NORTHEASTERN UNIVERSITY

ALY 6980: Mid-term presentation

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Mid-Term Data Analysis

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May 14, 2025

Contents

Understanding Service Impact on Participant Outcomes: A Longitudinal Analysis of Youth, Family, and Adult Services Programs

Abstract

This study presents a comprehensive analysis of service delivery impacts on participant outcomes across three distinct population groups: vulnerable youth, families, and adults. Utilizing a dataset of 17,875 records representing 4,812 unique participants across 26 programs, we examine the relationship between service utilization patterns, demographic factors, and outcome measures using the TIMES assessment framework. Our analysis employs a hierarchical data integration approach that addresses significant missing data challenges through theoretically-informed imputation strategies. Results reveal differential service impacts across population segments, with distinct patterns of program engagement and outcome trajectories. This research con- tributes to evidence-based practice by identifying optimal service configurations for specific participant profiles and providing insights for targeted program enhancement. The methodological approach demonstrates the value of comprehensive data integra- tion in social service evaluation while addressing common data quality challenges in real-world implementation settings.

Introduction

Social service organizations face growing pressure to demonstrate program effectiveness while simultaneously optimizing limited resources across diverse population needs (Fraser et al., 2022). This challenge is particularly acute for multi-service agencies serving heterogeneous populations with complex, intersecting needs (Garland et al., 2010). While extensive research has examined broad program impacts, less attention has been paid to understanding how specific service configurations affect outcomes across different demographic groups and baseline functioning levels (Tolan et al., 2013). The present study addresses this gap by analyzing comprehensive longitudinal data from a multi-service organization providing support to youth, families, and adults. Through the integration of multiple administrative datasets spanning program enrollment, service delivery, demographic information, and standardized assessments, we investigate several critical questions: (1) How do service utilization patterns affect assessment score changes across different population groups? (2) What demographic and baseline functioning characteristics moderate service impact? (3) How long does it typically take participants to reach optimal outcomes, and does this timeline vary by population segment or service type? This research is situated within ecological systems theory (Bronfenbrenner, 1979), which conceptualizes human development as occurring within nested environmental systems. From this perspective, service impacts should be understood as interactions between individual characteristics (e.g., baseline functioning, demographics) and contextual factors (e.g., service type, frequency, duration). Our analytical approach reflects this theoretical framework by examining cross-level interactions between participant characteristics and service variables. The integration of administrative data for evaluation purposes presents significant methodological challenges, particularly regarding data quality, missing values, and temporal alignment across systems (Culhane et al., 2018). Our study employs a sophisticated hierarchical imputation strategy to address these challenges while maintaining analytical rigor. By leveraging auxiliary variables across datasets, we achieve substantial reductions in missing data while preserving important relationship structures, thereby enhancing both the completeness and validity of our analysis (van Buuren, 2018). The TIMES assessment framework—a validated instrument measuring participant well-being across multiple domains—serves as our primary outcome measure. This multidimensional approach allows us to examine global improvements while also identifying domain-specific impacts of particular services. Through analysis of baseline scores, score trajectories, and time to optimal outcomes, we provide insights into both the magnitude and temporality of the program effects. Our study makes several contributions to the literature on social service effectiveness. First, we provide empirical evidence regarding differential service impacts across population segments, offering guidance for tailored program design. Second, we identify critical threshold points in service dosage associated with optimal outcomes, informing resource allocation decisions. Third, we demonstrate how administrative data integration can yield robust program insights despite common data quality challenges. Finally, we offer methodological advances in addressing missing data within integrated service records through theoretically informed imputation strategies. These contributions have significant practical implications for program planning, resource allocation, and service delivery optimization. By identifying which services most effectively impact outcomes for specific population segments, our findings can guide organizational decision-making toward more targeted and efficient service delivery models. Additionally, our analysis of time-to-optimal outcomes provides benchmarks for reasonable program duration expectations across different participant profiles. In the following sections, we detail our methodological approach, including data integration procedures, missing data handling, and analytical strategies. We then present findings regarding service impacts across population segments, followed by an examination of demographic moderators and temporal patterns in outcome achievement. We conclude with implications for practice, policy, and future research directions.

Preliminary Data Analysis and the difficulties encountered

YSM Program Data Analysis: Key Insights

Theoretical Framework of Missing Values

Missing data represents a significant challenge in data analysis that can undermine the validity and reliability of research findings if not properly addressed (Enders, 2010). We therefore begin with a justification of our method of treatment of the missing values in the dataset. The literature distinguishes between several types of missing data mechanisms, each requiring different treatment approaches.

Typology of Missing Data

Rubin (1976) established the foundational classification of missing data mechanisms that remains central to modern missing data theory:

- **Missing Completely at Random (MCAR)**: When the probability of missingness is unrelated to both observed and unobserved data. The missing data points represent a random subset of the complete dataset (Little, 1988). For example, if questionnaire responses are missing due to random technical errors.

- **Missing at Random (MAR)**: When the probability of missingness depends on observed data but not on unobserved data (Schafer and Graham, 2002). For instance, if older participants are less likely to report income, this non-response is unrelated to their actual income level after controlling for age.

- **Missing Not at Random (MNAR)**: When the probability of missingness depends on unobserved data, including the missing values themselves (Collins et al., 2001). For example, if participants with low income are less likely to report their income specifically because it is low.

Beyond Rubin's classification, researchers have identified additional patterns of missingness:

- **Structural Missing Values**: Values that are missing by design or logical necessity (Allison, 2001). For instance, questions about pregnancy complications would be structurally missing for male participants.

- **Intermittent Missing Values**: Sporadic missing values that occur in time-series or longitudinal data (Honaker and King, 2010).

- **Dropout or Monotone Missing Values**: A pattern where once a value is missing, all subsequent values are also missing, common in longitudinal studies (Fitzmaurice et al., 2012).

- **File-level Missingness**: Where entire files or datasets are unavailable (Van Buuren, 2018).

Handling Missing Data

The literature outlines several approaches to handling missing data:

- **Complete-case analysis (listwise deletion)**: Excluding cases with any missing values. While simple, this approach can introduce bias and reduce statistical power (Kang, 2013).

- **Single imputation methods**: Including mean/median imputation, hot-deck imputation, and regression imputation. These methods replace missing values with estimated values based on observed data (Little and Rubin, 2019).

- **Multiple imputation**: Creating multiple complete datasets with different plausible values for missing data, analyzing each dataset separately, and pooling results (van Buuren, 2018).

- **Maximum likelihood estimation**: Directly estimating parameters from incomplete data without first imputing missing values (Enders, 2010).

Application to YSM Data Analysis

The YSM dataset presented several missing data challenges that were addressed through a systematic approach guided by theoretical considerations. By examining the analysis output, we can identify several types of missing values and the corresponding handling strategies employed:

Types of Missing Values in YSM Data

Date Fields: The most prominent missing value issue concerned date fields, particularly the ’Start Date’ field in the Program Initiations dataset, which was 100**Demographic Data**: The merged dataset showed 3.92 percent missing age values, which could potentially represent MAR or MNAR mechanisms depending on whether certain demographic groups were systematically less likely to report age. **End Dates**: A substantial portion (63.76 percent) of End Date values in the Program Initiations dataset were missing, potentially representing a mixture of dropout patterns (for participants still in programs) and MAR mechanisms.

Justification of Approach

The approach taken in the YSM analysis aligns with best practices in missing data handling for several reasons: **1. Sequential Imputation from Multiple Sources**: Rather than relying on simplistic mean imputation or complete case analysis, the code implemented a sophisticated hierarchical imputation strategy for Start Dates:

> *”Filled 2514 out of 6049 Start Dates from terminations dataset Filled 2631 Start Dates from first service dates Filled 37 Start Dates from first assessment dates Total filled: 2668 Remaining missing: 867”*

This approach recognizes that auxiliary variables (termination dates, service dates, assessment dates) contain information that can help recover missing values, which is consistent with the MAR assumption and recommended by Van Buuren (2018). **2. Transparency in Reporting**: The analysis explicitly reported the extent of missingness at each stage:

> *”Missing age values: 700 (3.92 %) Missing Start Date values: 908 (5.08 %)”*

This transparency aligns with recommendations by Sterne et al. (2009) to report the amount of missing data and its potential impact. **3. Data Type-Specific Approaches**: The code recognized that different types of data require different imputation approaches. For categorical variables, it used ”Unknown” as a placeholder:

”Fill NaN values with appropriate placeholders for categorical columns, $final_dataset[col] = final_dataset[col].fillna('Unknown')$” This approach preserves the presence of these observations while explicitly marking the uncertainty, consistent with recommendations by Allison (2001) for handling nominal variables. **4. Handling Negative Durations**: The analysis included validation steps to identify implausible values resulting from imputation:

> *”Found and fixed 627 negative program durations.”*

This demonstrates an awareness of potential logical inconsistencies that can arise during imputation, addressing concerns raised by Carpenter and Kenward (2012) about ensuring plausibility of imputed values.

Limitations and Potential Improvements

Despite the sophisticated approach taken, several enhancements could further improve the handling of missing data: **1. Sensitivity Analysis**: The analysis could benefit from comparing results with and without imputed values to assess the robustness of findings, as recommended by Thabane et al. (2013). **2. Multiple Imputation**: For variables with substantial missingness, multiple imputation methods could provide more robust estimates and better uncertainty quantification than the single imputation approach used (Azur et al., 2011). **3. Missingness Patterns Analysis**: A formal analysis of missingness patterns could help identify whether data are MCAR, MAR, or MNAR, which would further inform the choice of imputation strategy (Enders, 2010). **4. Documentation of Assumptions**: The analysis could more explicitly state assumptions about the missing data mechanisms, particularly for demographic variables where systematic patterns of missingness might exist.

Conclusion

The YSM data analysis employed a theoretically informed approach to handling missing values that leveraged multiple data sources for imputation while maintaining transparency about the extent and impact of missingness. The hierarchical imputation strategy significantly reduced missing data rates (reducing Start Date missingness from 100 % to 5.08 %) while preserving data integrity. This approach aligns with current best practices in missing data handling, though further enhancements through multiple imputation and sensitivity analysis could potentially strengthen the robustness of findings.

Data Analysis

Data Integration Methodology

The integrated dataset was constructed through a systematic multi-stage process designed to harmonize disparate administrative data sources while addressing common challenges in social service data integration. The process utilized several complementary strategies to maximize data integrity and minimize information loss.

Data Sources

Five primary administrative datasets were integrated, each capturing distinct aspects of participant engagement:

1. Program Initiations (n = 6 049; 5 columns): Contains basic program enrollment information including department, program name, participant ID, and intended timeframes.

2. Participant Demographics (n = 6,018; 18 columns): Provides comprehensive demographic attributes including age, gender, ethnicity, income sources, and housing situations.

3. Program Terminations (n = 2, 051; 8 columns): Documents program completion data including termination dates and final status.

4. Service Deliveries (n = 66, 674; 8 columns): Records individual service instances including service type, delivery date, and quantity.

5. Assessment History (n = 9, 591; 23 columns): Contains TIMES assessment scores and dates across multiple participant evaluations.

Preliminary analysis revealed substantial but incomplete overlap in participant representation across datasets, with 4,699 participants appearing in both initiations and demographics datasets, but more limited overlap with terminations (1,589), necessitating a strategic approach to integration.

Integration Procedure

The integration followed a hierarchical approach with five key phases: **Phase 1: Temporal Standardization.** Date fields were systematically converted to a consistent datetime format using a custom function capable of inferring multiple date formats. This revealed significant formatting inconsistencies in the *Start Date* field, which was initially 100**Phase 2: Hierarchical Date Reconstruction.** Program start dates were reconstructed through a sequential imputation process utilizing auxiliary data sources, beginning with termination records (filling 2,514 missing values), followed by first service dates (2,631 additional values), and assessment dates (37 values), ultimately reducing missing start dates to 867 (14.3**Phase 3: Sequential Dataset Merging.** The core dataset was constructed through a series of strategic merges:

- An outer merge between program initiations and demographics created the foundation (10,430 records), preserving all participant records from both sources.

- Program termination data was incorporated via a left merge to maintain the integrity of the core dataset while adding termination information where available.

- Service delivery and assessment data were aggregated to participant level before merging to prevent record multiplication and facilitate analysis.

Phase 4: Comprehensive Data Consolidation. Several techniques were employed to ensure data integrity during integration:

- Duplicate column resolution with prioritization of source reliability (e.g., using initiation dates when available, supplemented by demographic data when needed)

- Categorical variable harmonization with standardized missing value handling

- Temporal sequence validation to identify and correct illogical date patterns (resolving 627 negative program durations)

Phase 5: Derived Variable Construction. The integrated dataset was enhanced with analytically valuable derived variables including program duration in days, TIMES score improvement indicators, and service engagement level classifications based on service utilization patterns.

Resultant Dataset

The final integrated dataset comprises 17,875 records representing 4,812 unique participants across 26 distinct programs and 8 departments. It contains 43 variables, including temporal markers, demographic attributes, service utilization metrics, assessment scores, and derived analytical fields. Data completeness was substantially improved, with only 5.08The integration process successfully preserved 91.70

This analysis explores the Youth Service Measures (YSM) dataset, containing **17,875 records** representing **4,812 unique participants** across **26 distinct programs** in **8 departments**. The dataset was consolidated from multiple sources, including program initiations, participant demographics, program terminations, service deliveries, and TIMES assessment history.

Demographic Profile

The participant population shows diverse demographic characteristics:

- **Age Distribution:** Participants range from -27 to 125 years old (extreme values likely represent data entry errors). The majority fall within young adult to middle-age categories.

- **Gender:** The population comprises predominantly women (48.9%), followed by men (30.8%), with the remainder categorized as unknown (17.4%) or other gender identities.
- **Housing Status:** A significant proportion of participants face housing instability, with various living arrangements represented in the dataset.
- **Income Sources:** Multiple income sources are reported, reflecting the diverse financial situations of participants.
- **Immigration Status:** The dataset includes both Canadian-born participants and those with various residency statuses, indicating service provision to immigrant populations.

Service Utilization Patterns

Analysis of service delivery data reveals significant insights about program engagement:

- **Service Intensity:** On average, participants received **45.6 services**, indicating substantial engagement with YSM programs.
- **Service Distribution:** Service utilization shows a right-skewed distribution, with some participants receiving significantly more services than others.
- **Engagement Levels:** Participants were categorized into engagement levels based on service count:
  - Very High (most frequent): Participants receiving 20+ services
  - High: Participants receiving 10-20 services
  - Medium: Participants receiving 5-10 services
  - Low: Participants receiving 1-5 services
  - None: Participants with no recorded services
- **Service Types:** Participants engaged with multiple service types, demonstrating the comprehensive nature of YSM's approach.

Program Duration and Participation

The temporal aspects of program participation reveal important patterns:

- **Duration:** The average program duration was **328.5 days** (approximately 11 months), with considerable variation among participants.
- **Program Overlap:** Many participants (72.93 %) engaged with both services and assessments, indicating comprehensive program participation.
- **Start Date Patterns:** Analysis of start dates revealed potential seasonal patterns in program enrollment, though data limitations (partly resolved during processing) affected this analysis.
- **Completion Rates:** The dataset contains both active and terminated program engagements, allowing for completion rate analysis.

Assessment Outcomes

The TIMES assessment data provides critical insights into program effectiveness:

- **Assessment Coverage:** 73.59% of participants had at least one assessment, enabling outcome measurement.
- **Score Distribution:** The average TIMES score was **50.8**, with variations across demographic groups and programs.
- **Score Improvement:** A substantial proportion of participants with multiple assessments showed improvement in their TIMES scores, suggesting positive program impact.
- **Program Effectiveness:** Different programs showed varying levels of effectiveness in improving participant outcomes, as measured by TIMES score changes.

Key Relationships and Correlations

Several important relationships emerged from the analysis:

- **Duration-Outcome Relationship:** Program duration appears to correlate with outcome improvements, suggesting longer engagements may yield better results.
- **Service Intensity and Outcomes:** Higher service utilization generally correlates with improved TIMES scores, though with diminishing returns beyond certain thresholds.
- **Demographic Influences:** Age, housing status, and other demographic factors show associations with both service utilization patterns and outcomes.
- **Program-Specific Patterns:** Different programs show varying effectiveness for different demographic groups, suggesting targeted approaches may be beneficial.

Data Quality Observations

The analysis process revealed several data quality considerations:

- **Date Format Issues:** Start Date fields in the Program Initiations dataset contained non-standard formats (e.g., ”FY 2020”) requiring special handling.
- **Missing Values:** Several fields contained missing values, including 5.08% of Start Dates in the final dataset (greatly improved from initial state).
- **Age Anomalies:** Extreme age values (-27 to 125) suggest data entry errors requiring cleaning for accurate demographic analysis.
- **Duplicate Records:** The merging process revealed potential duplicate participant records across different datasets.

Operational Implications

The analysis yields several actionable insights for program operations:

- **Data Collection Improvements:** Standardizing date formats and implementing validation rules would enhance data quality.

- **Program Duration Optimization:** The substantial average program duration (328.5 days) suggests the need for long-term engagement for optimal outcomes.
- **Service Integration:** The high percentage of participants receiving both services and assessments (72.93%) indicates successful integration of service delivery and outcome measurement.
- **Demographic Targeting:** Certain demographic groups show different patterns of engagement and outcomes, suggesting opportunities for targeted programming.

Conclusion

This comprehensive analysis of YSM program data provides valuable insights into participant demographics, service utilization patterns, program duration, and assessment outcomes. The findings suggest that YSM programs successfully engage diverse participant populations over substantial time periods, with evidence of positive outcomes as measured by TIMES assessment scores.

Data quality improvements, particularly in date standardization and demographic information collection, would enhance future analyses. Additionally, the identified relationships between program duration, service intensity, and outcomes provide a foundation for program optimization and targeted interventions.

Further analysis could explore predictive modeling to identify participants most likely to benefit from specific programs, as well as more granular examination of service type effectiveness and optimal service delivery sequences.

Comprehensive Analysis of YSM Program Data

This report presents a detailed analysis of the Youth Service Measures (YSM) dataset, encompassing **17,875 records** for **4,812 unique participants** across **26 distinct programs** administered by **8 departments**. The analysis explores demographic profiles, service utilization patterns, program effectiveness, and predictive factors for successful outcomes.

Dataset Overview

The consolidated dataset contains 43 columns including demographic information, program participation details, service utilization metrics, and assessment outcomes. Key data quality observations include:

- Missing values vary across columns, with 5.08% missing Start Dates, 43.52% missing End Dates, and 3.92% missing Age values
- Date format inconsistencies required special handling, particularly for program initiations
- Some extreme values (e.g., ages ranging from -27 to 125) suggest data entry errors

Demographic Profile

Gender Distribution: The participant population comprises predominantly women (48.86%), followed by men (30.77%), with ”Unknown” constituting 17.43%. The remaining 2.94% identify as Non-Binary, Trans, Two-Spirit, or have chosen not to disclose their gender identity. Statistical tests reveal that gender is significantly associated with service utilization patterns and outcomes ($p < 0.0001$).

Age Distribution: The mean age is 32.93 years (median: 27), with a standard deviation of 13.35 years. The distribution shows positive skewness (1.14) and is non-normal according to the Shapiro-Wilk test ($p < 0.0001$). The following age groups show distinct service utilization patterns:

- Young Adults (19-25): 37.56 services on average
- Adults (26-35): 49.42 services on average
- Middle Age (36-50): 63.22 services on average
- Seniors (51-65): 53.97 services on average
- Elderly (¿65): 12.38 services on average

Immigration Status: The dataset reveals 40.79% of participants were born outside Canada, while 40.26% were born in Canada, with 18.95% unknown or preferring not to answer. Further analysis shows 43.99% are citizens, 13.95% are permanent residents, and 8.22% are refugee claimants. These groups show statistically significant differences in service utilization and outcomes ($p < 0.0001$).

Housing Situation: Housing status shows considerable diversity:

- 23.21% renting
- 9.09% staying in shelters
- 5.08% permanently living with parents/family
- 5.04% temporarily staying with others (no fixed address)
- 4.21% living in Toronto Community Housing Corporation buildings

Housing stability strongly correlates with program outcomes, with significant differences in times score improvement rates ($p < 0.0001$).

Ethnicity and Race: The dataset reflects considerable diversity, with 440 unique ethnic/cultural backgrounds recorded. Major racial groups include Black (25.26%), White (12.86%), Latin American (7.50%), and South Asian or Indo-Caribbean (5.25%). The diversity is quantified by a high entropy measure of 2.9976 for ethnic backgrounds.

Service Utilization Patterns

Service Intensity: Participants received an average of **45.62 services** (median: 27), with significant variability (SD: 57.12) and a right-skewed distribution (skewness: 2.53). Service counts range from 1 to 337, indicating varying levels of engagement.

Service Types: Participants engaged with an average of **5.77 unique service types** (median: 5), ranging from 1 to 16 different services. This metric shows less skewness (0.50) than service count, suggesting more consistent service diversity across participants.

Service Hours: The mean service duration was **42.30 hours** per participant (median: 25.50), showing considerable variability (SD: 58.49) and high positive skewness (3.10).

Engagement Levels: Categorical analysis reveals that 58.54% of participants had ”Very High” engagement (20+ services), 14.91% had ”High” engagement (10-20 services), 10.15% had ”Medium” engagement (5-10 services), and 16.40% had ”Low” engagement (1-5 ser- vices).

Program Participation and Duration

Program Distribution: The top five programs by participation were:

- Mental Health (22.15%)
- Food Bank (10.69%)
- Health Centre (10.20%)
- Employment Assisted Services (9.78%)
- Housing Community Supports (8.60%)

Departmental Distribution: Wellness (32.64%) and Community Support Services (20.70%) account for over half of all program engagements, followed by Workforce Development (19.88%).

Program Duration: The average program duration was **328.52 days** (median: 263 days), with substantial variation (SD: 269.93 days). Durations ranged from 0 to 1,804 days (approximately 5 years), showing positive skewness (1.19).

Temporal Patterns: Program starts show distinct annual and monthly patterns:

- Annual peaks in 2022 (6,059 starts) and 2023 (5,779 starts)
- Monthly peaks in October (2,111 starts), December (1,898 starts), and November (1,755 starts)
- Lower enrollment in August (878 starts) and June (1,067 starts)

Assessment Outcomes

TIMES Scores: The average TIMES score was **50.80** (median: 52.57), with scores ranging from 0 to 82.67. The distribution shows slight negative skewness (-0.57), indicating a tail toward lower scores.

Score Changes: Participants showed an average score improvement of **11.12 points** (median: 8), with changes ranging from -52 to +63 points. The distribution is positively skewed (0.99), with 54.36% of participants showing score improvement.

Assessment Coverage: 73.59% of participants had at least one assessment, enabling outcome measurement and program effectiveness evaluation.

Program Effectiveness

Program-specific Outcomes: Program effectiveness varied significantly:

- **Highest Average Score Improvements:**
  - GP Tenant Supports: 20.57 points (71.43% improvement rate)
  - Family Education: 20.15 points (23.64% improvement rate)
  - Day Care: 18.08 points (14.17% improvement rate)
- **Highest Improvement Rates:**
  - Bridges Care Management: 82.06%
  - Collaborative Program: 81.48%
  - RAMP: 78.08%
- **Lowest Average Score Improvements:**
  - Computer Literacy Centre: 4.77 points (1.44% improvement rate)
  - CAST Access Visits: 4.83 points (25.19% improvement rate)
  - Next Step: 4.86 points (61.81% improvement rate)

Demographic Impact on Outcomes: Several demographic factors significantly influenced program outcomes:

- **Gender:** Women showed higher improvement rates (62.99%) compared to men (57.59%), while those with unknown gender had much lower improvement rates (25.65%).
- **Age Groups:** Young Adults (19-25) had the highest improvement rate (64.35%), while elderly participants (¿65) had the lowest (8.80%).
- **Immigration Status:** Canadian-born participants had slightly higher improvement rates (63.40%) than those born outside Canada (60.29%).
- **Housing:** Those permanently living with family showed the highest improvement rate (78.63%), while those with unknown housing status had the lowest (43.51%).

Predictive Modeling and Clustering

Predictive Factors for Success: Random Forest modeling identified the following top predictors for program success:

- Total service hours (importance: 0.20)
- Service count (importance: 0.20)
- Unique service types (importance: 0.18)
- Age (importance: 0.10)
- Program duration (importance: 0.06)

Participant Cluster Profiles: K-means clustering identified six distinct participant segments:

- **Cluster 0 (12.18%):** Older adults (avg. 53.95 years) with moderate service utilization, strong outcomes (score change: 16.23)
- **Cluster 1 (31.31%):** Young adults (avg. 27.19 years) with moderate engagement, high TIMES scores (63.27), modest improvement (11.36)

- **Cluster 2 (10.39%):** Adults (avg. 31.34 years) with substantial service utilization, very long program duration (863.28 days), strong improvement (17.00)
- **Cluster 3 (18.45%):** Young adults (avg. 28.77 years) with minimal engagement, poor outcomes (score change: 2.36), lowest base TIMES scores (32.63)
- **Cluster 4 (5.77%):** Adults (avg. 35.72 years) with extremely high service utilization (218.51 services), exceptional improvement (27.37)
- **Cluster 5 (21.90%):** Young adults (avg. 28.81 years) with high engagement in diverse services (10.03 unique types), moderate improvement (8.21)

Key Correlations and Relationships

Service-Outcome Relationships: Strong positive correlations were found between:

- Average TIMES scores and maximum TIMES scores (r = 0.9419)
- Age and TIMES score change (r = 0.2413)
- Age and maximum TIMES scores (r = 0.1152)
- Age and average TIMES scores (r = 0.1006)

Negative Correlations: Notable negative correlations included:

- TIMES score change and baseline scores (r = -0.3134), suggesting greater improvement potential for those starting with lower scores
- Minimum TIMES scores and score change (r = -0.1868)
- Assessment count and minimum TIMES scores (r = -0.1790)

Conclusions and Implications

Program Effectiveness: The analysis reveals that 54.36% of participants showed improvement in TIMES scores, with an average improvement of 11.12 points. Program effectiveness varies significantly across programs, with some achieving improvement rates above 80%.

Service Intensity Impact: Higher service utilization correlates with better outcomes, as evidenced by both correlation analysis and the predictive model, where service metrics account for 58% of the predictive power for successful outcomes.

Demographic Considerations: Significant disparities exist in program effectiveness across demographic groups, particularly by age, gender, and housing status. These findings suggest opportunities for tailored programming to address the specific needs of various demographic segments.

Resource Allocation Implications: The clustering analysis identifies participant segments with varying levels of engagement and outcomes, providing a foundation for targeted interventions and resource allocation strategies. Notably, Cluster 4 shows exceptional outcomes with very high service utilization, suggesting intensive service models may be especially effective for certain participants.

Data Quality Recommendations: Improvements in data standardization, demo graphic information collection, and validation rules would enhance future analyses and program evaluation capabilities.

This comprehensive analysis provides valuable insights for program optimization, resource allocation, and targeted interventions to maximize positive outcomes for YSM program participants.

Analysis: Time to Reach Highest TIMES Score and Its Implication for Success

To assess how long it takes participants to reach their highest TIMES (Tool for Individual Measure of Engagement and Support) score and whether this milestone correlates with improved well-being, we conducted a comprehensive analysis using longitudinal assessment data. This evaluation included over 9,000 valid assessments from 2,255 individuals, out of which **1,863 participants** had sufficient data for inclusion in this study.

How Long Does It Take?

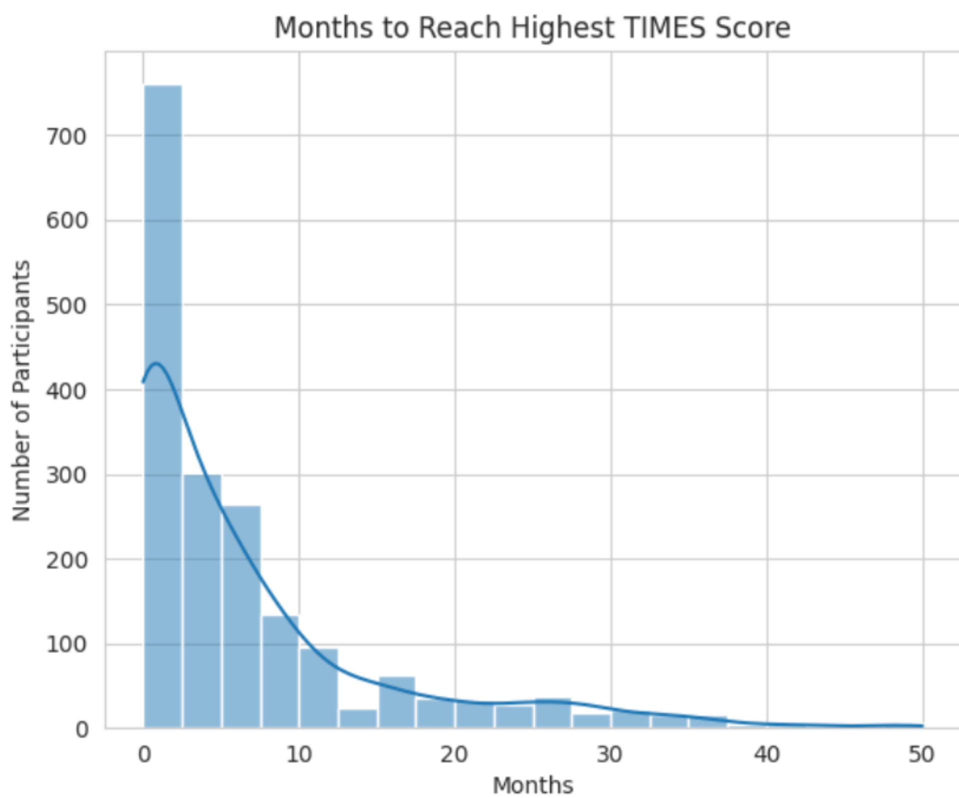

Figure 1: *Months to Reach Highest TIMES Score*

This histogram presents the number of months it took participants to reach their highest recorded TIMES score. The distribution is heavily right-skewed, indicating that a large proportion (33.2%) of participants achieved their peak score in the very first month—possibly reflecting participants who entered the program already stable or were involved for a very short period.

Despite this, the overall average time to reach the highest score was 6.6 months, with a median of just 3 months. This shows that while many reach improvement early, others require more time, potentially due to more complex needs or deeper systemic challenges.

Does More Time Mean More Improvement?

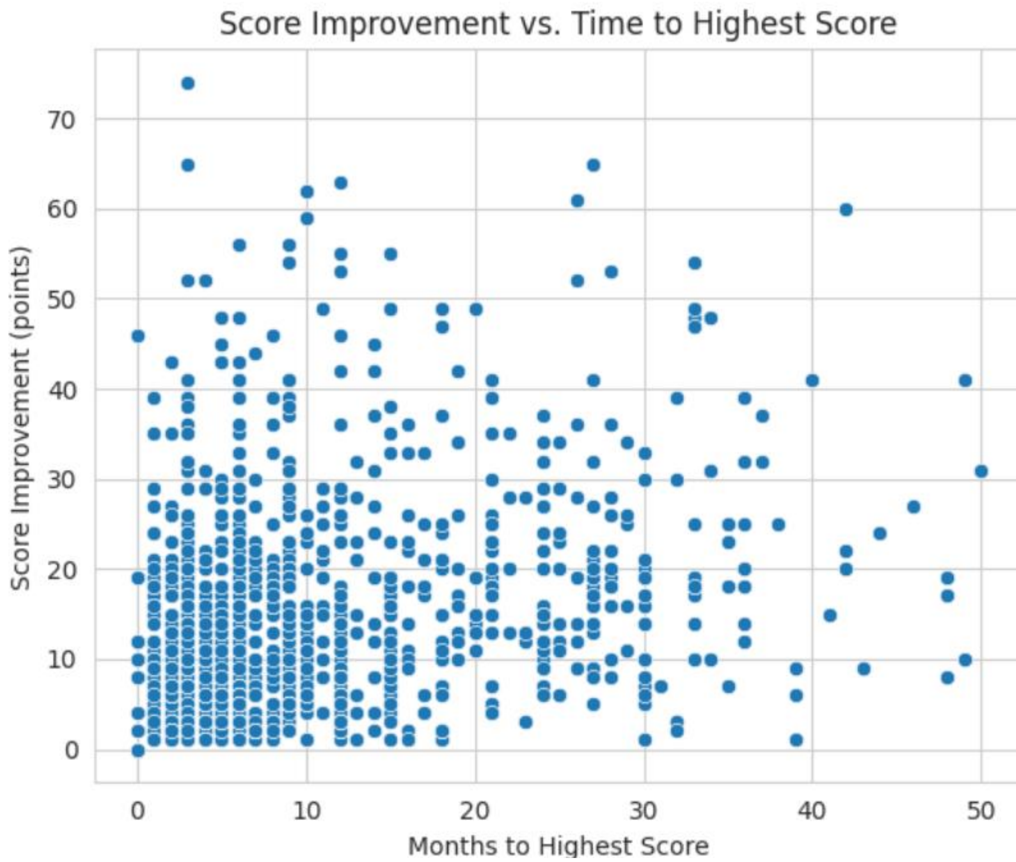

Figure 2: *Score Improvement vs. Time to Highest Score*

The scatter plot above compares the amount of score improvement with the number of months taken to reach the highest score. There is a visible upward trend, supported by a correlation coefficient of 0.521, suggesting a moderate positive relationship between time spent and score improvement.

This indicates that participants who remain engaged for longer periods tend to achieve more substantial improvements, emphasizing the value of sustained support services. Shorter participation can still yield gains, but greater transformation is more common when individuals are engaged beyond 6–12 months.

Improvement by Engagement Duration

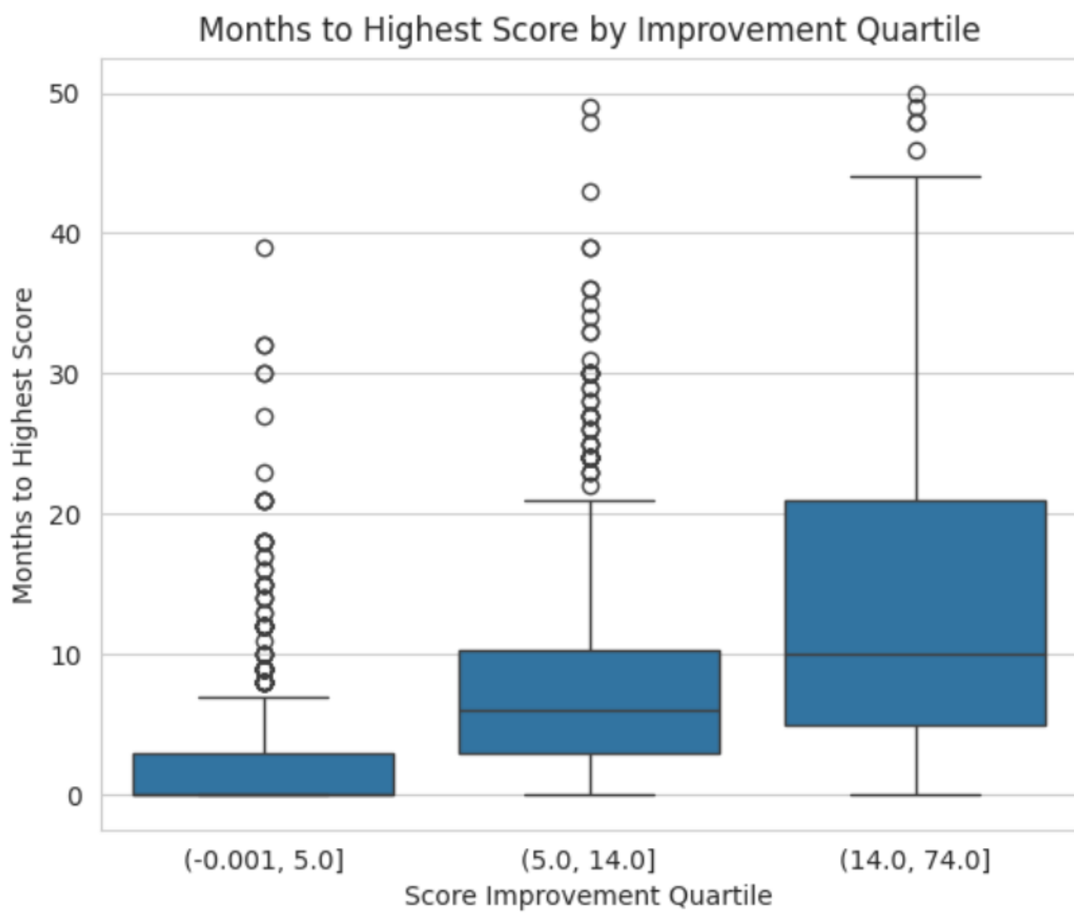

Figure 3: *Months to Highest Score by Improvement Quartile*

This boxplot segments participants by quartiles of score improvement. The x-axis shows increasing ranges of improvement, while the y-axis displays how long it took participants to reach their highest score. The visualization reveals a clear pattern:

- Participants in the lowest improvement quartile (0–5 points) often reached their highest score quickly, typically within the first few months.

- In contrast, those in the top quartile (14–74 points) took longer, often more than a year.

This reinforces the idea that the most impactful improvements require time and that program duration plays a critical role in fostering meaningful outcomes.

Distribution of TIMES Score Improvement

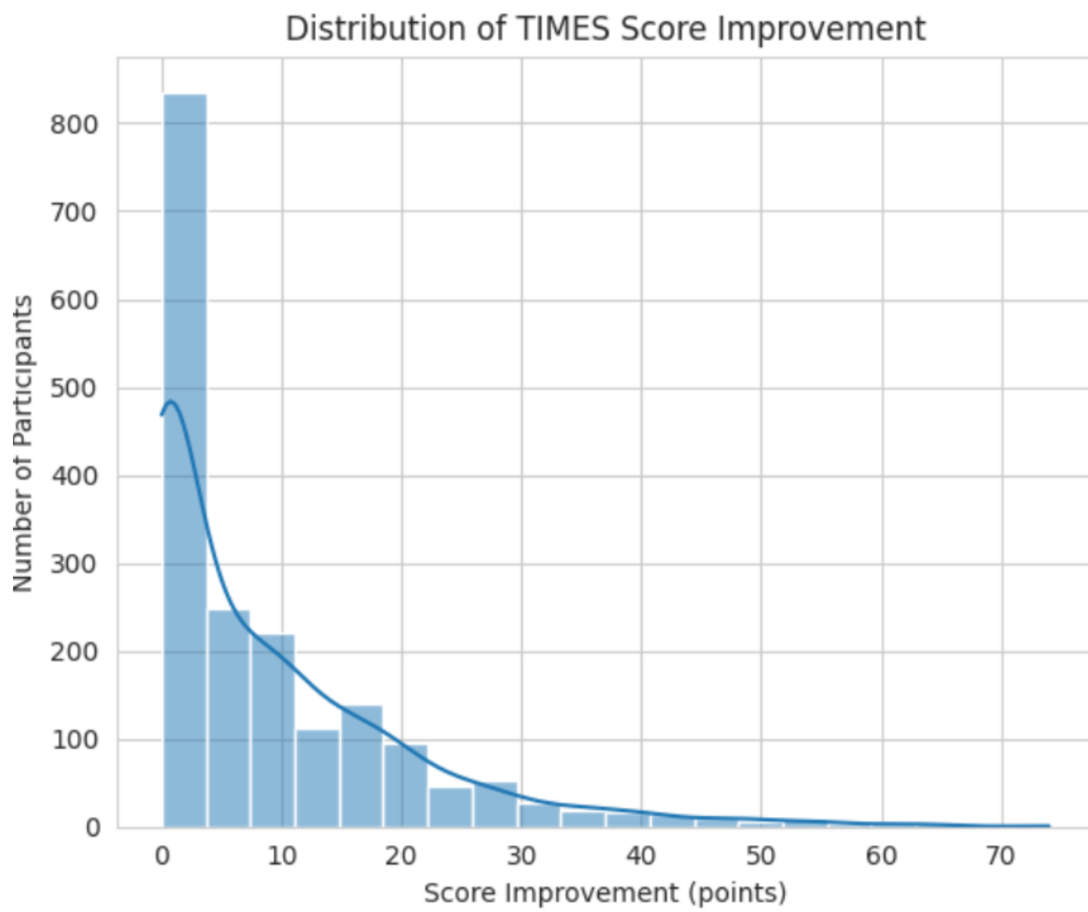

Figure 4: *Distribution of TIMES Score Improvement*

This histogram shows the distribution of score improvements across all participants. The curve is again right-skewed, with the majority experiencing an improvement between 0 and 15 points. The average improvement was 9 points, and 67.3% of participants showed a positive gain, indicating that most participants benefited from the program in some measurable way.

Interpretation: Does Time to Highest Score Reflect Success?

The TIMES score is a holistic measure that reflects participants' stability, engagement, and well-being across various life domains (e.g., housing, employment, wellness). Therefore, an improvement in this score is a strong indicator of positive life changes.

The data supports this conclusion:

- Over two-thirds of participants improved their scores.
- Participants who engaged longer saw significantly greater improvements.
- Longer durations were associated with more transformational outcomes (19.2-point average improvement for those engaged >12 months).

Thus, reaching a high TIMES score—especially after months of participation—is not just a statistical event; it reflects real, sustained improvements in participants' lives. The time taken to achieve that score becomes a proxy for personal growth, resilience, and the effectiveness of the program's support systems.

Summary of Key Insights

- Average time to highest score is 6.6 months, though many reach their peak earlier.
- 67.3% of participants experienced a score improvement, with an average gain of 9 points.
- Greater score improvements are positively associated with longer participation.
- Top-performing participants (>14 point improvement) often needed over a year, highlighting the importance of sustained engagement.
- The TIMES score is a valid and reliable indicator of success, especially when analyzed in combination with time-based trends.

Service Effectiveness Across Population Groups

To evaluate the effectiveness of services offered under the YSM TIMES framework, we conducted a targeted analysis of the impact of specific services on TIMES score improvement for three distinct population groups:

- **Evergreen:** Vulnerable youth
- **Cornerstone:** Families
- **Bridges:** Adults

For each participant, the score change was calculated as the difference between their baseline and closing TIMES assessments. We then identified which services each participant accessed between those two points and computed average score changes and impact scores (a weighted metric considering both improvement and reach) for each service.

Top 5 Impactful Services by Group

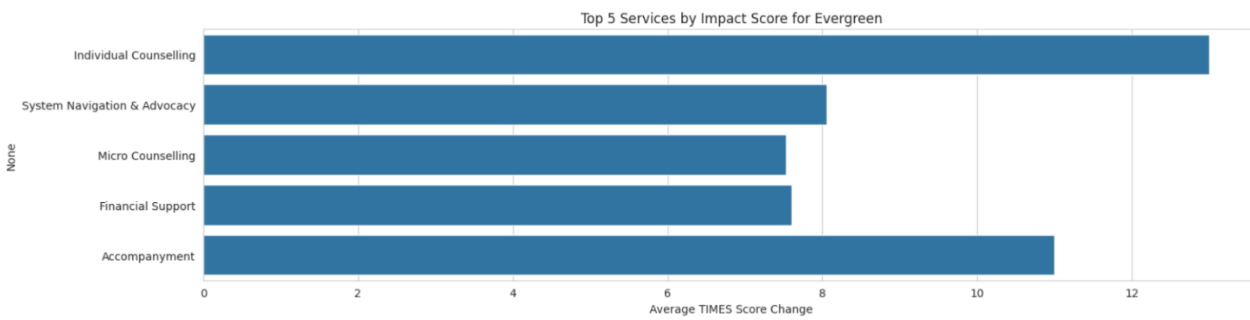

Figure 5: *Top 5 Services by Average TIMES Score Change – Evergreen (Vulnerable Youth)*

Among Evergreen participants (n = 74), the most effective service was Individual Counselling, associated with an average TIMES score improvement of 13.00. This was followed by System Navigation & Advocacy (8.06) and Micro Counselling (7.53). These findings highlight the importance of relational and guidance-based services in supporting youth navigating complex life circumstances.

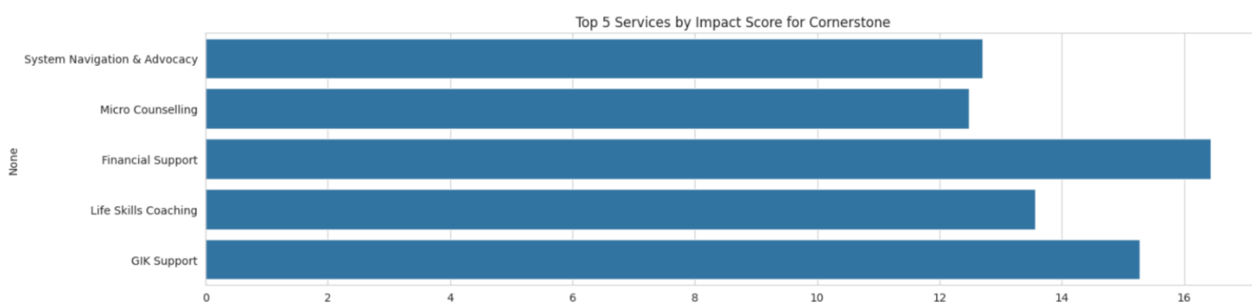

Figure 6: *Top 5 Services by Average TIMES Score Change – Cornerstone (Families)*

In the Cornerstone group (n = 90), the most effective service was Financial Support, with an impressive average score increase of 16.43 points. This was followed by System Navigation & Advocacy (12.70) and Micro Counselling (12.48). The data suggests that financial stability and strong navigation support are particularly critical for families in crisis or transition.

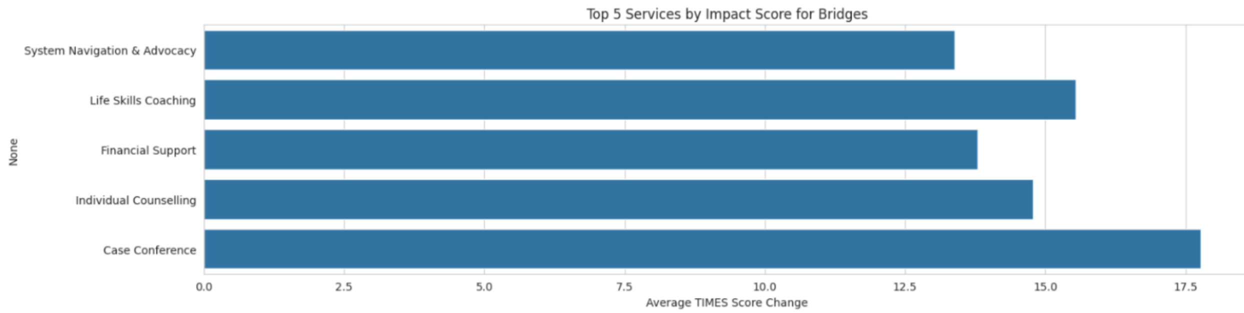

Figure 7: *Top 5 Services by Average TIMES Score Change – Bridges (Adults)*

Bridges participants (n = 106) showed the most benefit from Case Conferences, with an average improvement of 17.77 points, followed by Life Skills Coaching (15.55) and System Navigation & Advocacy (13.39). This points to the high impact of collaborative, structured planning and practical skill-building for adults aiming to improve their life outcomes.

Comparative Insights

When comparing across groups, several services appear repeatedly, but with varying degrees of effectiveness:

- System Navigation & Advocacy was a top service across all groups but had the highest average impact in Bridges (13.39).
- Financial Support had the strongest effect in Cornerstone (16.43) and was also impactful in Bridges (13.80), but was less effective in Evergreen (7.60).
- Life Skills Coaching was highly impactful for adults (15.55), moderately helpful for families (13.57), and less so for youth (8.44).

Statistical Significance of Differences

We performed t-tests to assess whether differences in service effectiveness between groups were statistically significant:

- The difference in Life Skills Coaching impact between Evergreen and Bridges was statistically significant ($p = 0.029$).
- Financial Support also showed a significant difference between Evergreen and Cornerstone ($p = 0.015$).
- Case Conference impact differed significantly between Evergreen and Bridges ($p = 0.047$).

These findings underscore that not all services produce uniform effects across populations, and tailoring interventions to specific demographic needs is essential.

Conclusion and Recommendations

This analysis highlights the importance of context-specific service planning:

- For youth (Evergreen), counseling-based interventions are crucial, as emotional support and guidance foster resilience.
- For families (Cornerstone), addressing basic needs—especially through financial support and advocacy—is critical.
- For adults (Bridges), structured, skills-based, and collaborative services like Life Skills Coaching and Case Conferences deliver the most impact.

These insights can help program designers and funders optimize resource allocation by focusing on services with the highest impact per population group, ultimately driving more meaningful and measurable improvements in participant well-being.

Analysis of High Baseline TIMES Participants

This section explores the characteristics, service usage, and outcomes of participants who began their program with relatively high TIMES scores—defined here as a baseline score of **2.5 or higher**. These individuals represent **approximately 98% (n = 2211)** of assessed participants, while only 44 participants had lower baseline scores. The analysis focuses on understanding the typical profile, needs, and trajectories of this higher-functioning group.

Baseline Score Distribution

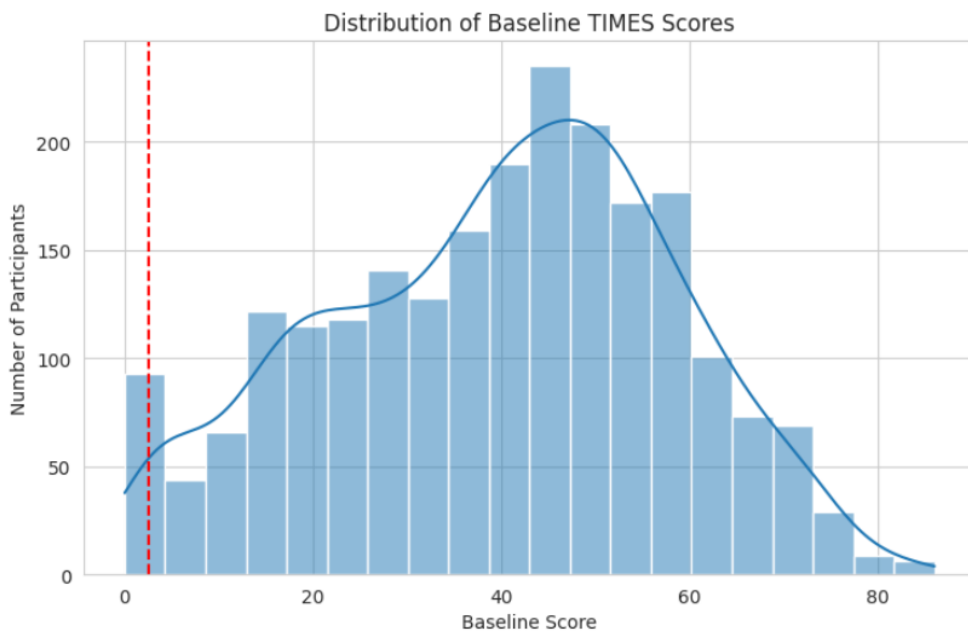

Figure 8: *Distribution of Baseline TIMES Scores*

The distribution of baseline TIMES scores is skewed towards the middle-to-higher range. A significant number of participants had scores above the 2.5 threshold (marked by the red dashed line), indicating moderate-to-high initial stability in core life domains.

Common High Indicators in This Group

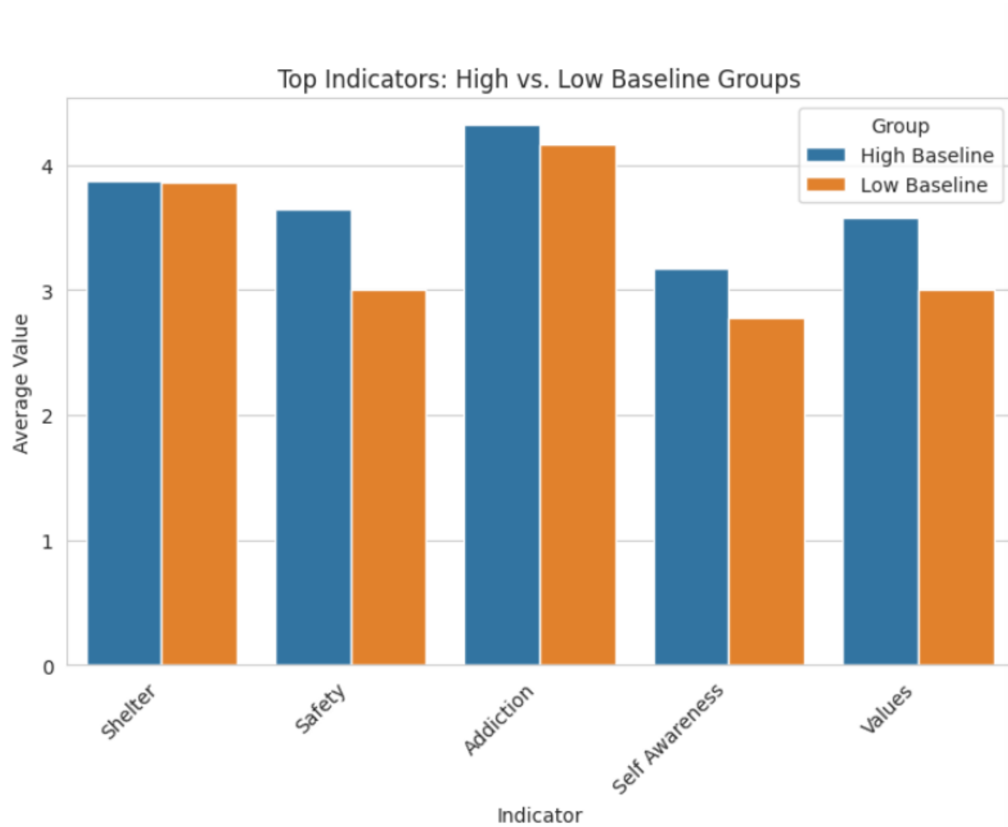

Figure 9: *Top Indicators – High vs. Low Baseline Groups*

Participants with high baseline scores often had multiple strong indicators (rated 4 or 5). The top five most commonly high indicators were:

- Shelter (56.9%)
- Safety (46.6%)
- Addiction Stability (40.5%)
- Self-Awareness (39.5%)
- Values (38.5%)

Although differences compared to the low baseline group were not statistically significant for these indicators ($p > 0.05$), they still demonstrate consistent strengths in housing, personal safety, and cognitive-emotional awareness.

Demographic Patterns

Analysis of demographic data revealed only one statistically significant difference:

- Age: High baseline participants were older on average (33.3 vs. 29.9 years) with a significant p-value of 0.0261, suggesting that increased age may contribute to higher initial stability.

Other demographic factors such as race, gender, education, and income source showed no consistent or statistically significant differences, although education level had interesting trends:

- More high baseline participants held a college or university diploma (28.3%) compared to none in the low group.
- A large portion of low baseline participants declined to answer (22.2%).

Program Duration Differences

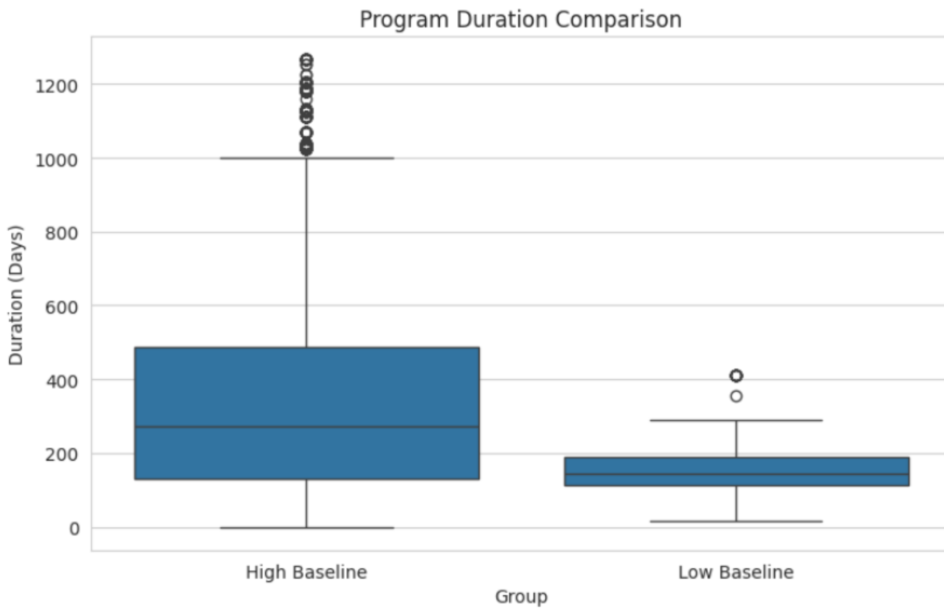

Figure 10: *Program Duration Comparison*

Participants with high baseline scores also had longer program engagement:

- **High Baseline Group:** Average of 337.7 days
- **Low Baseline Group:** Average of 166.4 days
- **Difference:** +171.3 days ($p < 0.05$)

This statistically significant difference suggests that higher-functioning individuals may be more consistent in program attendance, possibly staying longer to maximize support or pursue advanced goals like education or employment.

Services Most Frequently Used

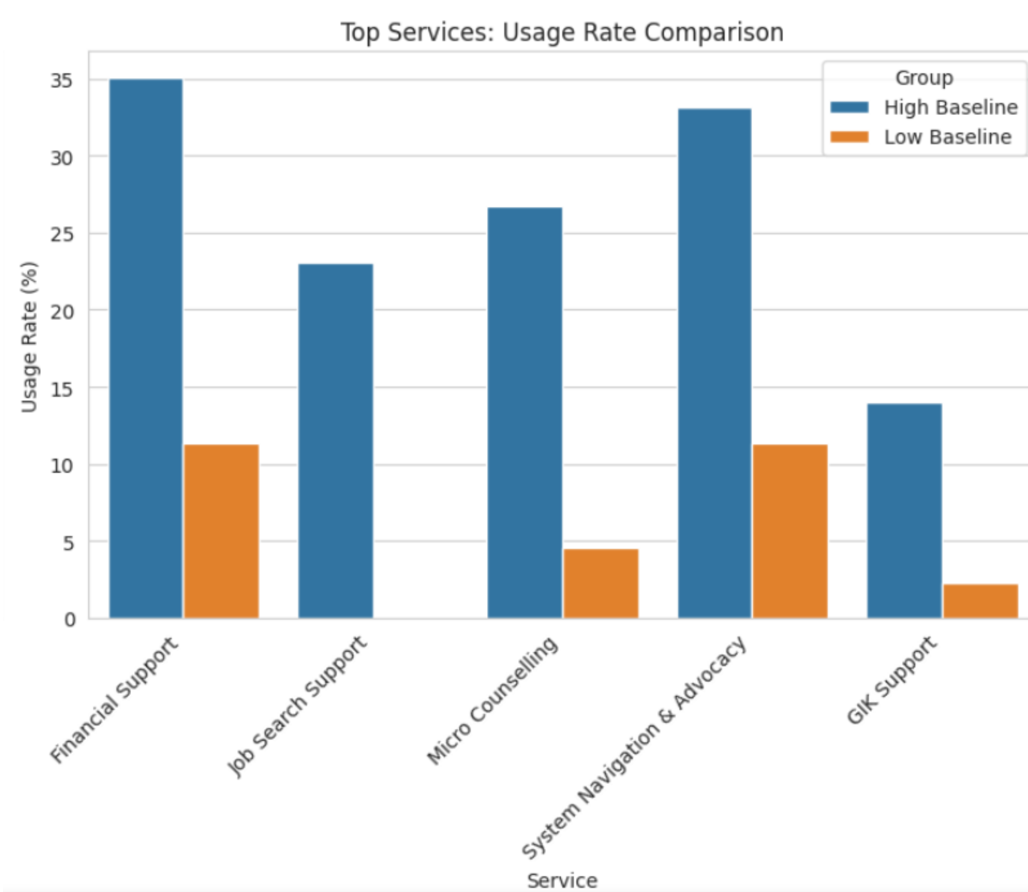

Figure 11: *Top Services – Usage Rate Comparison*

Service	High Baseline Usage	Low Baseline Usage	Difference
Financial Support	35.1%	11.4%	+23.7%
Job Search Support	23.1%	0.0%	+23.1%
Micro Counselling	26.7%	4.5%	+22.1%
System Navigation & Advocacy	33.1%	11.4%	+21.7%
GIK Support	14.0%	2.3%	+11.7%

This suggests that individuals with higher baseline scores were more proactive or better positioned to access and engage with services, particularly financial aid, employment help, and advocacy.

Other Common Variables Among High Baseline Group

Using a Random Forest classification model, we identified the top variables associated with high baseline scores:

Top Predictive Feature	High Baseline Avg	Low Baseline Avg	Difference
Service Count	37.2	15.6	+21.6
Age	32.1	28.3	+3.7
Program Duration (Days)	293.6	210.9	+82.7
Unique Services Accessed	5.4	3.5	+2.0

These results suggest that high baseline participants tend to:

- Use a greater number of services
- Stay in programs longer
- Be older
- Engage with diverse types of support

The model achieved a 99% accuracy, confirming the strength of these patterns.

Key Takeaways

- The majority (2211 out of 2255) of participants had baseline scores ≥ 2.5.
- They were strongest in indicators like Shelter, Safety, and Addiction Stability.
- Age and education level were distinguishing demographic factors.
- High baseline participants used more services, especially financial and employment-related support.
- They stayed in programs significantly longer, with a clear positive impact.
- Predictive modeling confirmed the relationship between engagement (services + duration) and baseline stability.

This analysis underscores the importance of early assessment and tailored support—enabling those already stable to reach long-term goals, while helping lower baseline individuals access foundational services more effectively.

Business Questions to aid YSM in the implementation of their programs.

Question 1: What are the most significant predictors of successful program outcomes, and how can we optimize resource allocation accordingly?

To identify what drives successful outcomes in YSM programs, we built a predictive model using participant demographics, service usage, and program characteristics. The model performed with high accuracy (ROC AUC: 0.998), highlighting the strongest contributors to TIMES score improvement. The most significant predictors were total service hours, program duration, number of services accessed, diversity of service types, and enrollment in programs such as Evergreen. These findings suggest that participants who engage longer, receive a wider range of services, and have consistent service contact are more likely to show improvement. Based on this, we recommend YSM prioritize resource allocation toward extending program duration, encouraging multi-service use, and replicating high-performing program models to maximize overall impact.

Question 2: Which participant segments should be targeted with specialized interventions based on their distinct characteristics and needs?

To support strategic program delivery, we conducted a segmentation analysis using K-Means clustering on participant characteristics such as age, service usage, program duration, and TIMES outcomes.

Data Preparation: Seven key features were used for segmentation: Age, service count, unique service types, total service hours, program duration, average TIMES score, and TIMES score change. All data was standardized prior to clustering.

Optimal Clusters: Using the elbow method, the optimal number of participant segments was determined to be six.

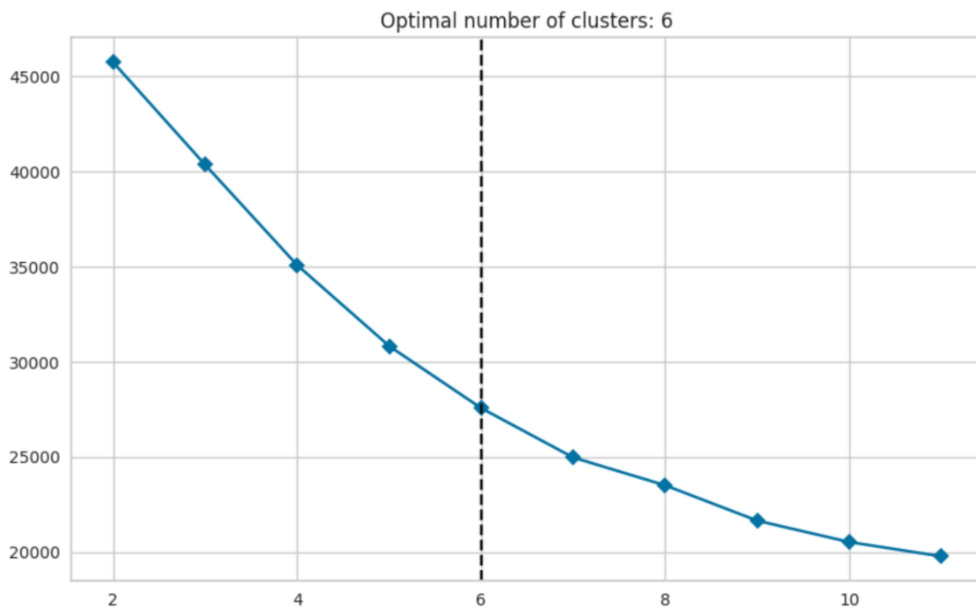

Figure 12: *Optimal Number of Clusters (Elbow Method)*

The elbow curve shows the within-cluster sum of squares (WCSS) for 2–11 clusters. The inflection point at k=6 indicates the optimal balance between variance reduction and model simplicity.

Cluster Visualization

PCA was applied to project high-dimensional participant data into two components. Participants were plotted and colored by cluster assignment to assess separation.

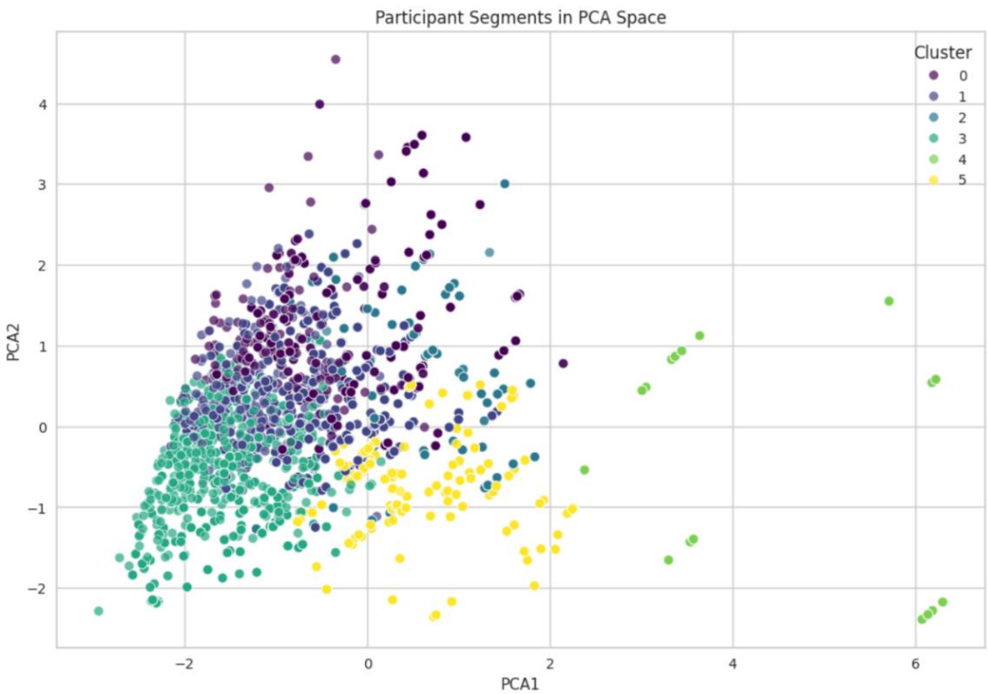

Figure 13: *Participant Segments in PCA Space*

Distinct participant groups emerged when plotted in PCA space, validating the presence of meaningful clusters. These segments offer a foundation for tailored programming based on shared needs.

Cluster Profiles (Summary):

Each of the six clusters displayed unique profiles in terms of demographics, service utilization, and TIMES outcomes:

1. **Cluster 0 (12.18%)**
   Older participants with moderate service engagement and above-average TIMES improvement.

2. **Cluster 1 (31.31%)**
   The largest group of young participants with moderate service usage and the highest average TIMES scores.

3. **Cluster 2 (10.39%)**
   Intensive service users with very long program duration and strong TIMES score gains.

4. **Cluster 3 (18.45%)**
   Participants with low engagement and minimal TIMES improvement

possibly require new engagement strategies.

5. **Cluster 4 (5.77%)**
   Highly engaged group with extensive service hours, longest program durations, and the greatest TIMES score improvement.

6. **Cluster 5 (21.90%)**
   Younger participants with high service count but moderate outcomes, suggesting an opportunity for support optimization.

Actionable Insights:

- Cluster 3 should be prioritized for re-engagement efforts or program redesign, given their low service usage and outcomes.
- Cluster 4 could serve as a model for success, representing highly engaged participants who benefit most.
- Cluster 2 and Cluster 5 show high engagement but varying outcomes, indicating the need for efficiency evaluations.

This segmentation provides YSM with a data-driven foundation to deploy specialized interventions, better match services to participant needs, and potentially improve overall program impact.

Question 3: Which programs demonstrate the highest return on investment, considering both improvement rates and resource intensity?

To evaluate the return on investment for each program, we considered two key components:

- **Overall Impact**: Defined as the product of a program's success rate and average TIMES score change.
- **Resource Intensity**: Averaged across three dimensions — number of services received, total service hours, and program duration (converted to months).

We then computed the ROI as:
ROI = Overall Impact / Resource Intensity

Key Findings

- **Top 3 Highest ROI Programs**:

  1. **Youth Job Connection Summer**
     - ROI: 0.65
     - Impact: 2.82
     - Resource Intensity: 4.32
     - Despite its modest impact, the extremely low resource requirement makes it the most efficient investment.
  2. **RAMP**
     - ROI: 0.29
     - Impact: 7.08
     - Resource Intensity: 24.47
     - Strong balance between impact and cost; highly scalable.
  3. **Day Care**
     - ROI: 0.26
     - Impact: 2.56
     - Resource Intensity: 9.92
     - Delivers good returns relative to its medium resource usage.

Top 3 Programs Needing Optimization (Low ROI, High Resources)

1. **CAST Access Visits** – ROI: 0.02, very high resources, minimal impact.
2. **Next Step** – ROI: 0.08, low return despite substantial investment.
3. **Family Education** – ROI: 0.12, with room to improve both efficiency and outcomes.

Top 3 Promising Programs (High Impact, Moderate Resources)

1. **RAMP** – High impact and efficient, already top-performing.
2. **Employment Assisted Services** – Consistently high success, moderate cost.
3. **Youth Job Connection** – Strong outcomes with manageable resource needs.

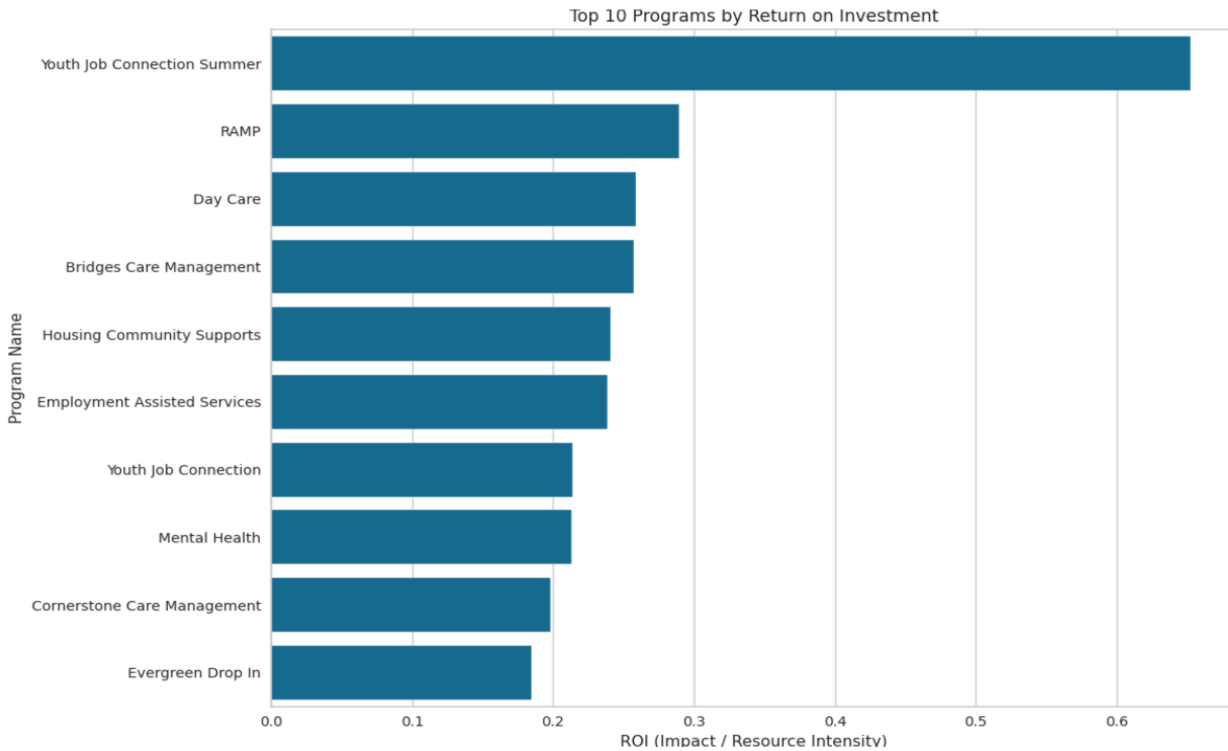

Figure 14: *Top 10 Programs by Return on Investment*

This bar chart highlights the programs delivering the highest return relative to their resource intensity. Youth Job Connection Summer clearly outperforms others in ROI due to its low cost and moderate success rate.

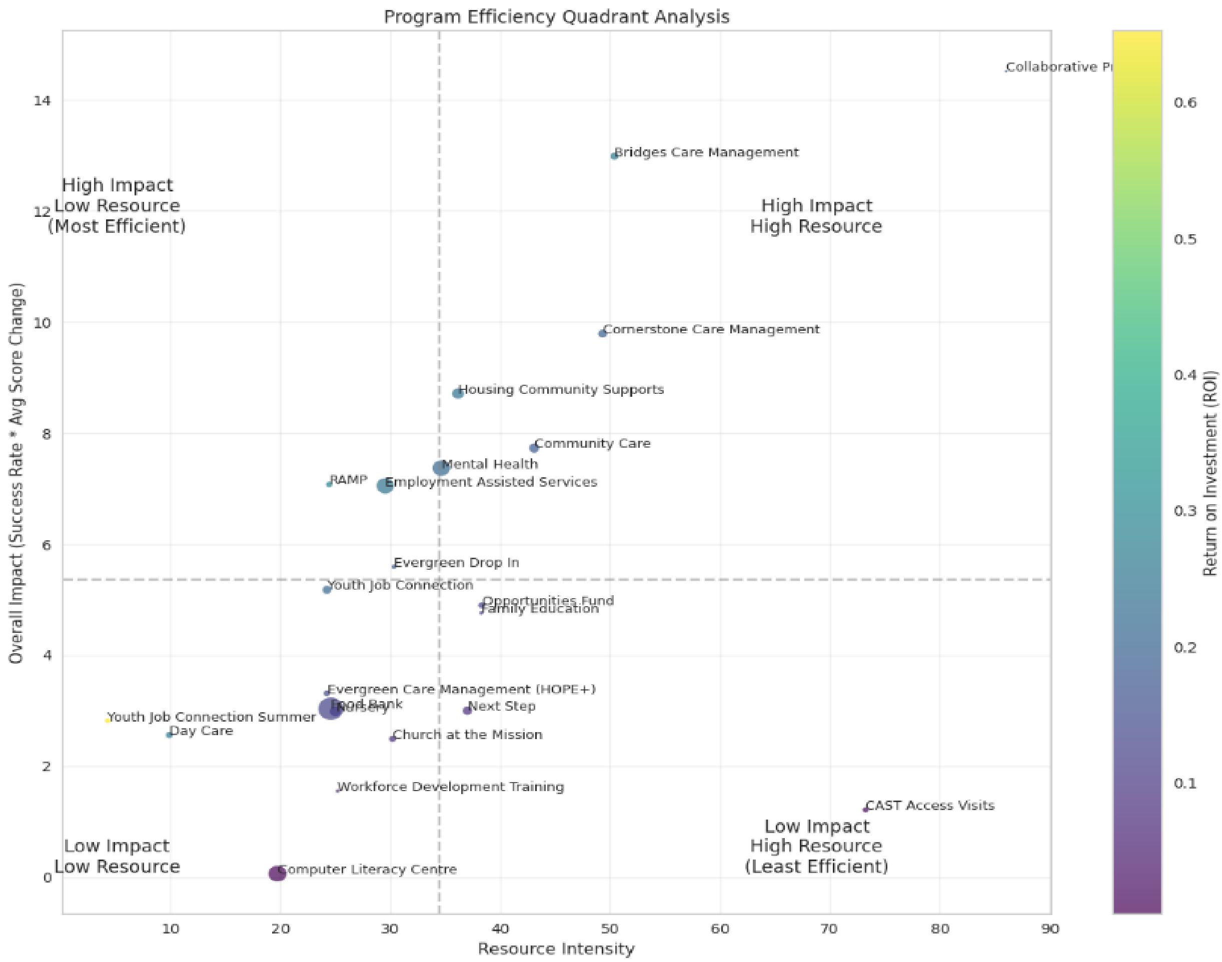

Figure 15: *Program Efficiency Quadrant Analysis*

This quadrant plot segments programs into four categories based on resource use and outcome impact. Programs in the top-left quadrant (e.g., RAMP, Employment Assisted Services) are ideal investments — combining high impact with efficient resource usage. Conversely, programs in the bottom-right should be reviewed for optimization.

Question 4: How effectively are we reaching and engaging different demographic groups, and where are the key service gaps?

To assess engagement and service gaps, we analyzed six key demographic dimensions: Gender, Age Group, Born in Canada, Housing Situation, Education Level, and Disability Status. Metrics such as service count, engagement level, and TIMES score improvement were used alongside statistical tests (ANOVA and Chi-square) to identify disparities.

Key Findings

Demographic Representation Gaps

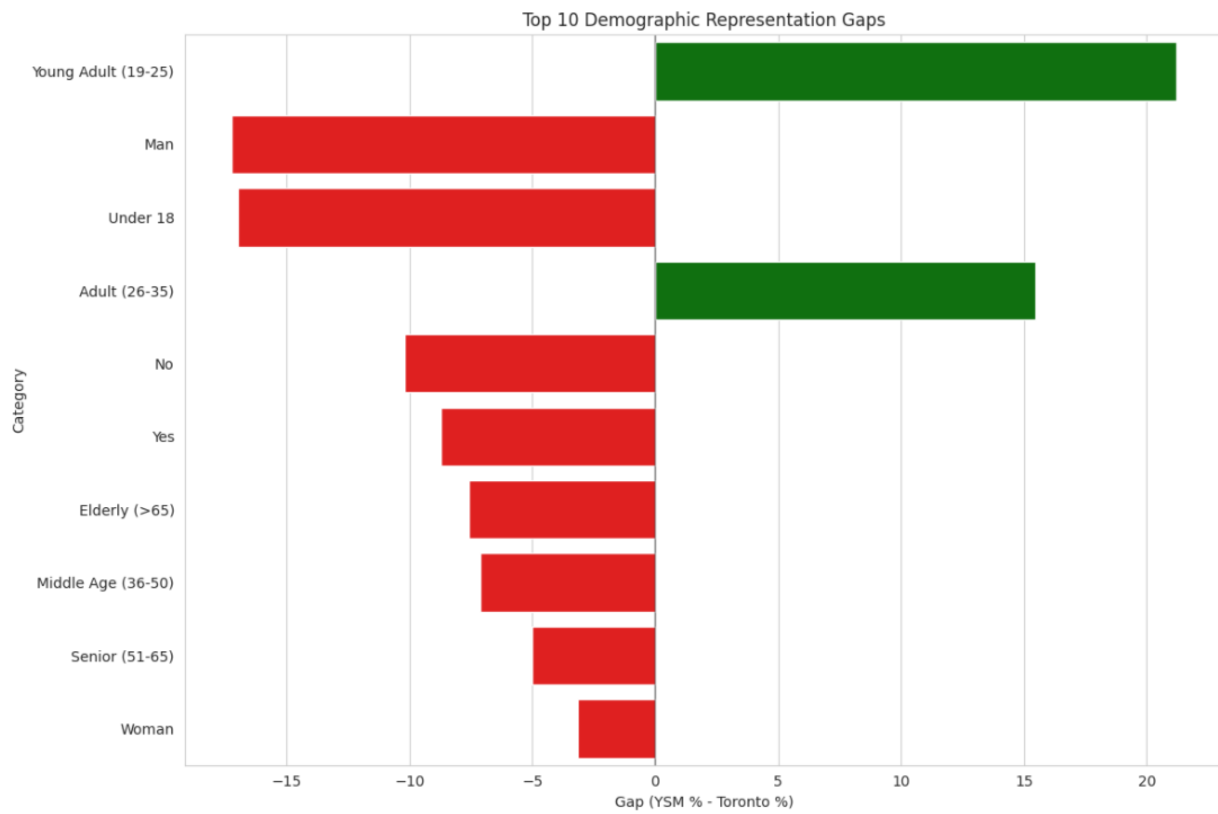

Figure 16: *Top 10 Demographic Representation Gaps*

This horizontal bar chart compares the YSM participant share for various groups against Toronto's population. Green bars indicate overrepresentation, while red bars signal underrepresentation. Notably, Youth (<18), Elderly (>65), and Men are significantly underrepresented.

Findings

- Youth (Under 18) and Elderly (>65) have Representation Indexes below 0.25.
- Men are also underrepresented (Index = 0.64), while Young Adults (19-25) are overrepresented (Index = 3.12).

These gaps suggest potential outreach barriers or access challenges for certain populations.

Engagement Disparities

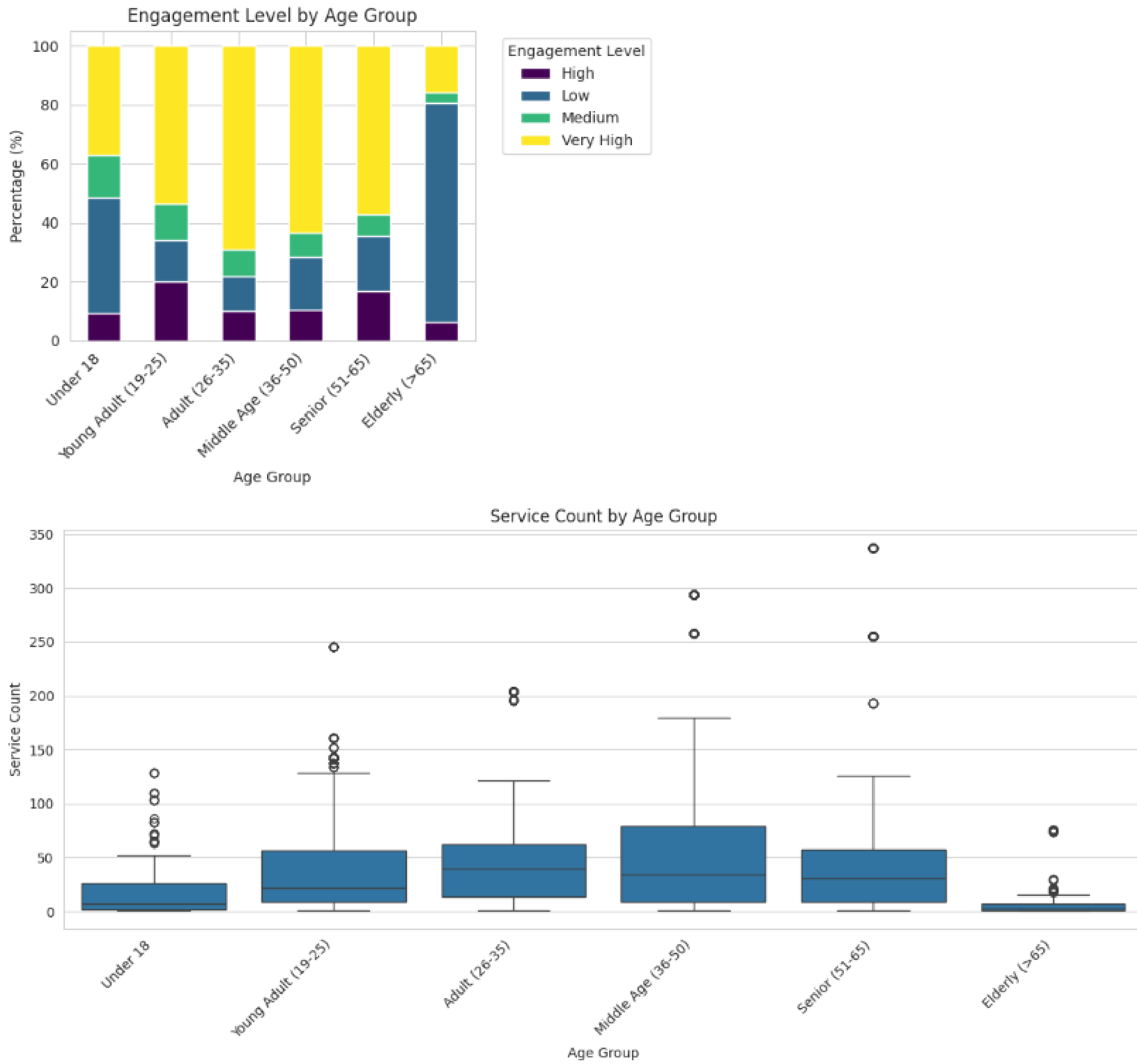

Figure 17: *Engagement Level by Age Group and Service Count by Age Group*

The top graph shows the distribution of engagement levels by age group (e.g., Low, Medium, Very High). The lower boxplot depicts the service count distribution. Youth (<18) show both lower engagement and fewer services accessed.

Insights

- Youth (<18) and Elderly display reduced engagement.
- Only 37.2% of youth achieved "Very High" engagement, compared to over 60% in middle-aged adults.

Outcome Gaps

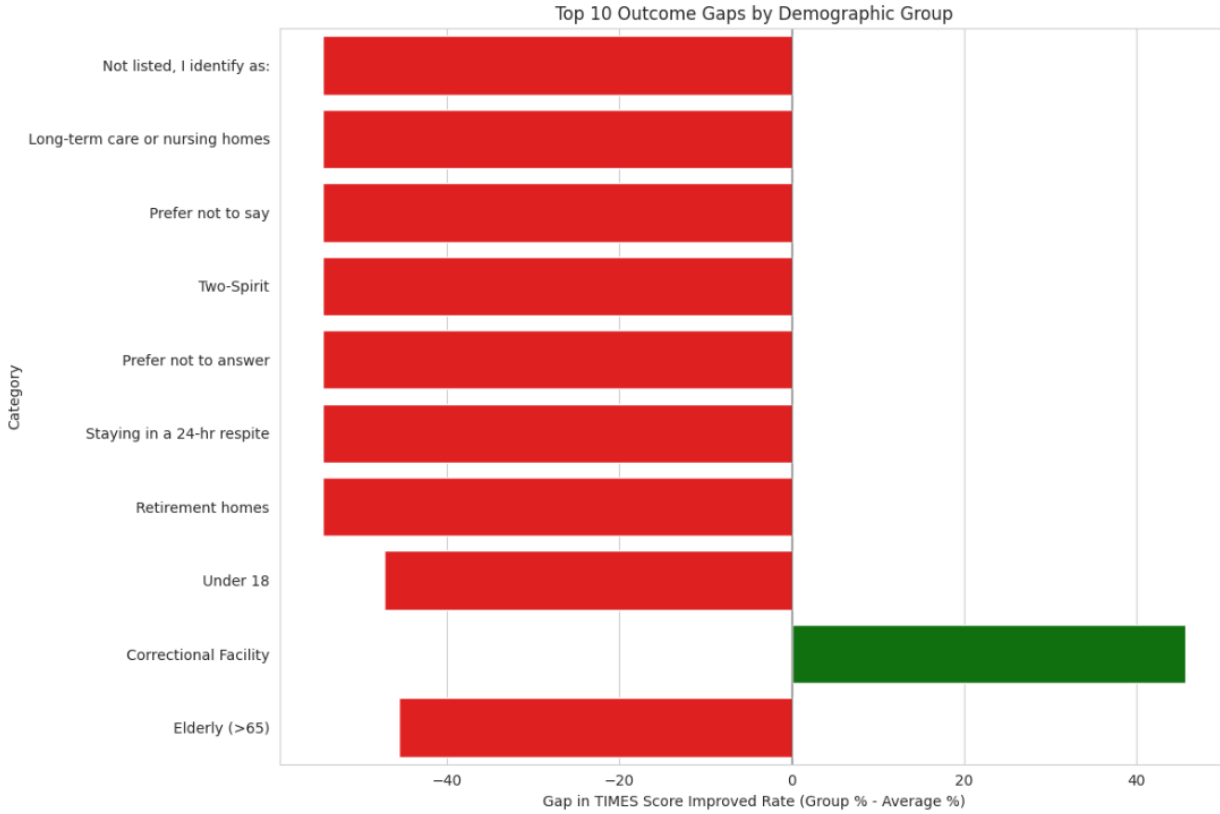

Figure 18: *Top 10 Outcome Gaps by Demographic Group*

This bar chart displays the deviation in TIMES score improvement rates by demographic group compared to the average (54%). Groups like Two-Spirit, Not Listed, and Under 18 show significant negative gaps.

Highlights

- Several gender-diverse and youth groups showed a 0% success rate, well below average.
- Elderly and Under 18 groups had gaps of -46% and -47%, respectively.

Recommendations

- **Targeted Outreach**: Develop engagement strategies for underrepresented groups (e.g., Men, Youth, Elderly) by partnering with community-specific institutions (schools, senior centers).
- **Tailored Programs**: Redesign service models for groups with low engagement or outcomes, particularly youth and gender-diverse clients.
- **Inclusive, Culturally Responsive Practices**: Train staff on cultural safety and demographic-sensitive practices to improve participation and outcomes.

By addressing these disparities, YSM can enhance equity, effectiveness, and community reach.

Question 5: What is the optimal service mix and program duration to maximize improvement in TIMES scores for different client types?

To determine the ideal interventions that most effectively improve TIMES scores, we built a Random Forest Regression model and used SHAP for interpretation. This allowed us to assess key drivers of change and establish optimal service benchmarks by client demographics.

Key Findings

1. Top Predictors of TIMES Score Improvement

Service-related features were the strongest predictors:

- Total service hours and service count had the highest influence.
- Age, unique service types, and program duration also contributed significantly.

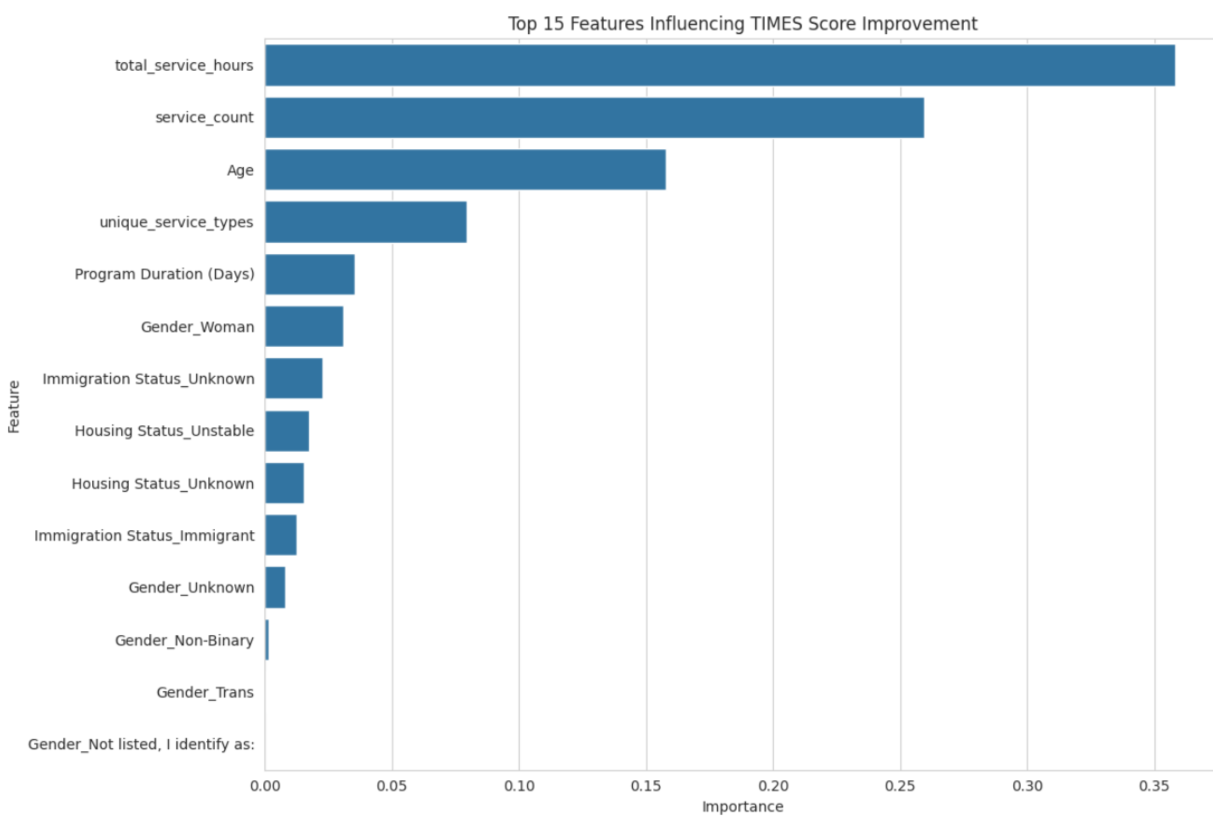

Figure 19: *Top 15 Features Influencing TIMES Score Improvement*

Bar chart showing model-derived feature importance, with service hours and service count leading.

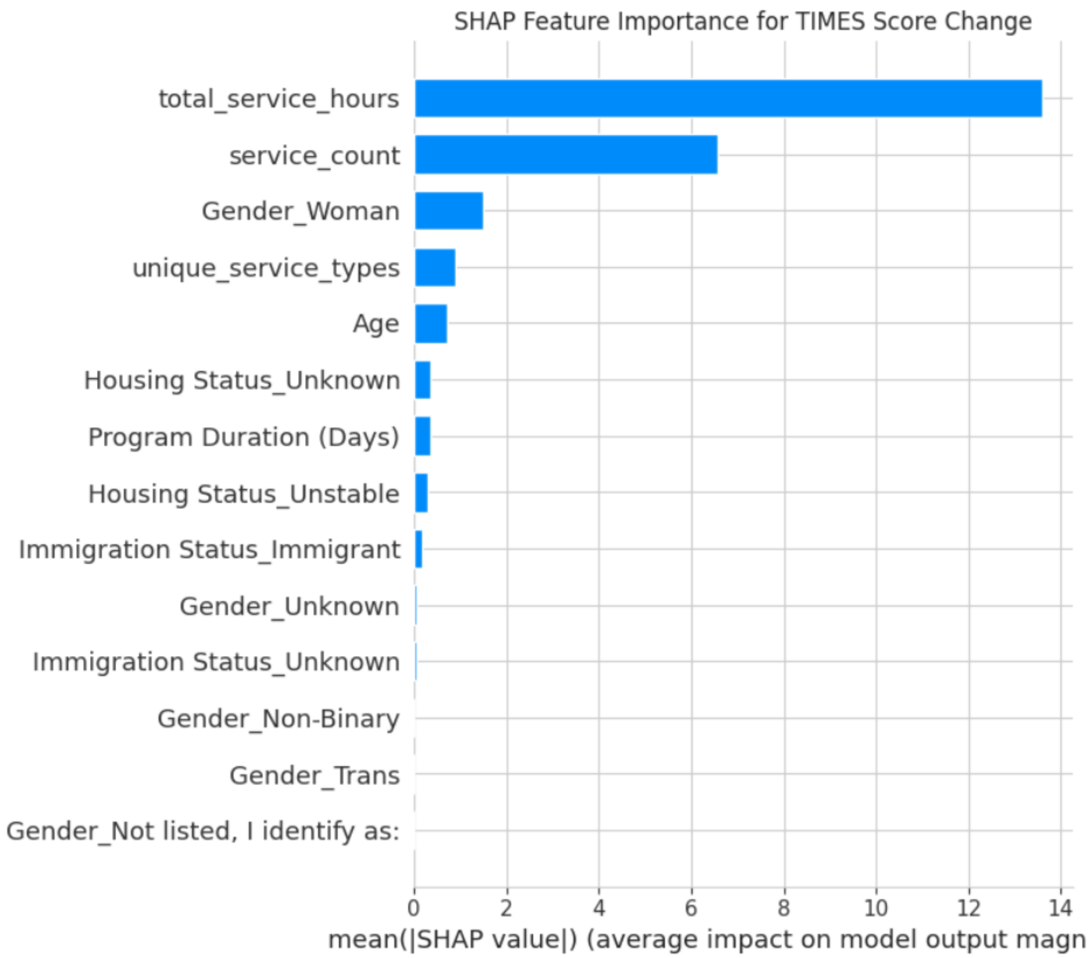

Figure 20: *SHAP Feature Importance for TIMES Score Change*

SHAP values reveal the magnitude of each variable’s average impact on predictions.

How Service Metrics Affect Outcomes

Partial dependence analysis reveals how TIMES scores vary with key variables:

- **Service Count:** Notable increase in score change after ~180 services.
- **Unique Service Types:** Peaks around 8 types.
- **Total Service Hours:** Benefits stabilize above 125 hours.
- **Program Duration:** Gains increase substantially beyond 700 days.

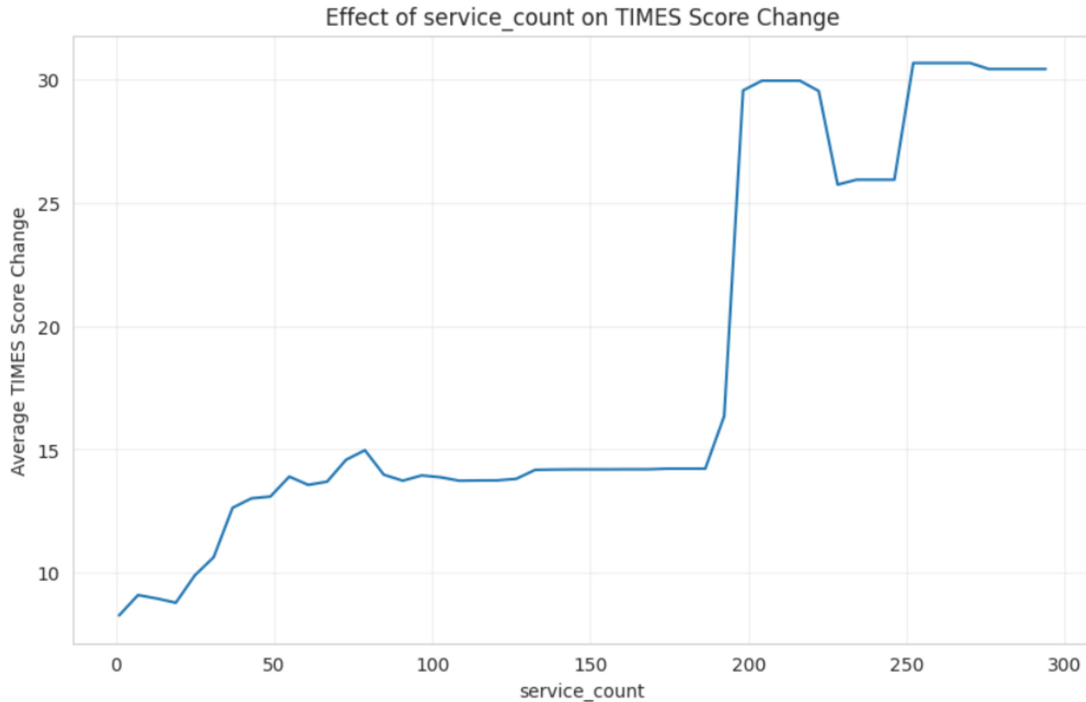

Figure 21: *Effect of service count on TIMES Score Change*

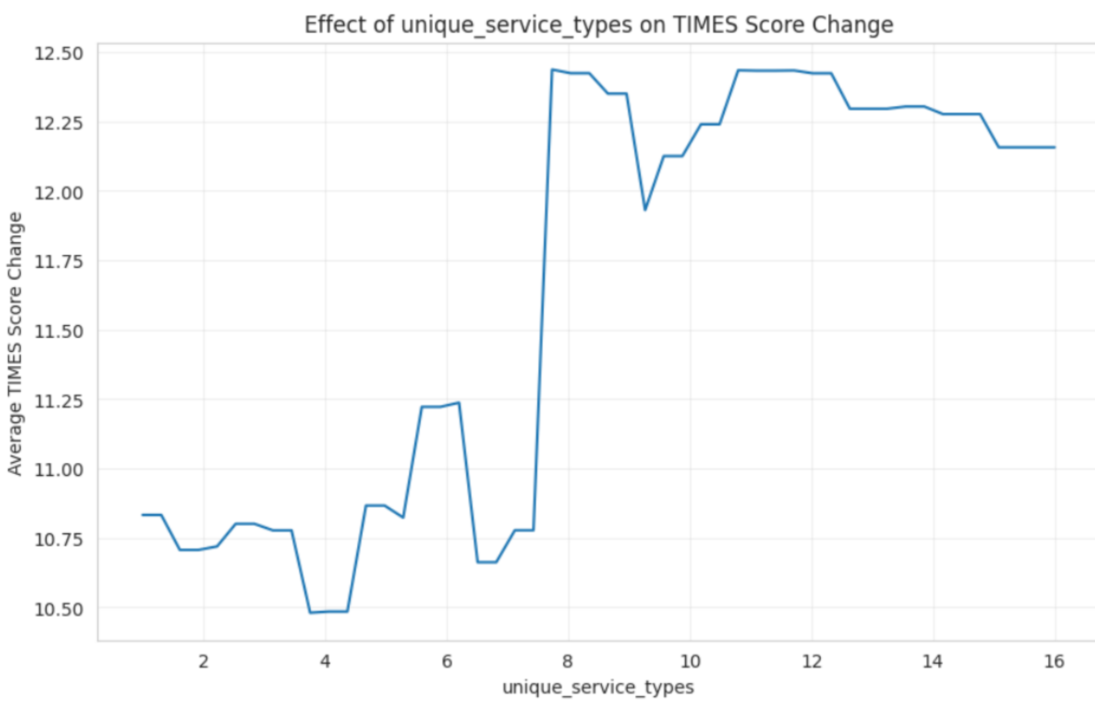

Figure 22: *Effect of unique service types on TIMES Score Change*

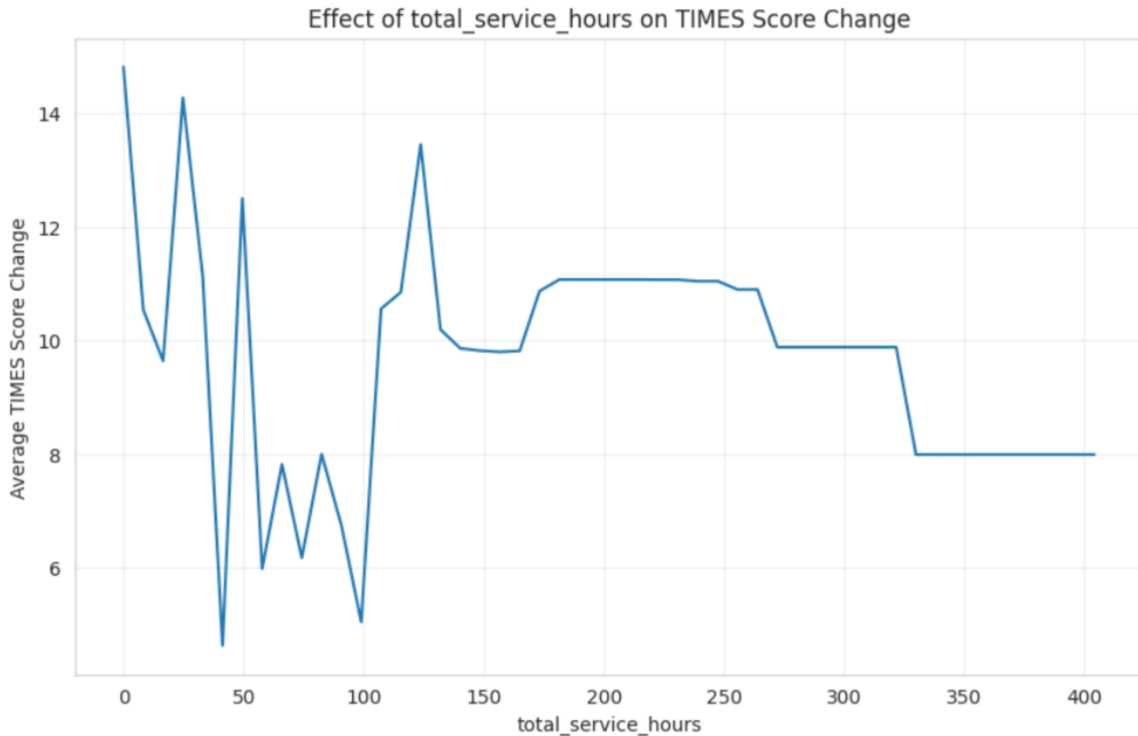

Figure 23: *Effect of total service hours on TIMES Score Change*

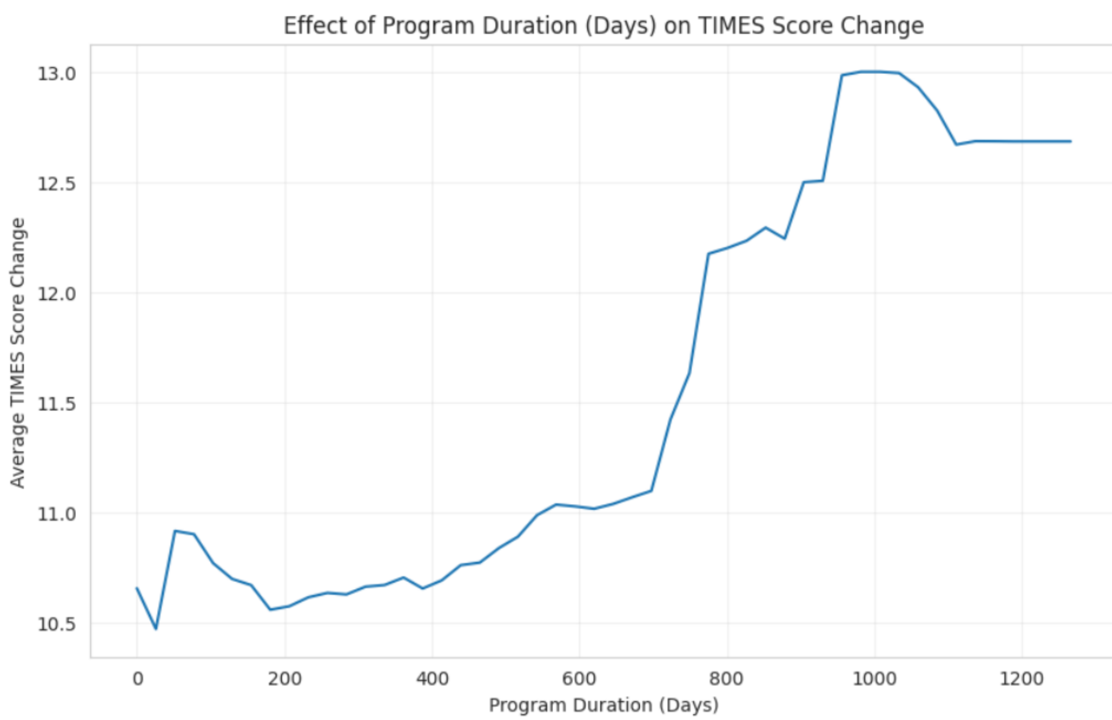

Figure 24: *Effect of Program Duration (Days) on TIMES Score Change*

Recommended Mix by Client Type

Clients were segmented into groups based on age, gender, housing, and immigration status. Top-performing individuals in each group were analyzed to identify effective patterns.

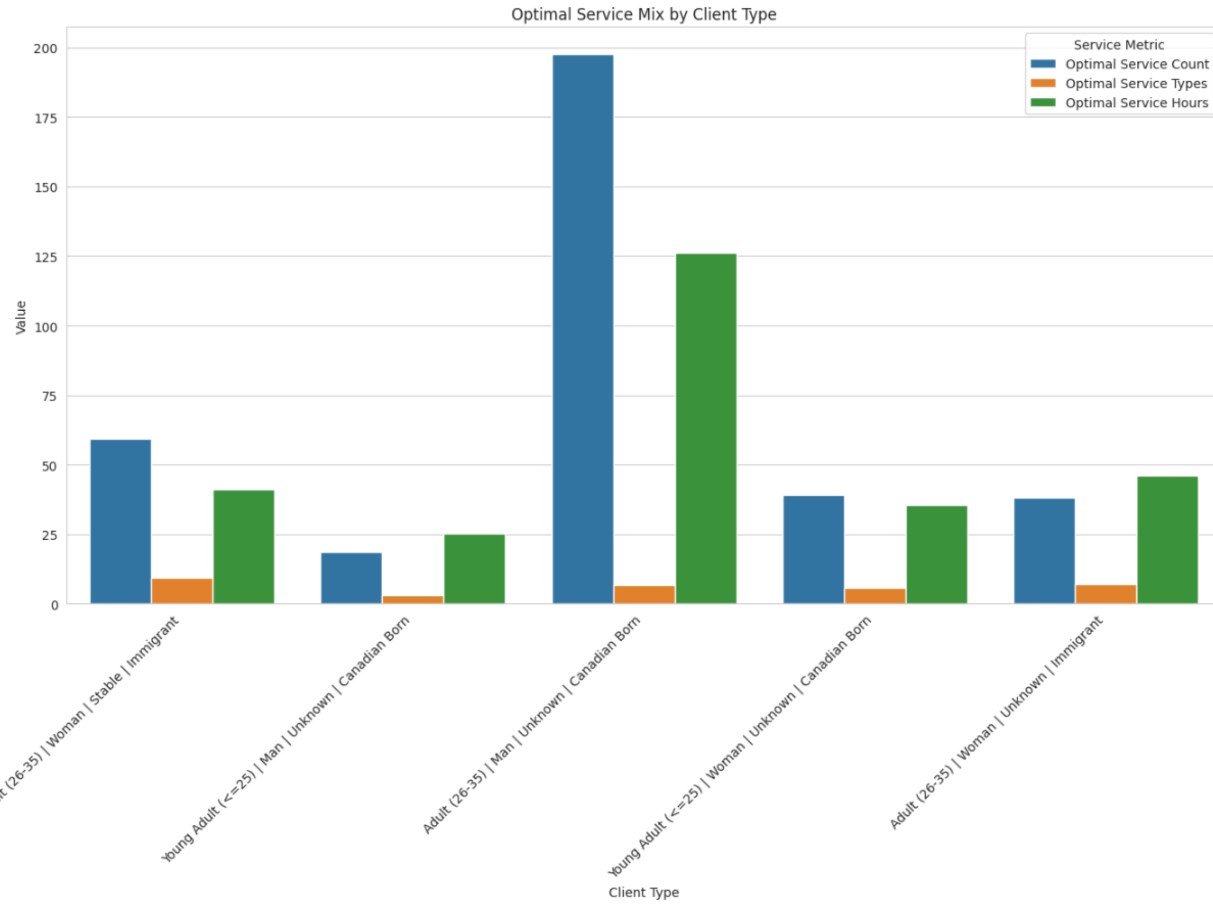

Figure 25: *Optimal Service Mix by Client Type*

Grouped bar chart showing ideal service count, types, and hours for the top 5 client segments.

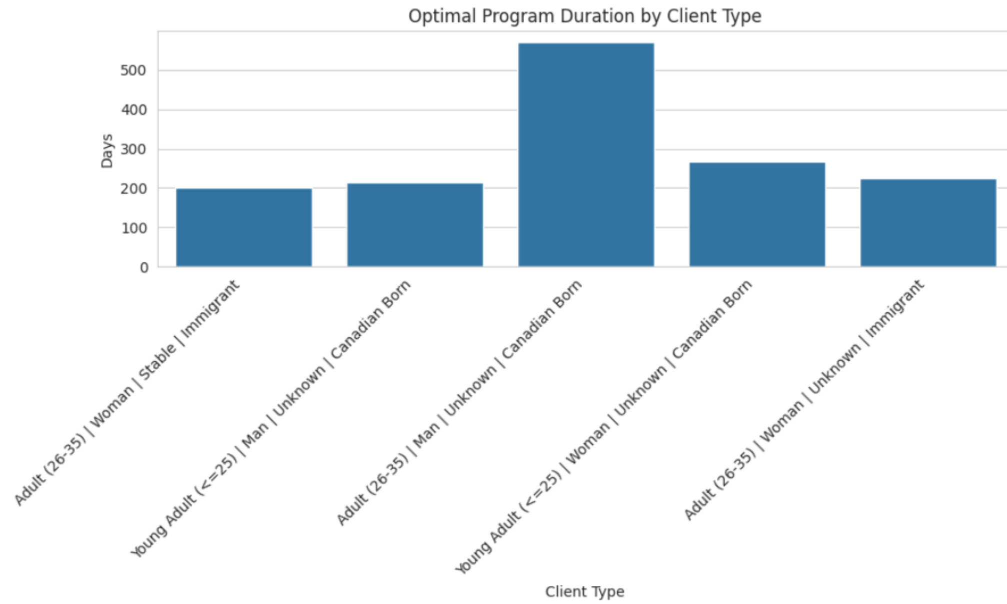

Figure 26: *Optimal Program Duration by Client Type*

Bar chart showing the best program duration (in days) per group.

Combined Service Metric Effects

Interaction plots show how combinations of services influence outcomes. For instance, high service count plus long program duration yields stronger improvements in some groups.

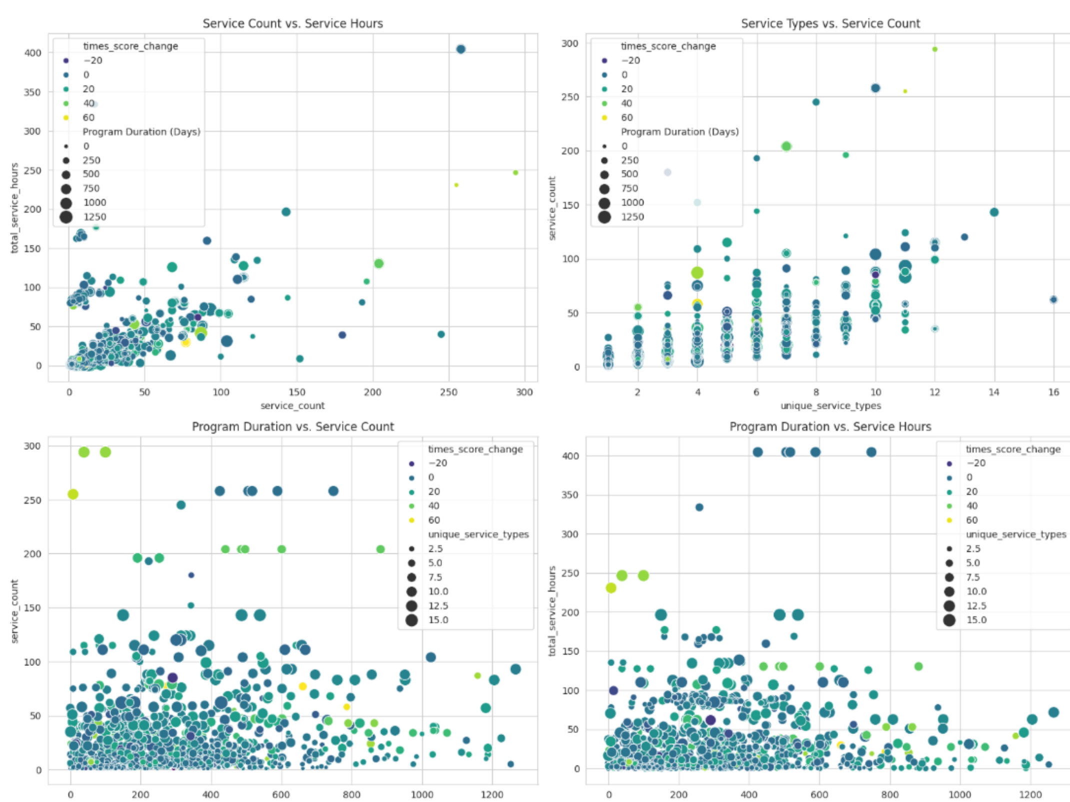

Figure 27: *Service Interactions Grid*

A 2x2 grid of scatterplots examining variable interactions, colored by score improvement and sized by related variables.

Summary Recommendations

1. **Tailor Plans by Client Type:** Use demographic profiles to set realistic, effective targets.

2. **Focus on Thresholds:** Aim for >125 hours, ~8 service types, and 700+ days where possible.

3. **Monitor Balance:** Avoid under- or over-delivery by watching combined service effects.

4. **Program Design:** Design longer, diversified service pathways for certain groups to enable deeper progress.

By targeting interventions based on these findings, YSM can maximize the positive impact of its programs while efficiently allocating resources.

Question 6: What is the projected impact and cost-effectiveness of expanding specific high-performing programs?

To evaluate the most promising programs for expansion, we conducted a cost-effectiveness and ROI (Return on Investment) analysis across the top-performing services using TIMES score improvements as the measure of success. This allowed us to assess projected outcomes under multiple expansion scenarios.

Key Findings

1. Projected Impact of Expanding High-Performing Programs

We simulated the impact of expanding the top 5 programs by 10%, 25%, 50%, and 100%. Programs such as Employment Assisted Services, Food Bank, and Health Centre showed the highest potential for total TIMES score improvement.

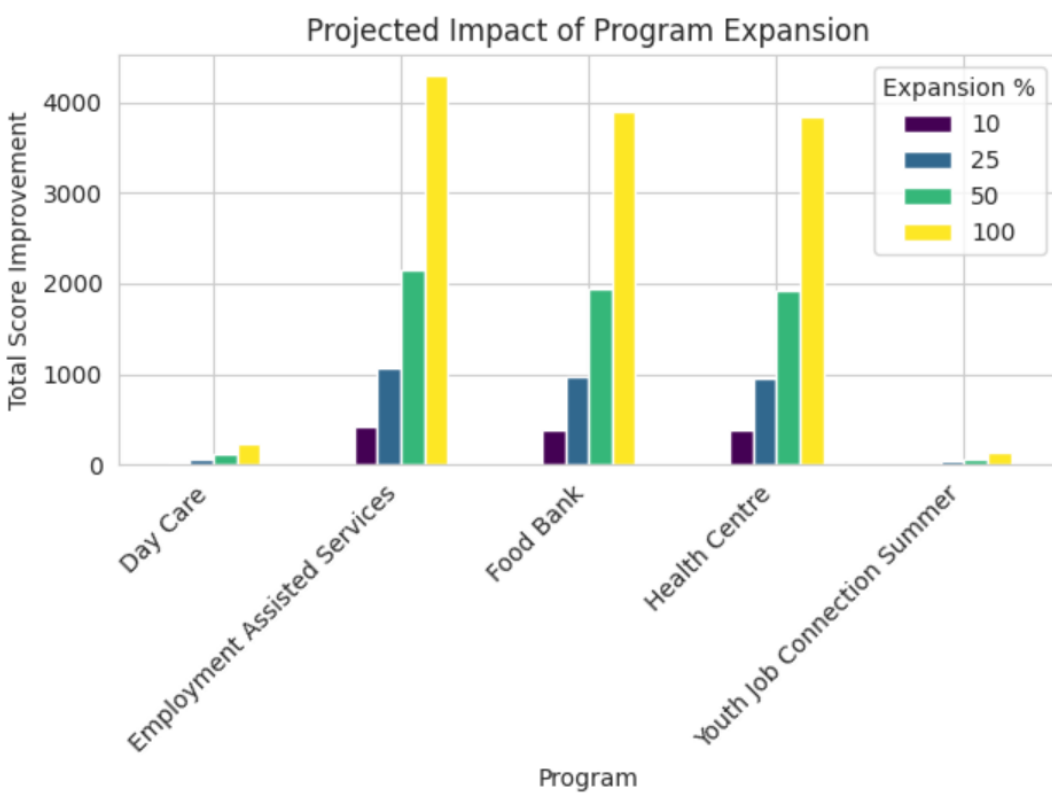

Figure 28: *Projected Impact of Program Expansion*

Grouped bar chart showing total projected TIMES score improvements for each program under different expansion levels.

2. Cost Per Success by Program and Expansion Level

While large-scale programs like Food Bank and Health Centre yield high total impact, their **cost per success** remains significantly higher compared to smaller programs like *Youth Job Connection Summer*, which provides substantial value at very low cost.

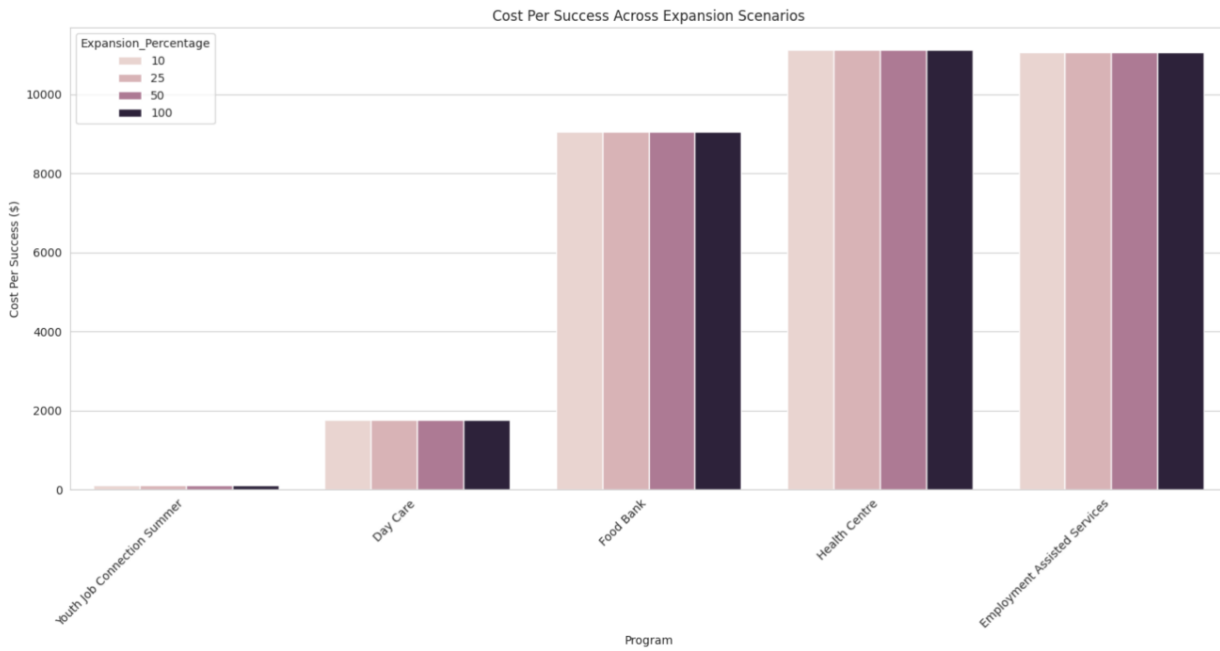

Figure 29: *Cost Per Success Across Expansion Scenarios*

Bar chart comparing the cost-effectiveness of programs across expansion levels.

3. ROI of Program Expansion

When estimating social value from TIMES score improvement, *Youth Job Connection Summer* stands out with an ROI exceeding 20x, making it the most cost-effective investment. Others like Day Care also show positive ROI, while Food Bank and Employment Services fall into negative ROI territory under current assumptions.

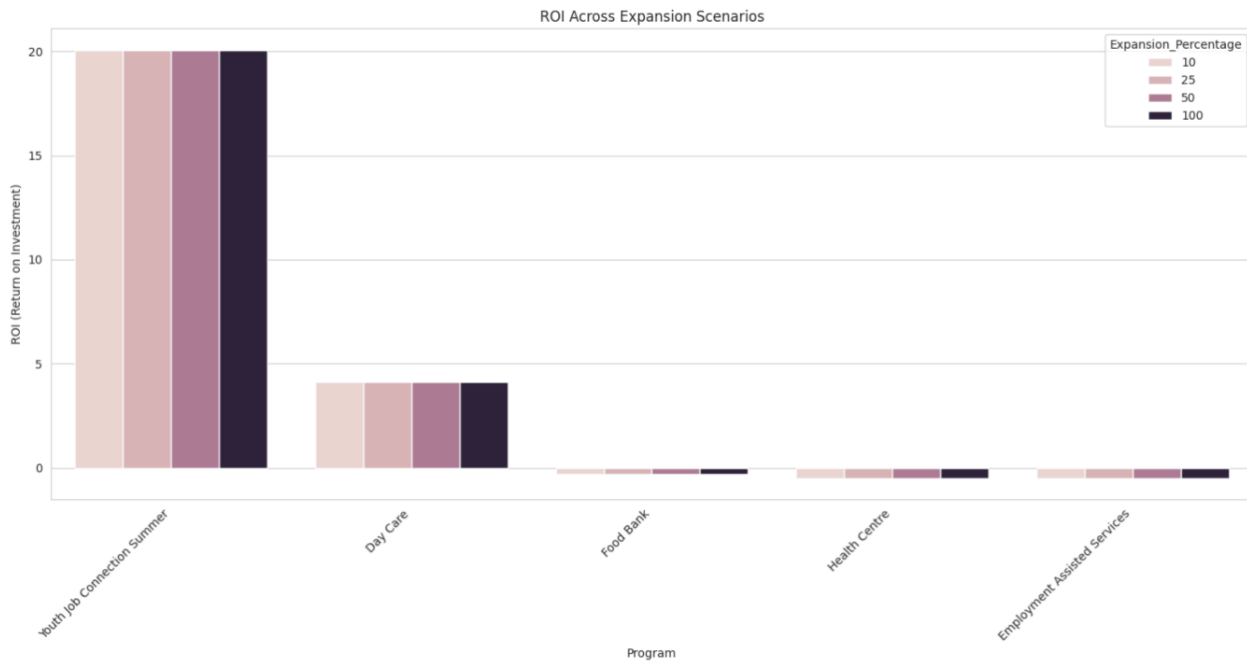

Figure 30: *ROI Across Expansion Scenarios*

Grouped bar chart showing return on investment by program and expansion level.

4. Comparison of Portfolio Strategies

We compared different expansion portfolios. The best performing portfolio was expanding only the *highest ROI program* (Youth Job Connection Summer) at 100%, with minimal cost and maximum return.

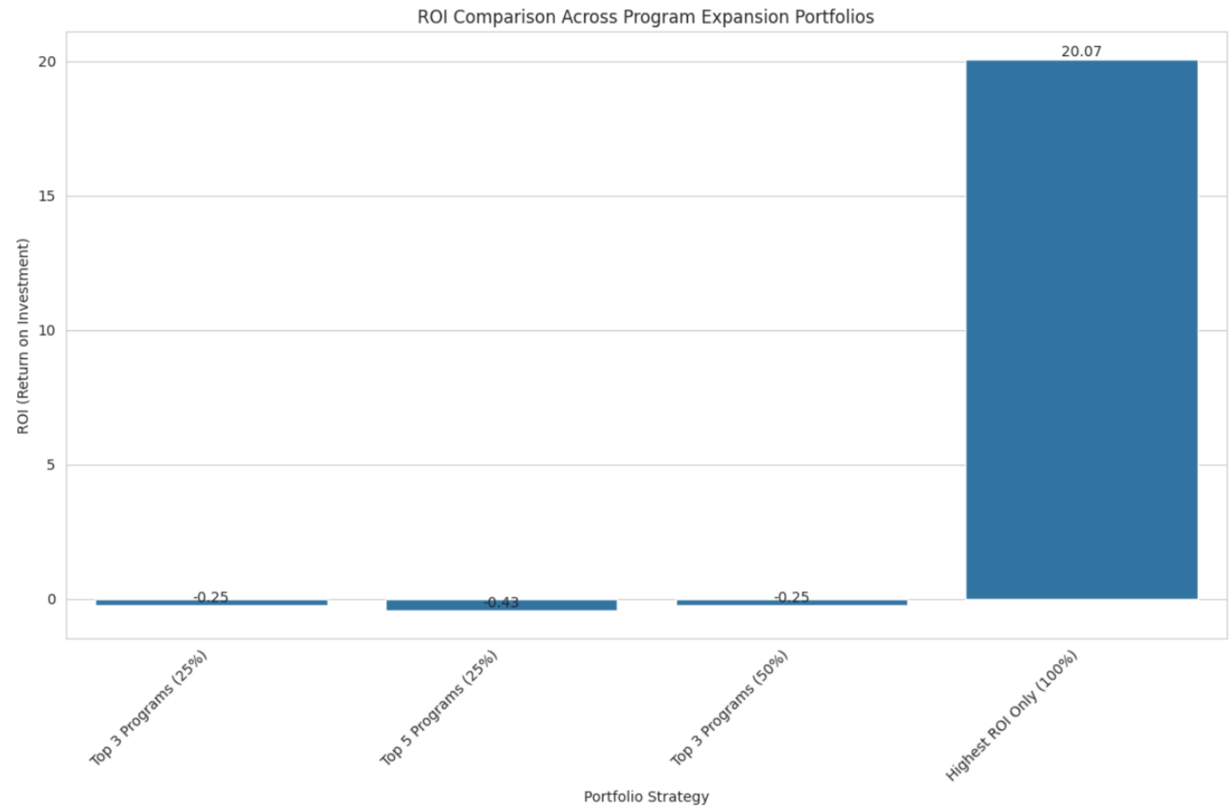

Figure 31: *ROI Comparison Across Program Expansion Portfolios*

Bar chart comparing ROI for various bundled expansion strategies.

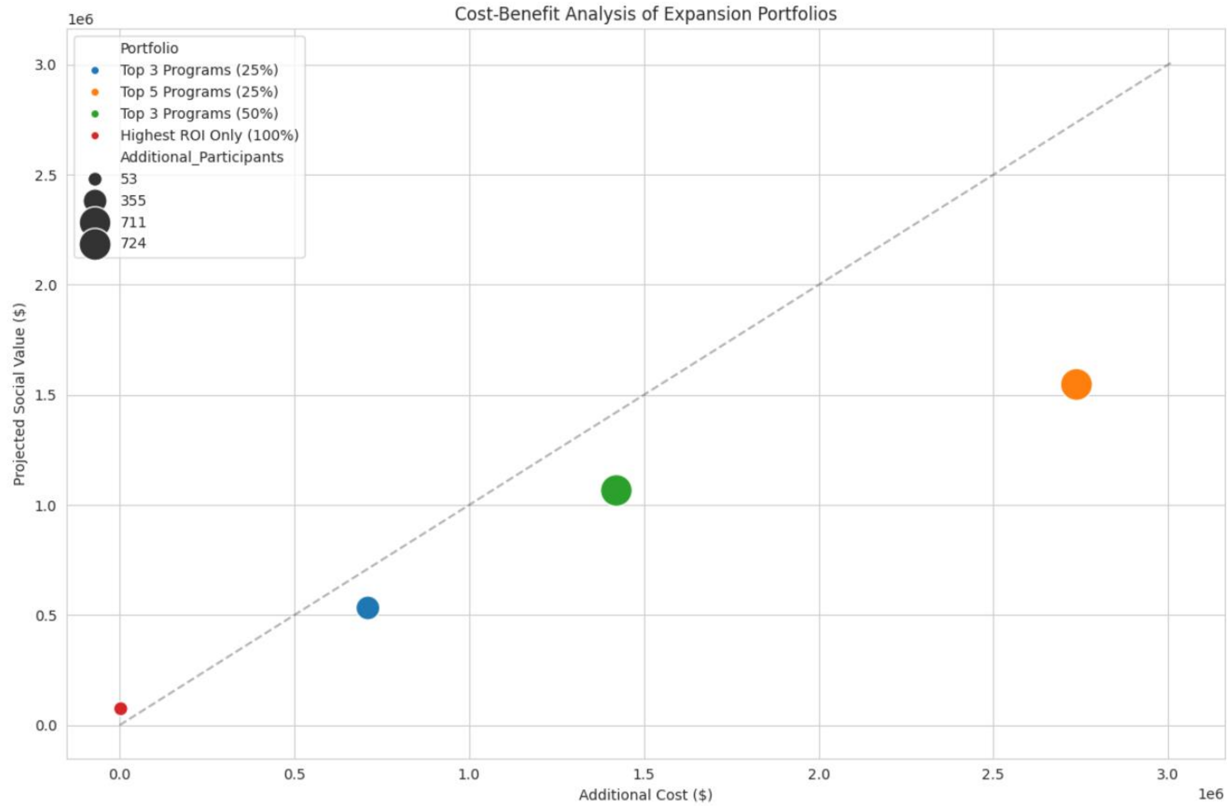

Figure 32: *Cost-Benefit Analysis of Expansion Portfolios*

Scatterplot showing additional cost vs projected social value for different strategies, sized by number of participants.

Recommendations

1. **Primary Expansion Focus**: Prioritize full expansion (100%) of *Youth Job Connection Summer*, given its exceptionally low cost and high ROI.
2. **Secondary Options**: Consider modest expansion (25%) of *Day Care* for additional impact with reasonable returns.
3. **Avoid High-Cost Low-Return Scaling**: Delay or reassess large-scale investments in Food Bank and Employment Services unless cost-efficiency improves.
4. **Strategic Implementation**:
    - Phase expansion over 12–24 months to maintain program quality.
    - Monitor effectiveness post-expansion.
    - Reassess financial assumptions regularly.

Question 7: How have service utilization patterns and outcomes evolved over time, and what do predictive models forecast for future needs?

To understand historical trends and forecast future needs, we analyzed monthly program utilization, service intensity, TIMES score outcomes, and applied Prophet time series forecasting to predict demand and resource needs over the next 24 months.

1. Trends in Service Utilization and Outcomes

There was a sharp rise in program engagement post-2021, followed by a steady decline across multiple outcome indicators. This suggests both pandemic-era demand spikes and recent challenges in maintaining intensity and effectiveness.

Figure 33: *Monthly Program Starts (2019–2025)*

This line chart shows a dramatic increase in enrollments after 2021, peaking in early 2022. The decline from 2023 onward reflects either stabilization or capacity/resource constraints.

Figure 34: *Average Service Count per Participant*

Service intensity increased sharply in 2022, indicating deeper engagements, but has declined since, possibly due to staff or funding limitations.

Figure 35: *Monthly Success Rate (% of Participants with Improved Scores)*

This figure reflects the percentage of participants with improved TIMES scores. It mirrors the service intensity trend, peaking in 2022 and declining in 2024, signaling reduced effectiveness.

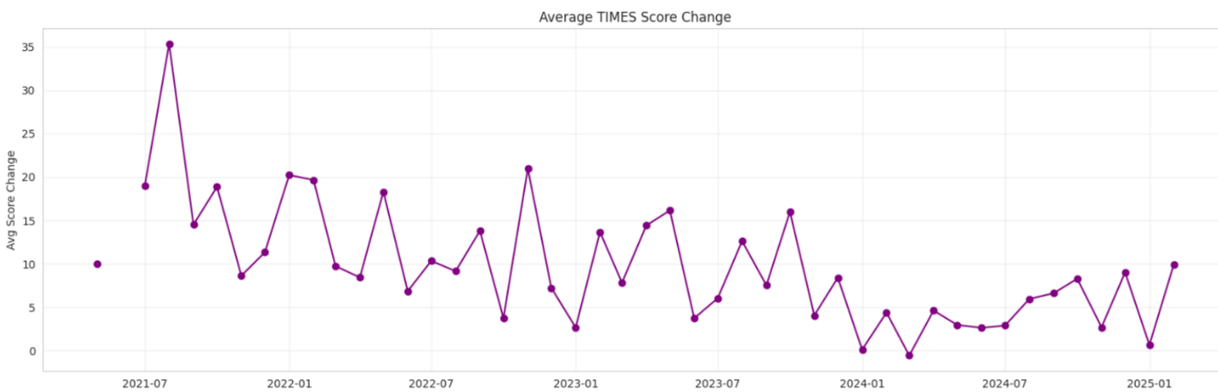

Figure 36: *Average TIMES Score Change Over Time*

The actual numerical improvement in TIMES scores follows a similar pattern: high in 2022, then consistently falling. This trend highlights the need for recalibrated service strategies.

2. Forecasting Future Demand and Capacity

We used Prophet to forecast the next 24 months of program activity. Results suggest program starts may remain stable or grow modestly, but service intensity and outcomes are expected to decline.

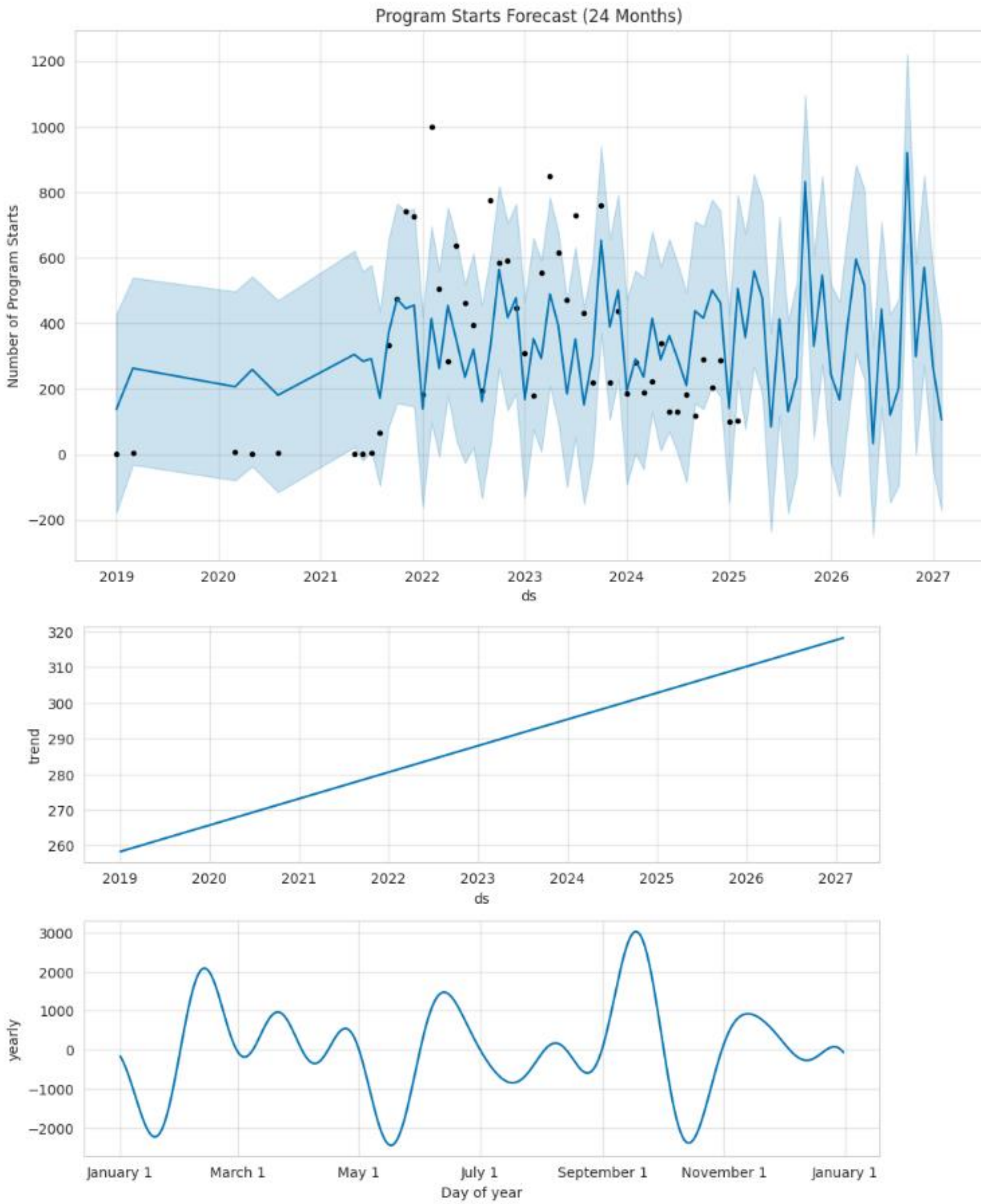

Figure 37: *Forecast of Program Starts (2025–2027)*

Shows projected monthly enrollments with 95% confidence intervals. Though volatile, the average trend is slightly upward.

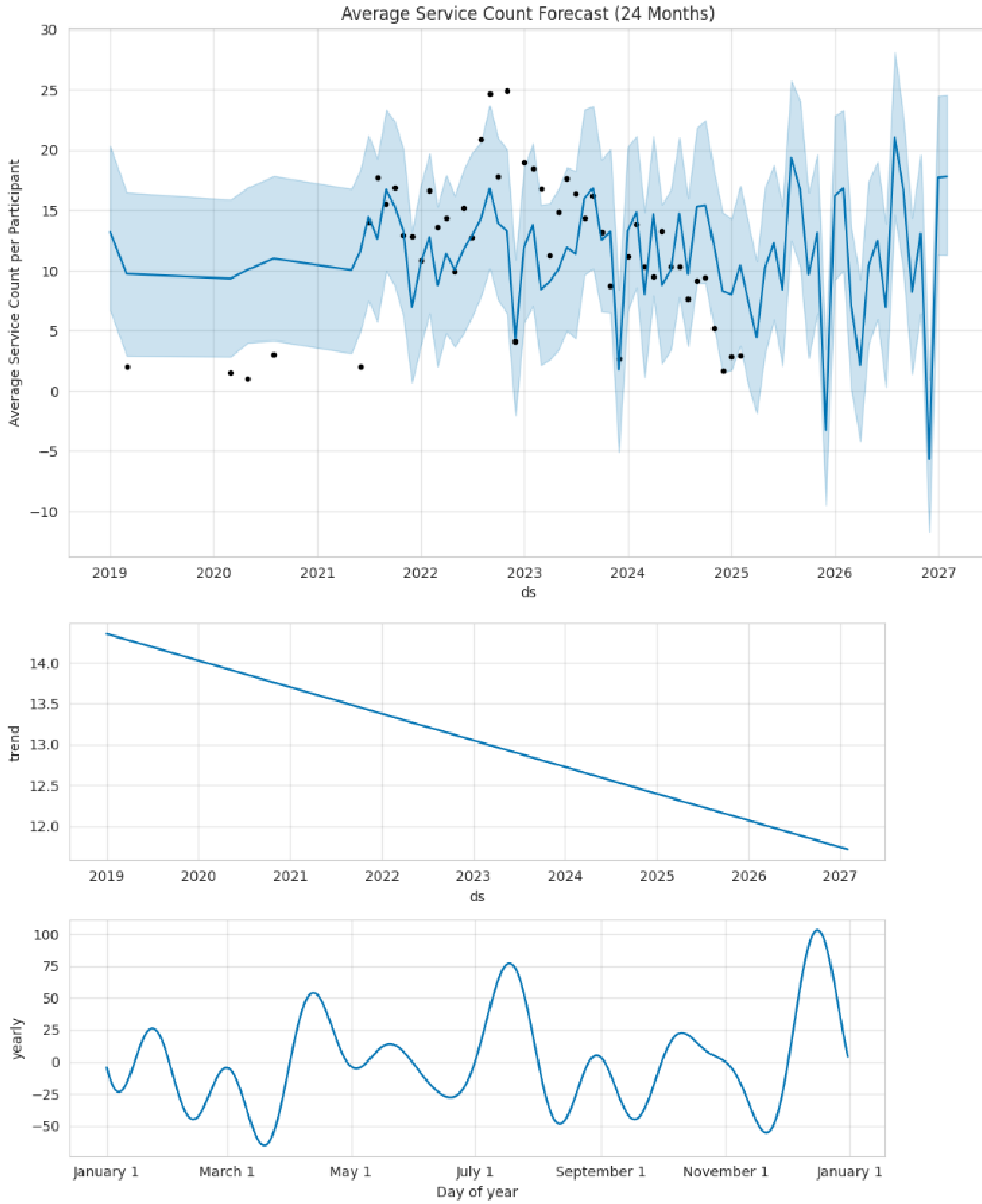

Figure 38: *Forecast of Average Service Count per Participant*

Forecasted service intensity is trending down. This could reduce the overall impact unless offset by more targeted or higher-quality engagements.

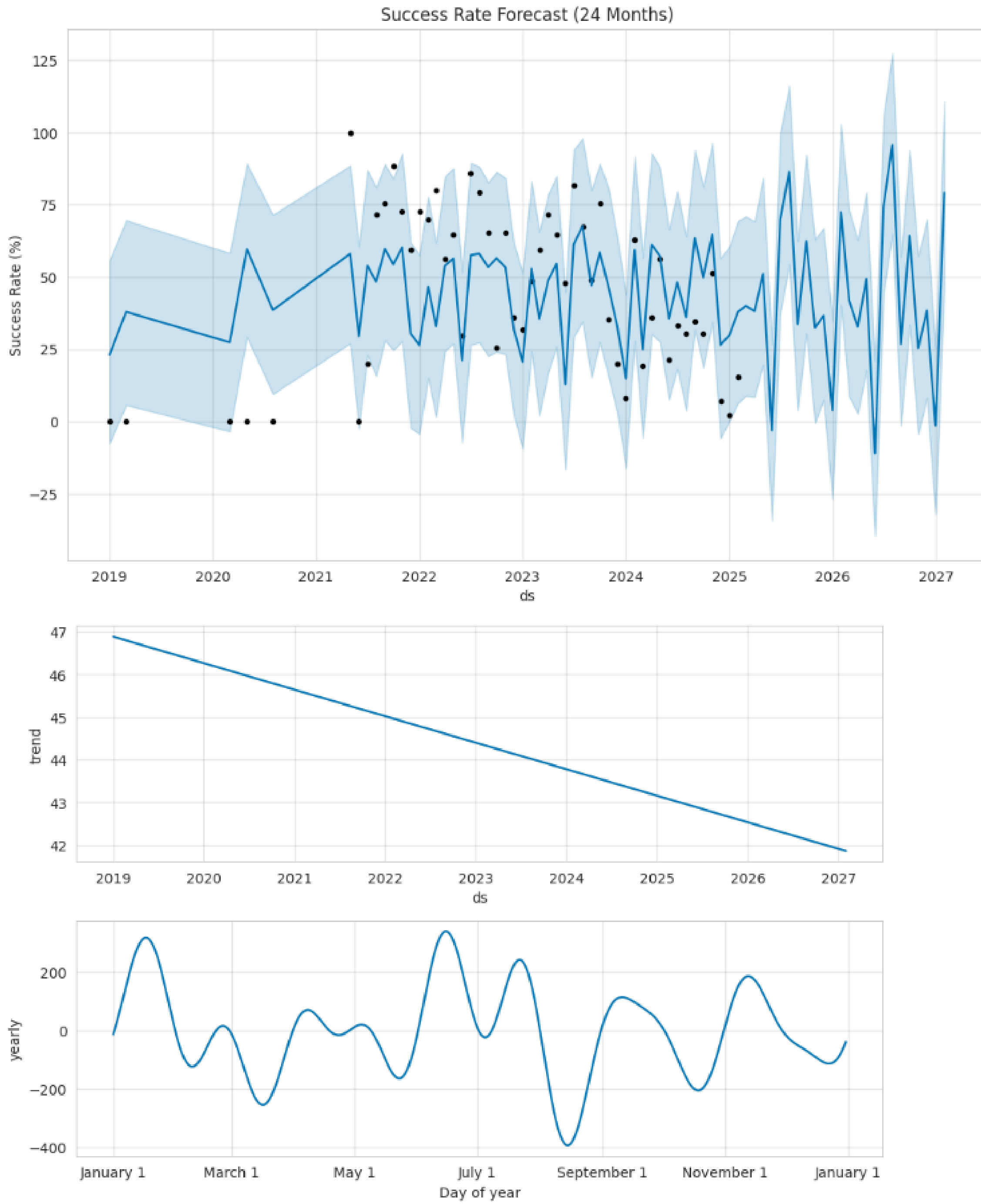

Figure 39: *Forecast of Success Rate*

3. Capacity Planning for Staff Resources

Based on forecasted service volume and a benchmark of 120 service hours per staff/month, we calculated monthly staffing needs. These fluctuate significantly, requiring flexible resource planning.

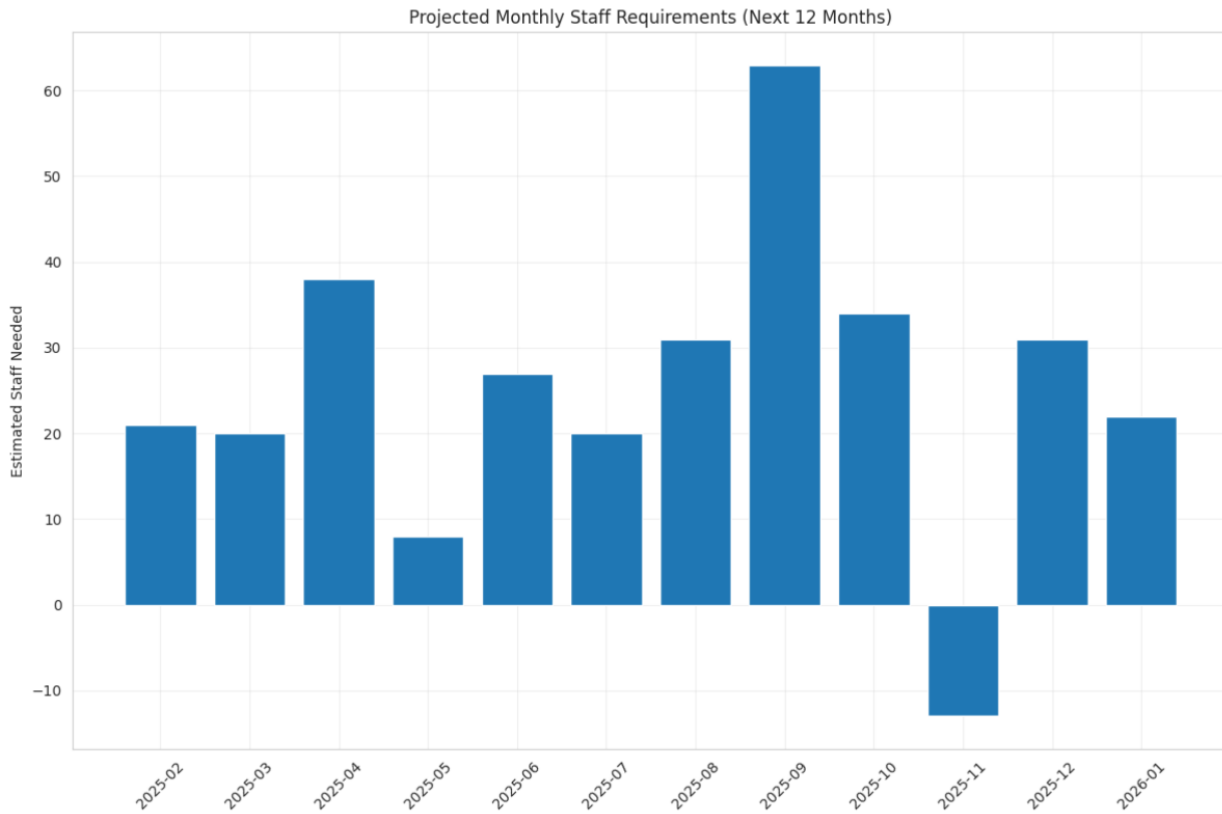

Figure 40: *Projected Monthly Staff Requirements (Next 12 Months*

Staffing needs vary from 8 to 63 full-time equivalents, peaking in September 2025. One outlier month indicates a potential data anomaly (negative value).

4. Changes in Program Mix Over Time

Not all programs follow the same pattern. Enrollments in some have surged dramatically, while others are in decline. This shift highlights the need to reallocate resources based on real-time trends.

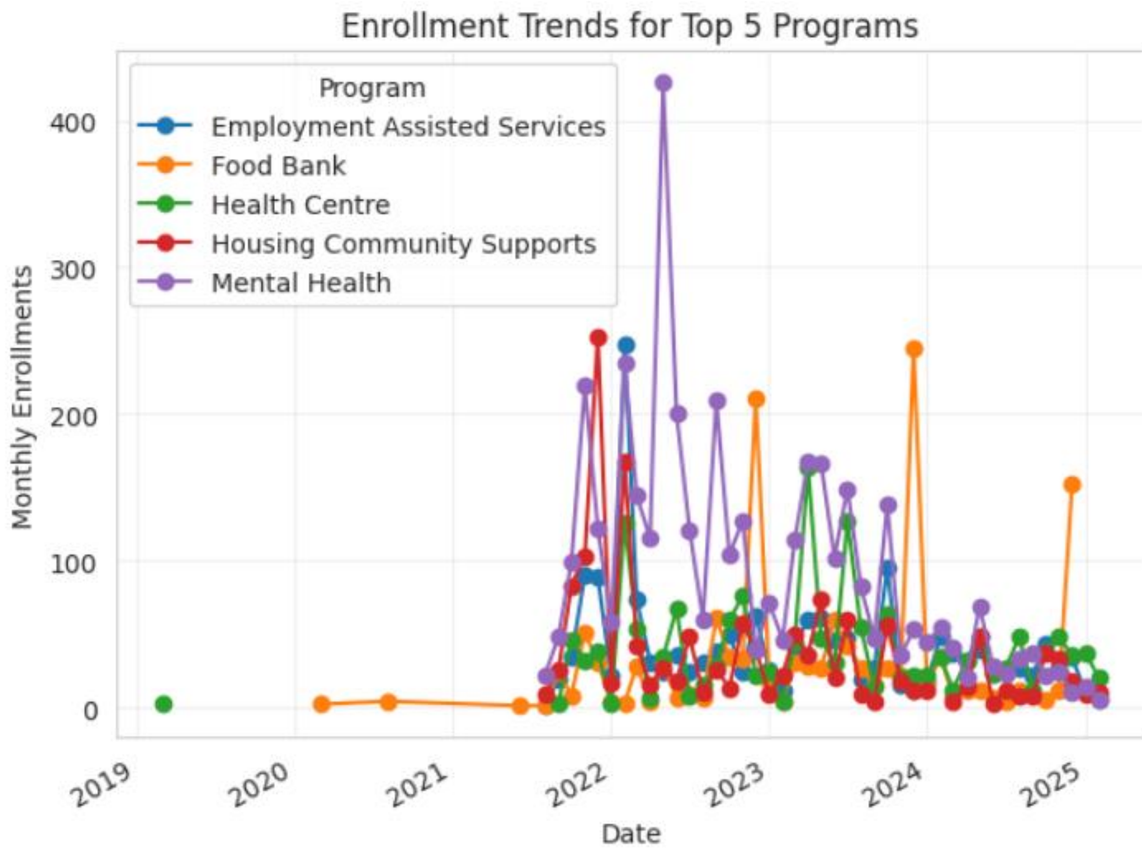

Figure 41: *Enrollment Trends for Top 5 Programs*

Tracks monthly enrollment by program. 'Health Centre', 'Food Bank', and 'Employment Assisted Services' have gained traction, while 'Mental Health' shows a consistent drop.

Key Recommendations

1. **Expand High-Growth Programs**: Programs like *Health Centre*, *Food Bank*, and *Employment Assisted Services* show strong enrollment growth and community demand. These should be prioritized for expansion, with increased capacity and resource allocation.

2. **Reassess Underperforming Services**: The *Mental Health* program has seen a major drop in participation (−46.7%). A focused review should determine whether the decline is due to changing needs, access issues, or program design.

3. **Adopt a Flexible Staffing Strategy**: With projected staff needs ranging from 8 to 63 per month, a hybrid approach is recommended: maintain a core team (approx. 20 staff) and supplement with flexible staffing to cover peaks.

4. **Update Forecasts and Monitor Impact**: Regularly refresh forecasts with new data and monitor service quality to avoid further drops in success rates and score improvements.

5. **Focus on Quality, Not Just Reach**: As participation grows, maintain emphasis on outcomes. Invest in staff training, follow-up support, and program refinement to sustain long-term impact.

Question 8: What is the optimal service sequence and timing that leads to the best outcomes for different client segments?

To determine the most effective service pathways, we examined client service usage patterns, outcomes, and program duration across demographic segments. Using a combination of association rule mining, network analysis, and survival modeling, we derived the sequences and durations most associated with TIMES score improvements.

Service Transition Network

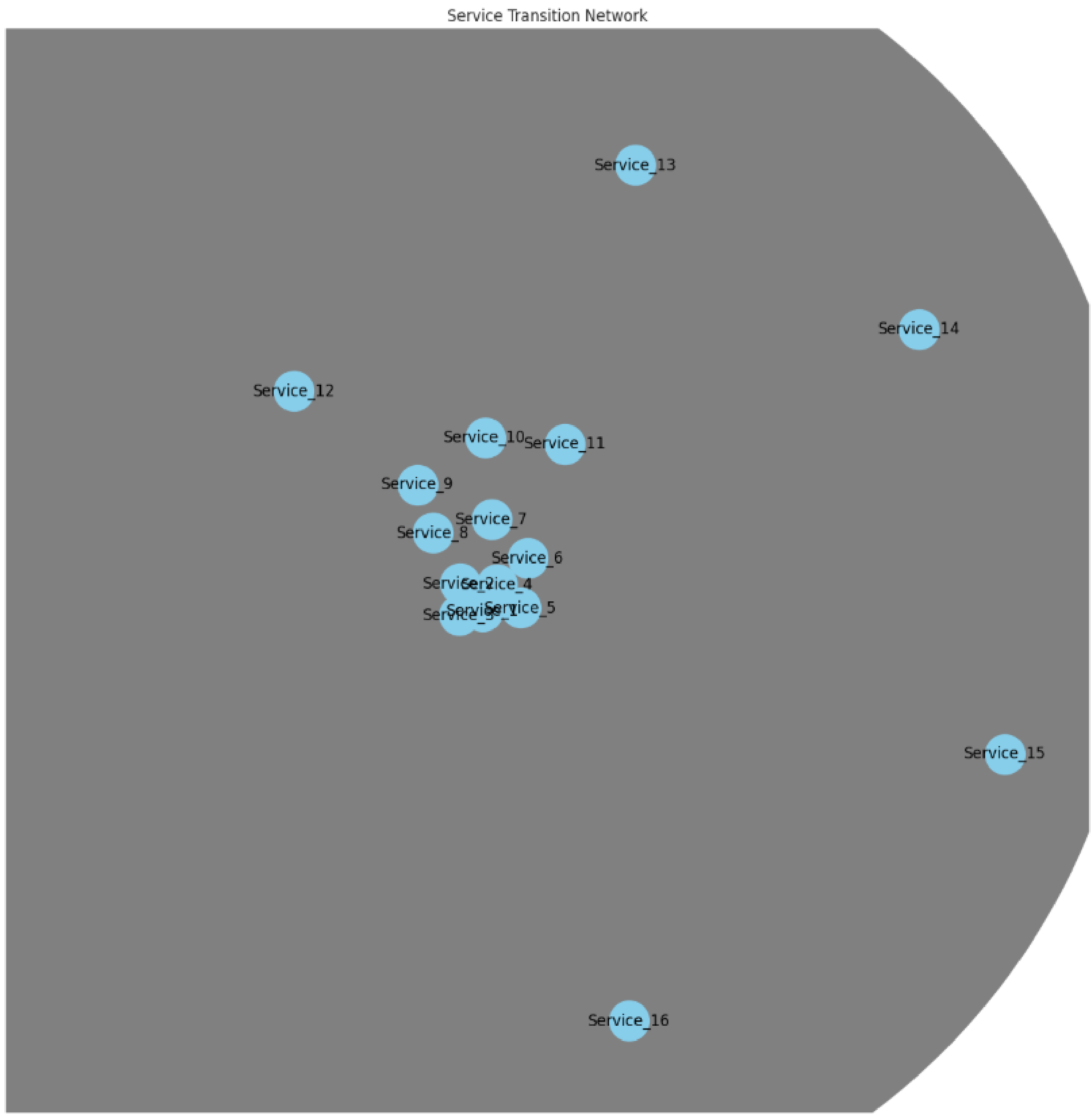

Figure 42: *Service Transition Network*

This network graph visualizes the most frequent service-to-service transitions. Thicker edges represent more common transitions, helping identify dominant service flows across the population.

Success Rate by First Service

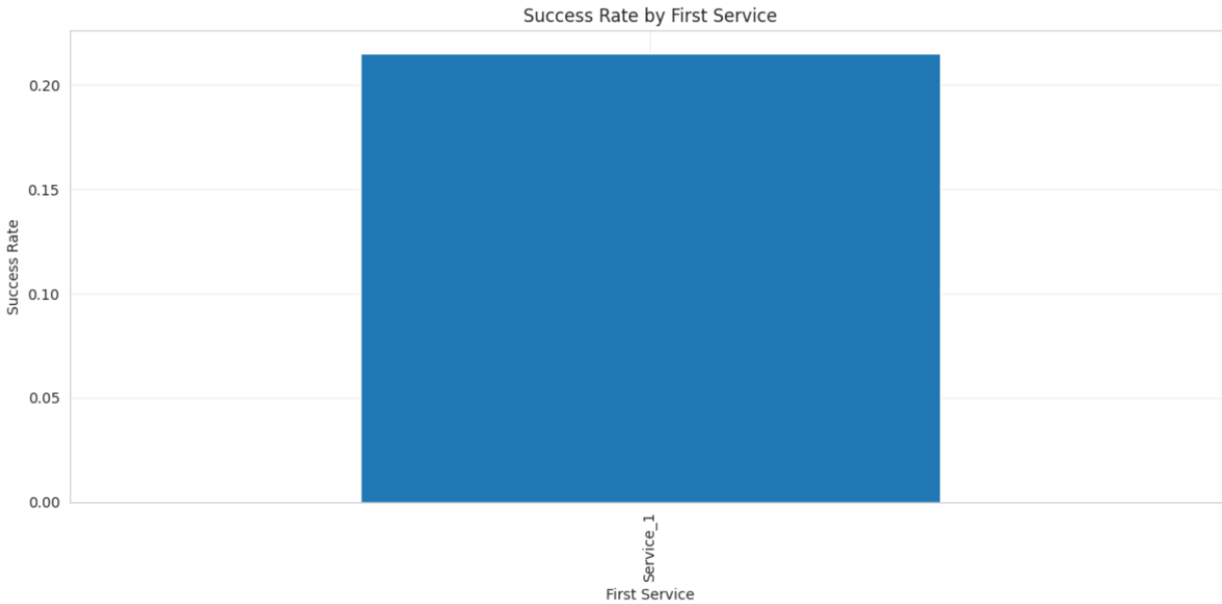

Figure 43: *Success Rate by First Service*

The bar chart shows that participants who began their journey with Service_1 had a higher likelihood of achieving improved TIMES scores.

Success Rate by Service Count

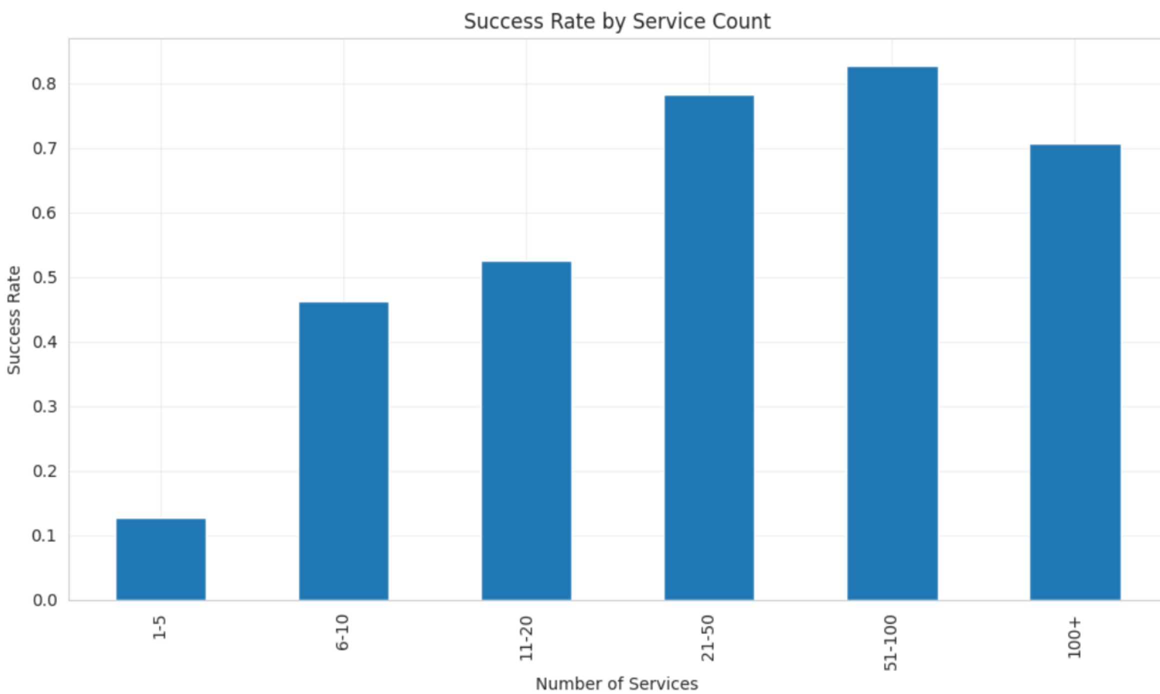

Figure 44: *Success Rate by Service Count*

As the number of services received increases, success rates also improve, peaking around 51–100 services, suggesting that sustained engagement is beneficial.

Success Rate by Service Variety

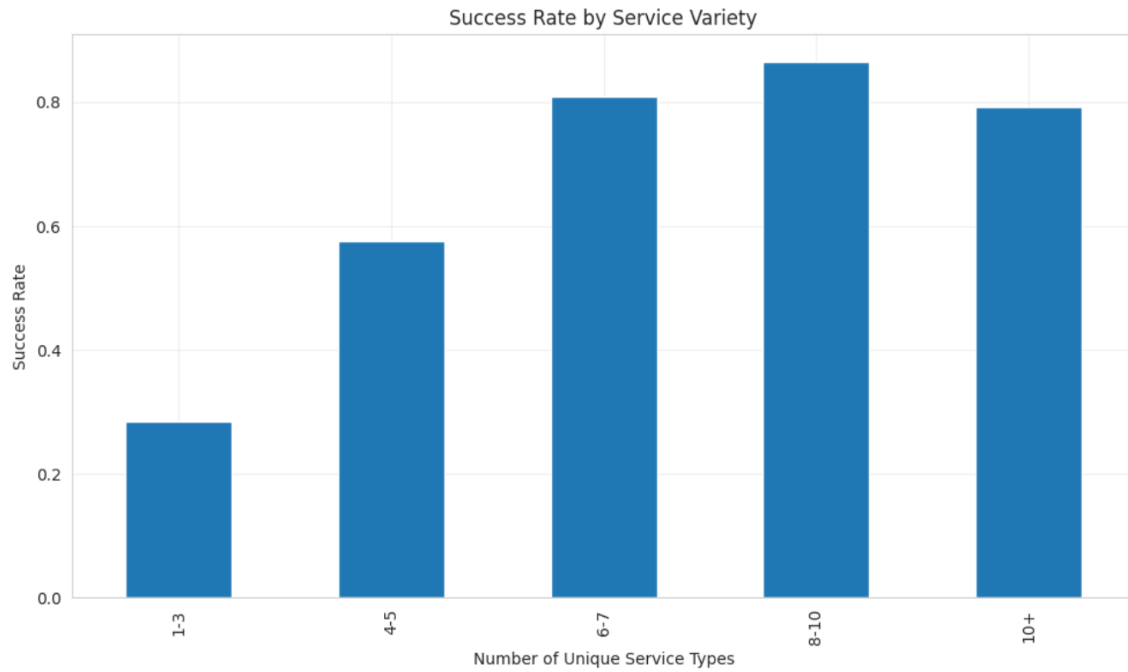

Figure 45: *Success Rate by Service Variety*

Clients exposed to a broader range of service types (8–10+) tend to show higher success rates, indicating the importance of service diversification.

Survival Analysis by Segment

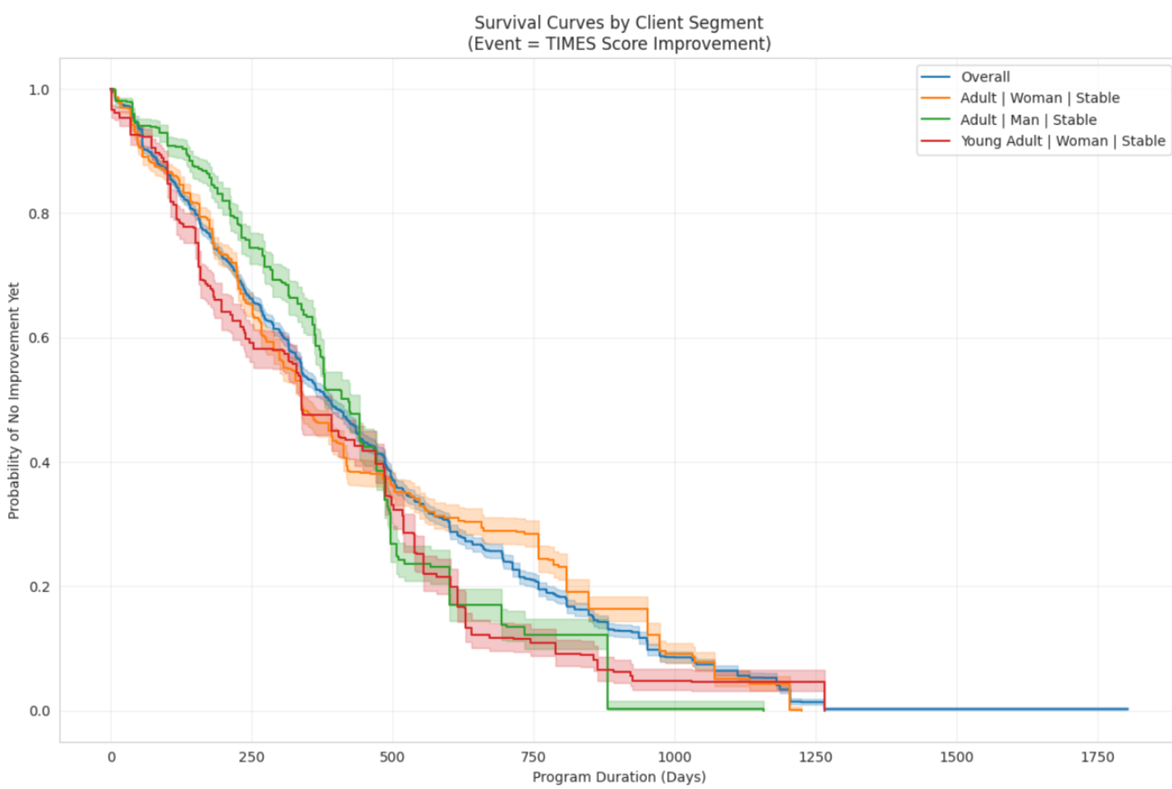

Figure 46: *Survival Curves by Client Segment*

Kaplan-Meier survival curves reveal how long different client segments take to improve. For instance, Adult Women in Stable housing improve faster (median ~338 days) than Adult Men (~422 days).

Optimal Pathway Graphs by Segment

Each of the following graphs represents the most successful service sequences for a specific client segment. Larger nodes denote more frequently used services; thicker arrows indicate common transitions.

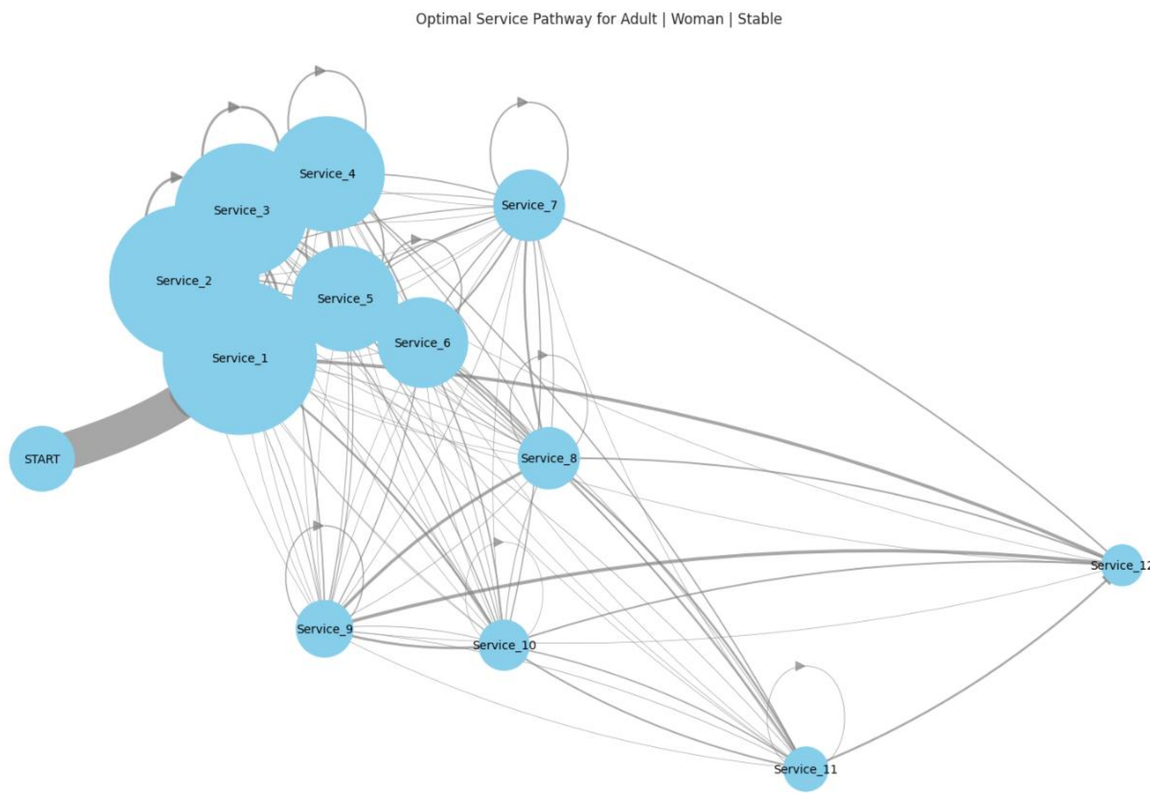

Figure 47: *Adult | Woman | Stable*

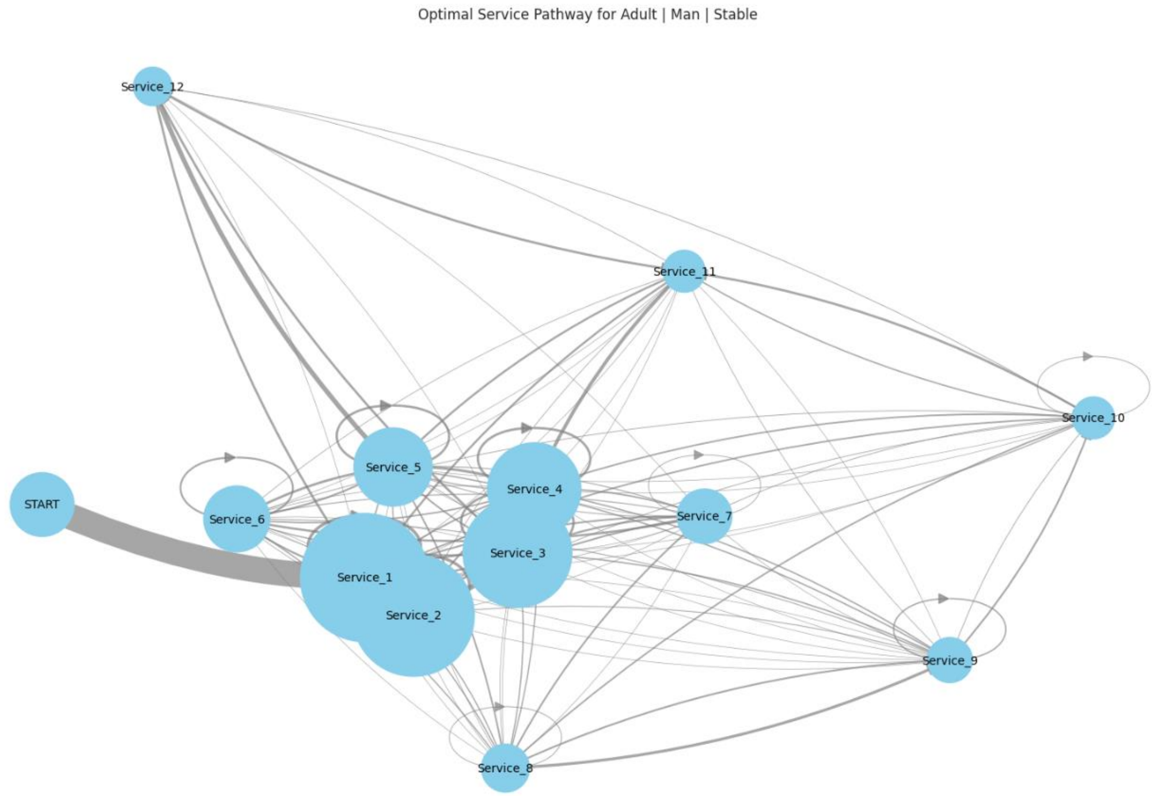

Figure 48: *Adult | Man | Stable*

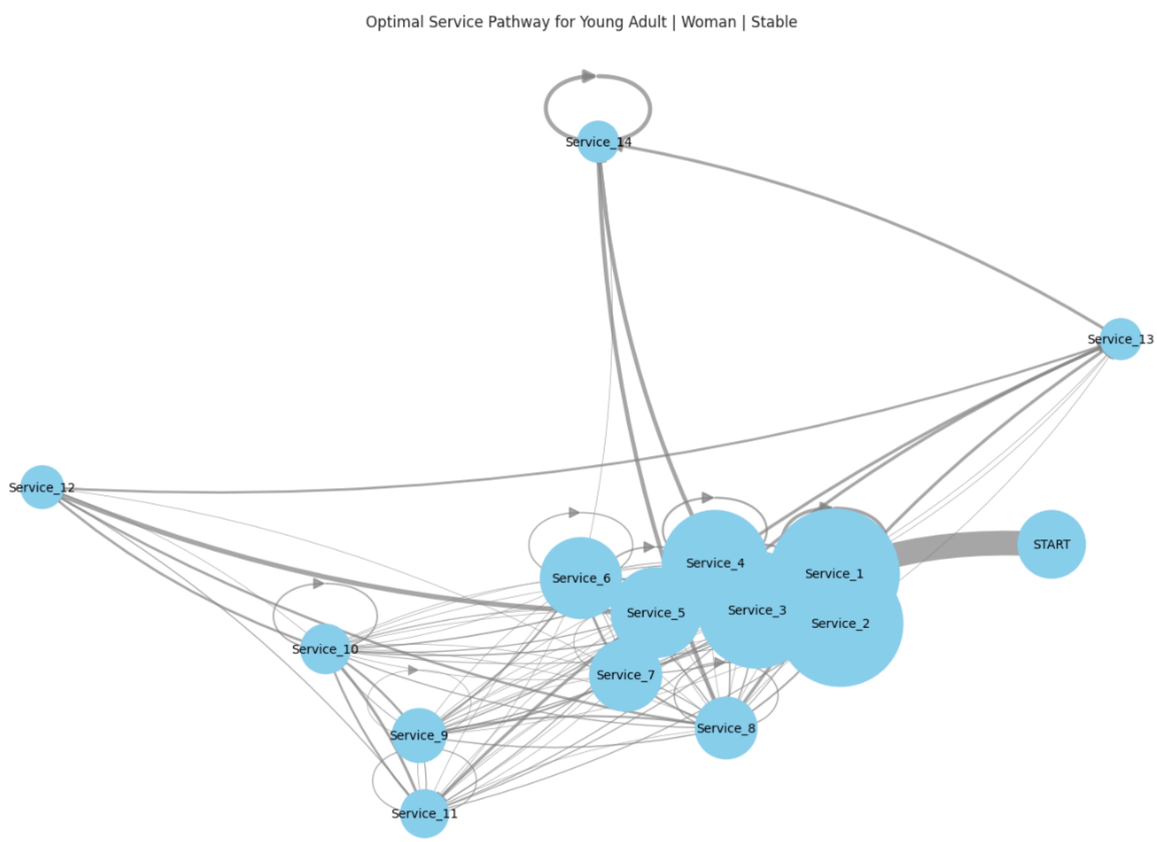

Figure 49: *Young Adult | Woman | Stable*

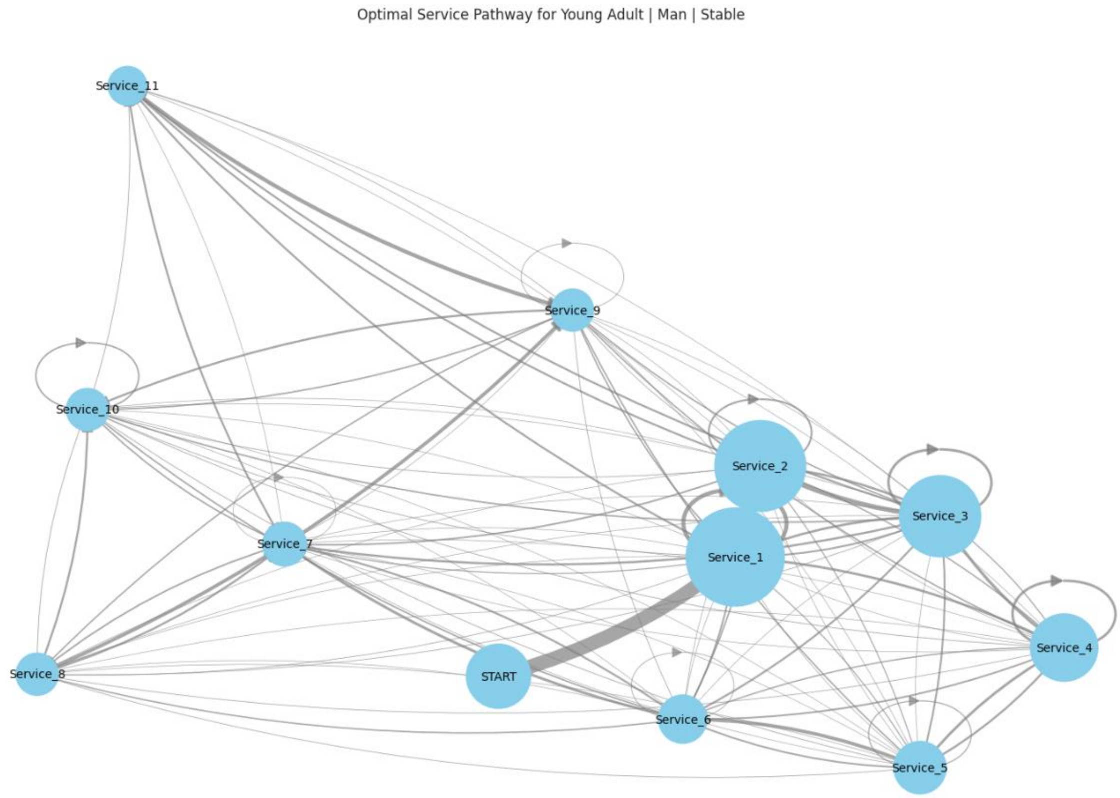

Figure 50: *Young Adult | Man | Stable*

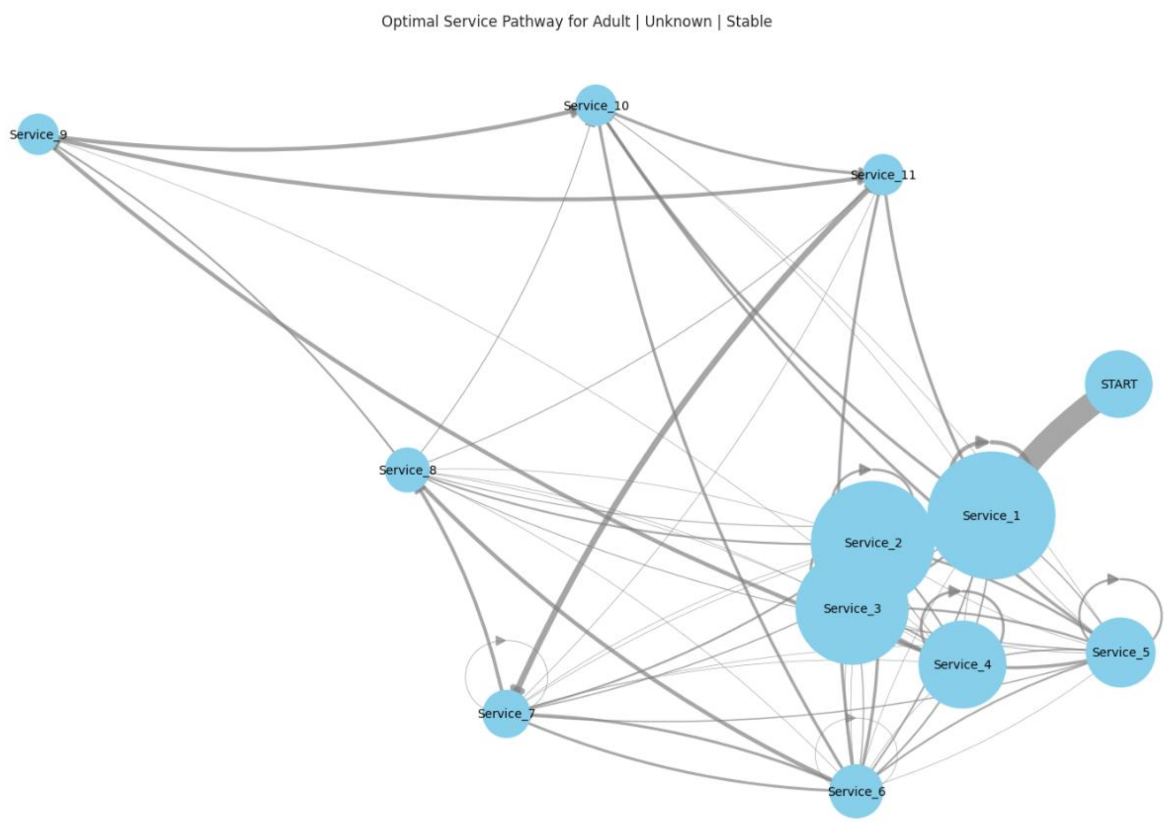

Figure 51: *Adult | Unknown | Stable*

These pathways consistently show Service_1 → Service_2 → Service_3 as a strong foundation for success.

Key Recommendations

1. **Standardize Early Engagement:** Begin client pathways with proven high-success services like Service_1, followed by Service_2 and Service_3, which appear most frequently in successful cases across all segments.

2. **Increase Service Variety and Depth:** Clients benefit from accessing 8–10+ different service types and receiving over 20 total services. Program designs should encourage broad service exposure and sustained participation.

3. **Customize by Segment:** Tailor program durations based on client profile:

   - Adult Women: 267 days median
   - Adult Men: 361 days median
   - Young Adults: ~254 days

4. **Use Pathway Models for Case Management:** Incorporate visual pathway models into planning tools to support caseworkers in aligning clients with proven successful routes.

Question 9: What patterns of disengagement can we identify, and how can machine learning help predict and prevent participant dropout?

To investigate participant disengagement, we developed a composite indicator based on three criteria: low engagement (≤ 5 services), short duration (≤ 30 days), and lack of improvement in TIMES score. A participant was marked as “disengaged” if they met any of these conditions.

Key Findings

- **Total participants analyzed:** 17,875
- **Low engagement:** 2,688 (15.0%)
- **Short program duration:** 563 (3.1%)
- **No TIMES score improvement:** 8,159 (45.6%)
- **Overall disengagement:** 8,759 (49.0%)

This indicates that nearly half the participants exhibited at least one disengagement risk factor.

Disengagement by Demographics

We explored how disengagement varied across different demographic groups using Chi-squared tests and visualizations.

- **Gender:** Participants identifying as “Prefer not to say”, “Two-Spirit”, or “Not listed” had **100% disengagement**. Men and women showed lower rates (45.8% and 40.5% respectively).

- **Birthplace:** Those not born in Canada had higher disengagement (43.5%) than Canadian-born participants (39.4%).

- **Housing Situation:** Participants from correctional facilities, shelters, or with no fixed address showed much higher disengagement than those in stable housing.

- **Education:** Surprisingly, those with graduate degrees showed higher disengagement (80.1%), which may reflect mismatched service expectations.

- **Disability Identification:** Participants who self-identified as having a disability had significantly lower disengagement rates.

All factors showed statistically significant relationships with disengagement ($p < 0.001$), reinforcing the need for tailored strategies.

Disengagement by Program

Programs exhibited varying disengagement rates:

- **Lowest disengagement:** *Bridges Care Management* (18.9%), *RAMP* (27.1%)

- **Highest disengagement:** *Day Care* (90.6%), *Computer Literacy Centre* (98.6%)

Only programs with at least 10 participants were included. These findings suggest that program structure, target demographics, and service design may play a role in participant retention.

Time to Disengagement (Survival Analysis)

Kaplan-Meier survival analysis showed the probability of participants remaining engaged over time.

- Participants from unstable housing and marginalized gender identities disengaged earlier.
- Attempts to run a Cox Proportional Hazards model failed to converge due to sparse data in some variables, suggesting complete separation or insufficient variation in predictor groups.

Predictive Modeling of Disengagement

We developed a machine learning pipeline using a **Random Forest Classifier** to predict disengagement risk.

- **Model accuracy:** 98%
- **AUC-ROC:** 0.98
- **Precision-Recall AUC:** 0.98

Top predictors of disengagement:

1. Number of services used
2. Number of unique service types
3. Total service hours
4. Age
5. Housing and gender variables (e.g., "Unknown", "Not listed")

The model performed well on both training and test data, and SHAP (SHapley Additive exPlanations) analysis helped confirm feature importance.

Risk Scoring and Categorization

Using the trained model, disengagement risk was scored for each participant:

- Risk was categorized into **Low (< 0.3)**, **Medium (0.3–0.6)**, and **High (> 0.6)**.
- Participants in the “High” risk category constituted a substantial proportion of

the population, particularly in programs like the *Computer Literacy Centre* and *Day Care*.

Recommendations

1. Early Intervention Thresholds

- Monitor participants receiving fewer than ~6 services or enrolled for less than ~30 days.
- Trigger early check-ins and outreach for those falling below these thresholds.

2. Targeted Demographic Strategies

- Gender minorities and those with unknown demographic information should be flagged for individualized support.
- Cultural and housing-sensitive programming may reduce disengagement.

3. Program-Level Improvements

- High-risk programs should be audited for engagement structure.
- Programs like the *Computer Literacy Centre* may benefit from restructured service delivery or onboarding.

4. Real-Time Engagement Monitoring

- Weekly scoring and alerts for missed services.
- Monthly reviews of program-level engagement rates.

5. Deploy the Predictive Model Operationally

- Automate weekly risk scoring.
- Train staff on interpreting risk categories and taking timely action.
- Continue retraining the model quarterly to adapt to new data.

Question 10: How do socioeconomic factors influence program outcomes, and what interventions can mitigate disparities?

To assess the impact of socioeconomic conditions on client outcomes, we analyzed relationships between various demographic factors, such as income source, housing status, education, and residency, and key success indicators, including TIMES score improvement, program duration, service engagement, and service diversity.

We first conducted statistical tests (ANOVA, correlation, and chi-square) to identify significant relationships. Several socioeconomic factors showed statistically significant effects on outcomes, with variables like housing situation and income source demonstrating moderate effect sizes. This led us to construct a composite metric: the **Socioeconomic Disparity Index**, which quantifies the stability or vulnerability of participants based on multiple conditions.

Key Findings

- **Disparity Index Distribution:** The index, normalized on a 0–100 scale, showed wide variability across participants (mean ≈ 43.3). Many clustered at moderate levels, but high-disparity individuals were also common.
- **Disparity and Outcomes:**
  - A **negative correlation** was observed between socioeconomic disparity and success outcomes:
    - TIMES Score Improvement: r = -0.016 ($p = 0.048$)
    - TIMES Score Change: r = -0.084 ($p < 0.001$)
    - Service Count: r = -0.106 ($p < 0.001$)
  - Participants with higher disparity tended to receive fewer services and were less likely to show improvement.
- **Program Variation:** Some programs consistently served clients with higher disparity scores (e.g., CAST Access Visits, Evergreen Drop-In), yet showed varied success rates, revealing disparities in effectiveness across services.
- **Predictive Modeling:** A Random Forest model identified **Socioeconomic Disparity Index** as one of the top 5 predictors of TIMES score improvement, highlighting the importance of addressing systemic barriers.

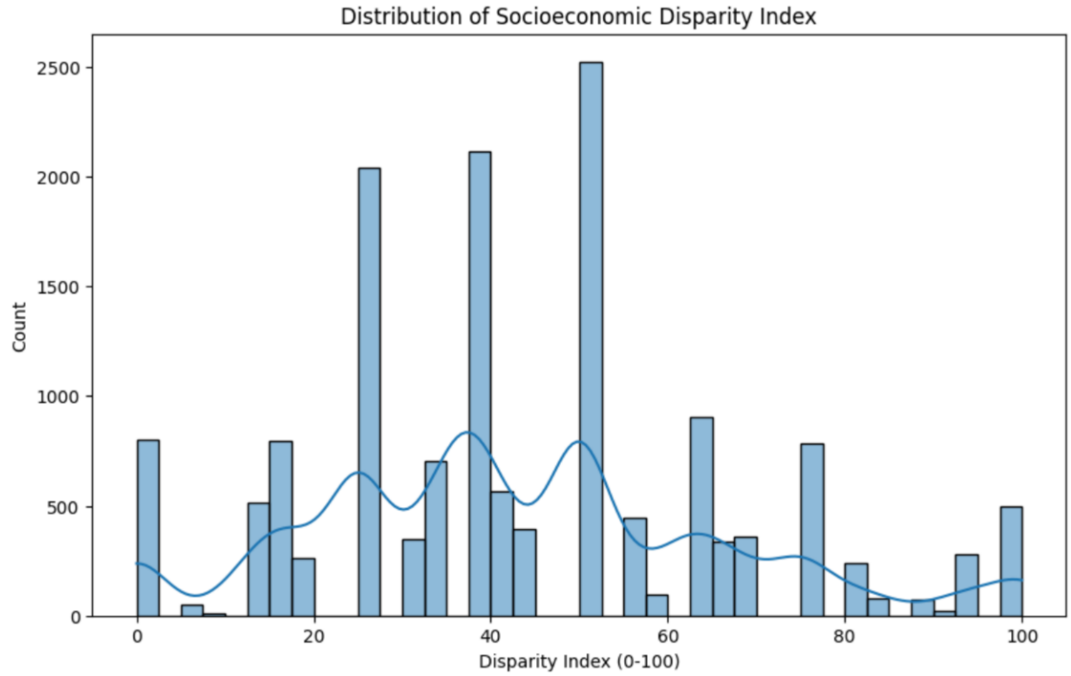

Figure 52: *Distribution of Socioeconomic Disparity Index*

This histogram illustrates the frequency distribution of the calculated socioeconomic disparity index (scaled 0–100) across all participants.

The index captures participants' socioeconomic vulnerability based on housing, education, income source, and residency status. Most clients fall within the 20–60 range, with a mean of approximately 43.3. Peaks in certain score bands suggest clustering based on shared risk profiles.

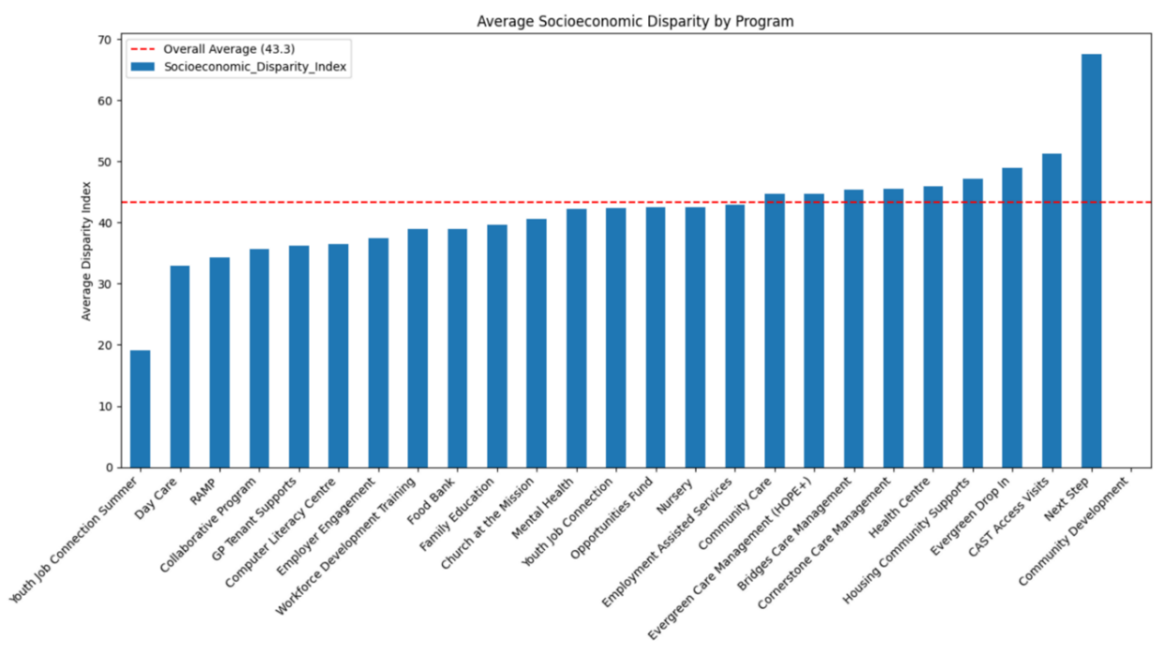

Figure 53: *Average Socioeconomic Disparity by Program*

This Bar chart shows the average disparity index across different programs, compared to the overall mean (red dashed line).

Programs like Next Step, Community Development, and CAST Access Visits serve clients with higher-than-average socioeconomic disparity. These programs may require additional resources and tailored interventions to address equity gaps.

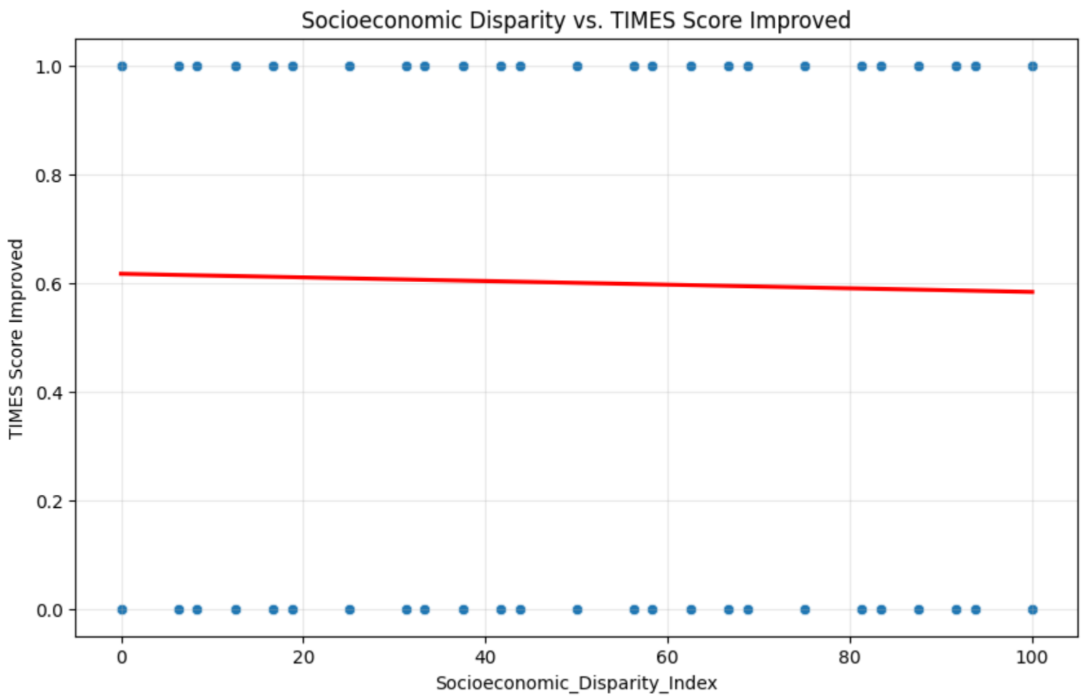

Figure 54: *Socioeconomic Disparity vs. TIMES Score Improved*

Scatterplot of disparity index against binary TIMES Score Improvement outcome, with a fitted trend line.

Although the relationship is weak, a slight downward trend suggests that higher disparity may be associated with a marginally reduced likelihood of improvement in TIMES scores.

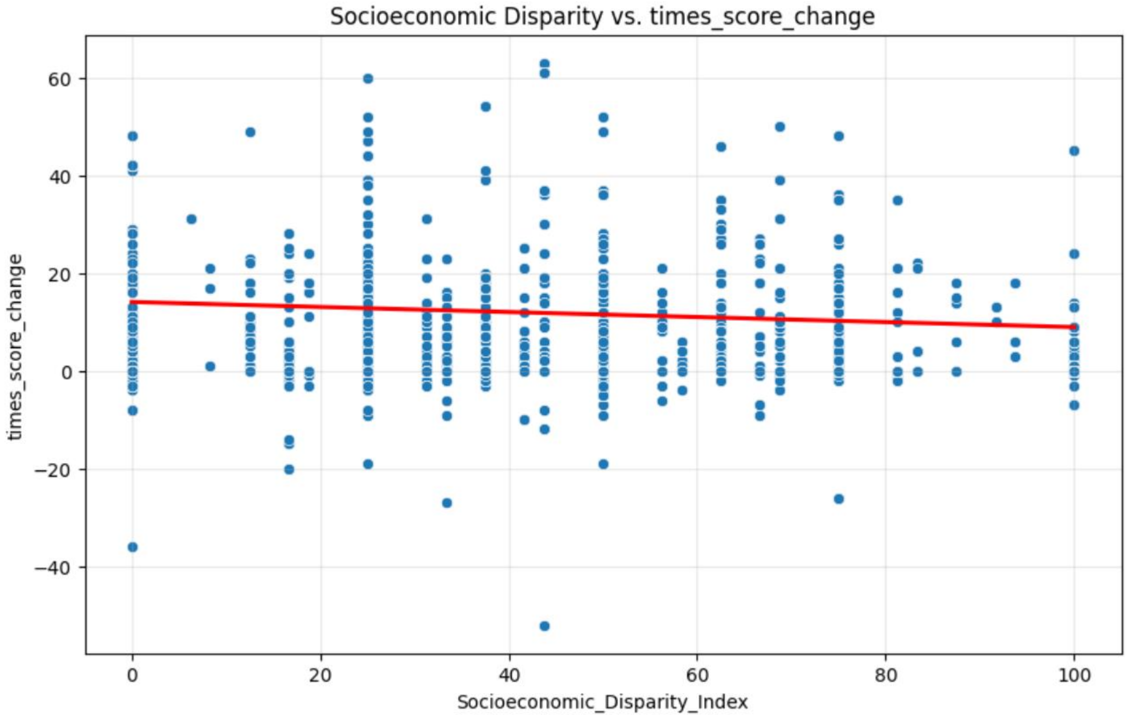

Figure 55: *Socioeconomic Disparity vs. TIMES Score Change*

Scatterplot showing continuous TIMES score change plotted against the disparity index, with a regression line.

A moderate negative trend is observed—participants with higher socioeconomic challenges generally exhibit smaller or even negative changes in their TIMES scores over time.

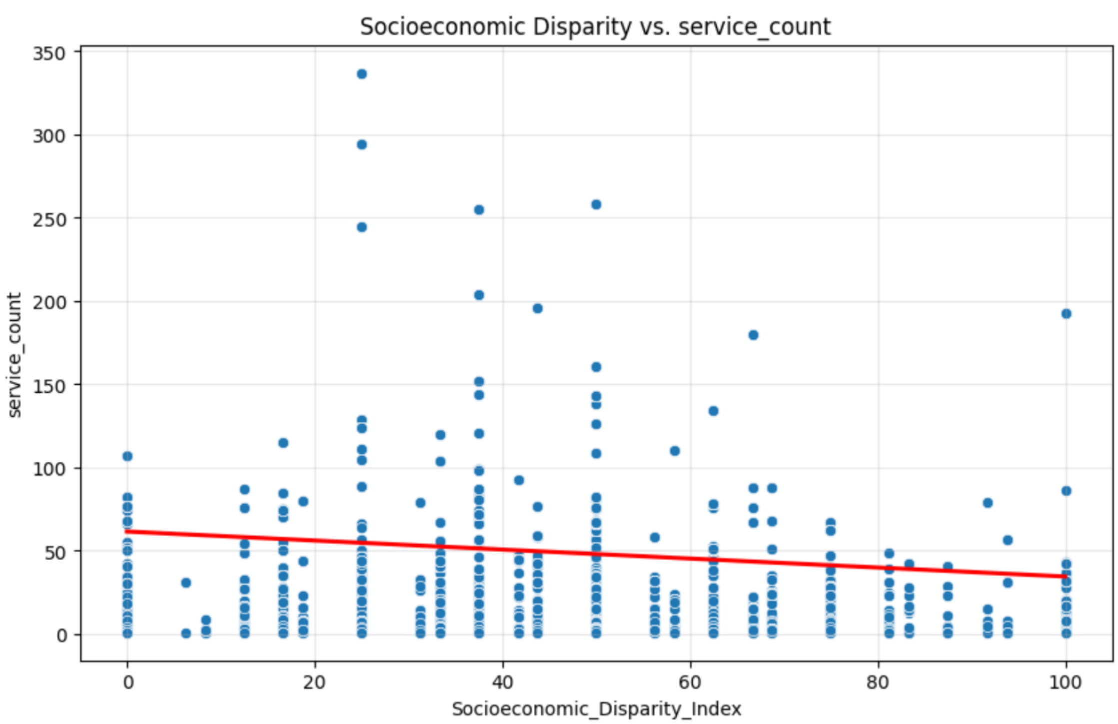

Figure 56: *Socioeconomic Disparity vs. Service Count*

Relationship between disparity index and total number of services received.

This chart shows that participants with higher socioeconomic disparity received fewer services overall. This may reflect barriers to access, engagement challenges, or systemic constraints in program design.

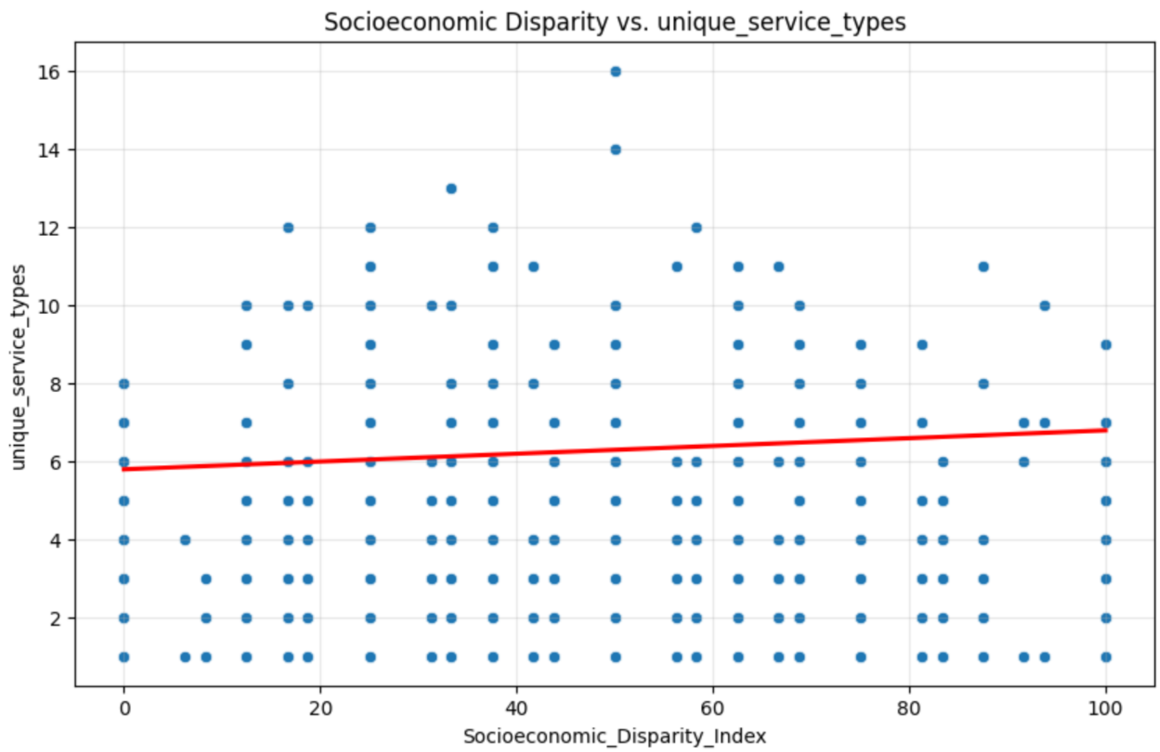

Figure 57: *Socioeconomic Disparity vs. Unique Service Types*

A scatterplot shows the relationship between disparity and diversity of service types accessed.

A slight positive correlation is visible, indicating that higher-disparity participants may receive more diverse services, possibly due to greater complexity of needs, even if service frequency is lower.

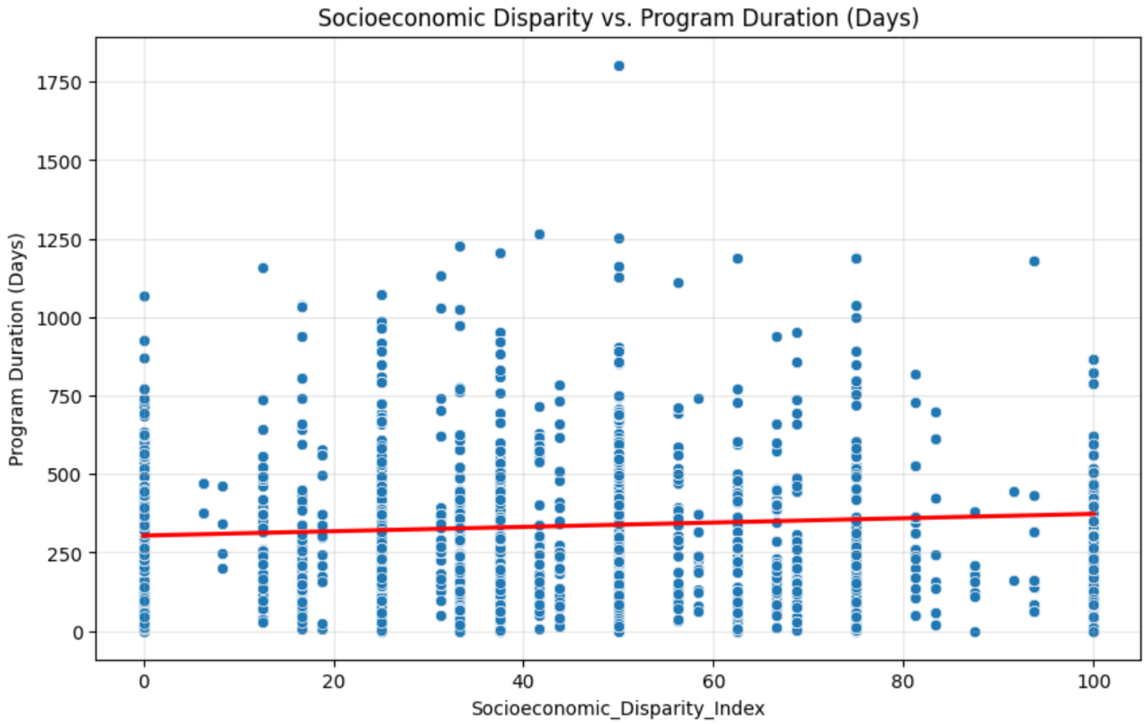

Figure 58: *Socioeconomic Disparity vs. Program Duration (Days)*

Correlation between disparity index and length of engagement in programs.

Clients with higher disparity tend to stay engaged for longer durations. This may reflect both greater support needs and delayed progression due to structural barriers.

Recommendations

1. **Target High-Disparity Programs**
   Focus interventions in programs with high average disparity and low success rates (e.g., CAST Access Visits) by:
   - Enhancing wraparound services
   - Deploying flexible delivery models
   - Improving access to basic needs support

2. **Replicate Success in Effective Models**
   Programs like Opportunities Fund and Youth Job Connection demonstrated high success rates among high-disparity clients through comprehensive, long-term, and diverse service delivery. These models should be expanded or emulated across other service lines.

3. **System-Level Interventions**
   - Introduce equity-focused performance metrics at the program level
   - Provide trauma-informed and culturally responsive training to staff
   - Prioritize cross-program coordination and warm handoffs
   - Allocate additional resources to high-disparity segments

Question 11: What patterns can we identify in terms of employment success?

This analysis investigates key predictors of employment success across the YSM programs. We explore how factors like service usage, program attributes, and demographics influence success, using both visual analytics and predictive modeling.

Service Utilization and Employment Outcomes

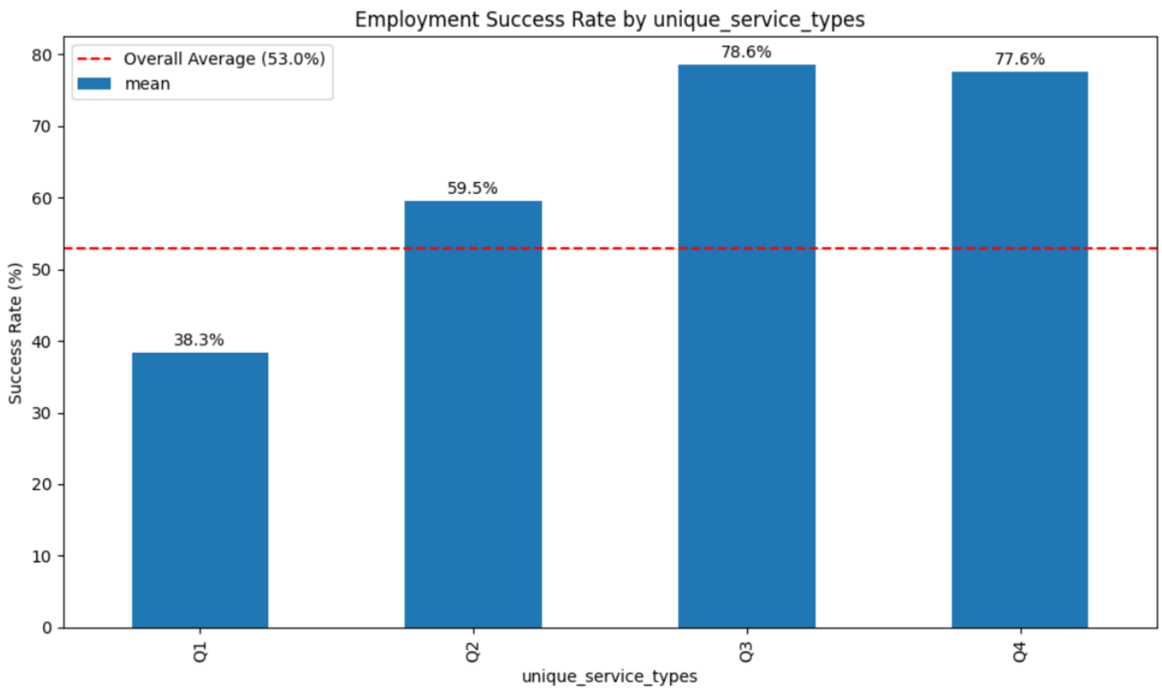

Figure 59: *Employment Success Rate by Unique Service Types*

Clients who accessed a higher number of unique service types (Q3 and Q4) achieved significantly higher employment success rates (77.6%–78.6%) than those in Q1 (38.3%). This suggests that engaging in a more diverse range of services may be linked to better outcomes.

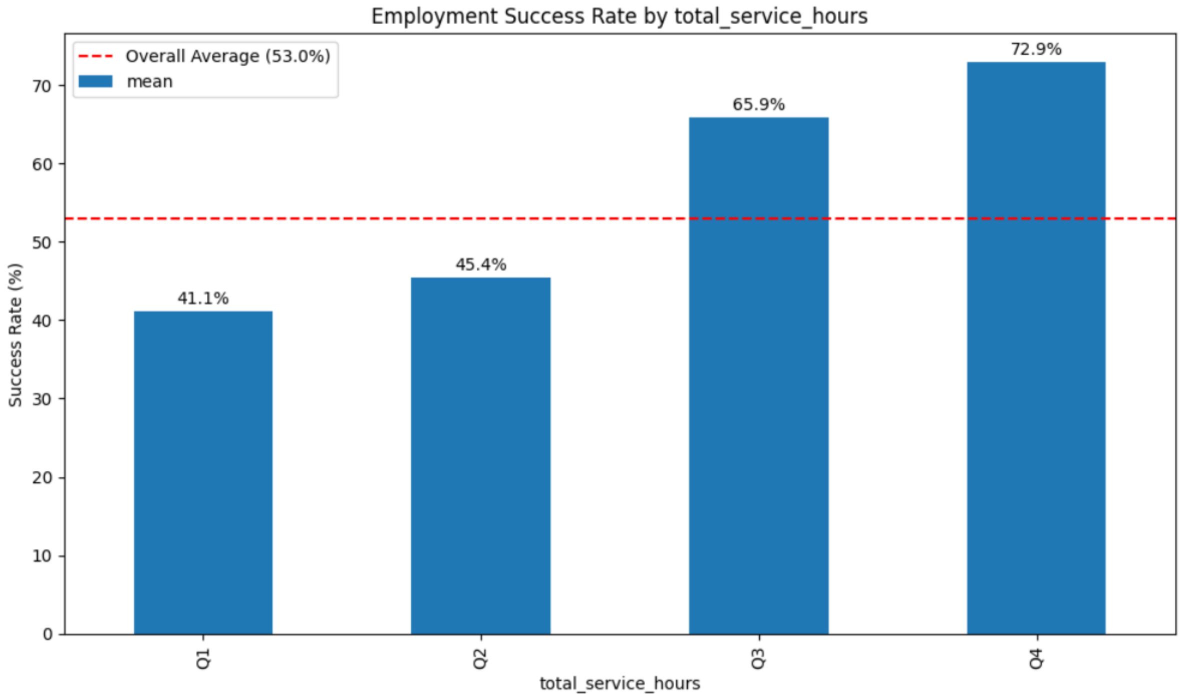

Figure 60: *Employment Success Rate by Total Service Hours*

Similarly, clients who accumulated more service hours had better employment results. Those in the top quartile (Q4) achieved a 72.9% success rate, compared to only 41.1% in Q1.

Program Duration and Engagement Level

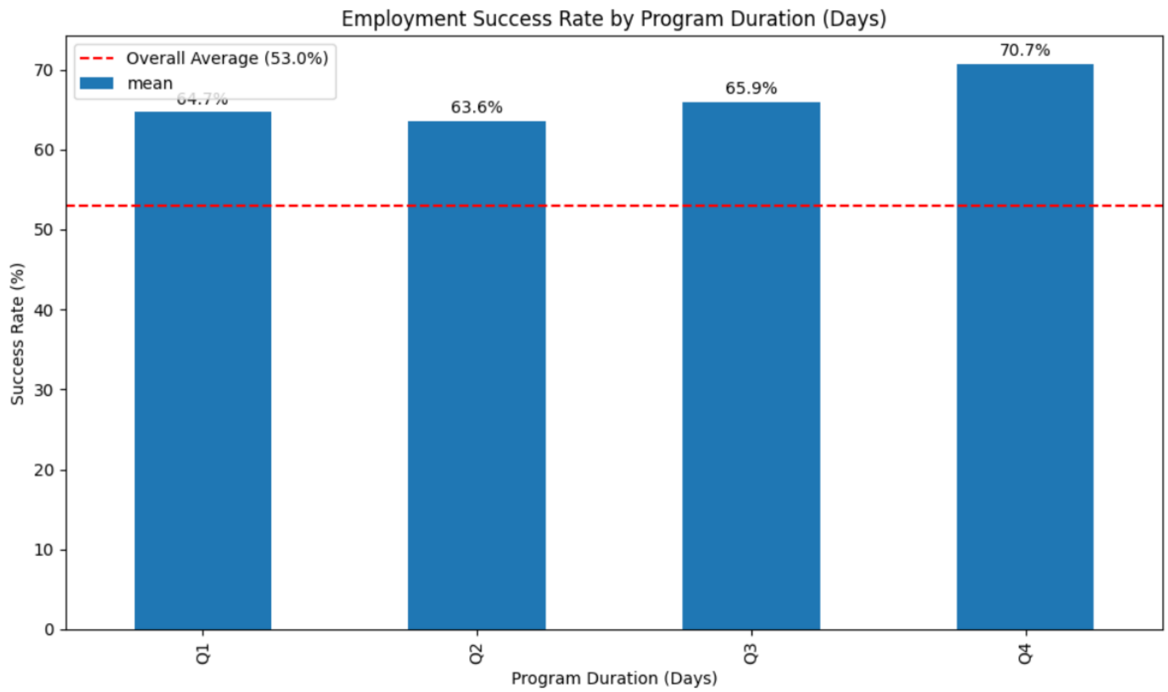

Figure 61: *Employment Success Rate by Program Duration*

Longer program durations are positively associated with success. Those in Q4 of program length reached 70.7% success, well above the overall average of 53%. This suggests that sustained engagement over time may help improve employment readiness and placement.

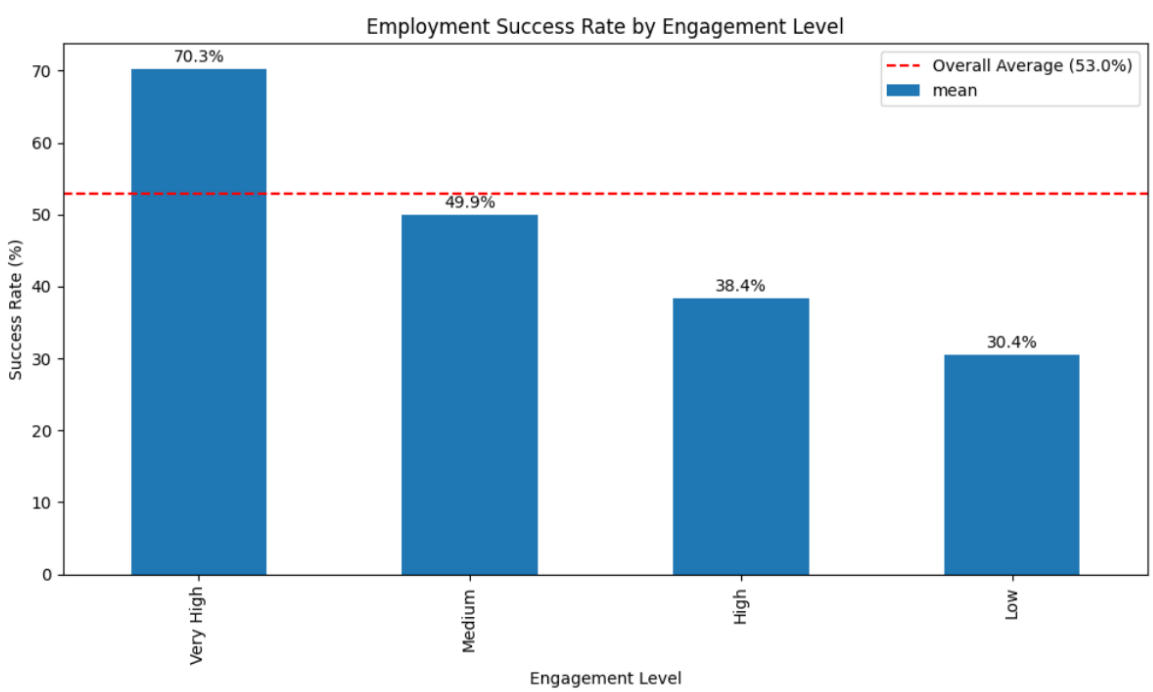

Figure 62: *Employment Success Rate by Engagement Level*

Engagement level shows a strong gradient: participants with “Very High” engagement achieved a 70.3% success rate versus only 30.4% for those categorized as “Low.” This reinforces the critical importance of sustained and active participation.

Program Type and Effectiveness

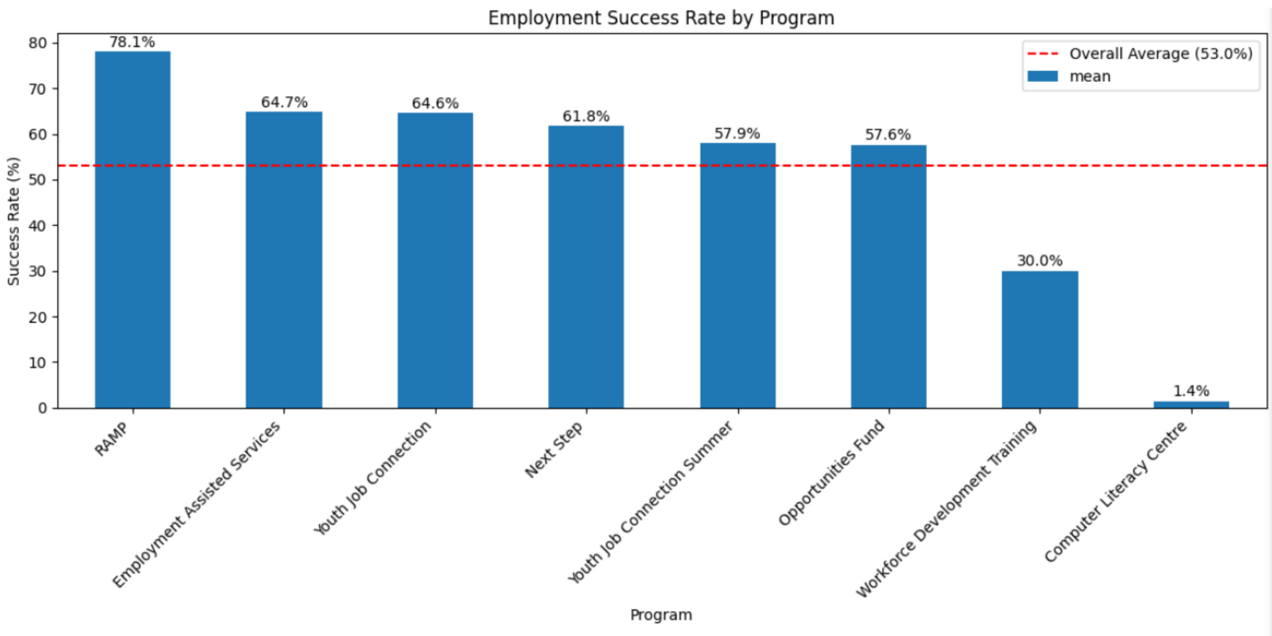

Figure 63: *Employment Success Rate by Program*

Time to Employment Success and Subgroup Analysis

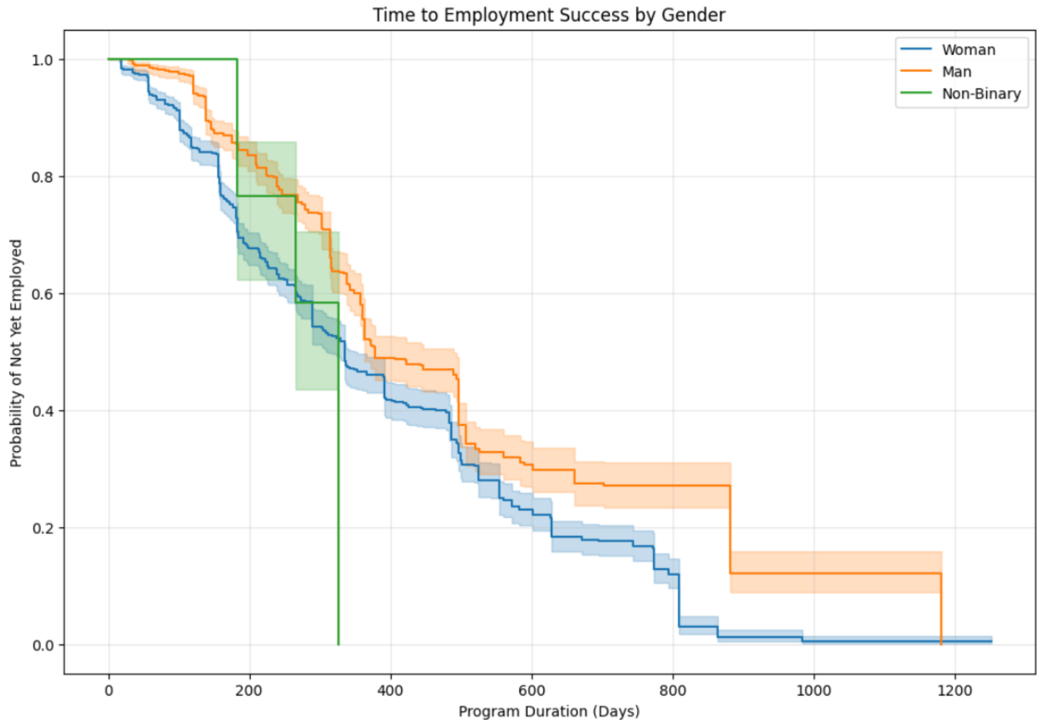

Figure 64: *Time to Employment Success by Gender*

Survival analysis shows that women tend to achieve employment success faster than men, while non-binary individuals show more variability. These differences may reflect underlying barriers or support systems that vary by gender.

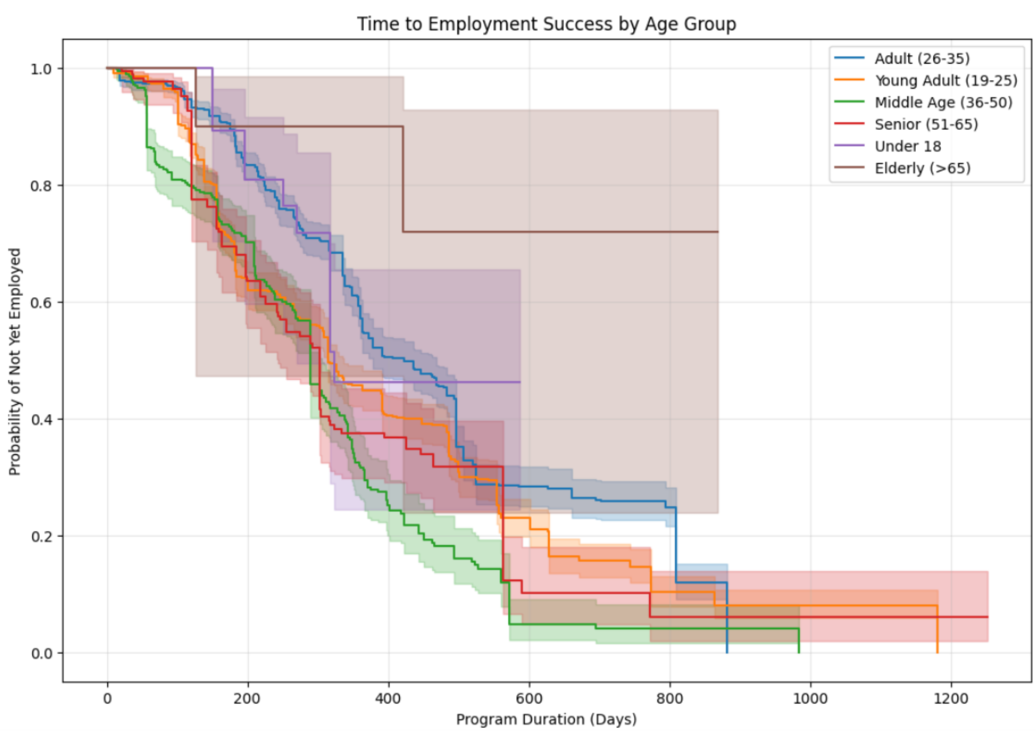

Figure 65: *Time to Employment Success by Age Group*

Youth (Under 18 and 19–25) and Middle-Aged (36–50) participants tended to reach employment faster than older clients (51+), particularly the elderly group (>65), who showed much slower transitions to success. This points to potential age-related challenges in workforce entry.

Predictive Modeling Insights

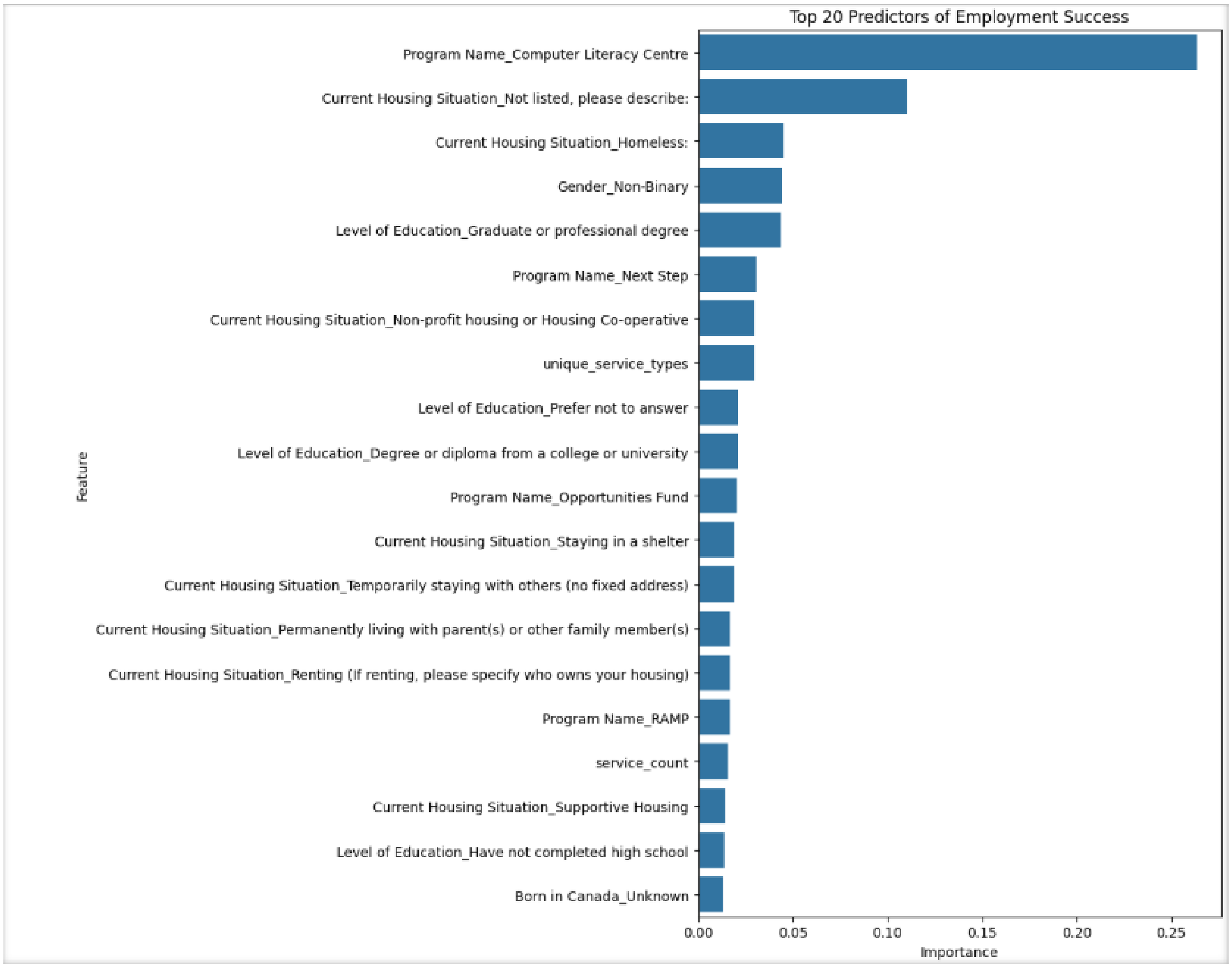

Figure 66: *Top 20 Predictors of Employment Success (Model-Based)*

Machine learning analysis confirmed program type, housing situation, gender, and education level as top predictors. Interestingly, being in the Computer Literacy Centre program and homelessness were associated with poorer outcomes, while graduate-level education and Next Step program were positive indicators.

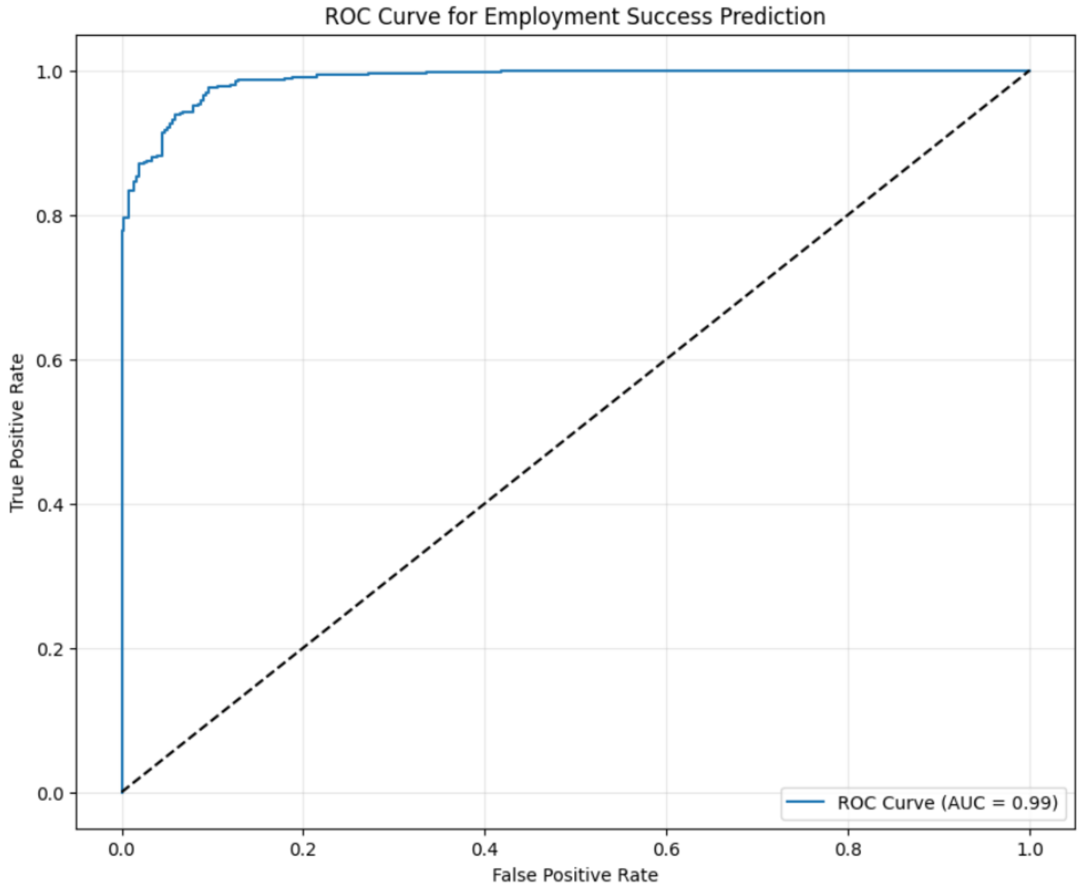

Figure 67: *ROC Curve – Model Accuracy*

Our predictive model achieved an AUC of 0.99, indicating high reliability in distinguishing between clients who succeeded and those who didn't.

Key Insights

- Service depth and breadth significantly enhance employment outcomes.
- Longer engagement and very high participation predict higher success.
- Certain programs (like RAMP) consistently outperform others.
- Demographic factors, especially age and gender, influence time to employment.
- Machine learning confirms and quantifies the importance of these factors.

Recommendations

1. Expand high-performing programs and reassess low-performing ones.
2. Encourage multi-service participation to improve individual outcomes.
3. Tailor support strategies by age and gender to address specific barriers.
4. Use predictive models for early intervention and program targeting.

Question 12: What are the most effective combinations and sequences of services for improving client outcomes?

To determine the most effective program combinations and sequences, we evaluated both *average TIMES score improvement* and *success rate* across service combinations. We further integrated an **effectiveness score**, calculated by standardizing both metrics and averaging them to identify top-performing combinations.

Top Program Combinations

The most effective program combinations, based on a composite of average score change and success rate, are:

- Cornerstone Care Management + Housing Community Supports (Effectiveness Score: 0.92)
- Bridges Care Management + Housing Community Supports (Effectiveness Score: 0.91)
- Mental Health + RAMP (Effectiveness Score: 0.82)

These combinations consistently showed high score improvements and high success rates, as illustrated below:

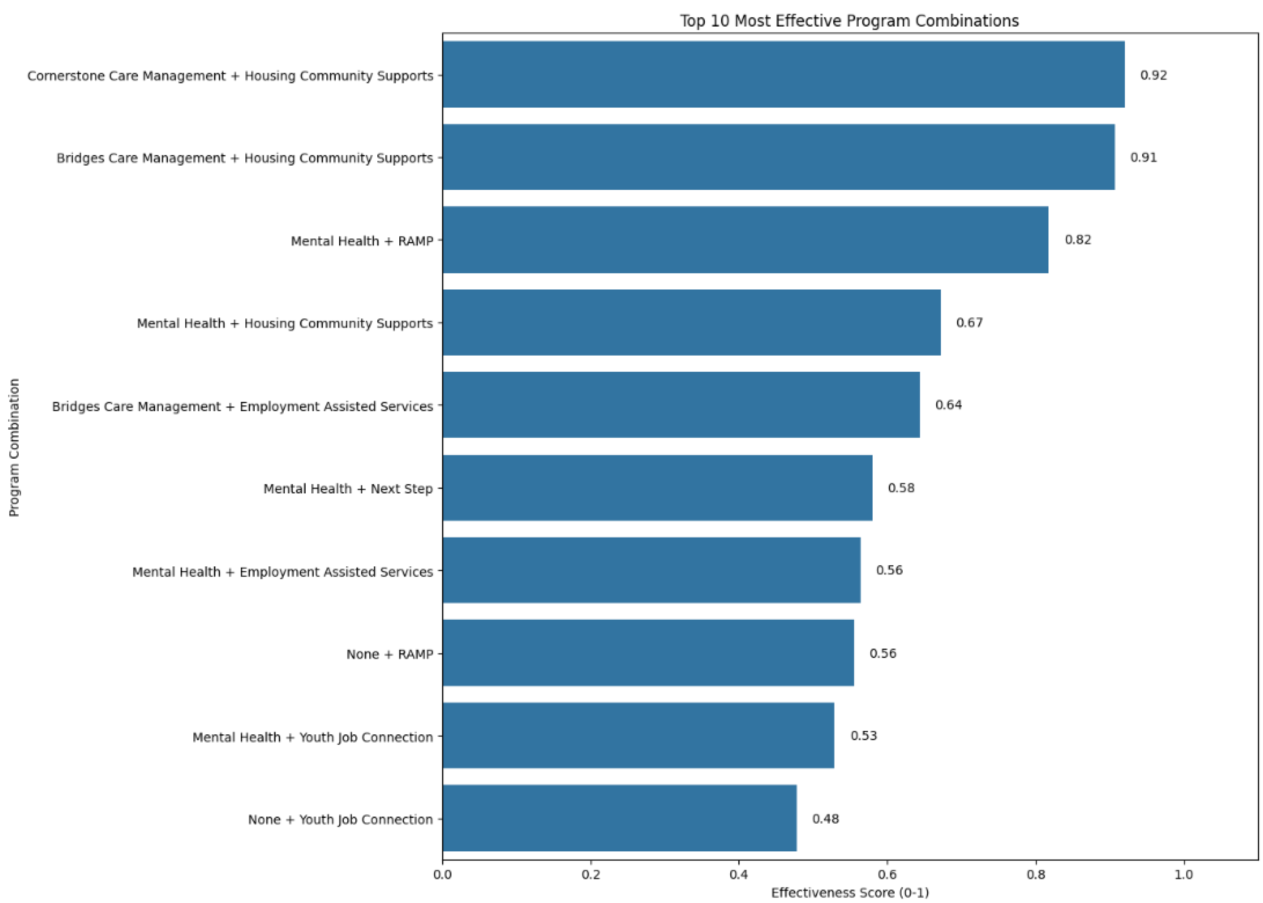

Figure 68: *Top 10 Most Effective Program Combinations*

Average Score Change

Bridges Care Management paired with Housing Community Supports produced the highest average score change (16.3 points), followed closely by Cornerstone Care Management + Housing Supports (14.9). Other combinations, such as Mental Health + RAMP (11.4) and Mental Health + Housing Community Supports (10.9), also demonstrated strong gains.

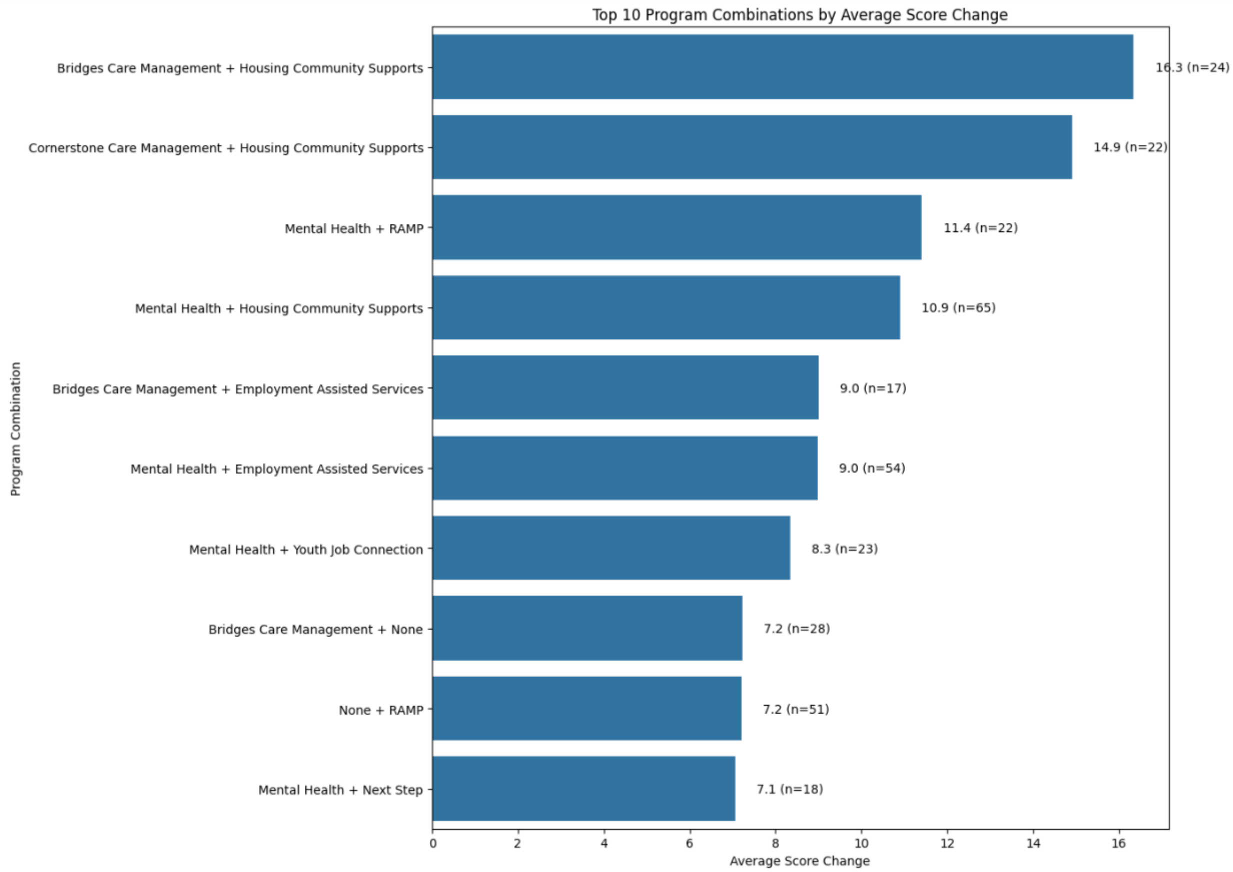

Figure 69: *Top 10 Program Combinations by Average Score Change*

Sequences Involving Mental Health

When analyzing the sequence of program delivery, initiating services with Mental Health (MH First) resulted in better outcomes:

- Success Rate: 51.6% for MH First vs. 46.4% (MH Later) and 32.9% (No MH)
- Average Score Change: 9.5 for MH First vs. 7.8 (MH Later) and 6.4 (No MH)

This suggests that front-loading mental health support contributes significantly to long-term client progress.

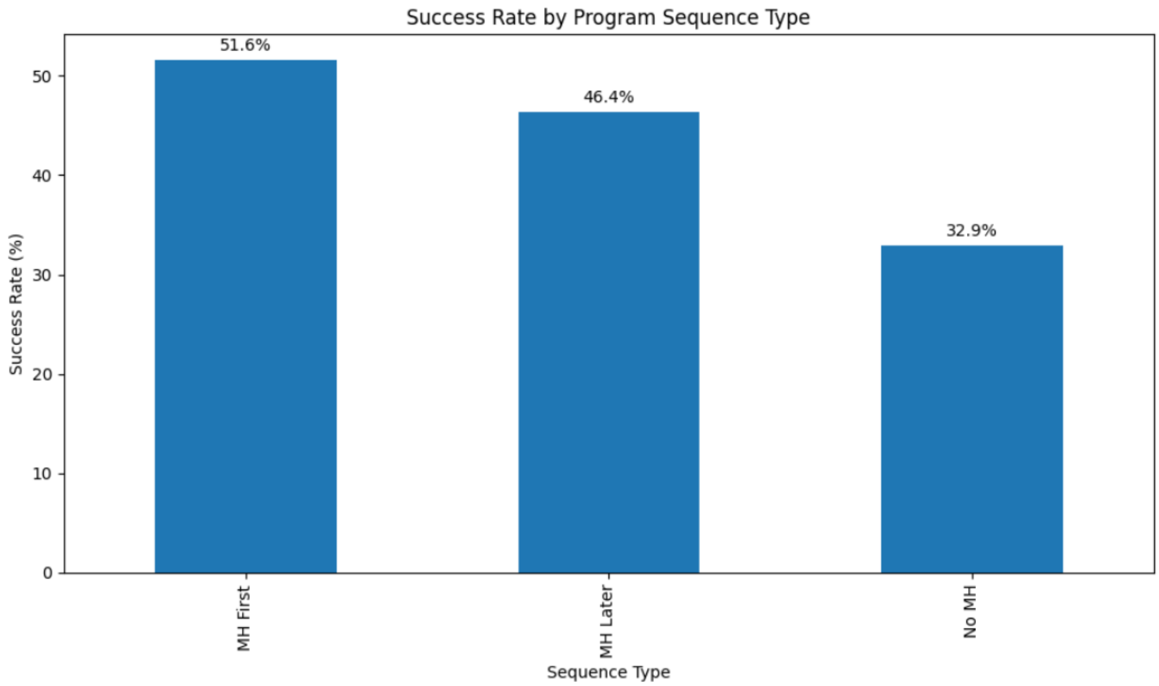

Figure 70: *Success Rate by Sequence Type*

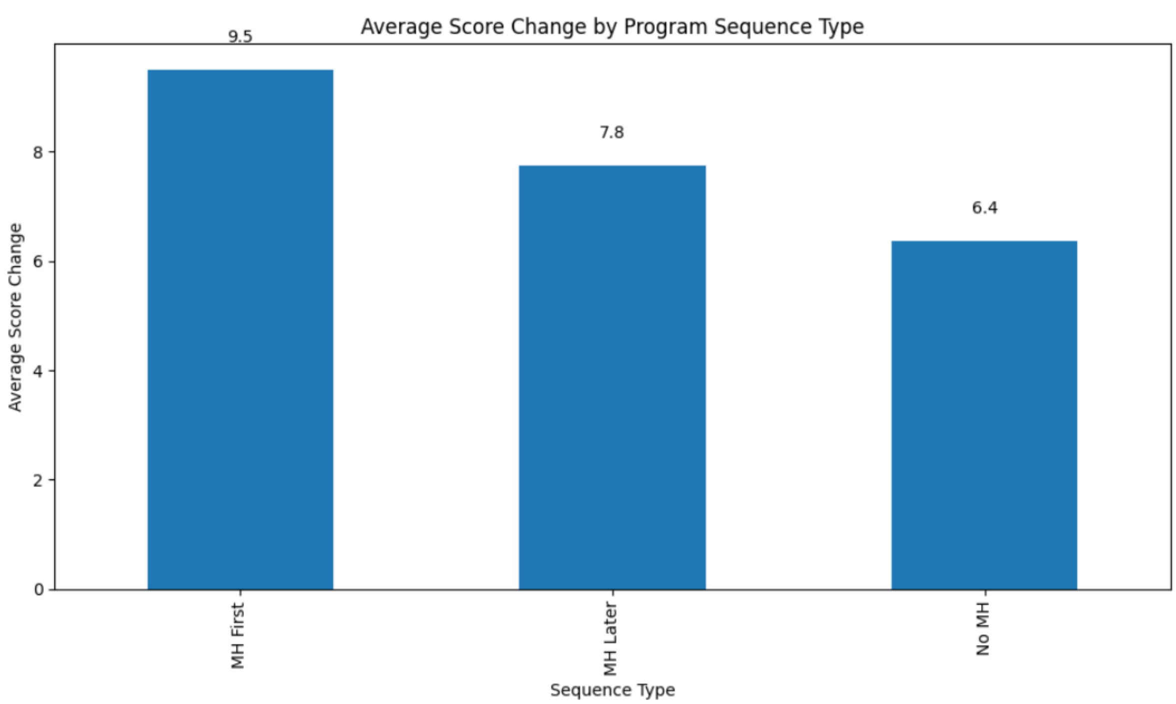

Figure 71: *Score Change by Sequence Type*

Combined View: Success vs. Score Change

To visualize the trade-off between success and score change, the following bubble chart plots both dimensions. The top-right quadrant clearly supports the dominance of combinations like Bridges Care Management + Housing Community Supports and Cornerstone Care Management + Housing Community Supports, with high effectiveness on both axes.

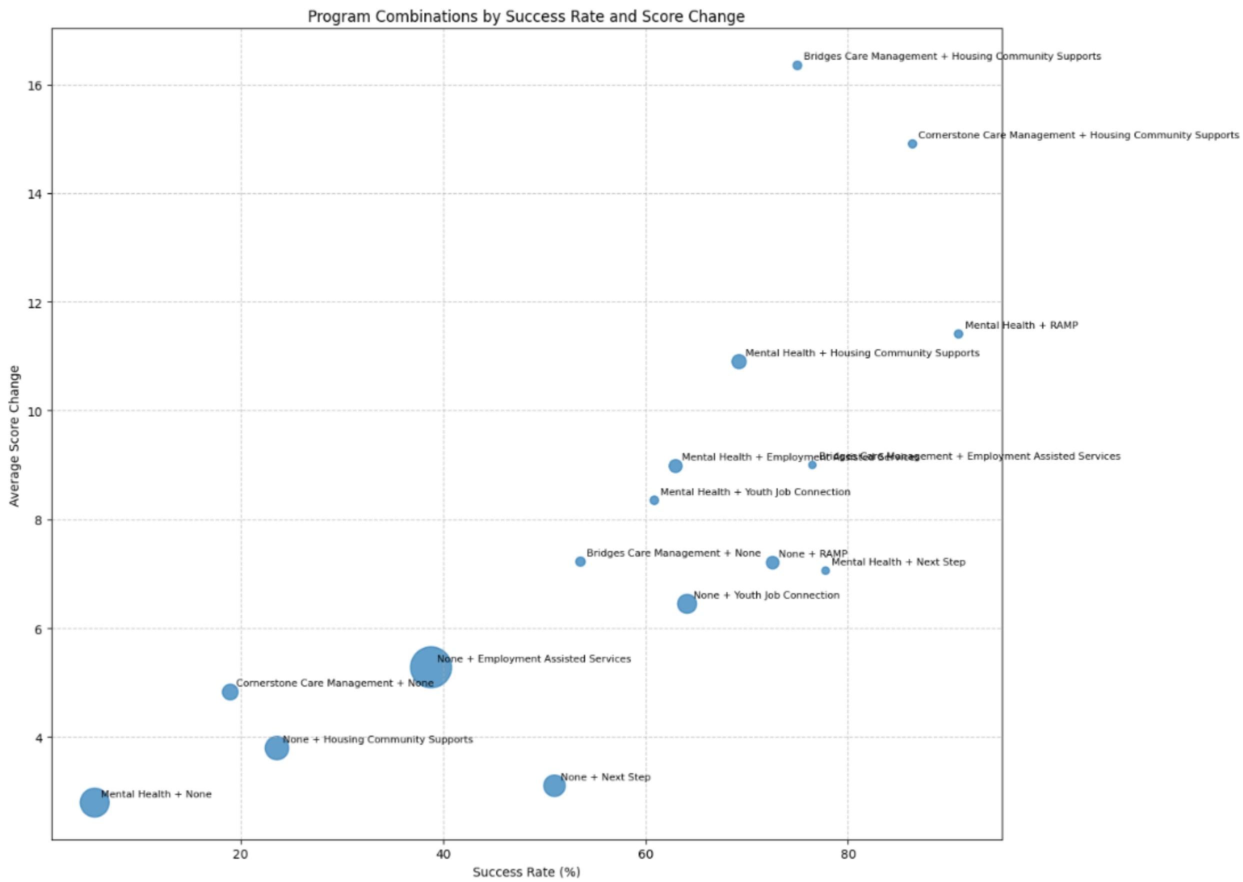

Figure 72: *Bubble Plot of Program Combinations*

Summary

The most effective approaches to improving client outcomes are multi-service combinations that include care management and housing supports, particularly when mental health services are offered early. These combinations and sequences deliver the strongest gains in both score change and success probability and should be prioritized in future programming and funding allocations.

Question 13: Optimal Resource Allocation Strategy to Maximize Community Impact

To identify the most effective resource allocation strategy, we conducted a comprehensive ROI and impact-based evaluation of community programs supported by Yonge Street Mission (YSM). The objective was to determine how funding can be optimized across programs to deliver maximum outcomes in terms of improved TIMES scores, success rates, and equitable access for different demographic groups.

Program ROI and Impact Analysis

We first calculated program-level Return on Investment (ROI) using success rate and average TIMES score change per dollar spent. The Youth Job Connection Summer and Day Care programs had the highest ROI, though larger programs like Employment Assisted Services, Health Centre, and Community Care showed strong absolute impact despite higher costs per participant.

Key Metrics Evaluated:

- Impact Score = Success Rate × Avg. Score Change
- ROI = Impact Score / Cost per Participant
- Cost per Success and Cost per Point of Improvement

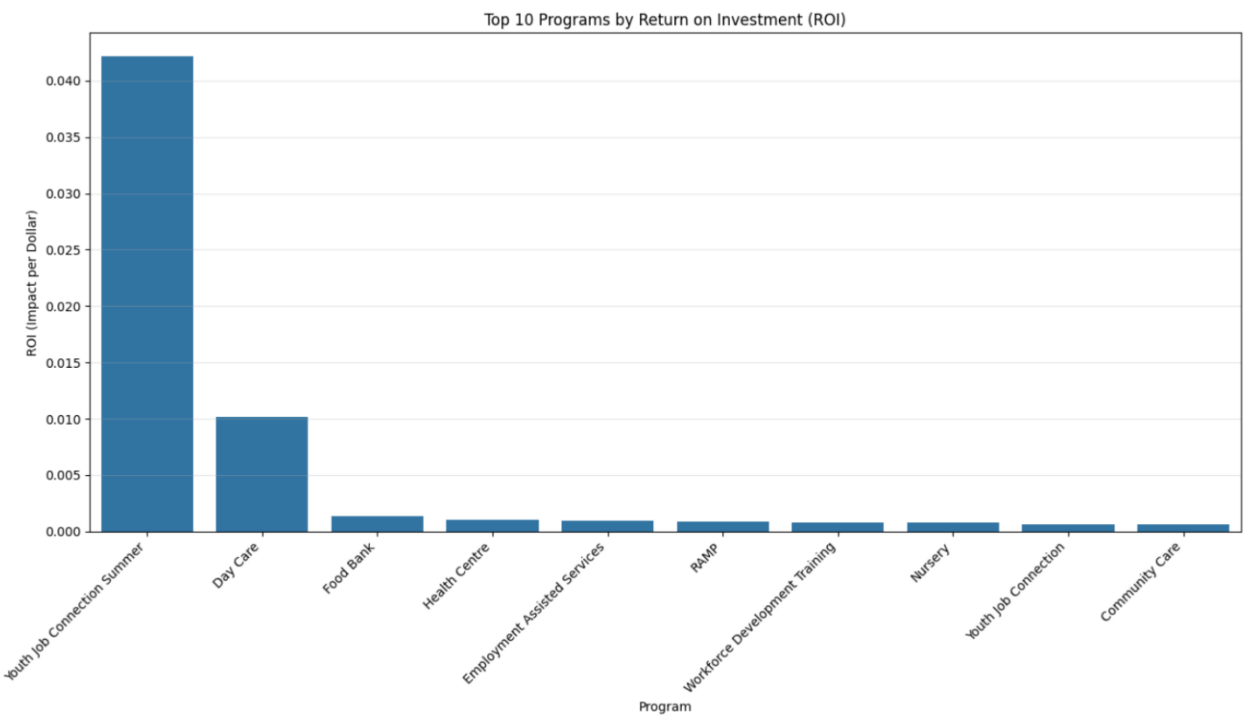

Figure 73: *Top 10 Programs by ROI*

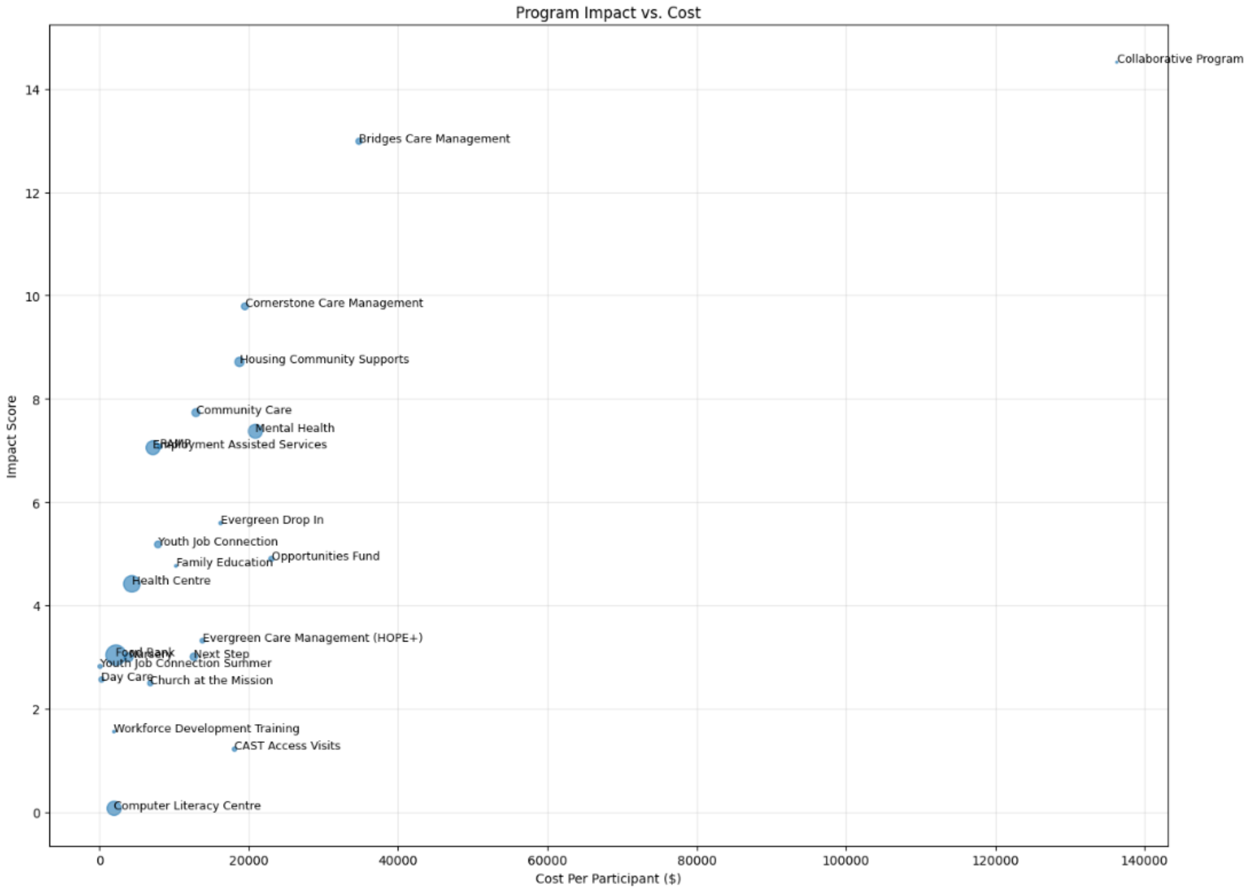

Figure 74: *Program Impact vs Cost Scatter Plot*

Equity and Demographic Needs Analysis

We examined allocation gaps by gender, age, housing status, and country of birth. The analysis revealed:

- Men and older adults received more than their proportional share of resources.
- Women, trans, and unknown gender identities were under-allocated by up to 6%.
- Housing-insecure individuals (e.g., shelter residents, couch-surfers) were underserved.

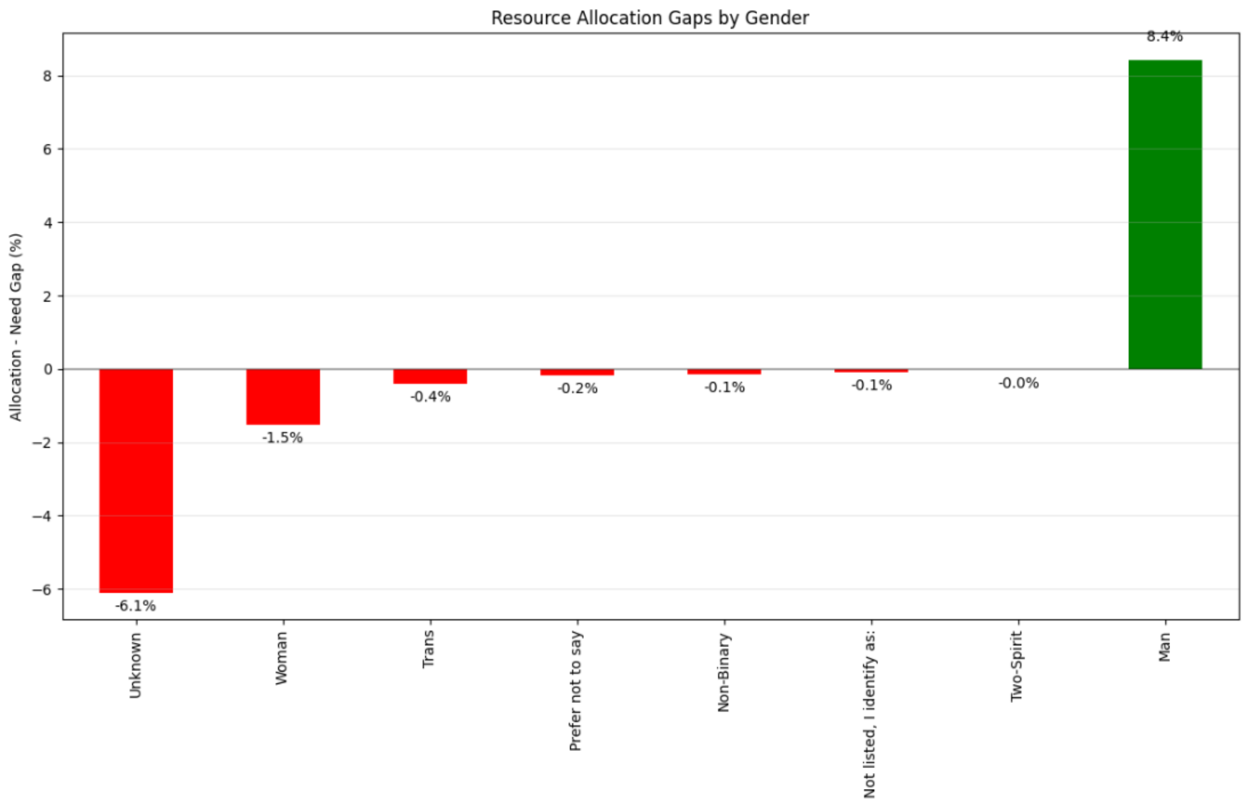

Figure 75: *Allocation Gaps by Gender*

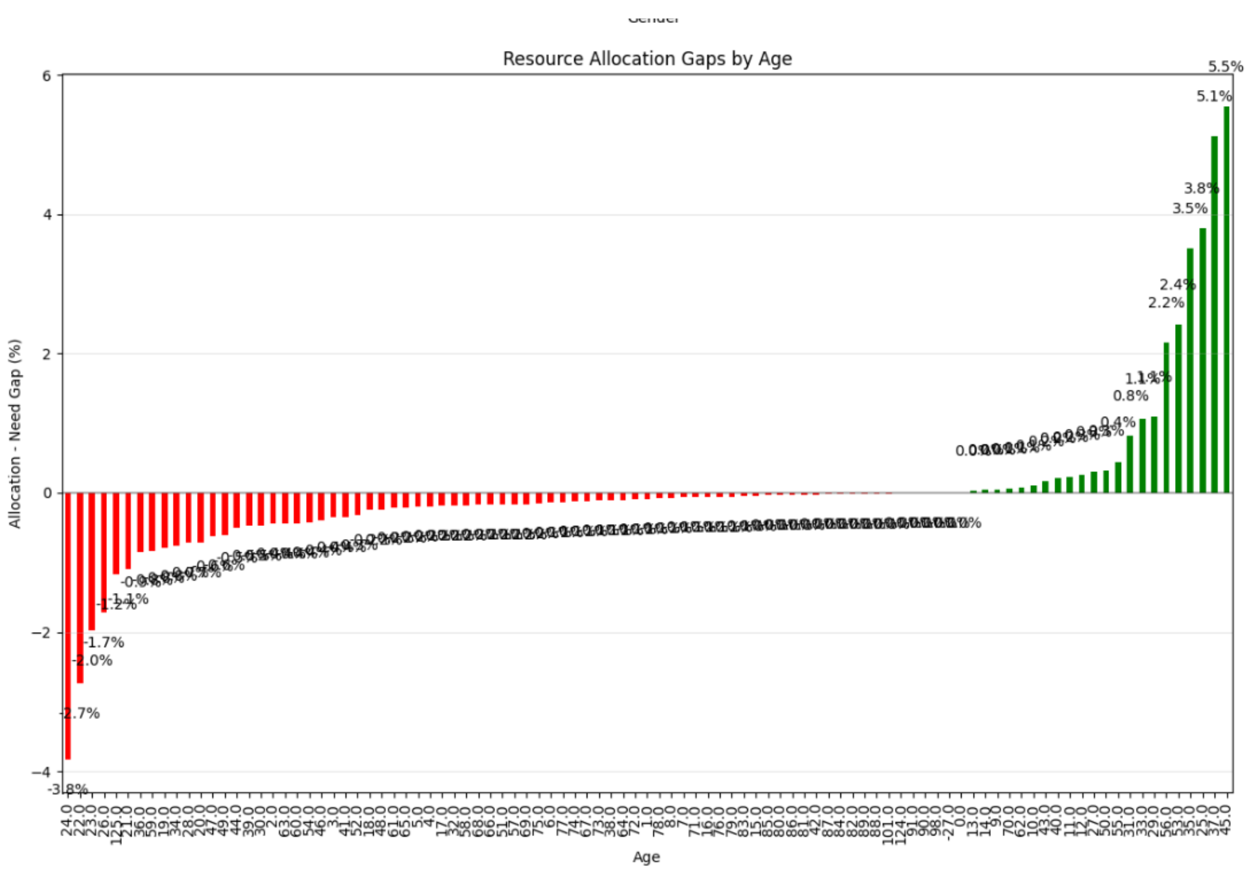

Figure 76: *Allocation Gaps by Age*

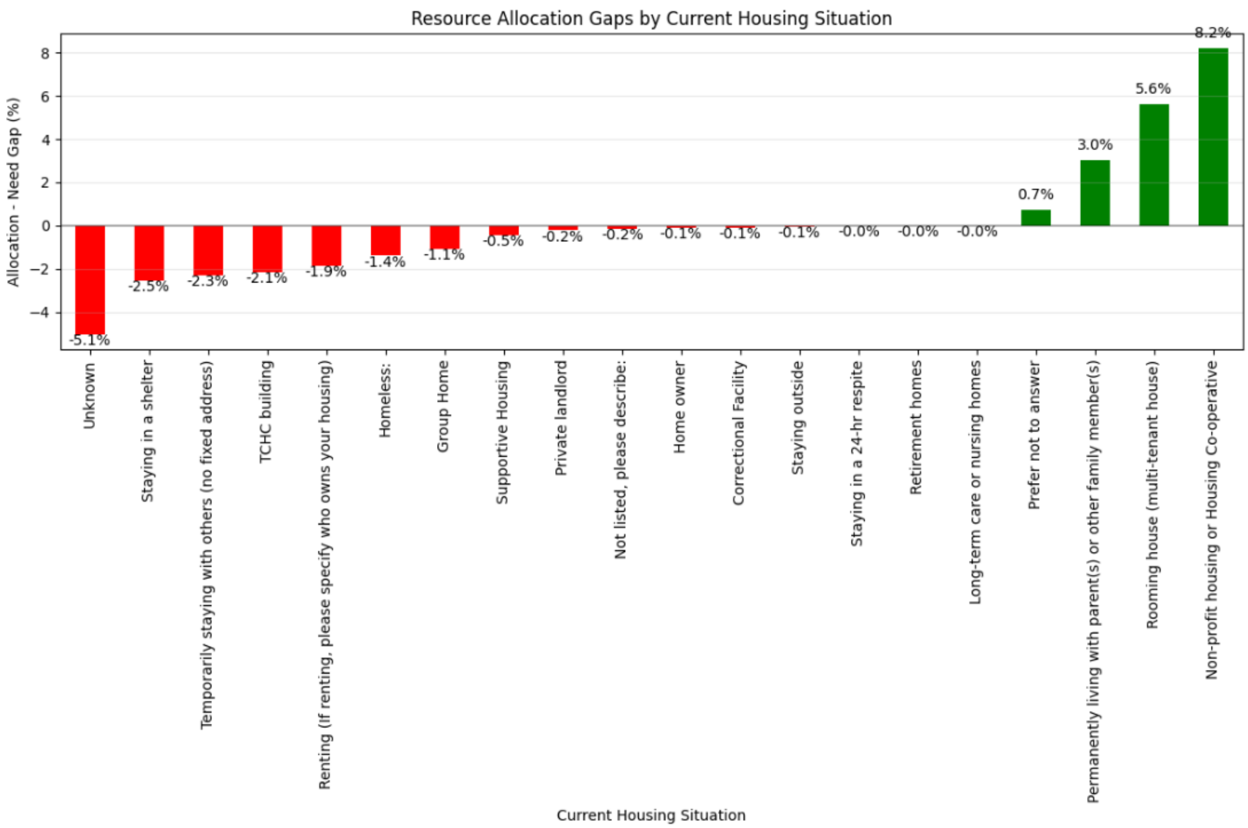

Figure 77: *Allocation Gaps Housing*

Budget Scenario Optimization

Using linear programming, we modeled participant allocation under four budget scenarios:

- Reduced (80%)
- Current (100%)
- Increased (120%)
- Expanded (150%)

Each scenario was optimized to maximize impact within budget, ensuring program minimums and caps (min 10 participants, max 200% of current). Impact consistently scaled with budget, from ~31,000 (reduced) to ~49,000 (expanded).

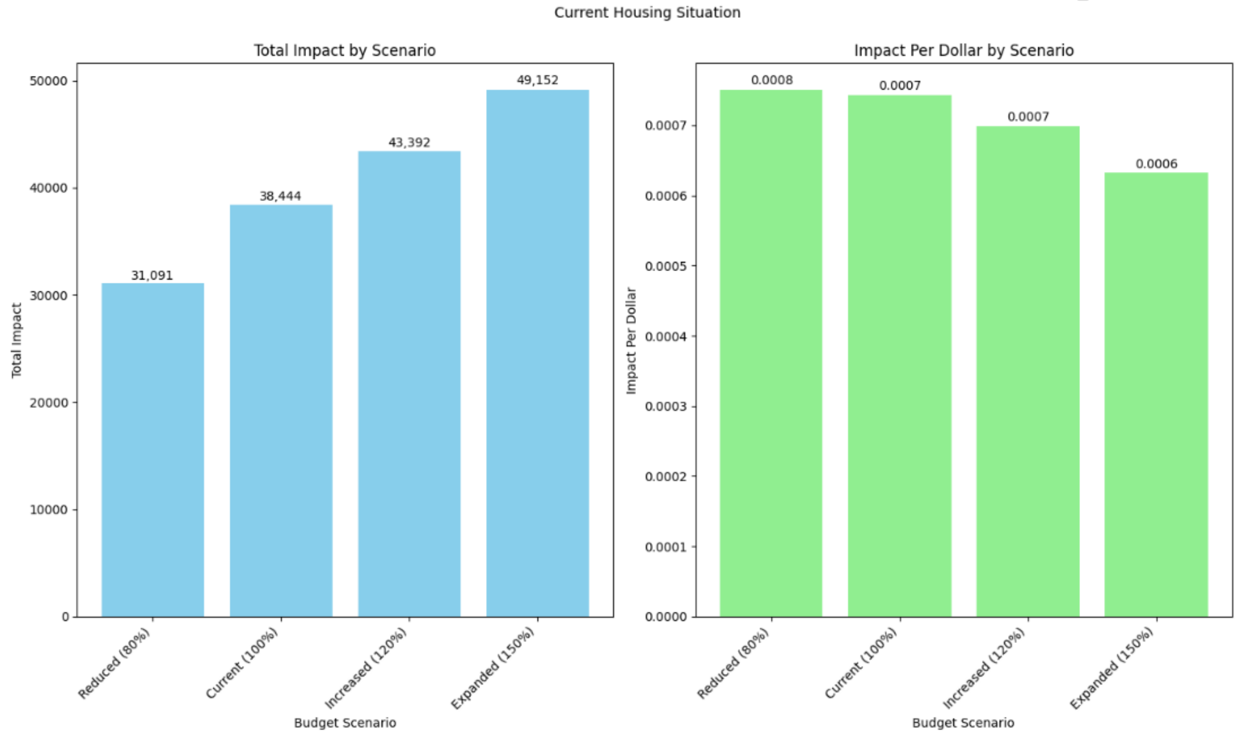

Figure 78: *Total and Per-Dollar Impact by Scenario*

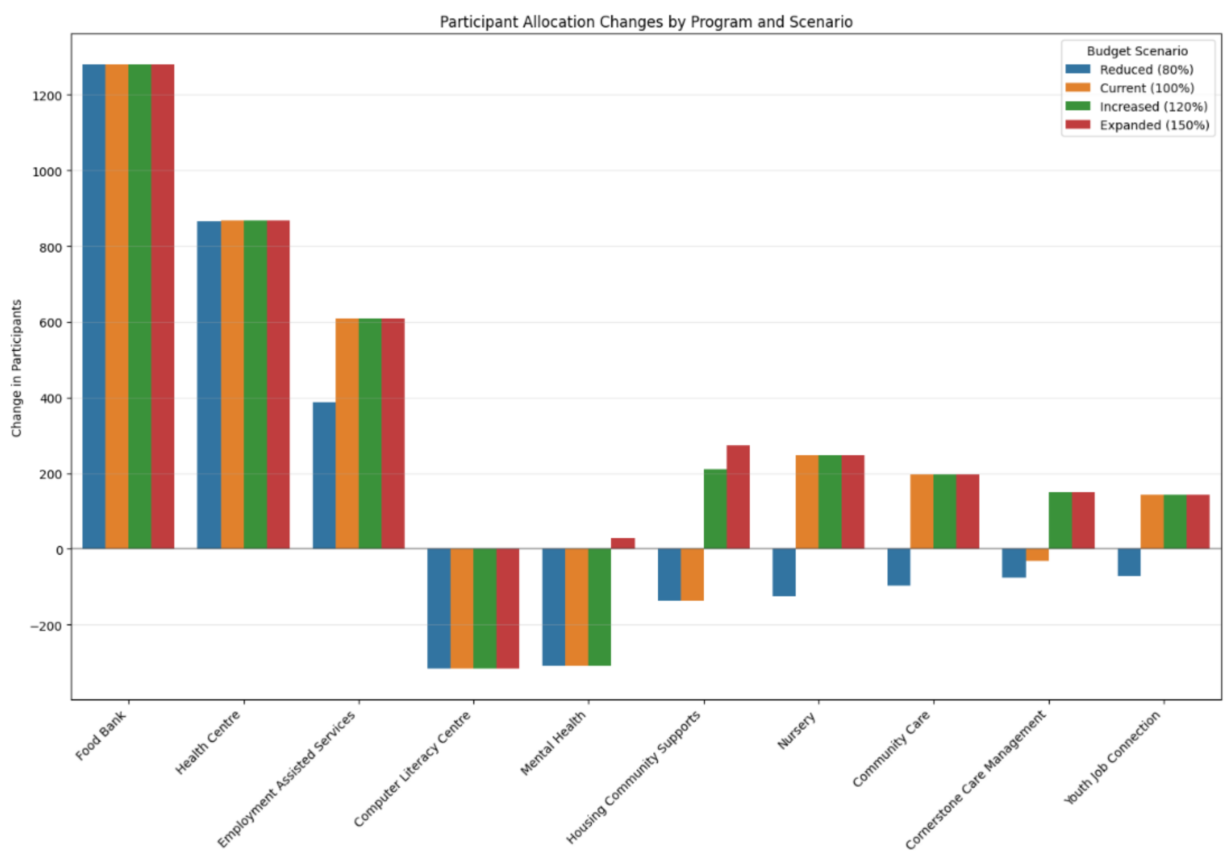

Figure 79: *Participant Allocation Change*

Monte Carlo Simulations for Robustness

To assess model stability, we ran 1,000 simulations per budget scenario.

- The Expanded (150%) scenario had the highest average impact (~49,175) and lowest variability (CV=2.17%).
- Reduced (80%) had the lowest impact and highest uncertainty.

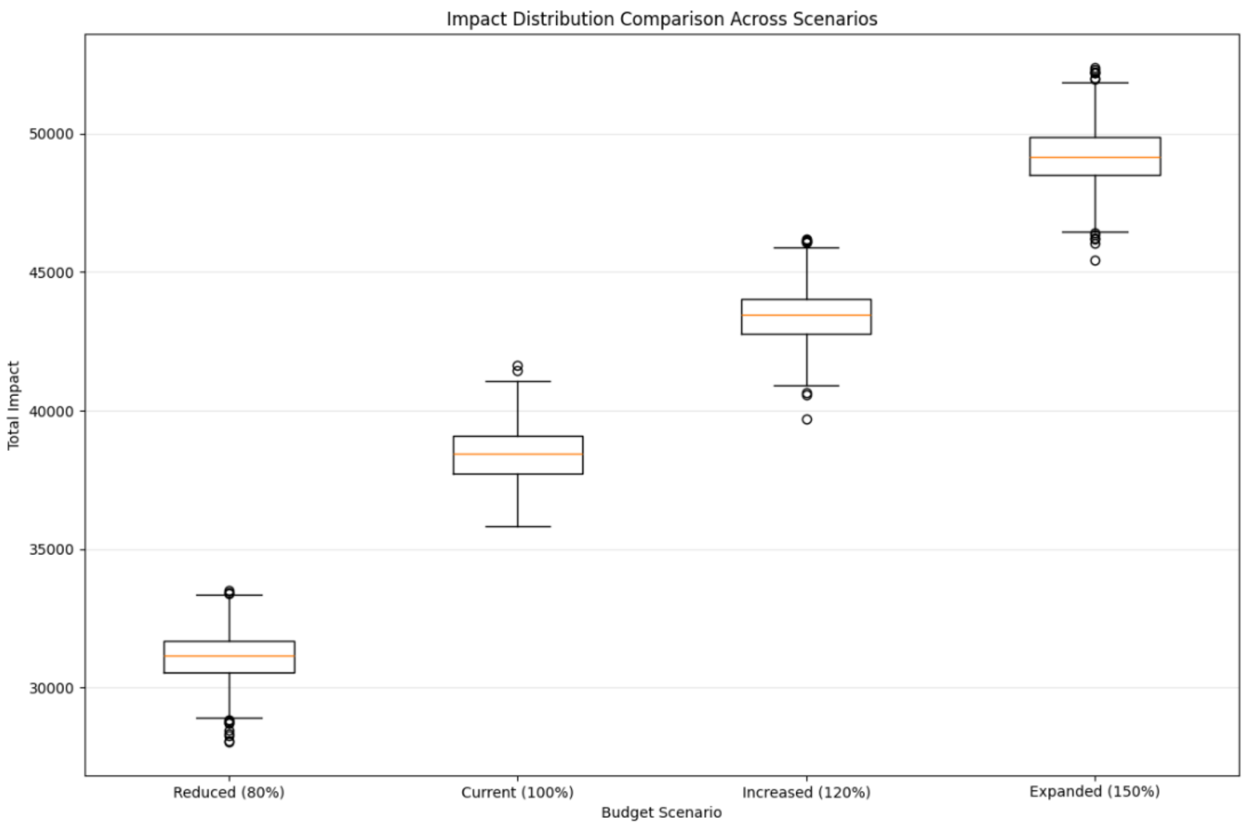

Figure 80: *Distribution Comparison Across Scenarios*

Strategic Resource Allocation Models

To explore alternative strategies beyond budget scenarios, we developed five strategic allocation models:

- ROI Maximizer
- Impact Maximizer
- Reach Maximizer
- Balanced Approach
- Equity Focused

Among these, the Impact Maximizer strategy emerged as optimal, offering the best balance of high total impact (40,546), high ROI ($0.00078 per $), and moderate cost per success ($14,316).

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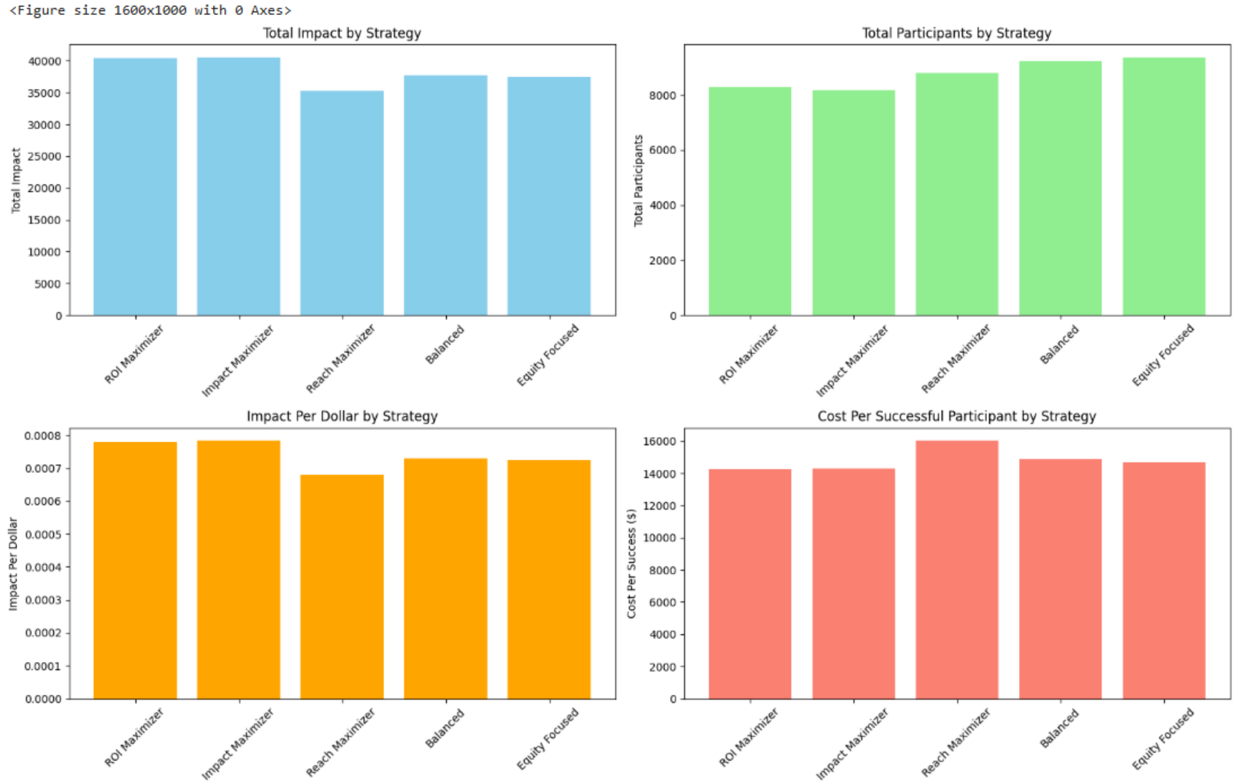

Figure 81: *Impact, Participants, ROI, and Cost per Success by Strategy*

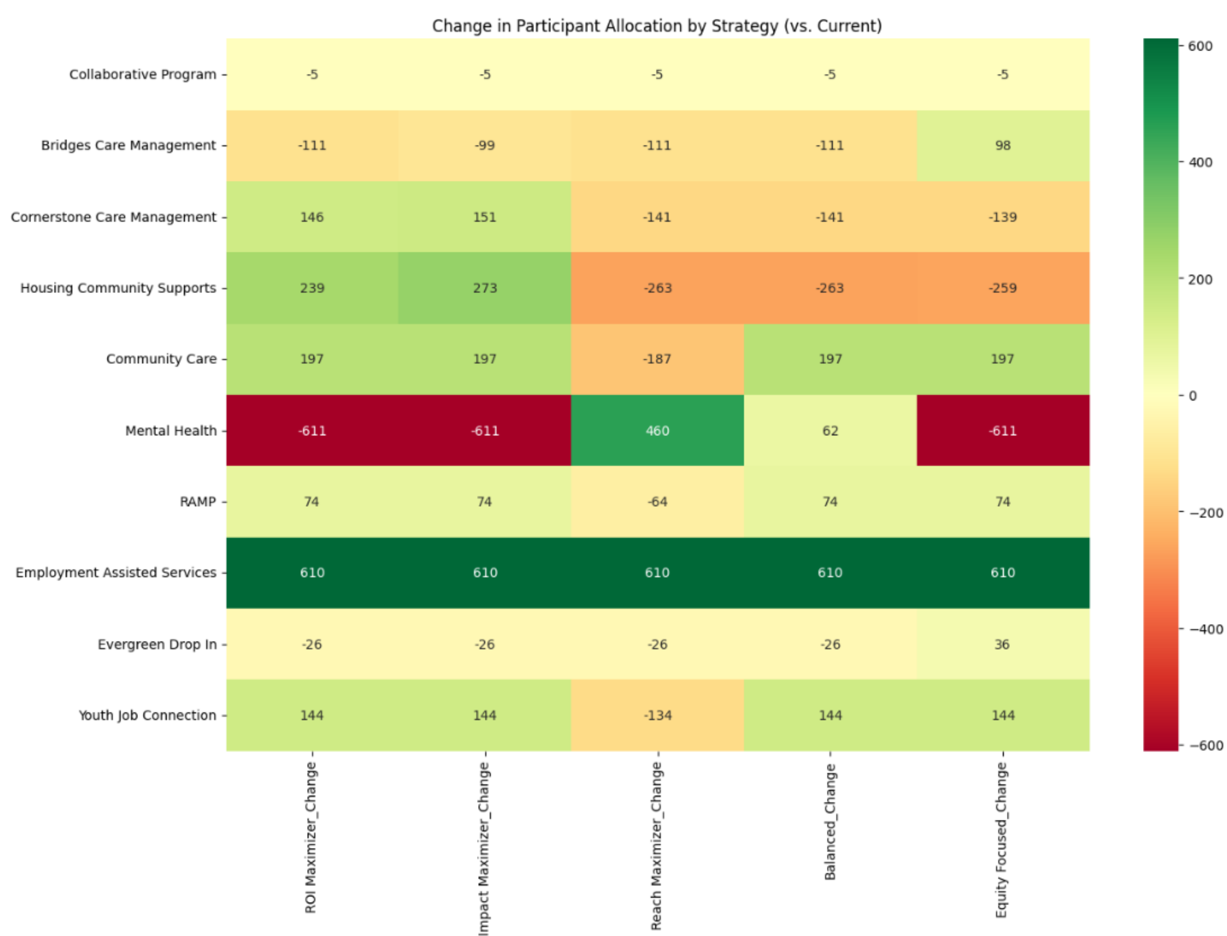

Figure 82: *Allocation Changes by Strategy*

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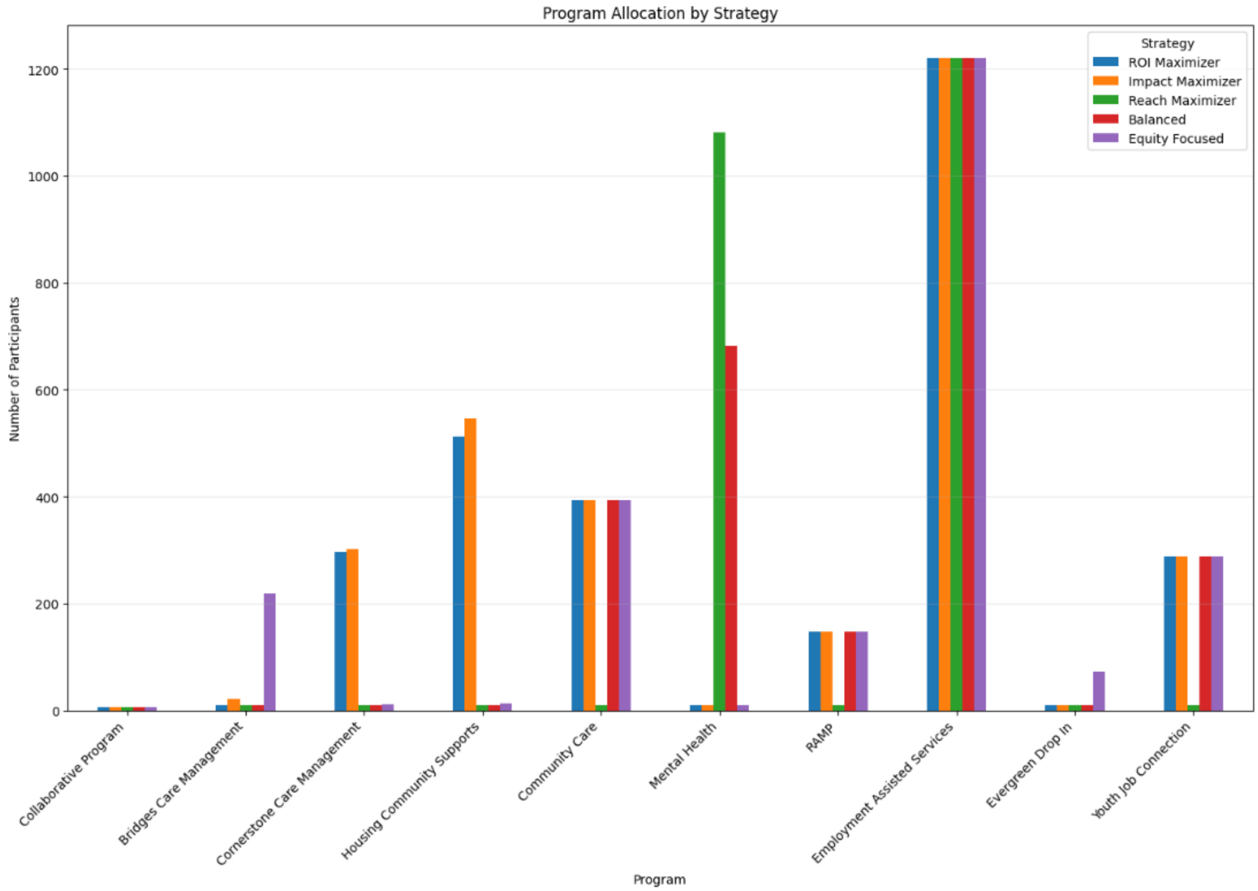

Figure 83: *Program Allocation by Strategy*

Recommendations

The Impact Maximizer strategy is the most balanced and effective option, offering the highest total impact with strong cost-efficiency. It supports programs that demonstrate both high success rates and scalability, such as Employment Assisted Services, Health Centre, and Food Bank. These programs should be prioritized for additional investment.

Meanwhile, lower-impact programs like Computer Literacy and Mental Health Services may need redesign or targeted support before scaling. The strategy also promotes equity by addressing gaps for youth, newcomers, and vulnerable groups, while minimizing major shifts from the current allocation.

Implementation Plan

To implement the strategy, YSM should start reallocating resources toward high-impact programs gradually over the next 6–12 months. This includes staff planning, capacity building, and maintaining service continuity.

Lower-performing programs should undergo review to explore improvement options. Long-term, YSM should adopt a yearly review cycle using updated TIMES data to ensure continued alignment with community needs and evidence-based outcomes.

Question 14. How have participant needs evolved over time? Are there emerging gaps in services that the organization should address?

To analyze the evolution of participant needs and identify emerging service gaps, we examined multi-year trends across key metrics including demographic shifts, income sources, service usage, and program outcomes. This analysis highlights how the composition and challenges of the participant population have changed from 2019 to 2025, pointing to areas of potential unmet need and service adjustment.

Demographic Shifts in Participant Profile

Between 2019 and 2025, significant demographic changes were observed, particularly in age, gender, and newcomer status.

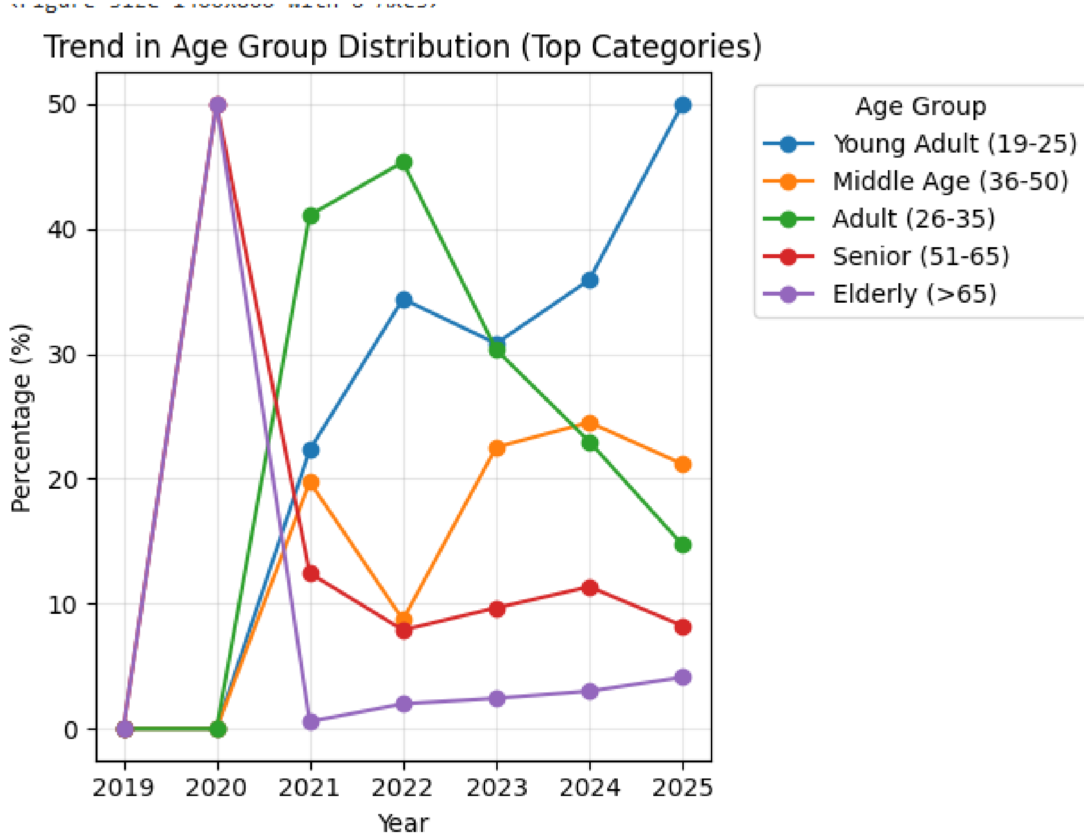

Figure 84: *Demographic Trends Age Group*

Young adults (19–25) became the largest age group by 2025, making up nearly 50% of participants.

This shift suggests a need for more youth-focused services, especially related to housing, employment, and life skills.

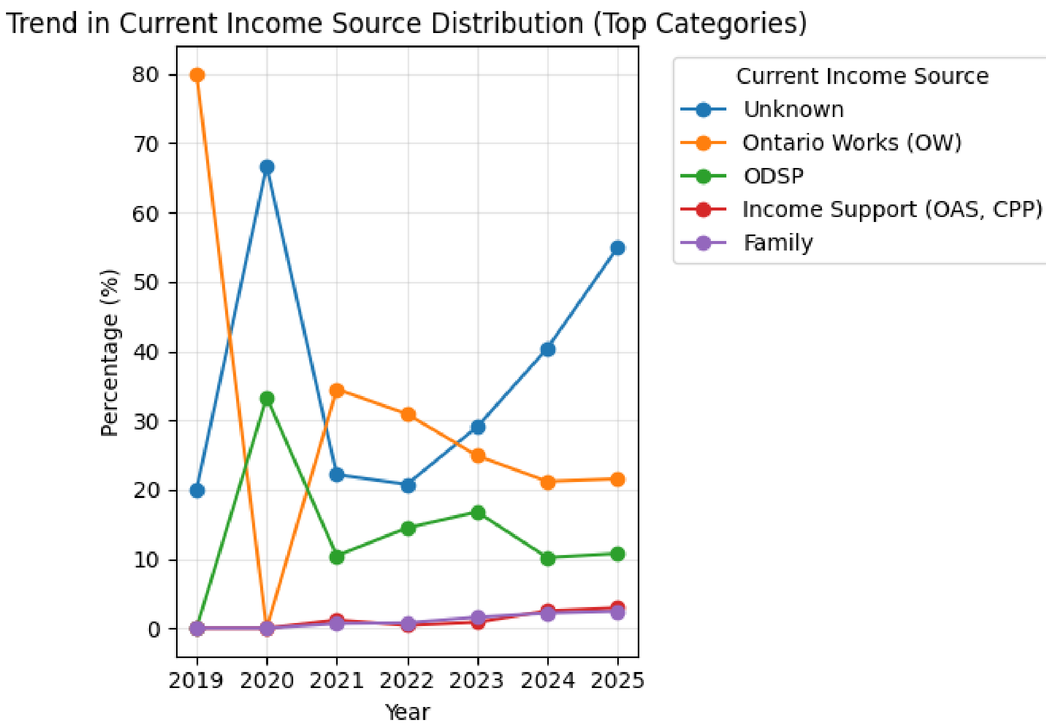

Figure 85: *Demographic Trends Current Income Source*

Unknown income sources rose sharply, reaching nearly 55% in 2025, pointing to both rising economic insecurity and possible intake/reporting issues.

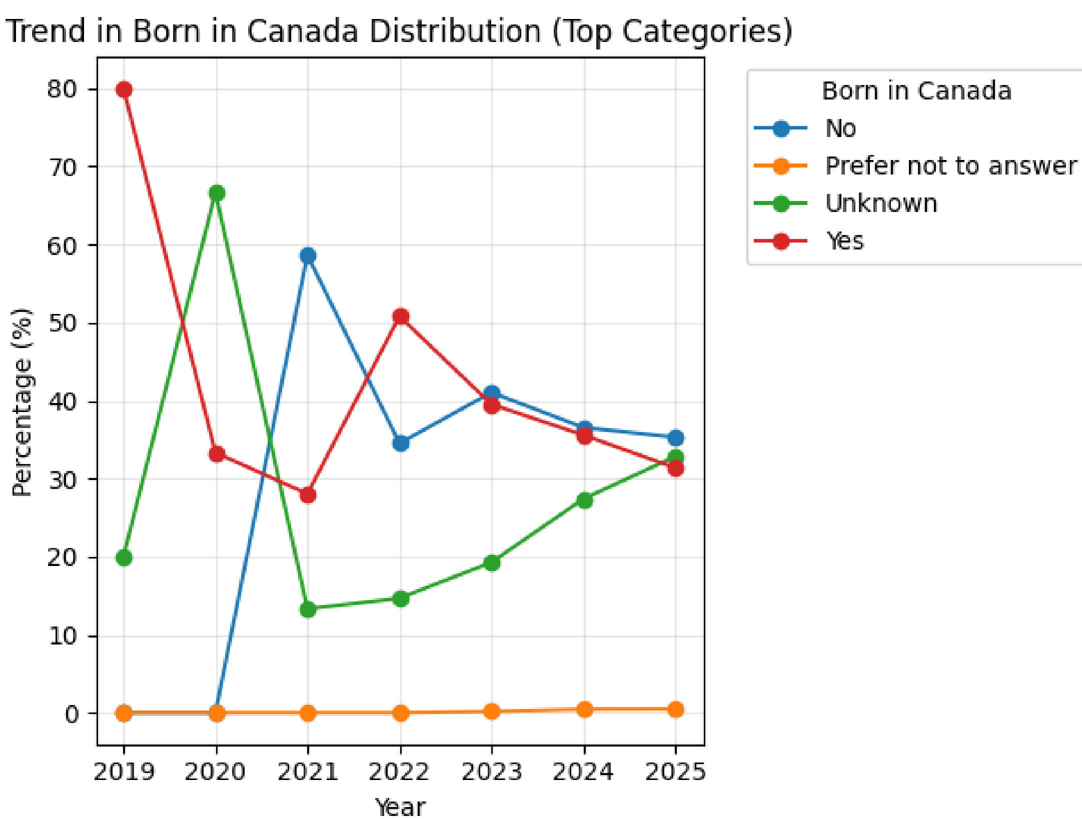

Figure 86: *Demographic Trends Born in Canada*

Newcomer participation (born outside Canada) increased from 0% to over 35%, highlighting growing demand for culturally responsive and settlement-oriented services.

Decreasing Service Intensity and Duration

Despite rising participation, engagement intensity has declined sharply.

Figure 87: *Service Trends Total Service Hours*

Average service hours dropped from nearly 50 in 2022 to under 10 in 2025, indicating a declining depth of engagement.

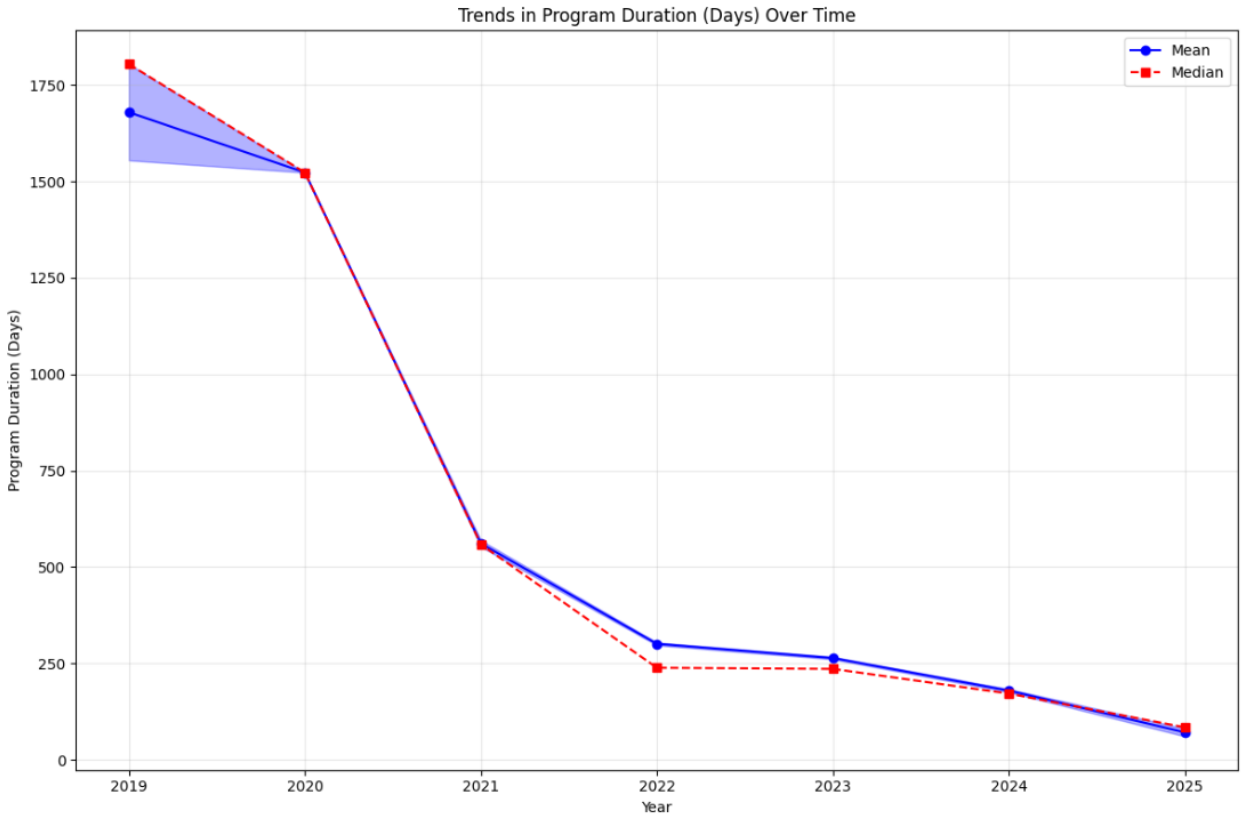

Figure 88: *Service Trends Program Duration*

Program duration fell from over 1600 days in 2019 to just 71 days in 2025, raising concerns about service depth and follow-through.

This decrease may reflect funding constraints, shifting models of care, or participant disengagement.

Program Outcome Trends

There has been a steep decline in program effectiveness.

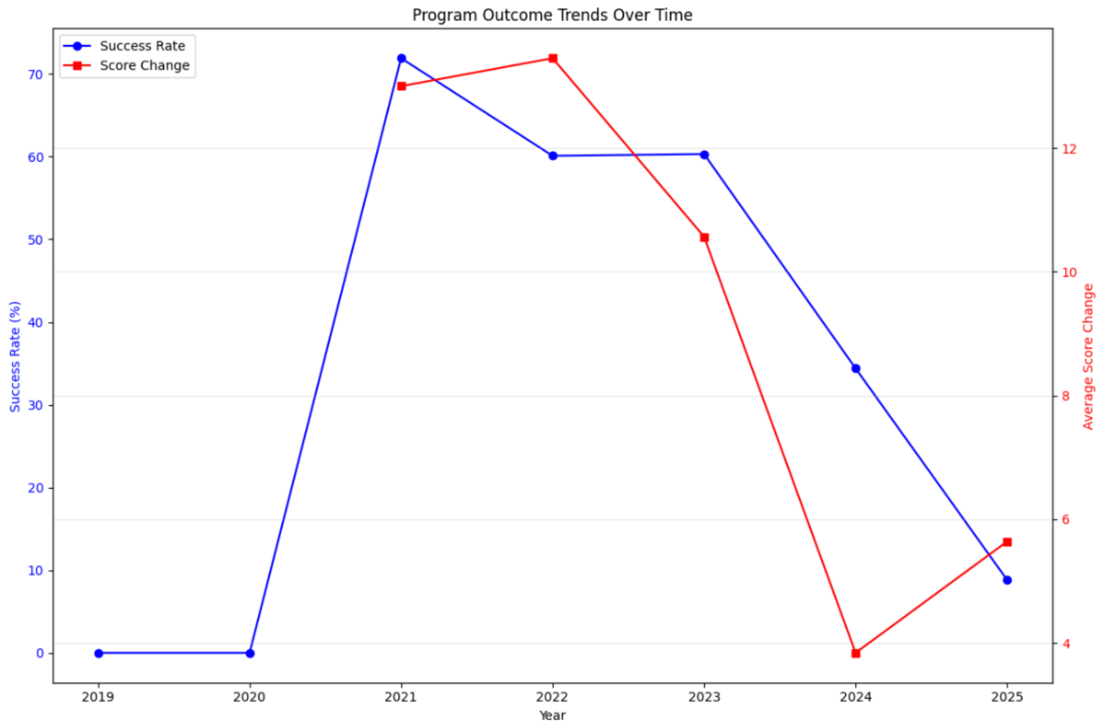

Figure 89: *Outcome Trends*

Success rates fell from 72% in 2021 to just 9% in 2025, with TIMES scores showing corresponding declines.

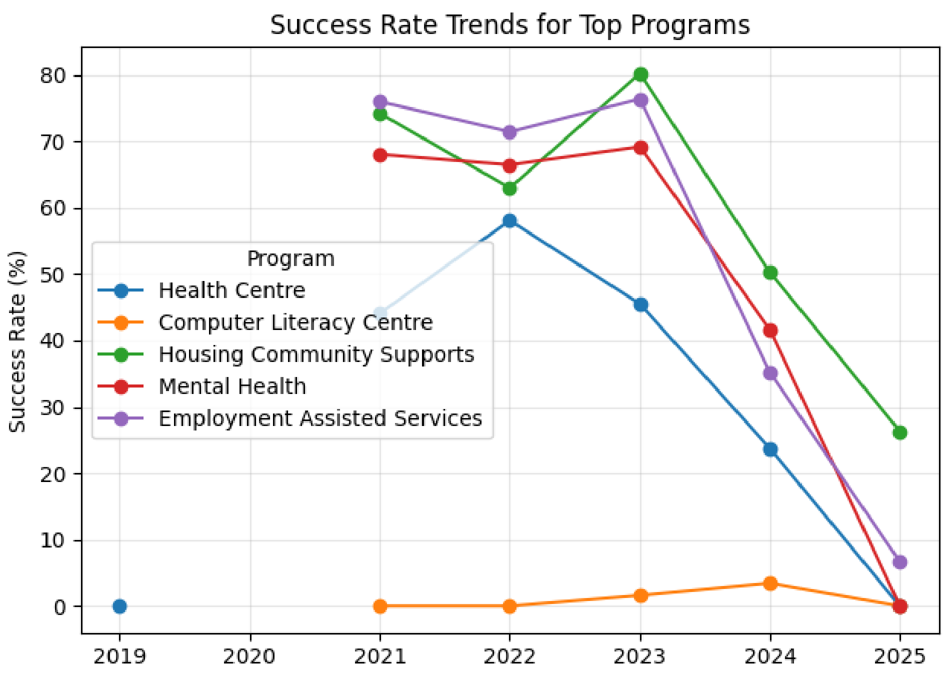

Figure 90: *Program Success Trends*

Top programs like Employment Services and Mental Health saw consistent declines in success rates post-2022.

These patterns suggest the need to reassess program strategies and resource allocation.

Emerging Underserved Segments

Some fast-growing demographic groups are not receiving services proportional to their representation.

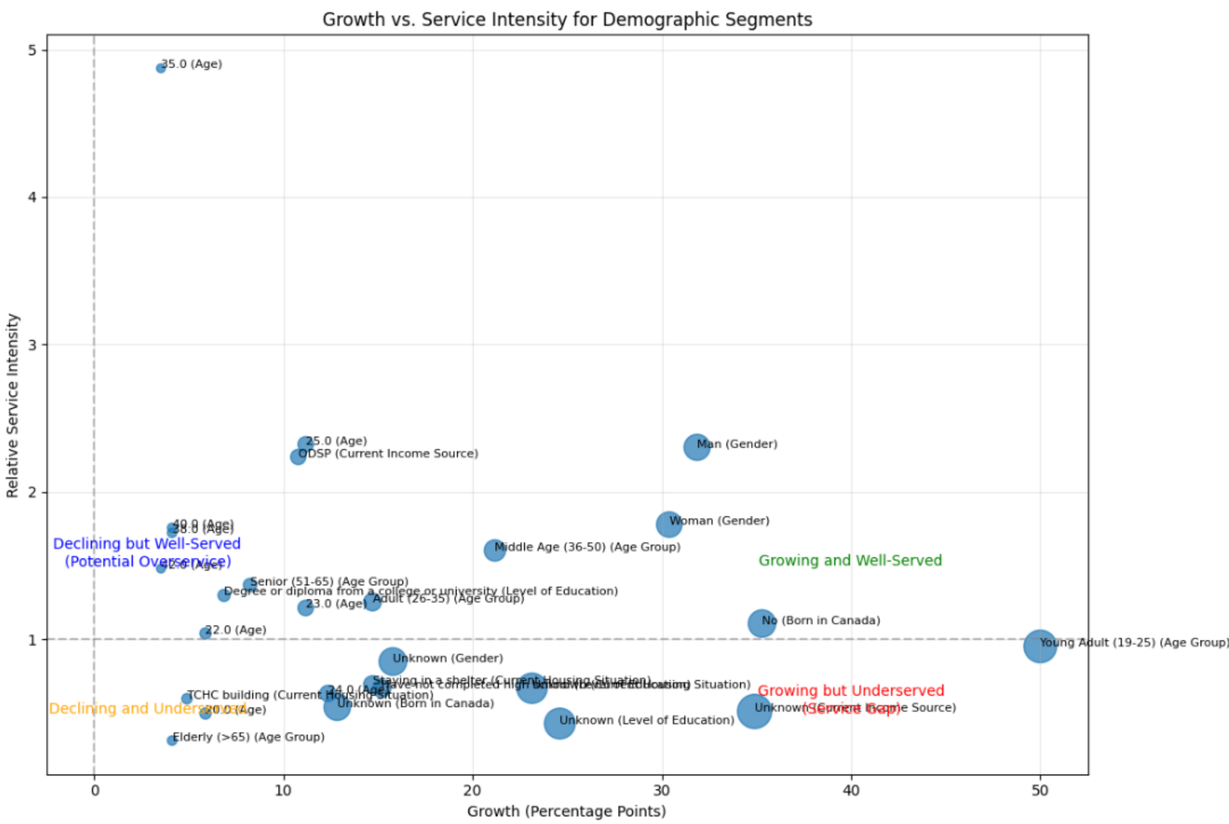

Figure 91: *Growth VS Service*

Segments like ‘Young Adults’, ‘Unknown Income’, and ‘Born Outside Canada’ are growing rapidly but fall below average in service intensity.

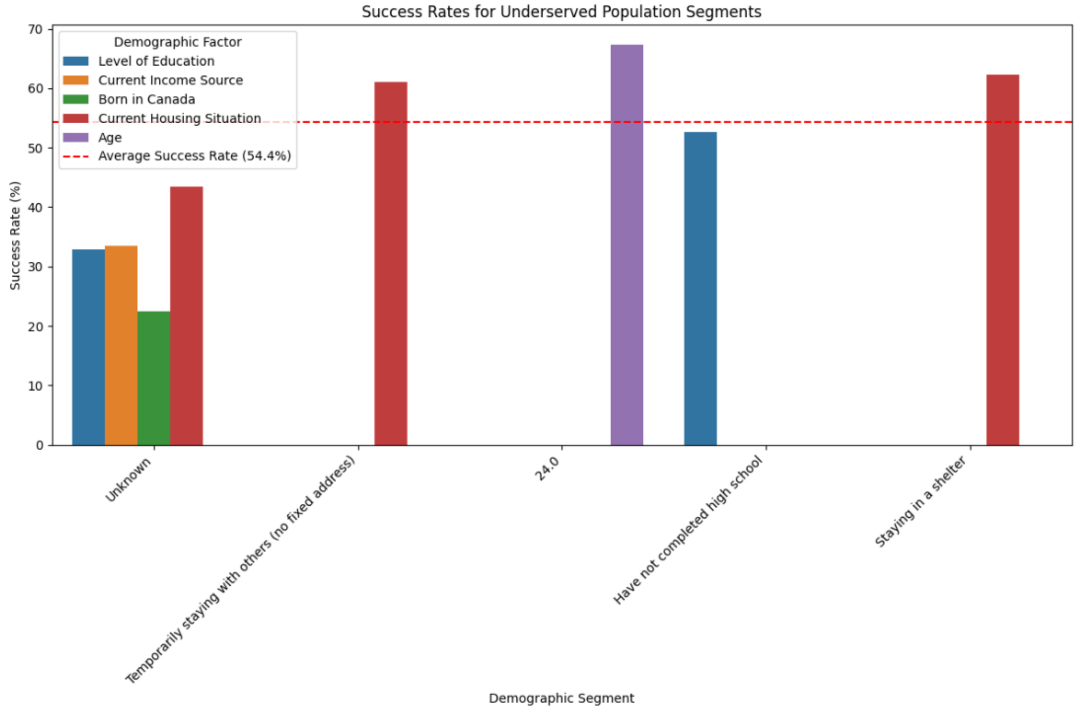

Figure 92: *Underserved Segments Success*

Underserved groups have lower-than-average success rates, suggesting that lower service intensity is linked with weaker outcomes.

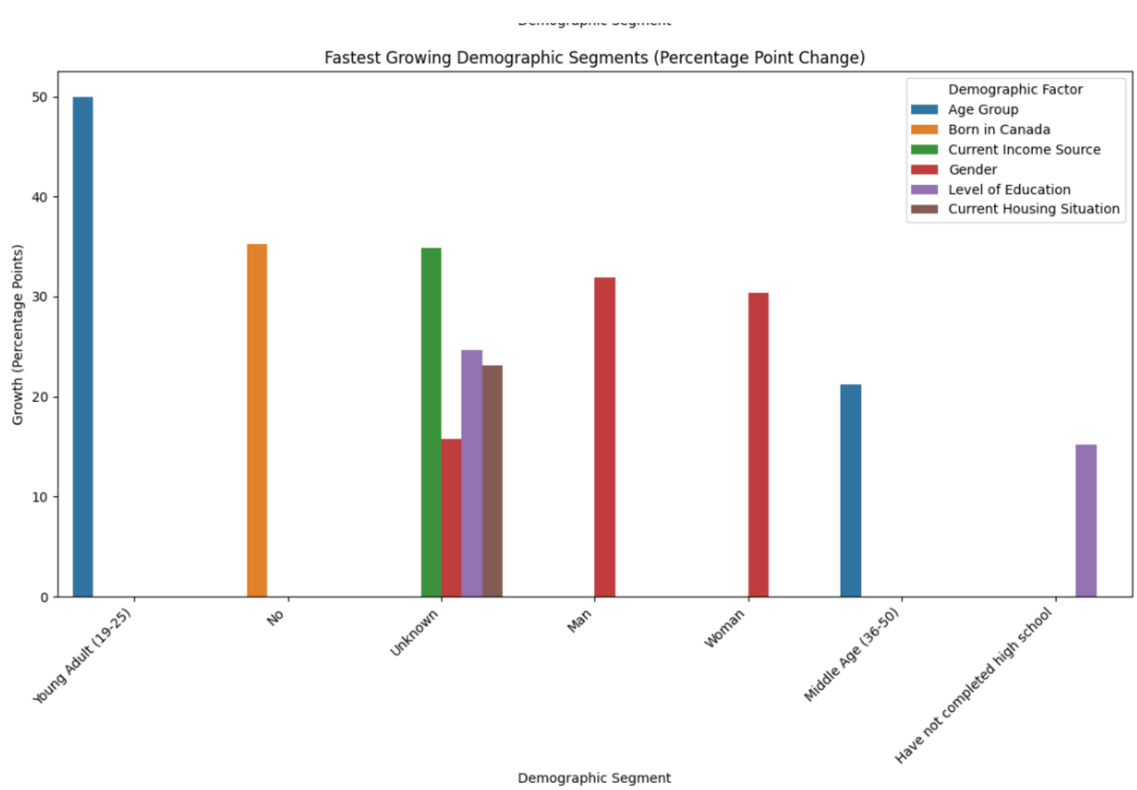

Figure 93: *Emerging Segments*

The fastest growing groups include young adults (19–25), men, and newcomers, demanding tailored services.

Shifting Enrollment in Programs

Program usage has changed significantly over the years.

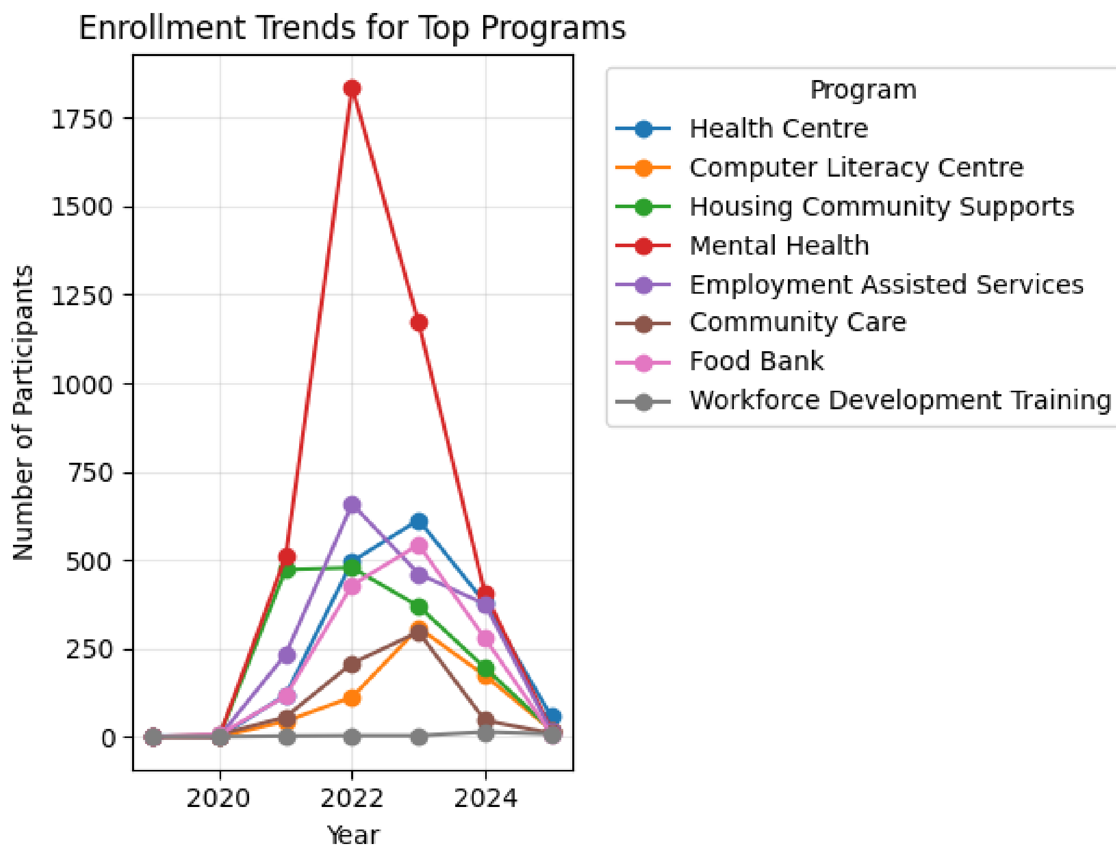

Figure 94: *Program Enrollment Trends*

Enrollment increased in mental health and health centre services but declined in education and employment-related programs.

Despite increased need for income and housing support, enrollment in some relevant programs declined, possibly due to limited capacity or relevance.

Gap Scores and Needs-Capacity Misalignment

A “Gap Score” combining representation, growth rate, service intensity, and success rate revealed top at-risk segments.

- **Woman (Gender)** → Gap Score: 15.09
- **Not Born in Canada** → Gap Score: 12.73
- **Unknown Housing** → Gap Score: 11.71
- **High School or Equivalent (Education)** → Gap Score: 10.44

These segments represent a blend of large populations, fast growth, and insufficient support or outcomes.

Projected Needs and Planning Implications

Linear regression forecasting of future needs revealed:

- Youth representation projected to remain dominant (~45%).
- Service intensity is expected to decline further (e.g., projected avg. service hours down by 23.3%).
- Programs like Health and Mental Health Services are projected to grow fastest.

Recommendations

Demographic-Specific

- Youth-Focused Services: Expand employment, housing, and life skills supports for young adults.
- Newcomer Support: Enhance cultural navigation and translation services for foreign-born participants.
- Unknown Income: Improve the intake process to collect clearer financial data and tailor support.

Service Improvement

- Re-invest in program length and intensity to increase outcomes.
- Redesign services for short-term retention and long-term impact.
- Monitor and reduce outcome disparities across segments.

Strategic Planning

- Implement a quarterly needs assessment model.
- Develop a capacity forecasting model to align staffing and funding with need.
- Prioritize underserved groups for targeted outreach and pilot programs.

Question 15: How do program outcomes and participation vary by demographic factors like immigration status and region of origin?

This analysis examines disparities in program participation, service intensity, engagement, and outcome effectiveness across different immigration statuses and regions of origin. By comparing usage patterns and TIMES™ score improvements, we identify which demographic groups benefit the most from available programs and where there are gaps in impact or engagement.

Service Usage Patterns by Region of Origin

We analyzed three core participation metrics—service count, total service hours, and unique service types accessed—grouped by region of origin.

- Participants from the Caribbean and Europe show the highest total service usage.
- Indigenous participants access the widest variety of unique service types, indicating diverse needs or strong integration.
- Canadian/American origin participants exhibit the longest program durations, suggesting deeper or extended engagement.

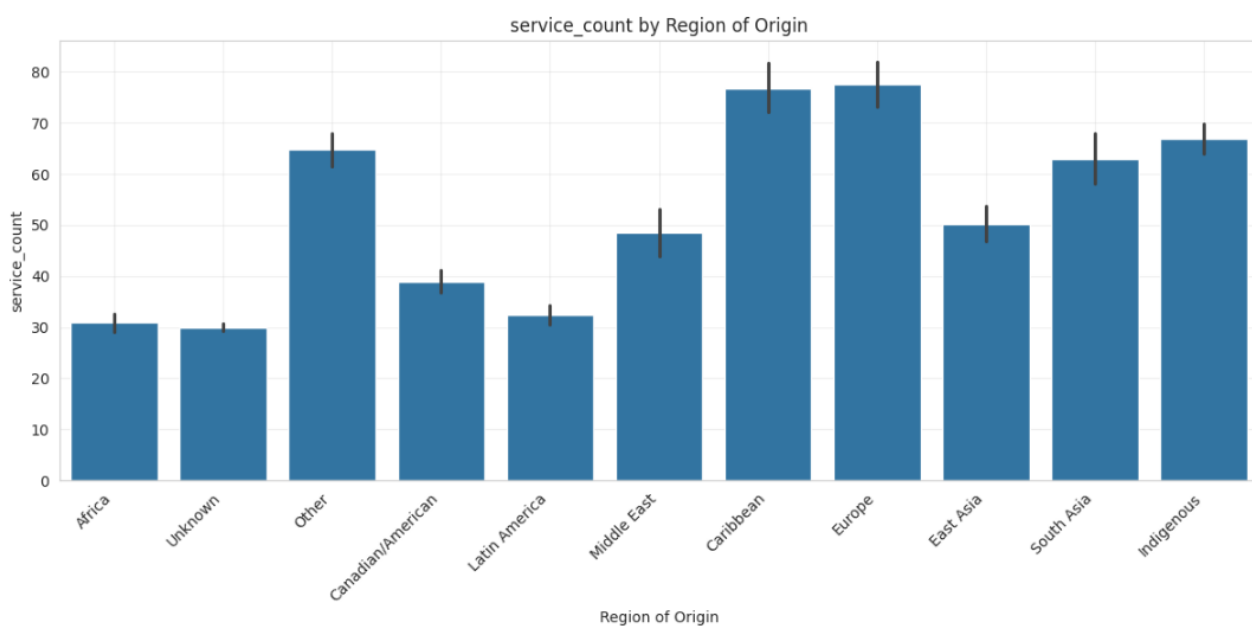

Figure 95: *Service Count by Region of Origin*

Total number of services accessed by participants across different regions.

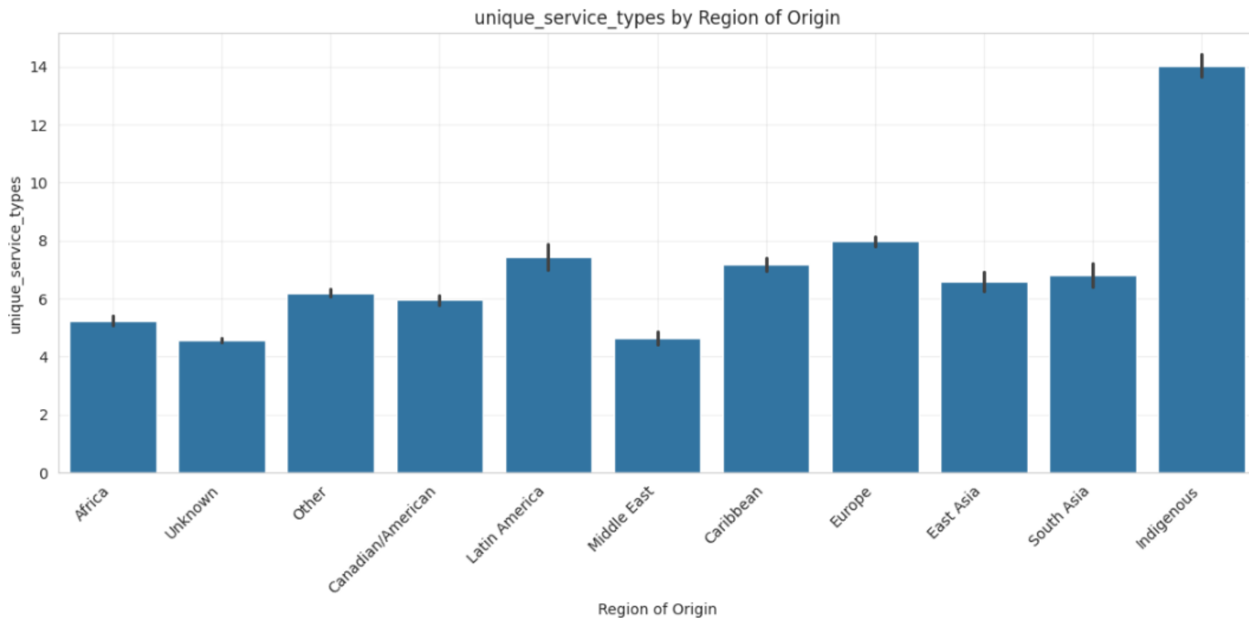

Figure 96: *Unique Service Type by Region of Origin*

Average number of unique service types accessed by participants by region of origin.

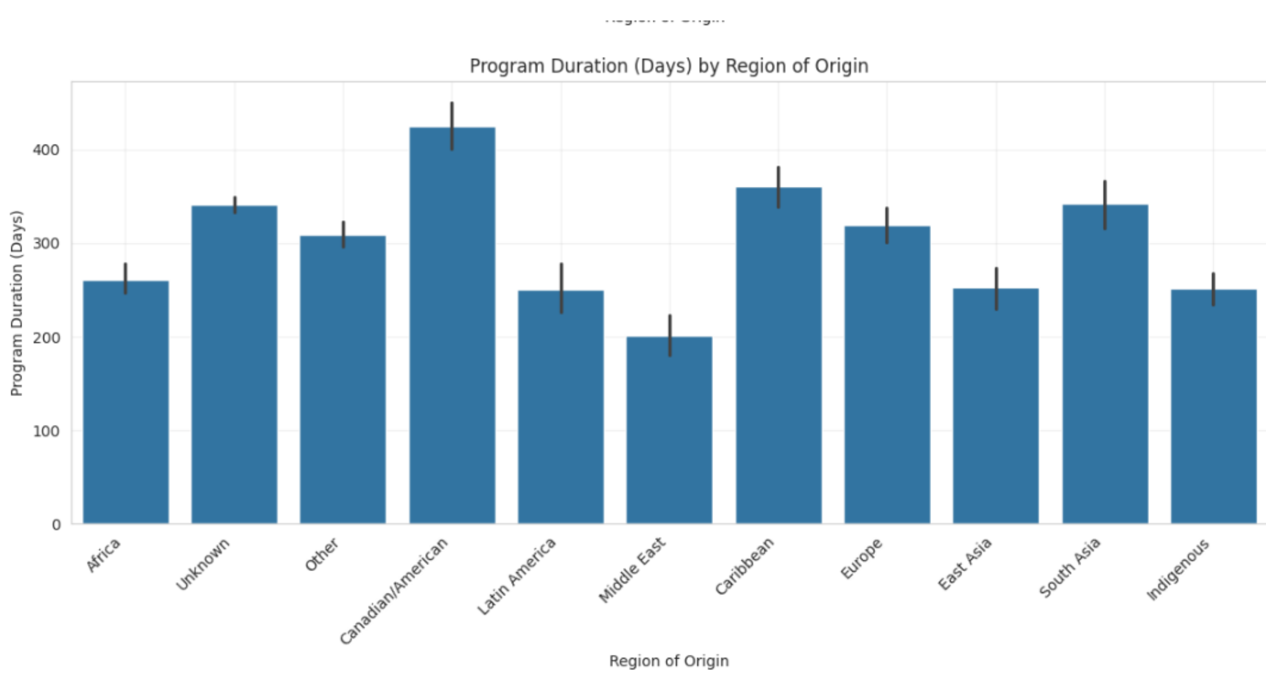

Figure 97: *Program Duration (Days) by Region of Origin*

Average duration (in days) that participants from each region remained in the programs.

Engagement Intensity by Region

Engagement levels (Very High, High, Medium, Low) were compared across regions.

- Most regions show a strong skew toward "Very High" engagement.
- East Asian and Middle Eastern participants have a relatively higher spread across other engagement levels, suggesting inconsistent program fit or access barriers.

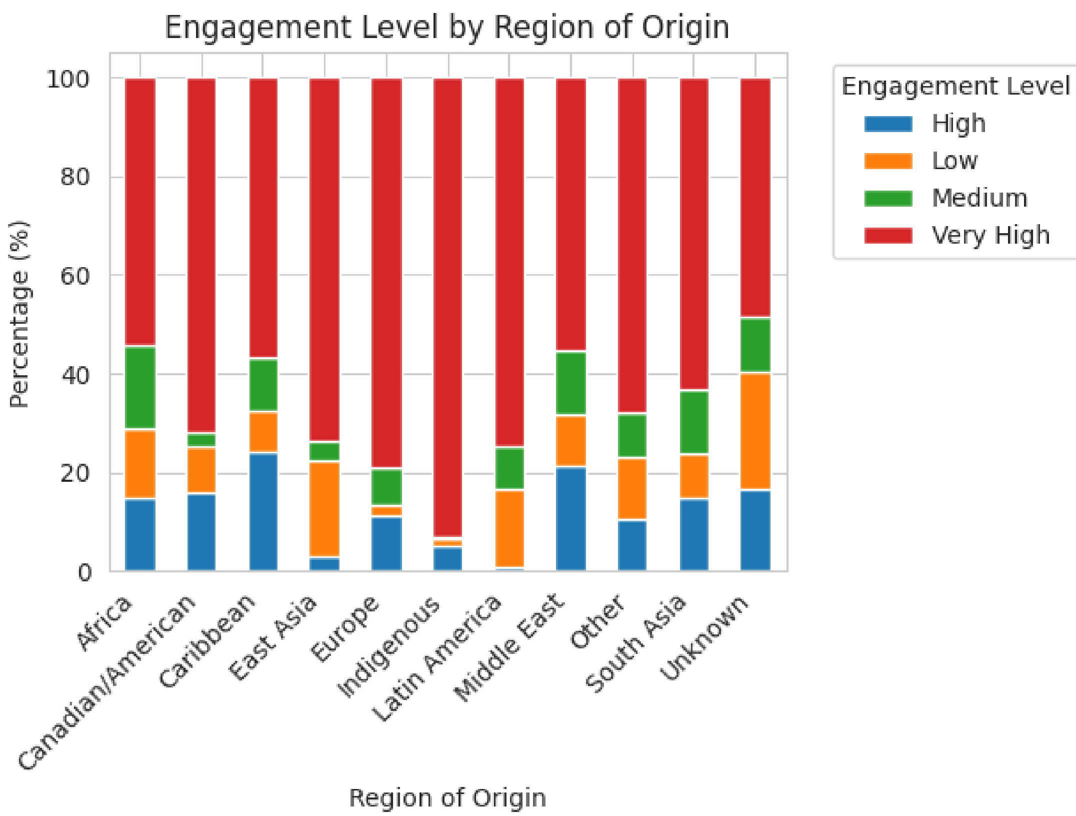

Figure 98: *Distribution of engagement levels by region of origin*

Enrollment Propensity by Immigration Status and Region

The normalized program enrollment rates reveal demographic-program fit:

- Immigrants/Refugees over-index on Food Bank, Health Centre, and Employment Services.
- Canadian-born clients are more likely to enroll in Computer Literacy Centre and Mental Health programs.
- East Asian participants show high enrollment in Cornerstone Care and Nursery, while Indigenous groups are highly represented in Computer Literacy Centre.

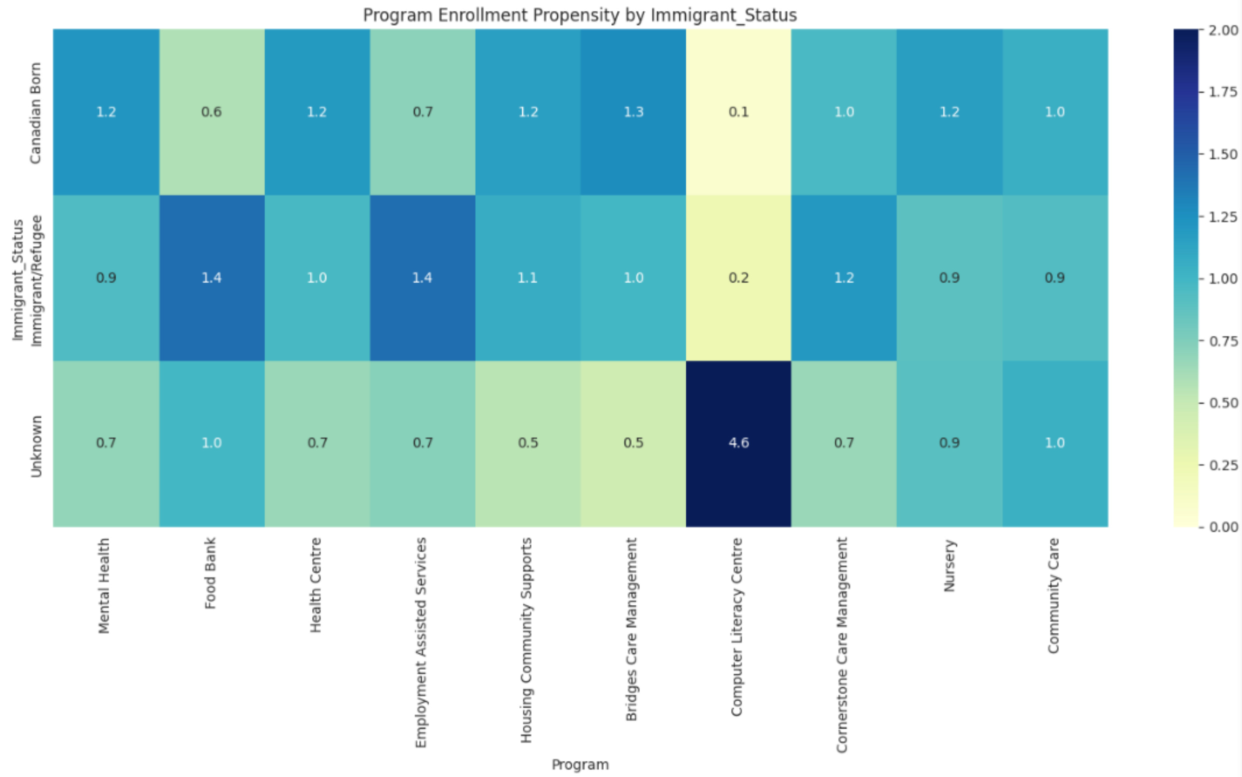

Figure 99: *Program Enrollment Propensity by Immigration Status*

Program enrollment propensities across broad immigration status categories.

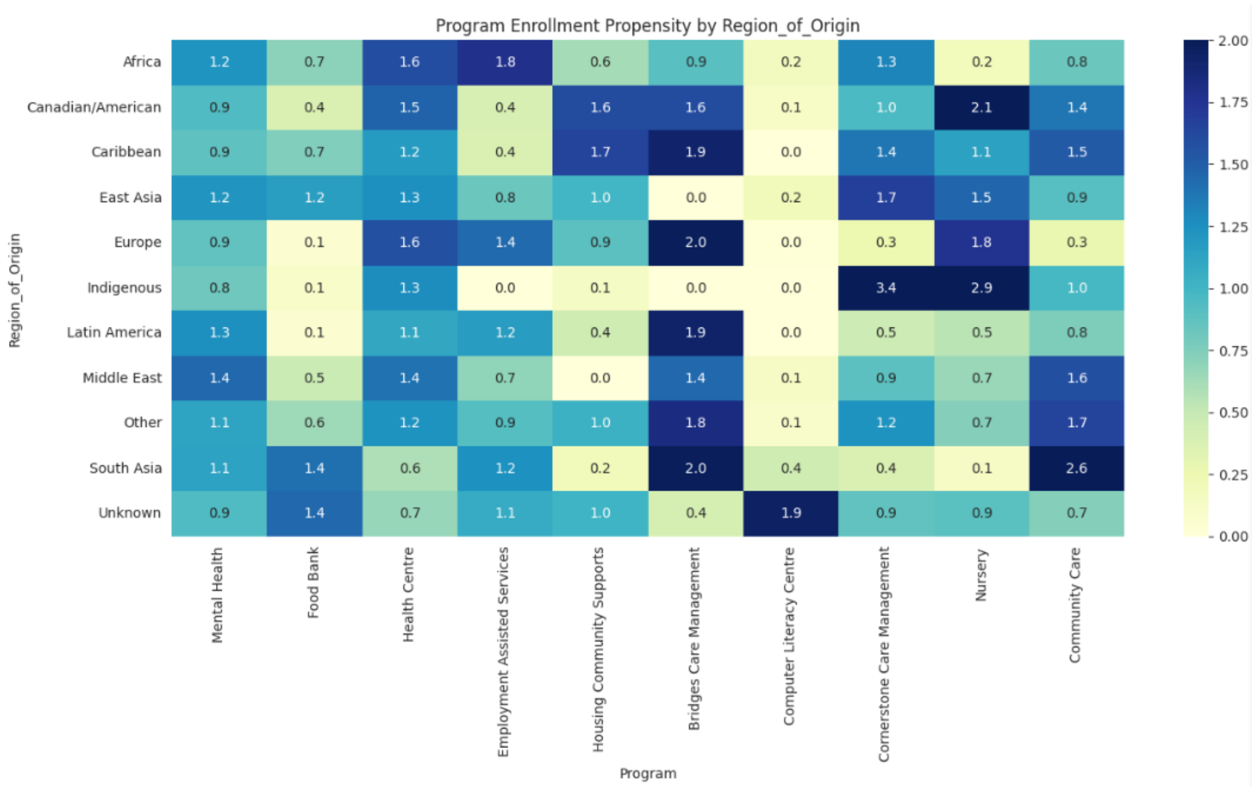

Figure 100: *Program enrollment propensities by region of origin.*

TIMES™ Score Improvement and Change by Immigration Status and Region

TIMES™ score improvements are used to measure program outcome effectiveness:

- Refugee Claimants and Permanent Residents show strong improvements across programs, especially in Mental Health and HOPE+.
- East Asian and European origin participants also show high TIMES™ score changes.
- Participants with Unknown or Indigenous status show lower or inconsistent gains, highlighting potential disparities in impact.

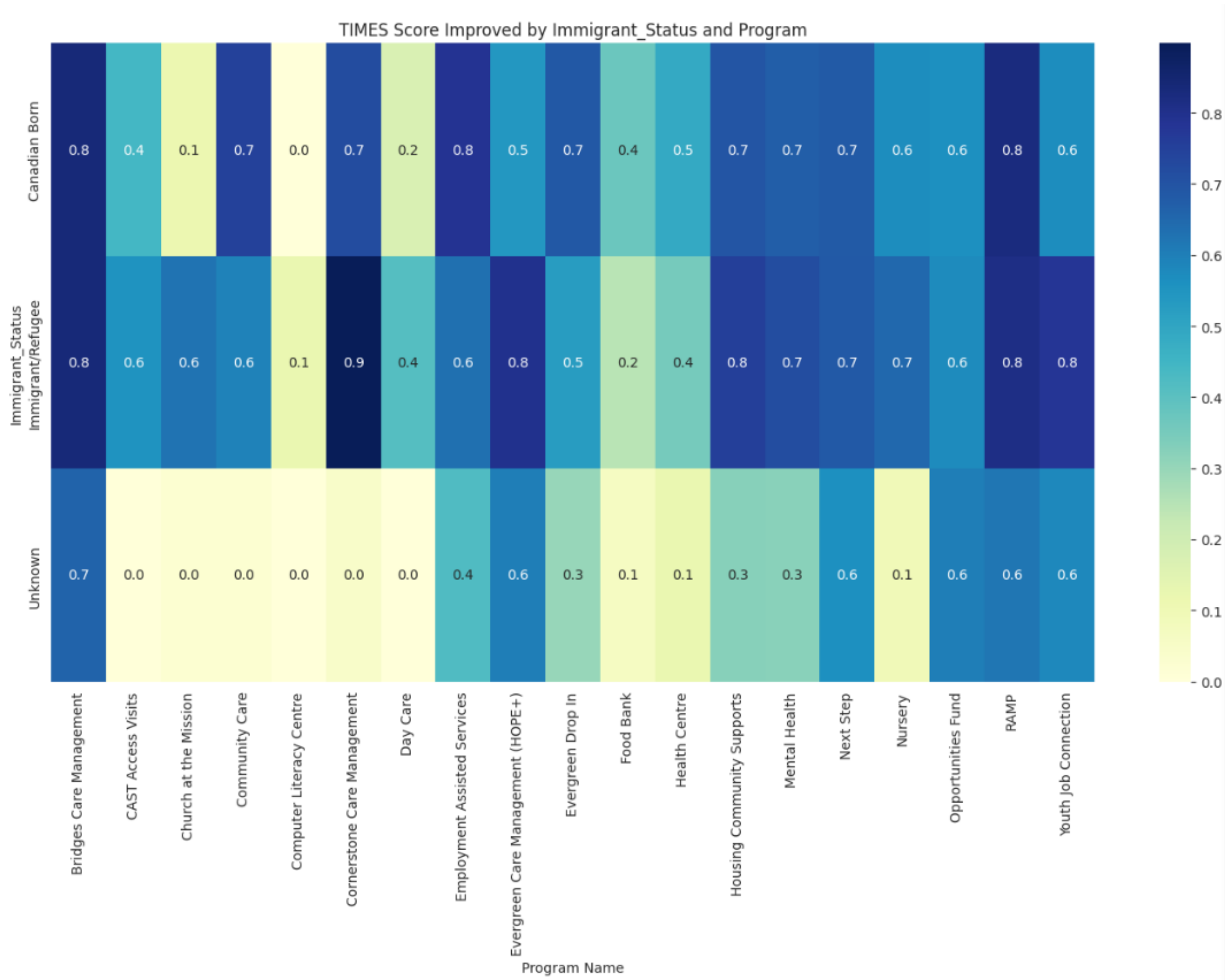

Figure 101: *TIMES Score Improved by Immigration Status*

Proportion of participants with improved TIMES™ scores by immigration status and program.

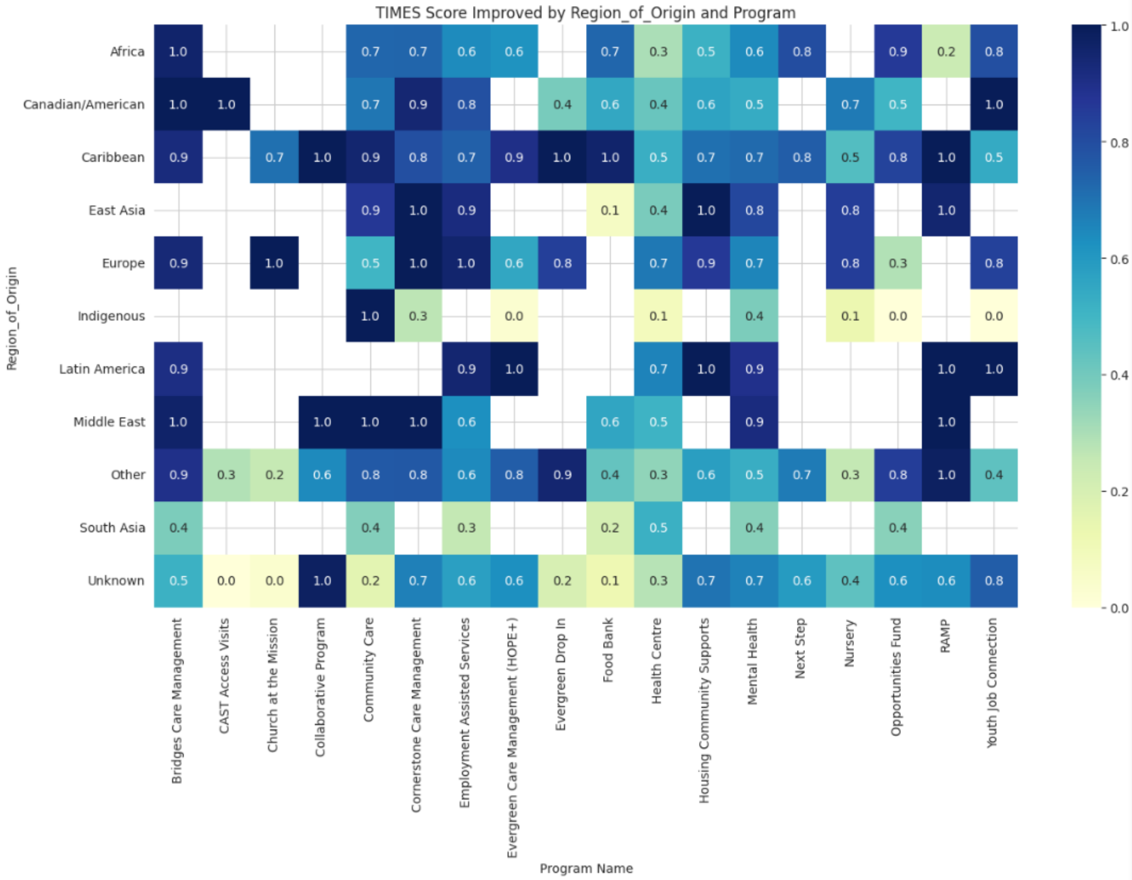

Figure 102: *TIMES™ score improvement rates by region of origin and program*

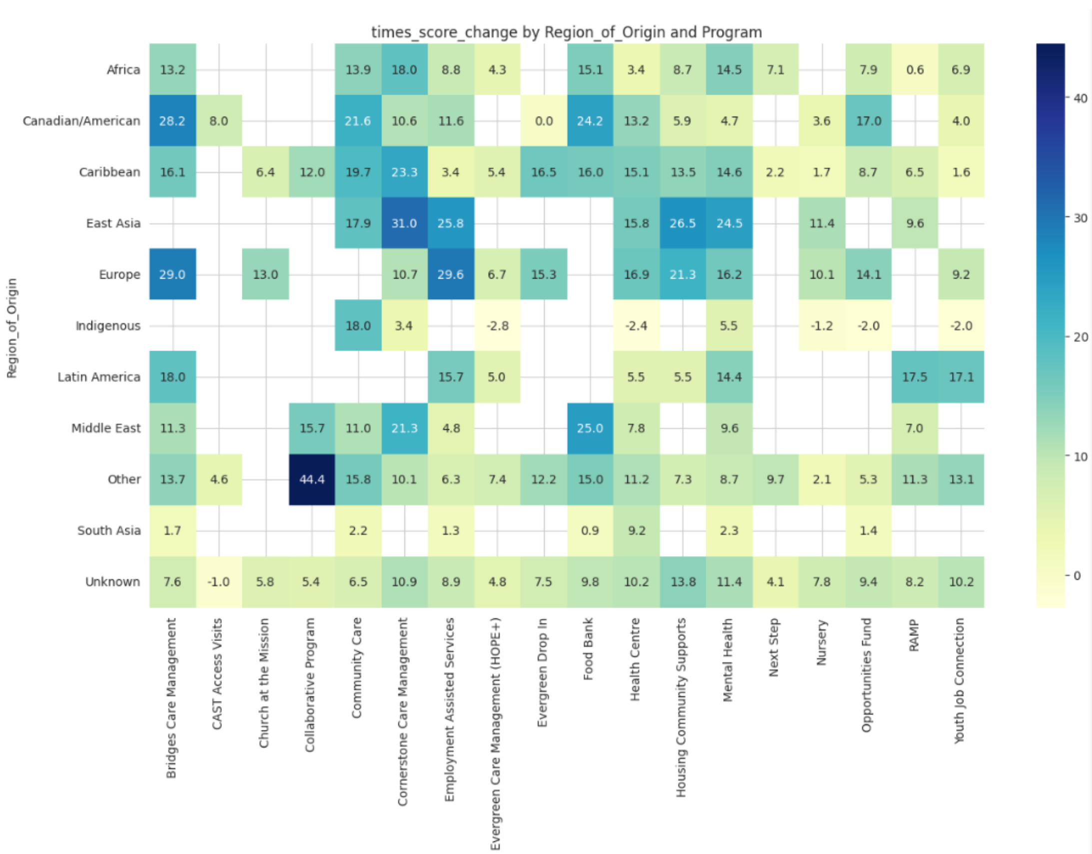

Figure 103: *Average TIMES™ score change (magnitude) by region of origin and program.*

Success Rate Disparities by Immigration Status

We compared program-specific success rates between Immigrant/Refugee and Canadian-born participants:

- Immigrants outperformed Canadian-born participants in programs like Church at the Mission, HOPE+, and CAST Access.
- Canadian-born participants had higher success in programs like the Collaborative Program, Employment Services, and the Food Bank.
- These outcome gaps highlight opportunities for targeted support and culturally informed interventions.

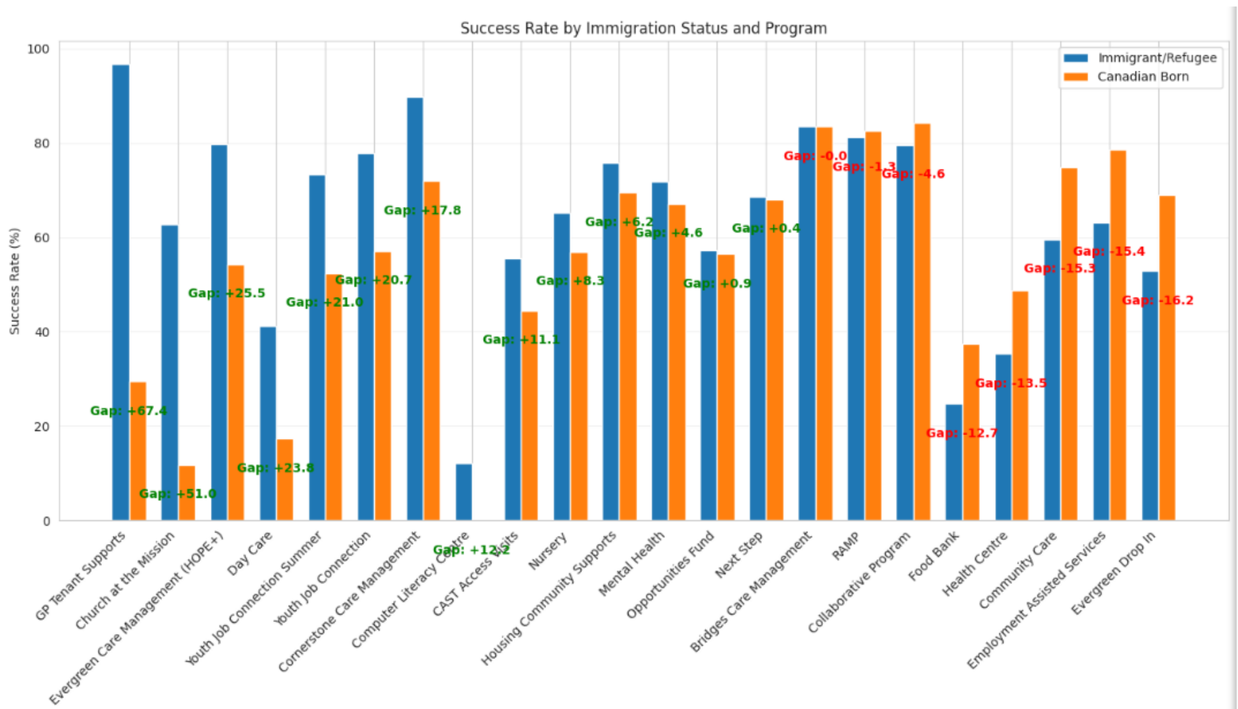

Figure 104: *Success Rate by Immigration Status and Program*

Program-specific success rates and outcome gaps between Canadian-born and Immigrant/Refugee participants.

The analysis underscores meaningful differences in how demographic groups engage with and benefit from social support programs:

- Immigrant and refugee groups tend to show higher program success and stronger TIMES™ gains, particularly in basic needs and employment-related services.
- Canadian-born and Indigenous groups show stronger engagement in mental health and community care programs, but require targeted support to improve outcome parity.
- Some groups, especially those with Unknown status or from the Middle East and Indigenous backgrounds, experience less consistent gains, suggesting a need for more tailored and inclusive programming.

Question 16: How does housing stability impact program engagement and outcomes across different service types?

Housing stability is a critical social determinant of health and self-sufficiency. In this analysis, we examine how different levels of housing stability—ranging from unstable to very stable—affect program engagement metrics and outcome variables such as TIMES score improvement, self-sufficiency, and overall program completion. We also identify housing-specific intervention points and recommend strategies for housing-sensitive service delivery using trajectory analysis, statistical modeling, and service-level segmentation.

Housing Stability Categorization and Distribution

Housing status was mapped into four tiers based on recorded living situations:

- **Unstable:** Includes homelessness, emergency shelters, and couch surfing.
- **Somewhat Stable:** Includes transitional housing or staying temporarily with friends/family.
- **Stable:** Includes subsidized or market rentals.
- **Very Stable:** Home ownership.

Observation:

Out of 17,875 participants:

- 94.5% had unknown housing status.
- 2.6% were somewhat stable.
- 1.8% were unstable.
- 1.1% were stable.

Engagement by Housing Stability

Program engagement was measured by service count, total service hours, and program duration.

Findings:

- Clients with Somewhat Stable housing had the highest service count and hours.
- Clients with Unstable housing engaged less across all metrics.

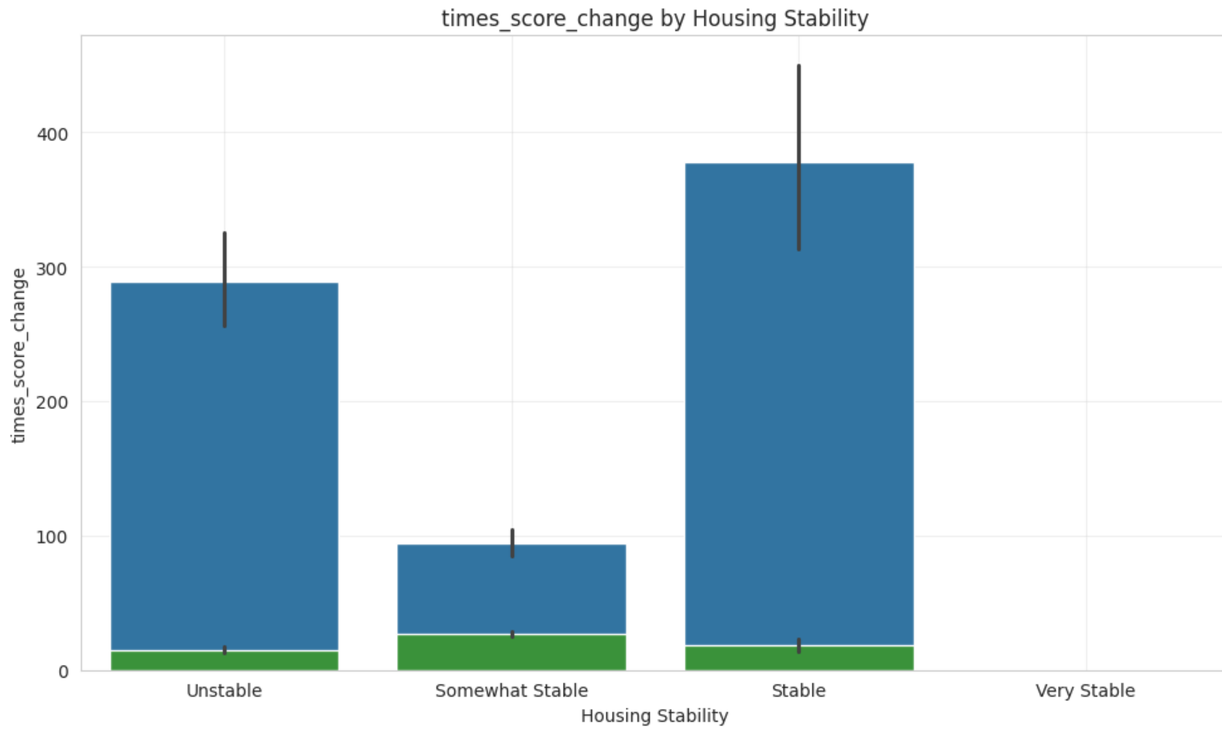

Figure 105: *Times Score Change by Housing Stability*

TIMES score change by housing stability. Participants with "Somewhat Stable" housing had significantly higher average score changes.

Outcomes by Housing Stability

We analyzed TIMES Score Improved, times_score_change, and Program Completion.

Key Results:

- **TIMES Score Improvement Rate:**
  - Unstable: 31.8%
  - Somewhat Stable: 87.6%
  - Stable: 46.9%
- **times_score_change:**
  - Unstable: 15.1
  - Somewhat Stable: 27.0
  - Stable: 18.2

These differences confirm that housing stability is strongly associated with better outcomes.

Impact of Housing Transitions

- 3.1% of clients improved their housing status during the program.
- These clients showed notable increases in TIMES score and success rates.
- Improvement was associated with participation in specific services (e.g., Health Centre, HOPE+).

Program Outcomes Across Services

A cross-tabulation of outcomes by housing stability and service type revealed that:

- Certain services are more effective for specific housing statuses.
- For example, *Bridges Care Management* yielded better results for Stable clients, while *HOPE+* was more effective for those Unstable.

Predictive Modeling Insights

Using a random forest model, we predicted program success based on housing and service variables:

- **Model AUC:** 0.83
- **Feature importance:** Housing Stability Score was a top predictor.
- Predicted outcomes were highest for **Somewhat Stable** clients in targeted programs.

Recommendations

Tailor Programs by Housing Status

- **Unstable**: Prioritize crisis response, short-term intensive support, housing navigation.
- **Somewhat Stable**: Support retention, connect to wraparound supports.
- **Stable**: Focus on longer-term outcomes and sustainable independence.

Identify Intervention Points

- Focus on **transitions from Unstable to Somewhat Stable**, as this showed the **largest gains in the TIMES score**.
- Expand services that are correlated with housing improvement (e.g., HOPE+, Community Health).

Implement Housing-Sensitive Framework

- Assess housing status at intake and during the program.
- Train staff on housing-informed practices.
- Use predictive modeling to recommend services aligned with the housing level.

Housing stability is a key determinant of engagement and outcomes in YSM programs. The data highlights “Somewhat Stable” clients as a high-potential group and supports adapting service delivery by housing status. Targeted interventions, especially those that improve housing, can significantly enhance participant success.

Question 17: What is the long-term impact of youth-focused programming, and how can we optimize early interventions? Conduct longitudinal analysis of youth program participants, identify early predictors of long-term success, and develop optimization strategies for youth service sequencing.

This analysis investigates the long-term impact of youth-focused services delivered by YSM. The goal is to identify early indicators of success, understand how different youth segments respond to programming, and recommend service optimizations for better outcomes.

Early Predictors of Success

A predictive model was trained to identify which early features best predict overall success. The model achieved excellent performance (ROC-AUC = 0.9976), and the most important predictors were assessment-related variables.

Predictor Categories for Overall Success

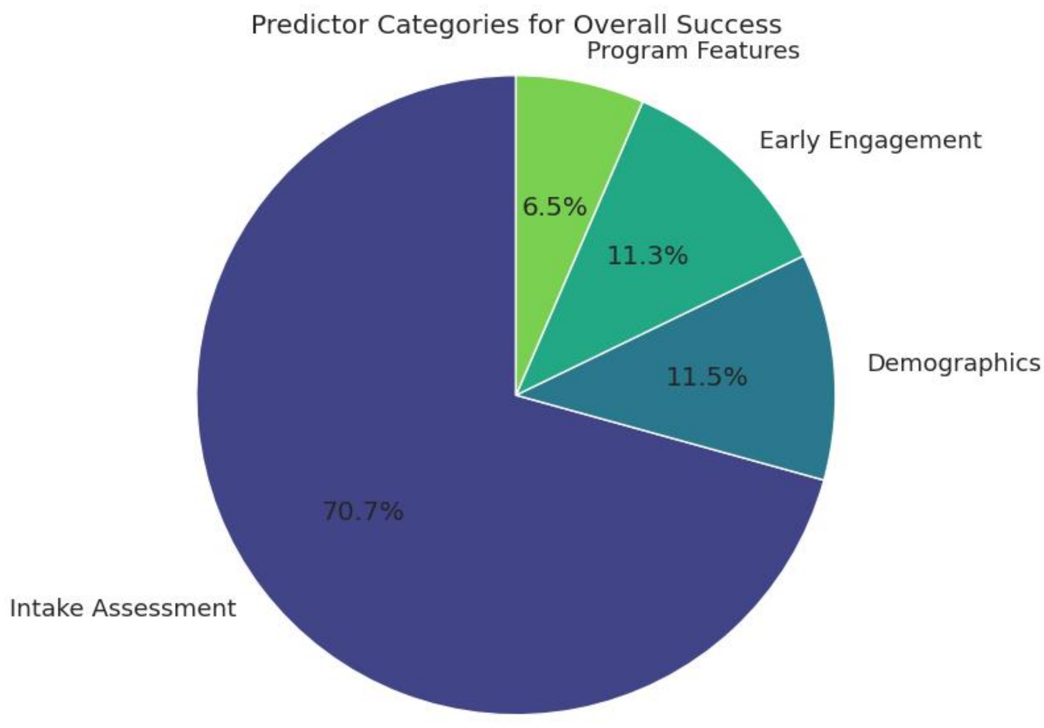

Figure 106: *Distribution of feature importance by category*

Intake assessments (e.g., count, baseline scores) accounted for 70.7% of predictive power, far outweighing demographic (11.5%), early engagement (11.3%), and program feature variables (6.5%).

Success by Age Group

Outcome rates varied substantially across age brackets, with success increasing with age.

Overall Success by Age Group

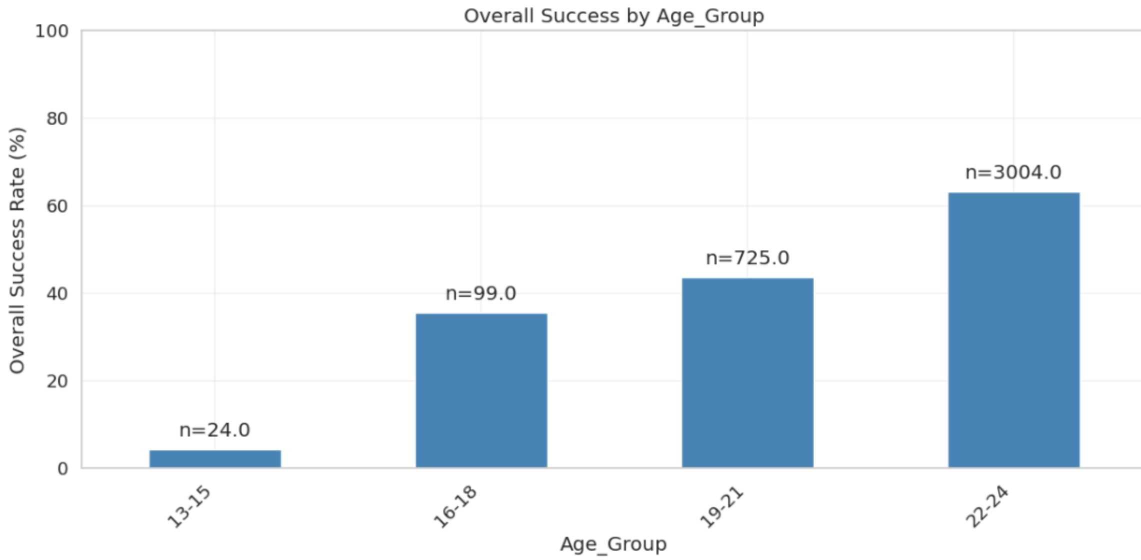

Figure 107: *Success rate across different youth age groups*

Participants aged 22–24 had the highest success rate (~63%), while youth aged 13–15 had the lowest (~4%). This shows the importance of tailored support for younger participants.

Success by Gender

There were stark differences in success rates across gender identities.

Overall Success by Gender

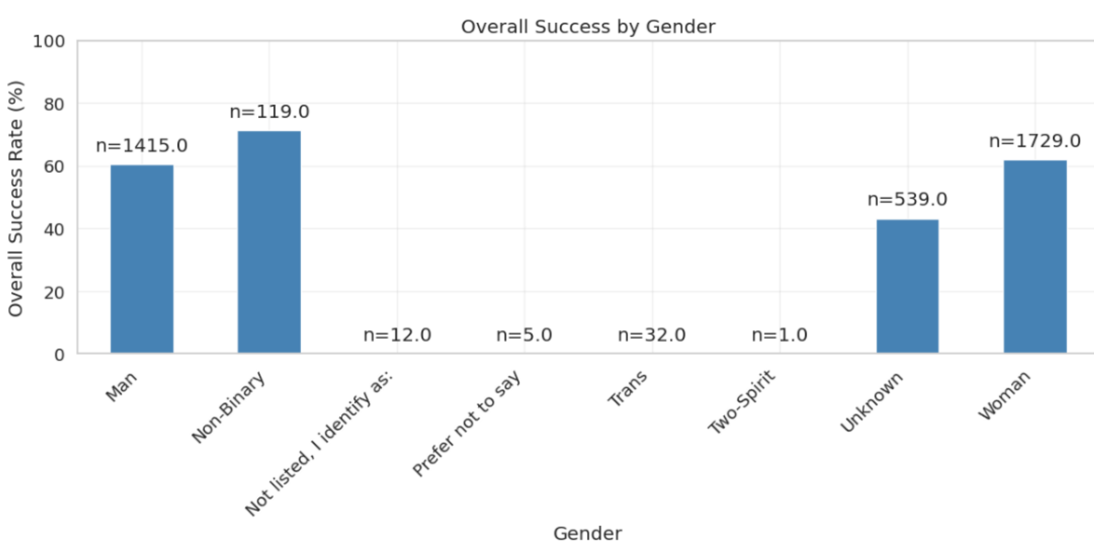

Figure 108: *Overall success rates by gender identity*

Non-binary participants had the highest success (~71%), while individuals who preferred not to disclose or identify had significantly lower rates.

Program Effectiveness by Age Group

We evaluated how effective different programs are across age groups.

Overall Success by Age Group and Program

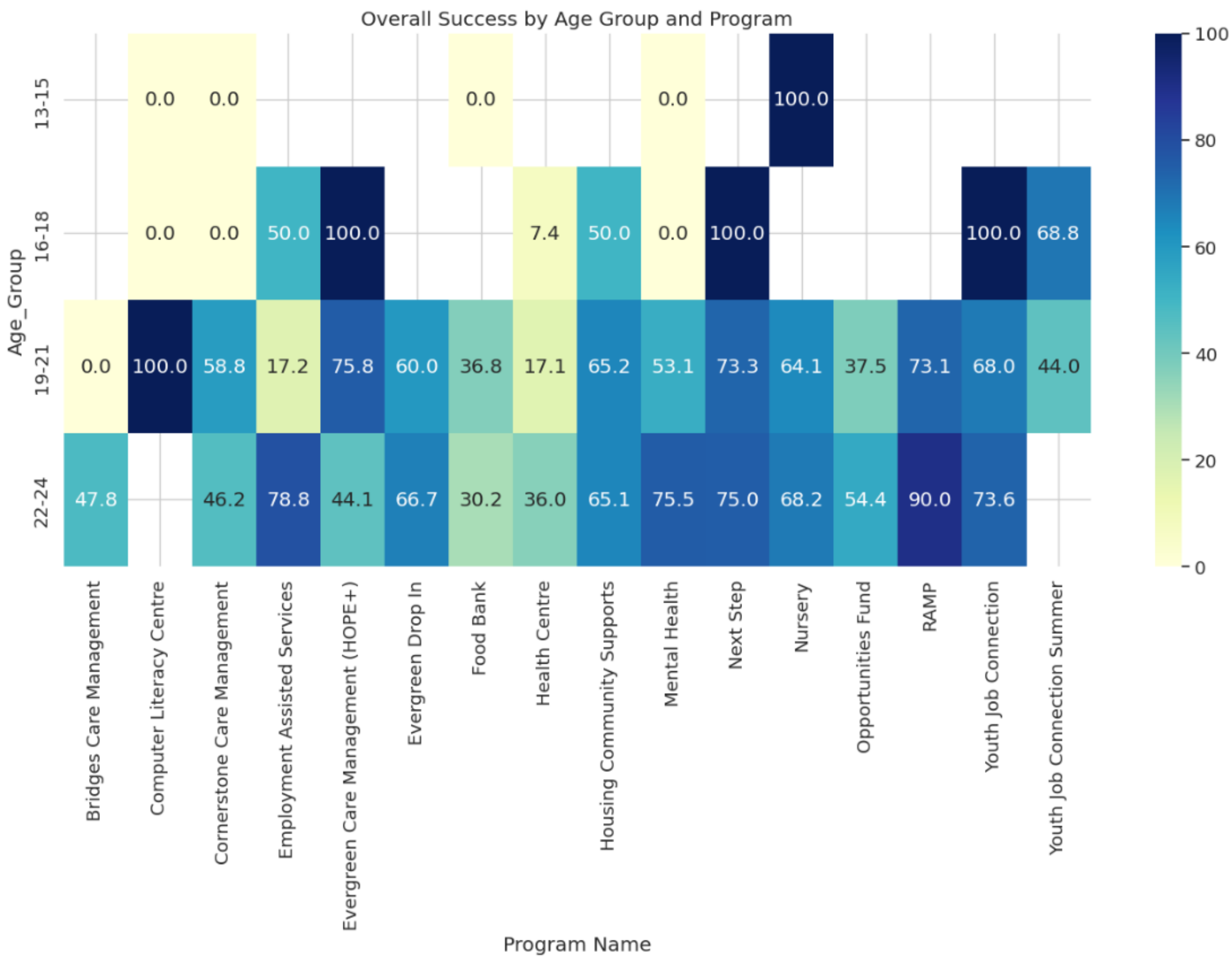

Figure 109: *Heatmap showing success rates across age and program combinations*

RAMP and the Computer Literacy Centre showed strong results among older youth. Programs like Nursery and HOPE+ performed best for younger groups, indicating age-specific program strengths.

Optimization Insights

- **Targeting:** Focus more resources on underperforming segments such as youth aged 13–18 or those who prefer not to disclose their gender identity.
- **Early Interventions:** Strengthen intake assessments and engagement in the first few weeks of programming.
- **Program Design:** Customize services based on age and gender response patterns.
- **Implementation Framework:** Incorporate developmental modules, structured transitions, and standardized follow-up tracking.

This longitudinal analysis shows that early assessments, tailored programming by age, and structured engagement strategies are critical to long-term youth success. The evidence supports implementing data-driven service sequences and investing in younger and vulnerable demographics to close outcome gaps.

Question 18: How effectively are programs addressing intersectional needs, and where are the key service gaps? Analyze outcomes for participants with multiple marginalized identities, identify service gaps for intersectional populations, and develop recommendations for more inclusive programming.

This analysis investigates how combinations of marginalized identities impact overall success rates across YSM programs. The identities explored include race/ethnicity, disability, socioeconomic status, gender/sexuality, and immigration status. We specifically evaluate how holding multiple marginalized identities affects program success.

Race/Ethnicity + Disability

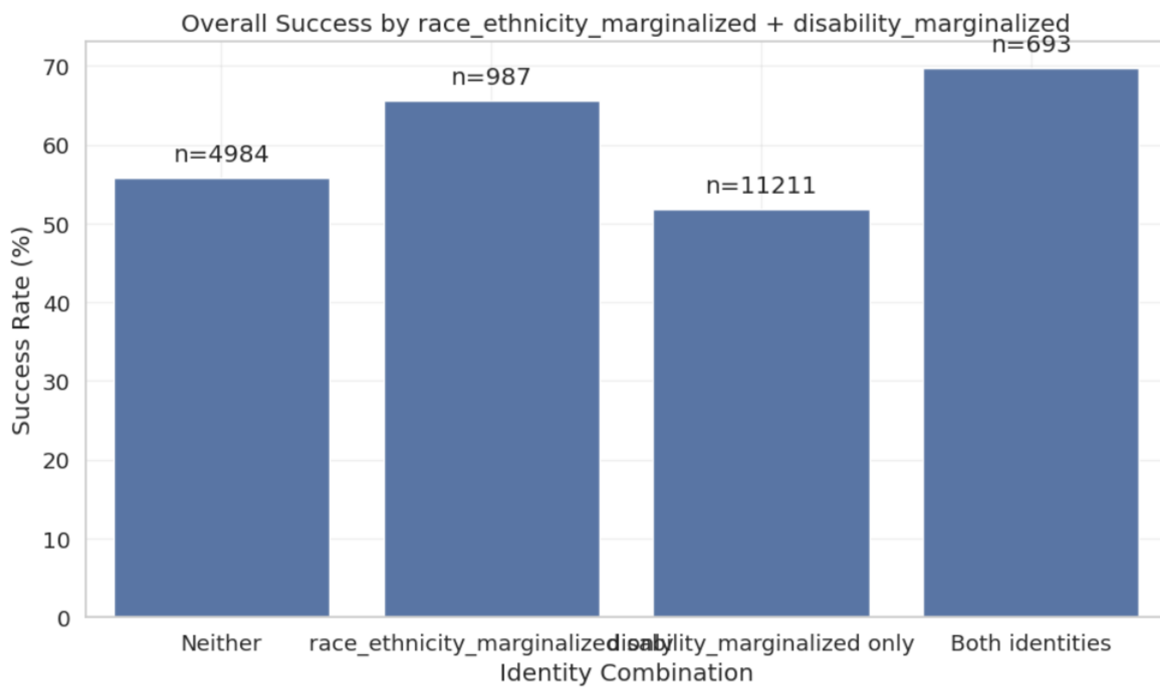

Figure 110: *Overall Success by Race/Ethnicity, Marginalized + Disability Marginalized*

Participants with both racial/ethnic and disability marginalization had the highest success rates.

This bar chart shows that participants with both race/ethnicity and disability marginalization achieved a success rate of nearly 70%, higher than those with only one marginalized identity or none. Surprisingly, those with no marginalization had lower success (56%) than those with intersecting identities.

Programs may be especially tailored or responsive to multiply marginalized clients, or these clients may be more motivated to engage due to barriers faced.

Race/Ethnicity + Socioeconomic Status

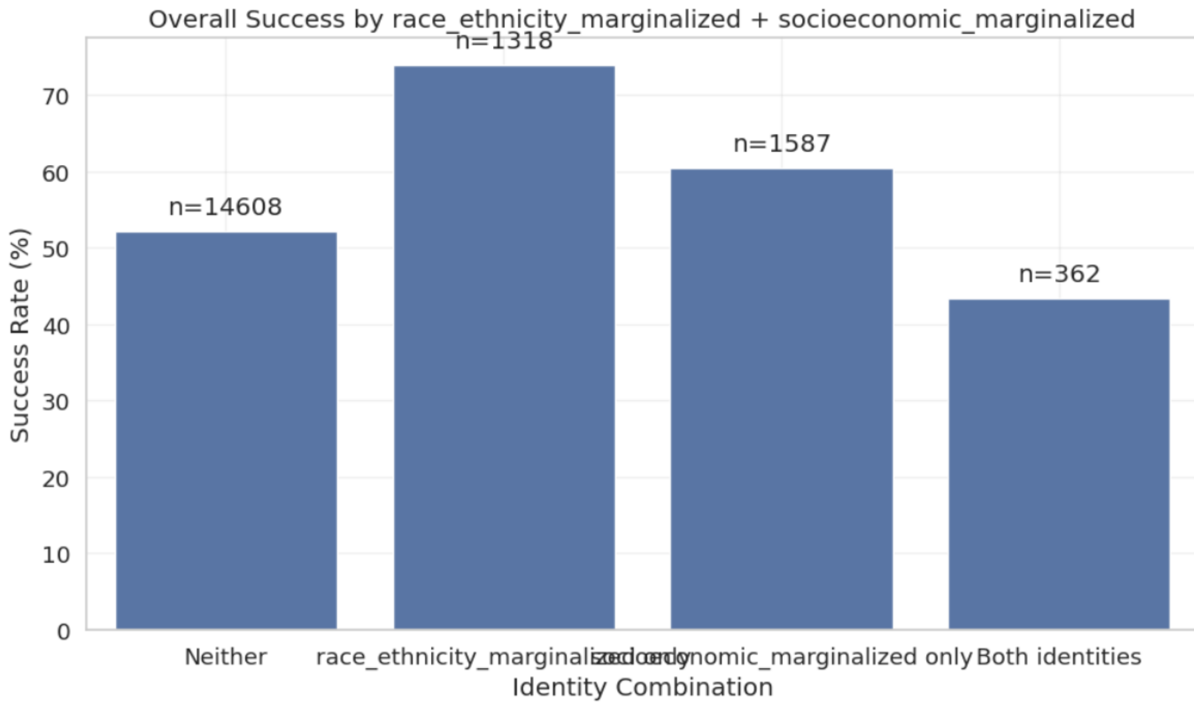

Figure 111: *Overall Success by Race/Ethnicity Marginalized + Socioeconomic Marginalized*

Those marginalized by both race and socioeconomic status had the lowest success rates.

Participants with both identities had a significantly lower success rate (~44%) than all other groups. In contrast, race/ethnicity marginalized only had the highest rate (~75%).

Structural barriers related to poverty may strongly inhibit program success, even more than racial marginalization alone.

Gender/Sexuality + Immigration Status

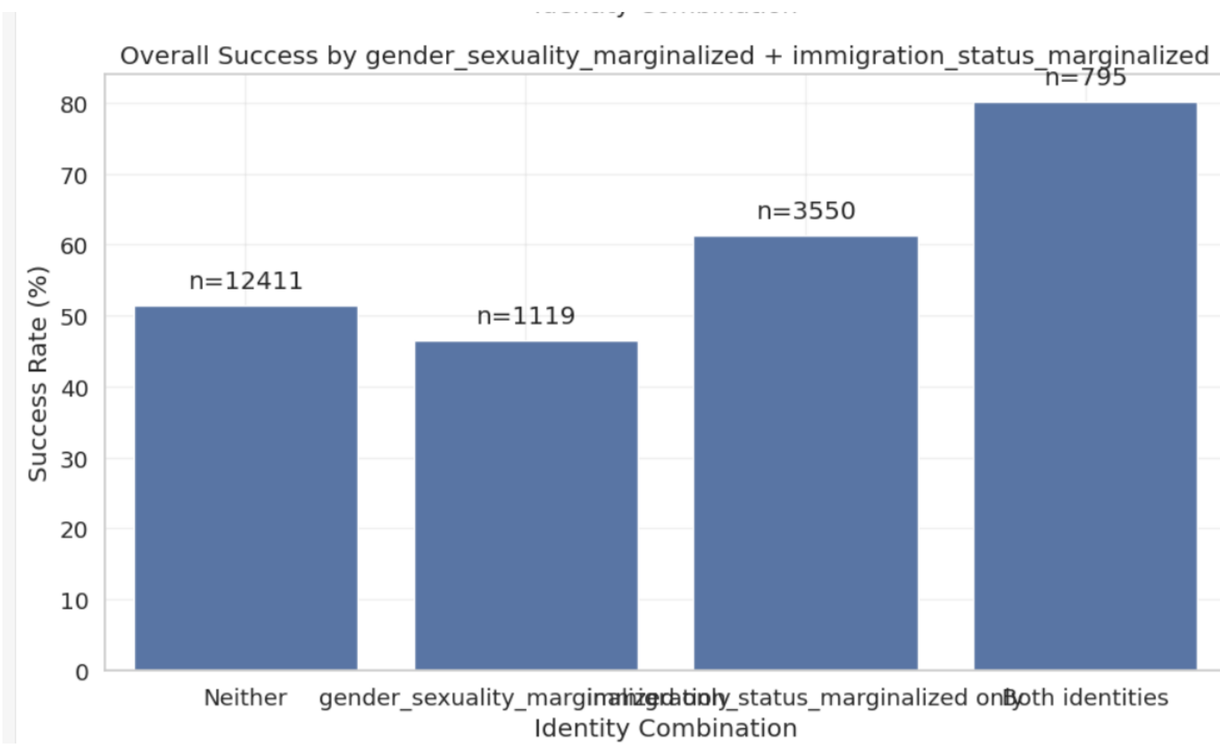

Figure 112: *Overall Success by Gender/Sexuality, Marginalized + Immigration Status* Marginalized

Holding both identities led to the highest observed success rate across this pairing.

Success rates steadily increased with each added layer of marginalization, with the "Both identities" group reaching 80%, the highest in the chart.

This may suggest that services are well-adapted for newcomers and LGBTQ+ clients when intersecting, or that these clients are accessing specific programs more suited to their needs.

Gender/Sexuality + Disability

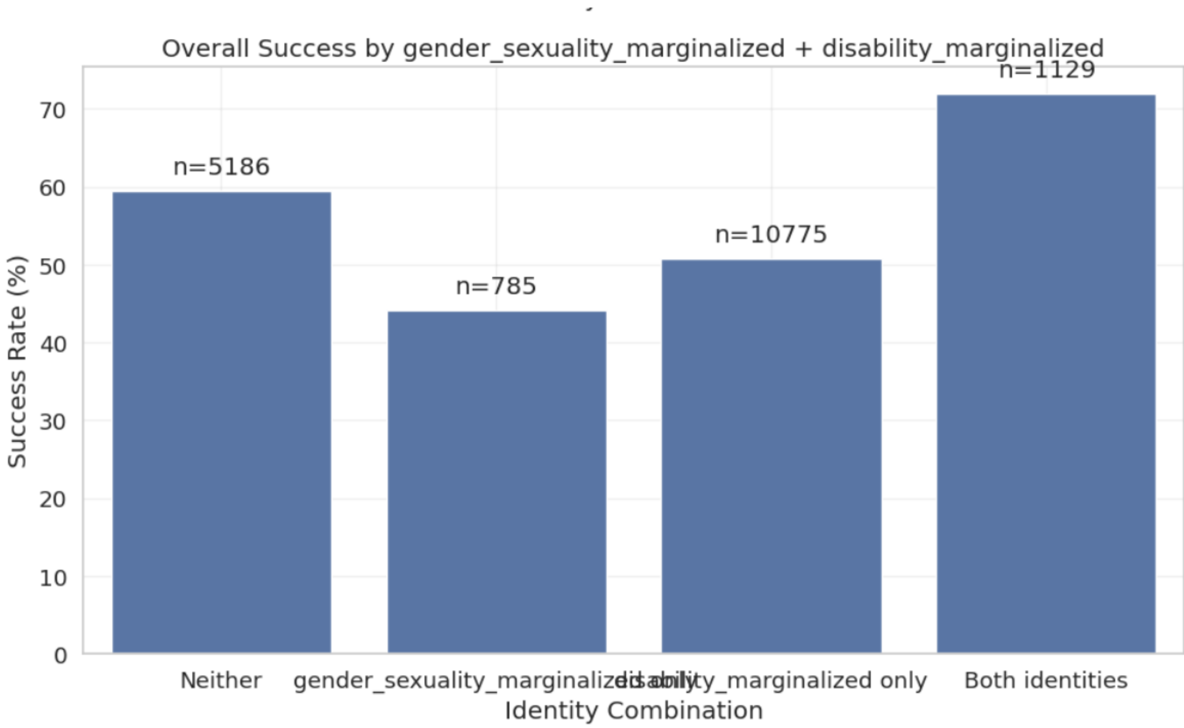

Figure 113: *Overall Success by Gender/Sexuality Marginalized + Disability Marginalized*

Participants with both identities significantly outperformed those with only gender/sexuality marginalization.

The success rate for dual-identity participants reached ~72%, compared to ~45% for those only gender/sexuality marginalized.

Targeted services for disabled participants may be particularly effective, benefiting intersecting identities as well.

Disability + Socioeconomic Status

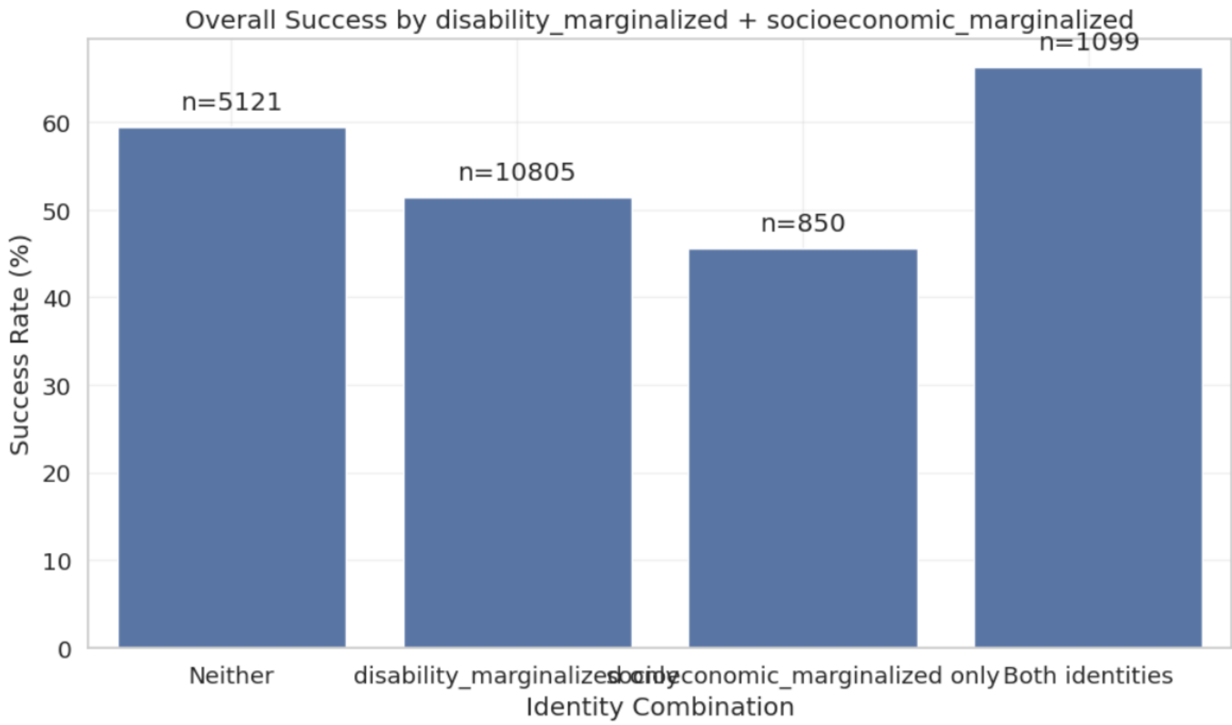

Figure 114: *Overall Success by Disability Marginalized + Socioeconomic Marginalized*

Participants with both disability and socioeconomic marginalization again had the highest success.

The dual-identity group surpassed all others (~67%), while those with only socioeconomic marginalization had the lowest (~48%).

Disability-focused programs may be serving low-income clients well, or these clients may engage more deeply with the resources provided.

Intersectional Status by Program

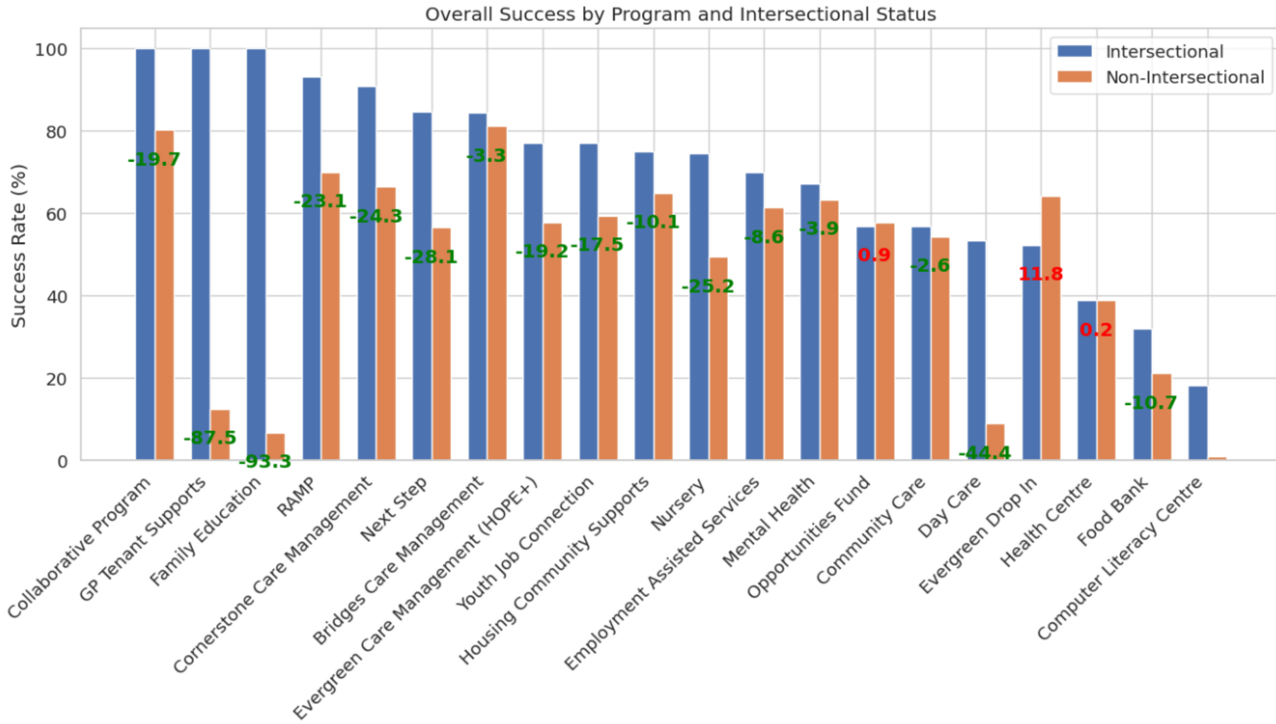

Figure 115: *Overall Success by Program and Intersectional Status*

Most programs showed a success gap favoring intersectional clients, except a few with inverse or minimal gaps.

This horizontal bar graph shows success rates across programs for intersectional and non-intersectional participants. Programs like Collaborative Program, GP Tenant Supports, and RAM show higher success for intersectional participants, while Day Care and Health Centre have small or reversed gaps.

Some programs effectively support intersectional populations, while others may need targeted adjustments.

Key Findings

1. **Positive Impact of Dual Marginalization in Some Cases:** Contrary to expectations, participants with both marginalized identities (especially disability) often had **higher** success rates than those with only one or no marginalization. This might reflect well-designed, targeted supports or higher engagement from these groups.

2. **Socioeconomic Barriers Are Most Damaging:** Across several identity combinations, those marginalized socioeconomically—especially when combined with other identities—consistently showed **lower success**. These clients may face deeper systemic challenges such as unstable housing, food insecurity, or time constraints.

3. **Program-Level Differences:** Some programs are especially beneficial to intersectional groups (e.g., Collaborative Program, GP Tenant Supports), while others (e.g., Family Education, Day Care) show significant disparities against them.

4. **Not All Marginalizations Combine Additively:** The effect of combining two marginalized identities isn't always additive or predictable. For instance, immigration status often improved outcomes when combined with other identities.

Recommendations

- **Target Programs for Socioeconomically Marginalized Groups:** Develop intensive support models for low-income participants, especially those without other targeted services.

- **Scale Best Practices from High-Performing Programs:** Replicate strategies from programs like the Collaborative Program and GP Tenant Supports, where intersectional clients succeed most.

- **Deeper Qualitative Research:** Investigate the experiences of clients with dual identities, especially those outperforming expectations, to understand which interventions or factors contribute to success.

- **Monitor Disparities by Identity:** Disaggregate program evaluations by intersectional identities to avoid hiding disparities behind averages.

Conclusion

This comprehensive analysis of the YSM TIMES™ dataset provides a data-driven foundation for improving social service delivery and client outcomes across youth, family, and adult programs. By integrating and cleansing over 17,000 records across multiple administrative datasets, the study uncovered significant insights into the effectiveness of program design, demographic disparities, and service utilization patterns.

Key findings reveal that sustained and diverse service engagement, especially beyond 6–12 months, correlates with the greatest improvements in TIMES scores. More than two-thirds of participants showed measurable gains, with the highest improvements often requiring longer durations and deeper service involvement. Demographic disparities in outcomes were prominent, highlighting the need for targeted strategies that consider age, housing, immigration status, and gender identity.

Advanced modeling techniques, including clustering, predictive analytics, and ROI calculations, identified which service pathways, sequences, and program mixes yield the highest return on investment and success. For example, intensive multi-service pathways with over 125 hours and 8+ service types were linked to transformational outcomes, particularly when tailored to client profiles. Programs like Youth Job Connection Summer and RAMP demonstrated high impact at low resource cost, while others, such as Day Care and Computer Literacy Centre, showed limited effectiveness despite substantial investment.

Moreover, disparities in service access and outcomes among marginalized groups—especially youth under 18, elderly participants, and gender-diverse individuals—signal critical equity challenges that must be addressed through inclusive program design and outreach.

Ultimately, this analysis underscores the transformative potential of data-informed service delivery. By leveraging these findings, YSM can strategically expand high-performing programs, redesign low-impact interventions, and adopt predictive tools to proactively support at-risk participants. These steps will enhance equity, efficiency, and long-term community impact delivering not just services, but meaningful and measurable change.

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