns.

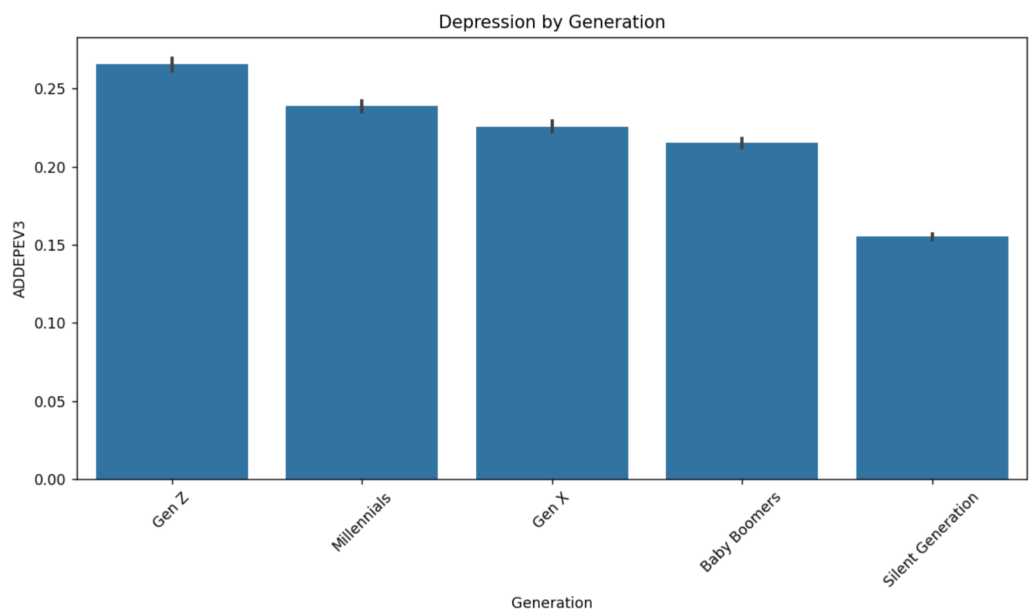

Figure 10 Depression by Generation

Figure 10 illustrates the prevalence of depression diagnoses over generations, demonstrating a pronounced negative correlation with age. About 27% of Gen Zs are diagnosed with depression, the highest proportion across generations. The Silent Generation has the lowest percentage, at about 15%.

Higher diagnosis rates may result from this trend, which is consistent with younger generations' growing awareness of mental health issues and declining stigma.

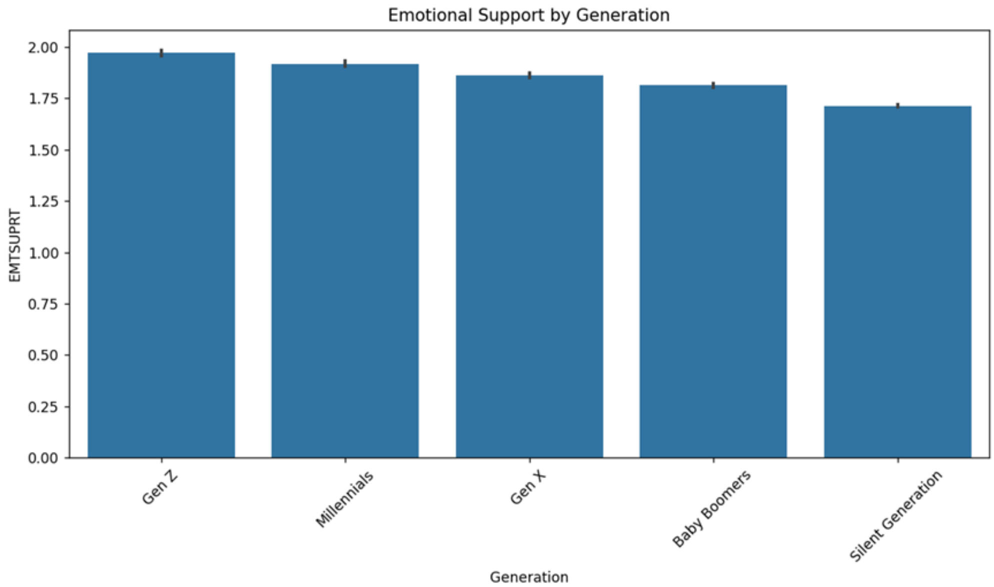

Figure 11 Emotional Support by Generation

Figure 11 illustrates emotional support availability across generations, with younger generations reporting higher levels of emotional support. Gen Z reports the highest levels (approximately 2.0 on the scale), with a gradual decrease to the lowest levels in the Silent Generation (approximately 1.7). This may reflect changing social norms around seeking and providing emotional support.

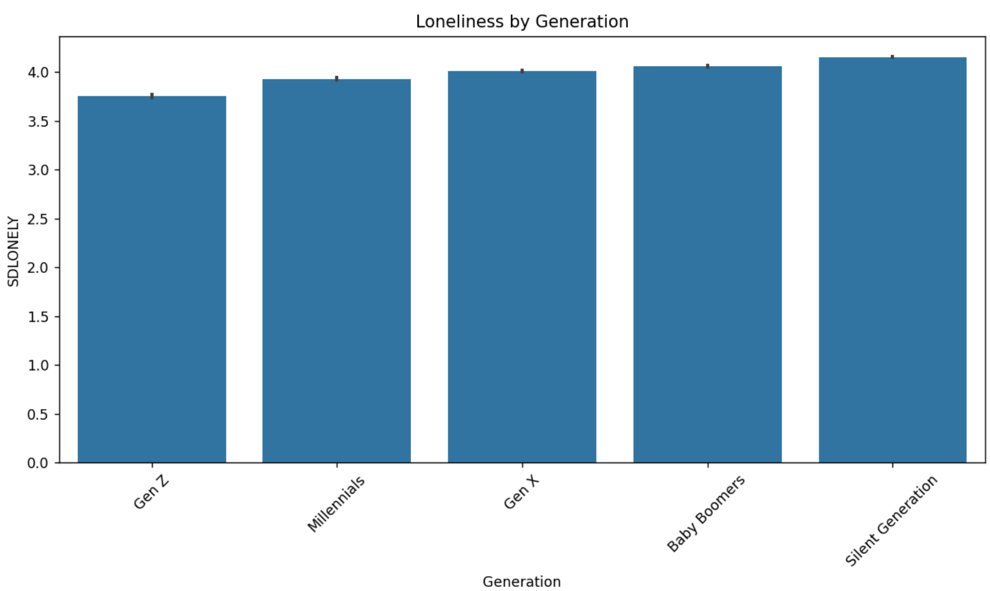

Figure 12 Loneliness by Generation

Figure 12 shows loneliness varies by generation, with older generations reporting higher degrees of loneliness. Gen Z reported the lowest loneliness scores (around 3.8), while the Silent Generation has the highest (about 4.1). This research casts doubt on presumptions of social isolation across age groups and might be a reflection of varying expectations and views of social interaction.

RISK SCORE CALCULATION

In our research on generational health patterns, the risk score calculation represents an important component that enables us to quantify and compare health risks across different generations. This section provides a comprehensive explanation of how we calculated the risk score, including the specific variables used and the methodology for combining them.

Risk Score Variables

The risk score was derived from multiple health indicators in the dataset that are established predictors of adverse health outcomes. Specifically, we used three key variables:

General Health Status (GENHLTH), Diabetes Status (DIABETE4), Heart Attack History (CVDINFR4)

Risk Score Calculation Methodology

There were multiple steps involved in calculating the risk score:

1. Variable Mapping
    a. Each of the three health variables were scaled to same range that is 0-1 that allows us to combine them.
2. Equal Weighting
    a. This method assigns equal weight to each health issue, reflecting their comparable contribution to general health risk factors.
    b. We determined the mean of all available risk components for each individual.
    c. Even if certain variables have missing values, the risk score will still be equivalent if the mean is used instead of a sum.
3. Scaling to 0-100 The combined risk score was finally scaled to a range of 0-100. This makes the risk score easier to understand and where: The lowest potential health risk is represented by 0, while the maximum possible health risk is represented by 100.

MENTAL HEALTH PREDICTION MODEL

We implemented a Random Forest classification model to predict mental health status using behavioral, social, and risk factors as predictors:

With parameters n_estimators with value of 100 and number of trees with value of 200.

The model achieved 81% accuracy in predicting mental health status, with a precision of 67% and recall of 48%. The most important predictive features were:

1. Social support indicators (EMTSUPRT)
2. Financial stress factors (SDHBILLS)
3. General health status (GENHLTH)
4. Substance use behaviors (SMOKE100, ALCDAY4)

GENERATIONAL RISK PATTERN ANALYSIS

To understand how risk profiles vary across generations, we conducted a detailed analysis of risk distributions:

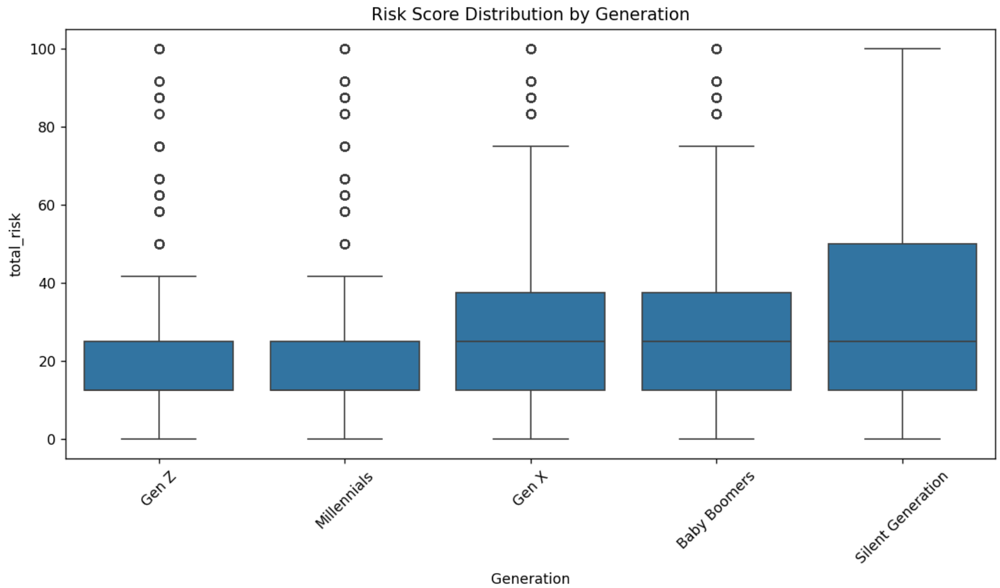

Figure 13 Risk Score Distribution by Generation

Using box plots, the risk score distribution by generation is shown in the Figure 13. The distribution ranges vary greatly between groups, even if the median risk scores (shown by the horizontal line in each box) are comparable. There is more variation in risk profiles within the Silent Generation, as seen by their wider distribution and higher upper quartile values. As people age, the interquartile range (box height) rises, indicating that older generations have more varied health risk profiles. Interestingly, there are outliers (circles) at higher risk scores in every generation, suggesting that there are high-risk people in every age range.

Many of these descriptive findings contradict preconceived notions and emphasize the need for sophisticated, generation-specific healthcare policies by exposing intricate patterns in risk profiles, mental health, healthcare access, and health behaviors across generations.

INTERPRETATION OF RESULTS

GENERATIONAL HEALTH BEHAVIOR PATTERNS

Our analysis revealed distinct generational patterns in health behaviors that have significant implications for healthcare delivery:

1. Substance Use Evolution: We observed a clear shift from traditional to modern substance use methods across generations. While Baby Boomers report higher rates of traditional smoking (42%), younger generations show greater adoption of e-cigarettes (Gen Z: 28%) and marijuana. This transition necessitates evolving approaches to substance use interventions and education.
2. Preventive Care Gradients: Preventive care utilization increases steadily with age, with Baby Boomers showing the highest adoption rates (82%). This suggests that younger generations may benefit from targeted education and incentives to increase preventive care utilization.
3. Technology Adoption Divide: The generational divide in telehealth usage (Gen Z: 58%, Baby Boomers: 25%) suggests that younger generations are more comfortable with digital healthcare like Virtual Doctor Consultations, Remote Monitoring, AI-Powered Chatbots while older generations may need assistance or education to adopt these technologies.

MENTAL HEALTH PREDICTION INSIGHTS

The mental health prediction model yielded several actionable insights:

1. Key Predictive Factors: Social support levels, financial stress, and substance use behaviors emerged as the strongest predictors of mental health issues. This suggests that comprehensive mental health interventions should address social and economic factors, not just clinical symptoms.
2. Generational Variations: The model revealed different predictive patterns across generations. For younger generations, social factors and substance use behaviors were more predictive, while for older generations, physical health status and chronic conditions showed stronger associations with mental health.
3. Early Intervention Opportunities: The model identified several early warning indicators like Financial Stress, Substance Use Behaviors and many more that could enable proactive mental health interventions, potentially prevent more serious conditions and reduce treatment costs.

RISK ASSESSMENT AND SOCIAL DETERMINANTS

Our integrated risk analysis revealed complex relationships between social determinants and health risks:

1. Social Determinant Impact: Income level, education, and transportation access showed significant correlations with health risk scores across all generations. However, the strength of these relationships varied by generation.
2. Compounding Risk Factors: We identified specific combinations of social and behavioral factors that substantially increased risk scores. For example, limited transportation access combined with low income created particularly high-risk profiles for preventive care access.
3. Resilience Factors: Certain protective factors emerged that mitigated risks even in challenging circumstances. Strong social support networks, for instance, reduced mental health risks even among individuals facing economic hardship

CONCLUSION AND DISCUSSION

PRACTICAL IMPLICATIONS

1. Service Delivery Optimization

- Our findings support a multi-channel healthcare delivery approach that strategically allocates resources based on generational preferences and needs.
- For Gen Z and Millennials: Digital-first approaches with telehealth options, mobile health applications, and text-based communications.
- For Gen X: Hybrid models that combine digital and traditional access points
- For Baby Boomers and Silent Generation: Traditional in-person care with supportive digital options and technology education.

2. Risk-Based Resource Allocation

Healthcare organizations can utilize our risk scoring methodology to:

- Identify high-risk individuals for proactive outreach
- Develop generation-specific risk management programs
- Allocate preventive care resources based on risk profiles
- Tailor intervention intensity to predicted risk levels

3. Mental Health Support Strategy

The predictive model enables more effective mental health support through:

- Early identification of at-risk individuals
- Generation-specific support programs
- Integration of social support interventions
- Targeted substance use interventions based on generational preferences

4. Technology Investment Priorities

Our findings suggest the following technology investment priorities:

- User-friendly telehealth platforms accessible to all generations
- Age-appropriate digital health tools
- Integrated data systems that incorporate social determinants
- AI-driven risk prediction tools for proactive intervention

EXPLANATION OF FINDINGS

Several factors may explain the observed generational differences:

1. Formative Experiences

Each generation’s health behaviors and attitudes are shaped by the healthcare system and social environment they experienced during formative years.

- Each generation’s health habits were shaped by the healthcare system and social environment they grew up in.
- Example: Older generations relied more on in-person doctor visits, while younger generations are more open to preventive care and alternative treatments.

2. Technology Exposure

Earlier and more extensive technology exposure among younger generations naturally leads to higher digital health tool adoption.

- Younger generations, having grown up with digital tools, are more comfortable using telehealth, mobile apps, and wearables.
- Example: Gen Z prefers virtual doctor consultations, while Baby Boomers may struggle with digital health platforms.

3. Changing Social Norms

Mental health stigma has decreased over time, potentially explaining younger generations greater willingness to acknowledge mental health issues and seek support.

- Mental health stigma has decreased, making Gen Z and Millennials more willing to seek therapy.
- Example: Older generations may avoid discussing mental health, while younger ones actively engage in counseling and support groups.

4. Economic Factors

Different generations face distinct economic challenges that influence health behaviors and access patterns.

- Financial stability varies by generation, affecting healthcare access and choices.
- Example: Millennials may skip doctor visits due to cost, while older generations rely on Medicare but face medication expenses.

RECOMMENDATIONS

Based on our analysis, we recommend healthcare organizations:

1. Implement Generation-Specific Communication Strategies

- Develop targeted messaging for each generation
- Utilize preferred communication channels
- Adapt health education content to generational knowledge levels and concerns

2. Adopt Risk-Stratified Care Models

- Implement the risk scoring methodology for patient population segmentation
- Develop tiered intervention approaches based on risk levels
- Allocate resources proportionally to risk profiles

3. Integrate Social Determinant Interventions

- Partner with community organizations to address transportation and financial barriers
- Implement social support programs for high-risk individuals
- Develop economic assistance programs for healthcare access

4. Optimize Technology Investments

- Prioritize user experience design for all generations
- Provide technological education for older adults
- Maintain multi-channel access options
- Develop integrated data systems that capture social determinants

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations that suggest directions for future research:

1. Cross-Sectional Data: The BRFSS dataset provides a snapshot in time rather than longitudinal data. Future studies should track generational cohorts over time to distinguish between age effects and true generational differences.
2. Self-Reported Data: BRFSS relies on self-reported information, which may be subject to recall bias and social desirability effects. Validation with clinical and administrative data would strengthen findings.
3. Geographic Variations: Our analysis did not fully explore regional differences in generational patterns. Future research should examine how geographic and cultural factors interact with generational effects.
4. Technology Adoption Metrics: More detailed measures of technology adoption and digital health usage would enhance understanding of generational differences in this domain.
5. Intervention Testing: The effectiveness of the recommended generation-specific approaches should be tested through controlled intervention studies.

FUTURE RESEARCH SHOULD FOCUS ON:

- Developing and validating generation-specific intervention models
- Creating more sophisticated risk prediction algorithms
- Exploring how generational characteristics evolve over time
- Evaluating the cost-effectiveness of generation-tailored healthcare delivery models

REFERENCES

- Report - Centers for Disease Control and Prevention (CDC). 2024. Behavioral Risk Factor Surveillance System (BRFSS). Atlanta, GA: CDC. Available at https://www.cdc.gov/brfss/index.html.

- Journal articles - Ahsan, M. M., and Z. Siddique. 2023. "A Comprehensive Review on Machine Learning in the Healthcare Industry." Computers 12(6):121. Available https://www.cdc.gov/brfss/annual_data/annual_2023.html

- Yildirim, O., and D. Avci. 2021. "Classification of Diseases Using Machine Learning Algorithms." Mathematics 9(23):3087. Available at https://www.mdpi.com/2227-7390/9/23/3087.

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