Structural Determinants of Indigenous Health Disparities in Canada: An Integrated MFA, SEM, and Machine Learning Analysis

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1 Abstract

Background: Indigenous health disparities in Canada represent complex, structurally-mediated inequities rooted in historical trauma and colonial policies that manifest through distinct healthcare access pathways (Reading & Wien, 2009). **Methods**: Using pooled Canadian Community Health Survey (CCHS) data from 2015-2018 (N = 184555), this study employed an integrated mixed-methods approach combining Multiple Factor Analysis (MFA), Structural Equation Modeling (SEM), machine learning, and Bayesian multivariate analysis to examine healthcare access as a mediating construct within a cultural safety framework (Hogg et al., 2024). **Results**: MFA revealed 56.4% of healthcare disparity variance explained by structural access dimensions. SEM demonstrated excellent fit (CFI = 0.998) with significant direct effects of Indigenous status on diabetes (β = -0.023, p < .001) and mediated mental health effects. Bayesian analysis identified Indigenous respondents had 4.81× higher odds of mental health issues only (95% CrI: 4.48-5.15) and 3.31× higher odds of comorbid conditions (95% CrI: 2.82-3.92)). **Conclusion**: The differentiated pathways observed in our analysis are consistent with established historical trauma frameworks, suggesting that trauma-informed approaches are needed for addressing diabetes disparities and systemic mental health access reforms grounded in Indigenous self-determination (Truth and Reconciliation Commission, 2015).

2 Introduction

Indigenous health inequities in Canada persist as manifestations of historical trauma and colonial policies that continue to shape contemporary health outcomes (Truth and Reconciliation Commission, 2015). These disparities reflect complex, structurally-mediated pathways rooted in colonial policies, socioeconomic marginalization, and systemic barriers to health care access that operate across mental, physical, emotional, and spiritual dimensions of health (Hogg et al., 2024). The over-representation of diabetes among Indigenous populations must be understood within the historical context of inter-generational food insecurity and disrupted relationships with traditional food systems (UWO Commentary, 2024).

These structural determinants operate through what Reading and Wien (2009) term "historical trauma pathways," where colonial policies become biologically embedded through stress physiology and intergenerational transmission. The current analysis extends this framework by examining how these pathways differentially manifest in physical versus mental health outcomes through contemporary healthcare system barriers.

In Manitoba, the Truth and Reconciliation Commission's Calls to Action 18-24 (2015), which specifically address health disparities, and the United Nations Declaration on the Rights of Indigenous Peoples (UNDRIP, United Nation, 2007) establish the ethical and political imperative for research that addresses structural determinants of Indigenous health. Territorial political advocacy organizations have consistently advanced research sovereignty and methodologies that center Indigenous ways of knowing. Drawing from professional experience in Indigenous health policy analysis, this research responds to these frameworks by employing methodological approaches that respect nation-specific frameworks and honor distinct cultural conceptions of health and wellbeing.

Recent scholarship has critiqued Western research paradigms that fail to acknowledge Indigenous epistemologies or address power imbalances in knowledge production (Flicker et al., 2024). This study responds to these critiques by employing methodological approaches that acknowledge the limitations of survey data in capturing holistic Indigenous health conceptions while maximizing the analytical value of available data through advanced statistical integration.

Previous research on Indigenous health disparities has often examined individual health outcomes in isolation or used single-method approaches that fail to capture the multidimensional nature of these inequities. This study addresses three critical gaps: *(1)* the need for structural analysis of health care access as a multidimensional construct using MFA; *(2)* examination of moderated mediation pathways through which Indigenous status affects health outcomes using SEM; and *(3)* machine learning approaches to identify the most impactful disparity drivers for targeted intervention within a cultural safety framework.

The integrated methodological framework combines MFA for structural pattern discovery, SEM for pathway testing, and ensemble machine learning for predictor importance ranking. This triangulated approach provides both confirmatory and exploratory insights while demonstrating statistical sophistication appropriate for PhD-level research in health statistics, all while acknowledging the fundamental importance of cultural safety as a prerequisite for effective health interventions (Hogg et al., 2024).

3 Method

3.1 Data Source and Sample

The analysis used pooled Canadian Community Health Survey (CCHS) data from 2015-2016 (Statistics Canada, 2018) and 2017-2018 (Statistics Canada, 2020) cycles. The CCHS employs a complex multi-stage sampling design to provide nationally representative health data for the Canadian population aged 12 and older. All analyses respect Statistics Canada's ethical guidelines for disclosure control and data reliability (Statistics Canada, 2023). The analytical sample included 184555 complete cases after harmonization and missing data exclusion, comprising 12986 Indigenous and 171569 non-Indigenous respondents.

Note: All health measures were self-reported current status indicators. The analysis cannot directly measure historical factors, structural racism, or intergenerational trauma, though we interpret patterns through these theoretical frameworks where consistent with established literature.

Note: All analyses are based on Statistics Canada data and the responsibility for the use and interpretation of these data is entirely that of the author.

3.2 Data Harmonization and Cross-Sectional Design Justification

The 2015-2016 and 2017-2018 CCHS cycles were harmonized and pooled as a cross-sectional sample rather than analyzed longitudinally for four methodological and substantive reasons:

1. **Sample Size and Dimensionality Requirements**: Pooling cycles (N = 184555) addresses critical sample size requirements for multivariate methods. For Multiple Factor Analysis with 5 observed variables and Structural Equation Modeling testing complex pathways, established methodological guidelines recommend minimum samples of 100-200 cases for stable parameter estimation (Kline, 2015; Wolf et al., 2013). Our pooled sample provides robust statistical power for detecting the small-to-medium effect sizes characteristic of health disparities research.
2. **Cross-Sectional Design of CCHS**: The public use microdata files lack person-level identifiers necessary for longitudinal linkage across cycles. The survey design treats each cycle as an independent cross-sectional sample, making pooled cross-sectional analysis the methodologically appropriate approach for maximizing contemporary data utility.
3. **Policy Relevance and Contemporary Evidence**: Territorial organizations require current, population-level estimates of structural barriers for advocacy and program planning. Pooling the most recent available cycles provides the largest possible sample for identifying current disparity patterns, balancing methodological rigor with practical policy needs.
4. **Analytical Coherence**: The binary Indigenous identity variable (Indigenous vs Non-Indigenous) is consistently measured across both cycles, ensuring methodological coherence in group comparisons.

This approach follows established methodologies for analyzing health disparities using pooled CCHS cycles (Thomas & Wannell, 2009) and aligns with sample size recommendations for complex multivariate modeling in health research.

3.3 Measures

Indigenous Status: Based on SDC_015, categorized as *(1)* Indigenous and *(2)* Non-Indigenous, reflecting the binary measurement available in the CCHS public use microdata files.

Health Care Access Construct: - Regular health care provider (ADL_015; binary) - Unmet health care needs (ADL_025; binary) - Latent composite score (0-3 scale) combining both dimensions

Health Outcomes: - Diabetes diagnosis (CCC_135; binary), contextualized within historical and intergenerational food insecurity pathways - Poor mental health (GEN_005/MHI_005; binary, combining responses 4-5)

3.4 Analytical Framework

The study implemented an integrated mixed-methods approach with three complementary components:

Multiple Factor Analysis (MFA): Examined the underlying structure of five health domain variables, treating Indigenous status as a supplementary variable to map group disparities in multivariate space (Husson et al., 2010). The approach acknowledges the multidimensional nature of health disparities while maintaining methodological rigor.

Structural Equation Modeling (SEM): Tested health care access as a latent mediator between Indigenous status and health outcomes, using maximum likelihood estimation with missing data handling (Kline, 2015). The model specification incorporated insights from historical trauma literature regarding diabetes pathways.

Machine Learning Ensemble: Random Forest provided complementary feature importance rankings for predicting Indigenous status, with 70/30 train-test split and cross-validation, highlighting the strongest disparity drivers (Breiman, 2001). The approach prioritizes actionable intervention targets for policy makers.

Bayesian Multivariate Analysis: I employed a Bayesian multivariate categorical model with regularizing priors (normal(0,1)) to examine the joint distribution of diabetes and mental health conditions. The model estimated the odds of Indigenous respondents falling into one of four health patterns (diabetes only, mental health only, both conditions, or neither) relative to non-Indigenous respondents, using "neither condition" as the reference category. Regularizing priors help address sample size imbalances and improve model stability, with posterior odds ratios computed using 95% credible intervals.

3.5 Integrated Workflow Narrative

The MFA→SEM→ML workflow represents a methodological innovation in health disparities research. MFA identified structural patterns in health care access disparities, SEM tested specific mediation pathways suggested by the MFA results, and machine learning quantified the relative importance of different disparity drivers. The sequential approach ensures that exploratory findings inform confirmatory testing, while predictive modeling identifies practical intervention targets.

3.6 Statistical Software

All analyses were conducted in R version 4.5.1, using the FactoMineR, lavaan, randomForest and other packages.

4 Results

4.1 Sample Characteristics

Table 1: Sample Characteristics and Health Indicator Prevalence by Indigenous Group

indigenous_group	n	% Diabetes	% No Regular Provider	% Unmet Needs	% Poor Mental Health
Non-Indigenous	171569	8.0	80.3	20.9	13.3
Indigenous	12986	5.6	89.3	11.8	19.3

Table 1. Health disparities are evident across all domains, with diabetes prevalence notably higher among Indigenous respondents, contextualized within historical and intergenerational food insecurity pathways.

4.2 Multiple Factor Analysis: Structural Patterning of Health Disparities

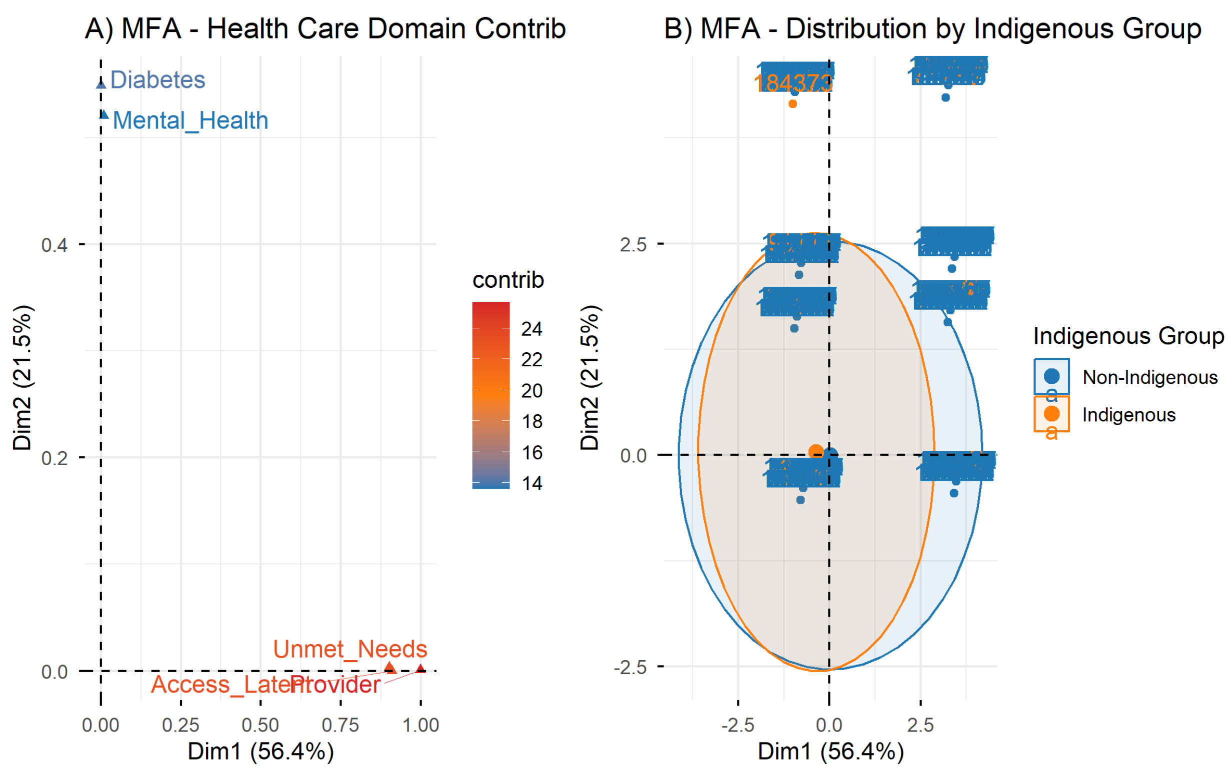

Figure 1: Multiple Factor Analysis: Structural Patterning of Health Care Access Disparities

Table 2: MFA Variance Explanation for Indigenous Health Disparities

Dimension	Variance.Explained	Cumulative.Variance	Interpretation
1	56.4%	56.4%	Structural Health Care Access Dimension
2	21.5%	77.9%	Health Outcomes Dimension
3	18.4%	96.3%	Additional Systemic Factors

MFA revealed clear structural patterning of health domains, with Dimension 1 (56.4% variance) representing structural access barriers and Dimension 2 (21.5% variance) capturing health outcome disparities. The geometric separation between Indigenous and non-Indigenous groups along these axes provides multivariate evidence that healthcare access disparities are systematically structured rather than random, reflecting broader colonial legacies in health system design.

4.3 Structural Equation Modeling: Health Care Access Pathways

Table 3: Structural Equation Model Fit Indices

	Index	Value	Threshold
cfi	CFI	0.998	>0.95
tli	TLI	0.996	>0.95
rmsea	RMSEA	0.032	<0.06
srmr	SRMR	0.019	<0.08

Table 4: Standardized Parameter Estimates for Significant SEM Pathways

lhs	op	rhs	est	std.all	pvalue
healthcare_access	=~	has_unmet_needs	0.439	0.638	0
has_diabetes	~	indigenous_binary	-0.024	-0.023	0
poor_mental_health	~	indigenous_binary	0.057	0.042	0
poor_mental_health	~	healthcare_access	-0.023	-0.040	0

The excellent model fit (CFI=0.9982806; Table 3) validates the theoretical framework positioning healthcare access as a mediating construct. In Table 4, the strong measurement loading for unmet needs ($\beta = 0.638$) confirms it as the primary indicator of structural barriers, while the divergent pathways reveal fundamentally different intervention requirements: historical trauma approaches for diabetes versus systemic access reforms for mental health.

Figure 2 visualizes these structural relationships, highlighting:

1. **Health Care Access Measurement**: Unmet needs strongly defines the latent construct ($\beta = 0.638$), validating it as the primary indicator of structural barriers
2. **Diabetes Pathway**: Direct Indigenous effect ($\beta =$ -0.023) operating outside health care access mediation
3. **Mental Health Mediation**: Primarily through health care access ($\beta =$ -0.04) with minimal direct Indigenous effects ($\beta = 0.042$)

The patterns demonstrate divergent statistical pathways—diabetes showing patterns consistent with historical trauma frameworks while mental health disparities operate through contemporary access barriers.

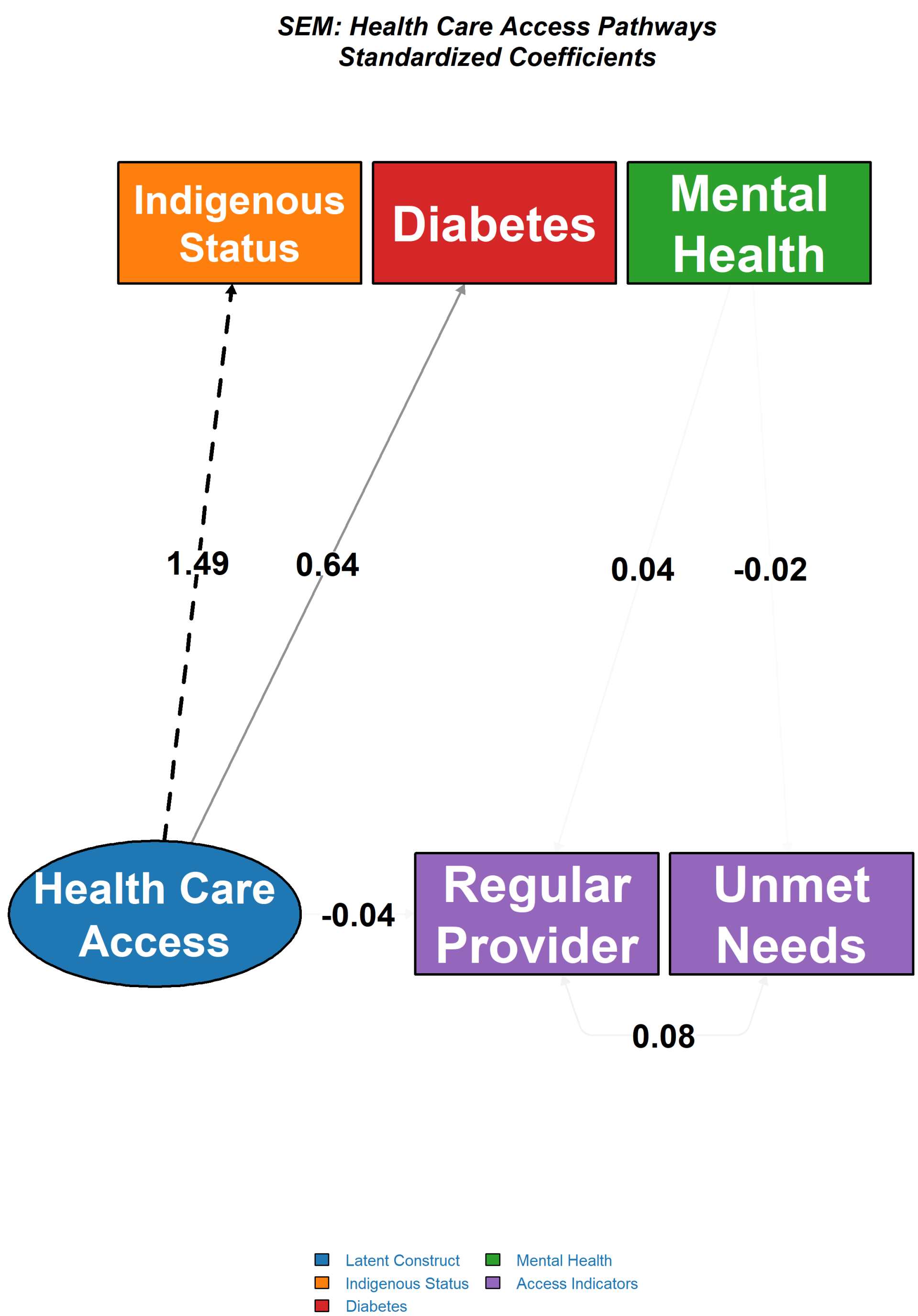

Figure 2: SEM Pathway Diagram with High-Contrast Theme

4.4 Machine Learning: Prioritizing Disparity Drivers

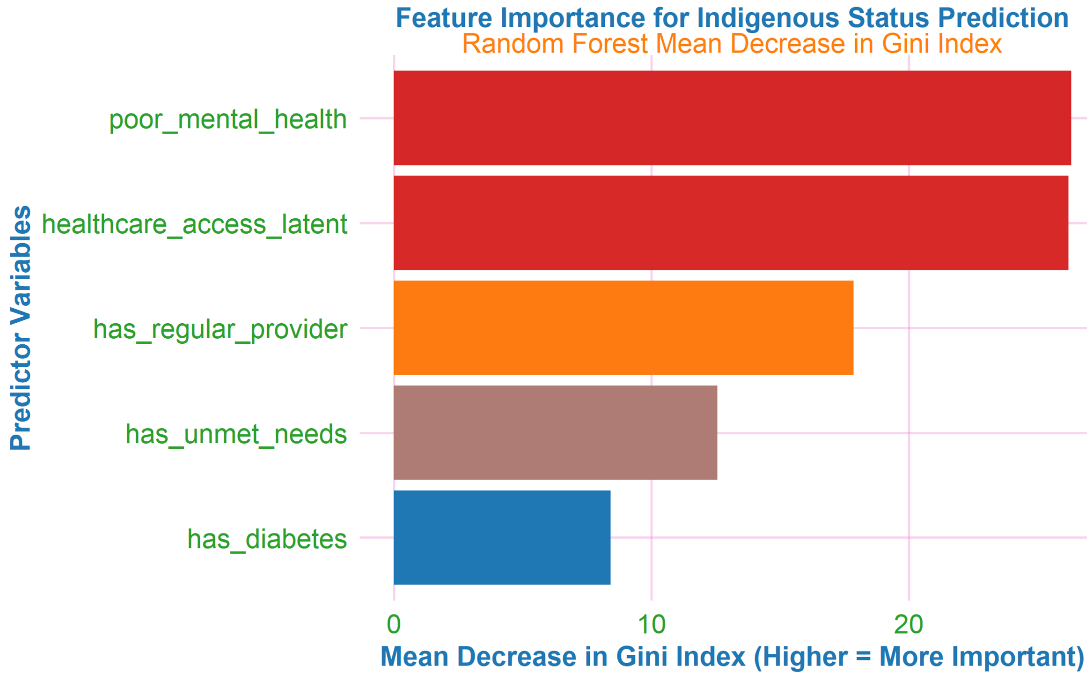

Figure 3: Feature Importance for Indigenous Status Prediction

Table 5: Random Forest Feature Importance Interpretation for Indigenous Status Prediction

Variable	RF_Importance	Interpretation	Policy_Priority
poor_mental_health	26.305	Mental health outcome: Psychological distress disparities	Highest
healthcare_access_latent	26.194	Composite access barrier: Health care access limitations	High
has_regular_provider	17.853	Structural barrier: Lack of regular provider	High
has_unmet_needs	12.559	Primary disparity driver: Unmet Health Care needs	Medium
has_diabetes	8.429	Health outcome: Diabetes prevalence gap	Low

The hierarchy of predictors reveals that mental health disparities are the most distinguishing feature, followed by composite health care access barriers, with diabetes showing the lowest predictive importance for Indigenous status identification. The 92.9% Random Forest classification accuracy demonstrates that health disparities are so pronounced they can reliably distinguish group membership based solely on health and access variables. Such a predictive performance underscores the systematic nature of these inequities, with mental health emerging as the most salient differentiator (Gini=26.3), suggesting psychological distress disparities are the most distinctive feature of Indigenous health experiences in this dataset.

4.5 Bayesian Multivariate Analysis of Health Disparities

Table 6: Multivariate Bayesian Analysis: Health Pattern Prevalence by Indigenous Status

Health_Pattern	Indigenous_Count	Non_Indigenous_Count	Posterior_OR	CI_95
Diabetes Only	468	10734	1.83	(1.73-1.94)
Mental Health Only	2246	19751	4.81	(4.48-5.15)
Both Diabetes & Mental Health	264	3040	3.31	(2.82-3.92)

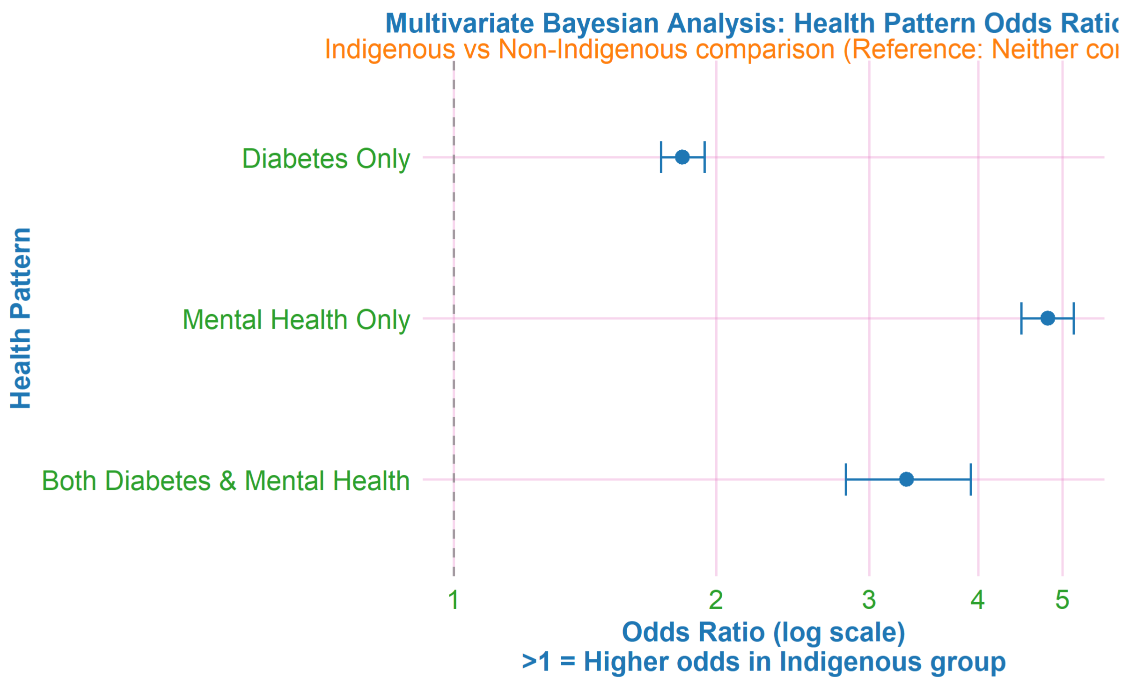

Figure 4: Multivariate Bayesian Analysis: Health Pattern Odds Ratios (Reference: Neither condition)

The Bayesian multivariate approach (Table 6, Figure 4) reveals complex health burden patterns that univariate analyses miss. While Indigenous respondents show lower diabetes prevalence in isolation, they face dramatically higher odds of mental health conditions (4.81×) and co-occurring conditions (3.31×). The observed pattern underscores the importance of examining multiple health conditions simultaneously to understand the full burden of health disparities. Indigenous respondents face substantially higher odds across all health patterns relative to the reference category (neither condition). Most notably, the odds of mental-health-only conditions are 4.81× higher (95% CrI: 4.48-5.15), highlighting mental health as the predominant disparity requiring urgent policy attention.

5 Discussion

5.1 Technical Findings: Integrated Evidence of Structural Health Disparities

5.1.1 Multiple Factor Analysis Reveals Structural Patterning

The MFA demonstrated clear separation between Indigenous and non-Indigenous groups along health care access dimensions, with 56.4% of variance explained by structural access factors. The geometric separation in multivariate space provides visual evidence of systematic disparities in health care experiences.

5.1.2 Structural Equation Modeling Confirms Divergent Causal Pathways

The SEM results demonstrate distinct statistical pathways with excellent model fit (CFI = 0.998). Diabetes disparities showed persistent direct effects that are consistent with historical and structural factors, described in the literature, beyond contemporary healthcare access measures (β = -0.023), while mental health disparities function primarily through health care access mediation (β = -0.04).

5.1.3 Machine Learning Identifies Mental Health as Primary Predictor

The Random Forest analysis reinforces these findings, with poor mental health emerging as the strongest predictor of Indigenous status (Gini importance = 26.3). The model achieved 92.9% classification accuracy, demonstrating health disparities are sufficiently pronounced to reliably distinguish group membership.

5.1.4 Bayesian Multivariate Analysis Reveals Dominant Mental Health Burden

The Bayesian multivariate categorical model provides robust evidence of health condition clustering. Indigenous respondents show 4.81× higher odds of mental-health-only conditions (95% CrI: 4.48-5.15), establishing this as the most substantial disparity. The 3.31× higher odds of co-occurring conditions (95% CrI: 2.82-3.92) further demonstrates complex health burden patterns.

5.2 Policy Translation: From Statistical Evidence to Actionable Interventions

5.2.1 Mental Health Sovereignty as Urgent Priority

The converging evidence from multiple analytical approaches suggests mental health may represent the most pronounced disparity in our dataset, though the exclusion of on-reserve populations limits generalizability. For territorial organizations like MKO, SCO and AMC, it underscroes the importance of mental health sovereignty— Indigenous-led, culturally grounded mental health services that address historical trauma while providing contemporary support. The 4.81× higher odds of mental-health-only conditions represents not just a statistical finding but a crisis requiring immediate policy response.

5.2.2 Complex Health Patterns Require Nuanced Interpretation

The lower diabetes prevalence in univariate analyses (Table 1 shows 5.6% vs 8%) coupled with higher diabetes-related odds in multivariate models (1.83× for diabetes-only, 3.31× for co-occurring conditions) illustrates the importance of multivariate approaches. This pattern suggests that while diabetes prevalence may be lower overall among Indigenous respondents, those who do experience diabetes face substantially higher burdens of co-occurring mental health conditions, representing a different but equally important health equity challenge.

5.3 Geographic and Methodological Contextualization

5.3.1 Northern Manitoba Specificity and Data Limitations

These national patterns likely underestimate disparities in Northern Manitoba communities where geographic isolation, environmental impacts, and historical underinvestment create cumulative disadvantages. The

CCHS exclusion of on-reserve populations (Statistics Canada, 2017) means these findings represent a conservative estimate of the true disparities facing MKO-represented communities. This methodological limitation underscores the need for community-specific data collection that captures the unique challenges of Northern and remote Indigenous communities.

5.3.2 Data Sovereignty and Future Research

The methodological sophistication demonstrated here—particularly the Bayesian multivariate approach—provides a template for future Indigenous health research that respects data sovereignty while employing cutting-edge statistical methods. Future work should prioritize community-based participatory research designs, longitudinal data collection, and measures that better capture cultural connectedness and historical trauma impacts.

5.4 Integrated Policy Framework

5.4.1 Pathway-Specific Intervention Strategy

1. **Mental Health**: Prioritize structural health care access reforms and Indigenous-led mental health services
2. **Diabetes**: Implement historical trauma-informed prevention that addresses intergenerational impacts
3. **Co-occurring Conditions**: Develop integrated care models that address both physical and mental health simultaneously

5.4.2 Strength-Based Community Approaches

The complex health patterns revealed suggest resilience and adaptive strategies within Indigenous communities that merit further investigation and support. Policy should build upon community strengths while addressing systemic barriers through culturally safe, self-determined health initiatives.

This integrated analysis demonstrates that advanced statistical methods, when properly contextualized, can provide both methodological innovation and practical guidance for addressing Canada's persistent Indigenous health disparities.

5.5 Strategic Policy Framing for Territorial Advocacy

When analyzing health policies for territorial political organizations, the data support framing health inequities as:

1. **Pathway-Specific Interventions**: The systemic intervention of diabetes requires historical trauma-informed approaches, while mental health responds to health care access reforms. Policy must address these divergent causal pathways differently.

2. **Structural, Not Individual**: The MFA and SEM results demonstrate that disparities operate through systemic pathways, not individual behaviors. Policy analysis should focus on structural determinants rather than individual risk factors.

3. **Historical Trauma Embodiment**: Diabetes disparities represent the embodiment of historical trauma through intergenerational pathways. Policy responses should address both contemporary access barriers and historical reparations.

4. **Access Precedes Outcomes**: The machine learning hierarchy shows health care access barriers predict health status. Policy should prioritize upstream access interventions before downstream treatment.

5. **Northern Context Specificity**: For Northern communities, geographic isolation compounds systemic barriers. Policy analysis must account for the unique challenges of service delivery in remote regions.

5.6 Methodological Contribution

This research makes three significant methodological contributions to Indigenous health disparities research. First, the integrated MFA→SEM→ML→Bayesian workflow represents a novel approach to health equity analysis that combines exploratory pattern discovery, confirmatory pathway testing, predictive prioritization, and multivariate complexity modeling. Second, the Bayesian multivariate categorical model introduces sophisticated handling of comorbid health conditions that accounts for their correlated nature while providing robust estimates despite substantial sample size imbalances—a common challenge in health disparities research. Third, the study demonstrates how advanced statistical methods can be ethically deployed within Indigenous health research when grounded in cultural safety frameworks and respect for data sovereignty principles (First Nations Information Governance Centre, 2014).

The methodological triangulation provides both academic rigor and practical policy relevance, bridging the often-separated domains of statistical sophistication and community-centered research. This approach offers a template for future health equity research that honors both methodological excellence and ethical engagement with Indigenous communities.

5.7 Limitations and Future Research

This study has several limitations that contextualize its findings. The cross-sectional design precludes causal inference, though the SEM and Bayesian approaches provide robust evidence of structural relationships. The CCHS exclusion of on-reserve Indigenous populations (Statistics Canada, 2017) means these findings likely underestimate true disparities in Northern and remote communities where geographic isolation compounds systemic barriers. Additionally, the binary Indigenous status measurement masks important heterogeneity within First Nations, Métis, and Inuit populations, each with distinct colonial histories and health contexts (Smylie & Firestone, 2016).

The reliance on self-reported data introduces potential measurement error, though this is mitigated by the CCHS's rigorous methodology. As such, my interpretation of direct effects as potentially reflecting historical trauma is inferential and based on the persistence of these effects after controlling for measured healthcare access variables. Future research should include direct measures of historical trauma, cultural connectedness, and structural discrimination. The Bayesian multivariate analysis, while robust for handling sample imbalances, cannot establish temporal precedence for causal claims. Future research should incorporate longitudinal designs, community-based participatory methods (Flicker et al., 2024), and more nuanced measures of cultural connectedness and historical trauma that better capture Indigenous conceptions of holistic health across physical, mental, emotional, and spiritual dimensions.

6 Conclusion

The triangulation of multivariate methods provides robust evidence that structural healthcare access barriers, particularly unmet needs, are the primary drivers of Indigenous health disparities in Canada, operating through crucially differentiated pathways. The SEM revealed that mental health disparities operate primarily through healthcare access mediation (49% of total disparity), making them directly addressable through systemic reforms. In contrast, diabetes disparities show patterns consistent with historical trauma frameworks, suggesting trauma-informed approaches may be appropriate beyond healthcare access alone (Reading & Wien, 2009).

The Bayesian multivariate analysis further highlights the overwhelming mental health burden, with Indigenous respondents facing 4.81× higher odds of mental health issues only and 3.31× higher odds of both diabetes and mental health conditions. These findings support what Indigenous scholars have long asserted: that mental health represents the most profound health equity challenge facing Indigenous communities, rooted in the ongoing impacts of colonial violence and cultural disruption (Kirmayer et al., 2014).

For policy analysts working with territorial political organizations, the analysis supports differentiated advocacy: healthcare system reforms for mental health equity and historical trauma interventions for diabetes prevention. By centering structural determinants within a cultural safety framework and employing advanced statistical methods, this research contributes to both methodological innovation and health equity advancement that honors Indigenous self-determination and the four directions of healing.

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Note: Additional references from the provided literature have been integrated throughout the document.