Peel Region

Using Data-Driven Prioritization Methods to Support the Launch of Needs-Based Subsidies

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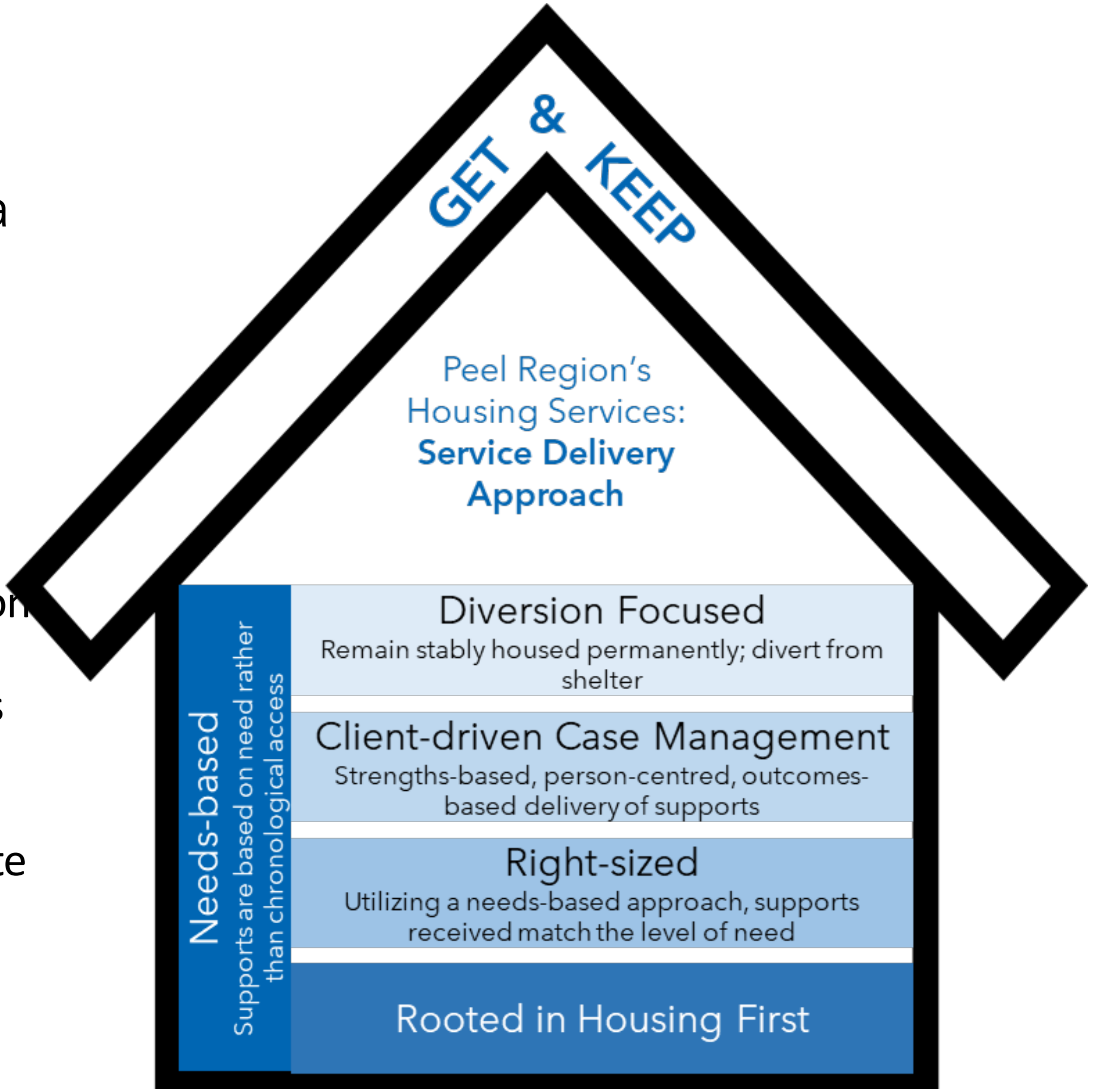
Objectives

- Provide an overview of the Needs Based Portable Subsidies (NBPS) in Peel Region
- Introduce By-Name List/Co-ordinated Access Stream
- For BNL-Stream: Review of data, takeaways, and outcomes to date.
- Prevention Stream: Describe model and current progress

Why Needs-Based?

As part of a council-endorsed service transformation, a needs-based approach was identified as the way to deliver supports; to ensure supports were based on need rather than chronological or program-based access.



Some of the benefits of a needs-based approach to subsidy administration include:

- Limited resources are allocated to clients with the most urgent needs
- More subsidized housing options will be available beyond the centralized wait list
- Improved ability for clients to retain units [keep housing] in the private market
- Address and alleviate housing issues before they escalate to a crisis. This will ease the growing pressures on emergency shelters

This supports our **overall goal of get and keep housing**

Overview of Needs Based Portable Subsidies (NBPS)

- There is no unit attached to the subsidy, clients are to secure a rental unit in Peel
- Clients have the flexibility to relocate and rent in Mississauga, Brampton, or Caledon
- If client is on the Centralized Wait List for Subsidized Housing in Peel, they must agree to be removed from it once subsidy is in pay
- Client is required to pay their OW or ODSP Shelter Allowance or 30% of income towards their rent
- Portable subsidy is paid directly to the landlord
- Portable subsidy will continue to be issued as long as client is found eligible during their annual reviews
- Clients are offered ongoing case management supports and services to help maintain their housing

Portable Subsidy Amounts

Unit Size	150% AMR
1 Bedroom	$2441
2 Bedroom	$2798
3 Bedroom	$3072
4 Bedroom	$3072
5 Bedroom	$3072
6 + Bedroom	$3072

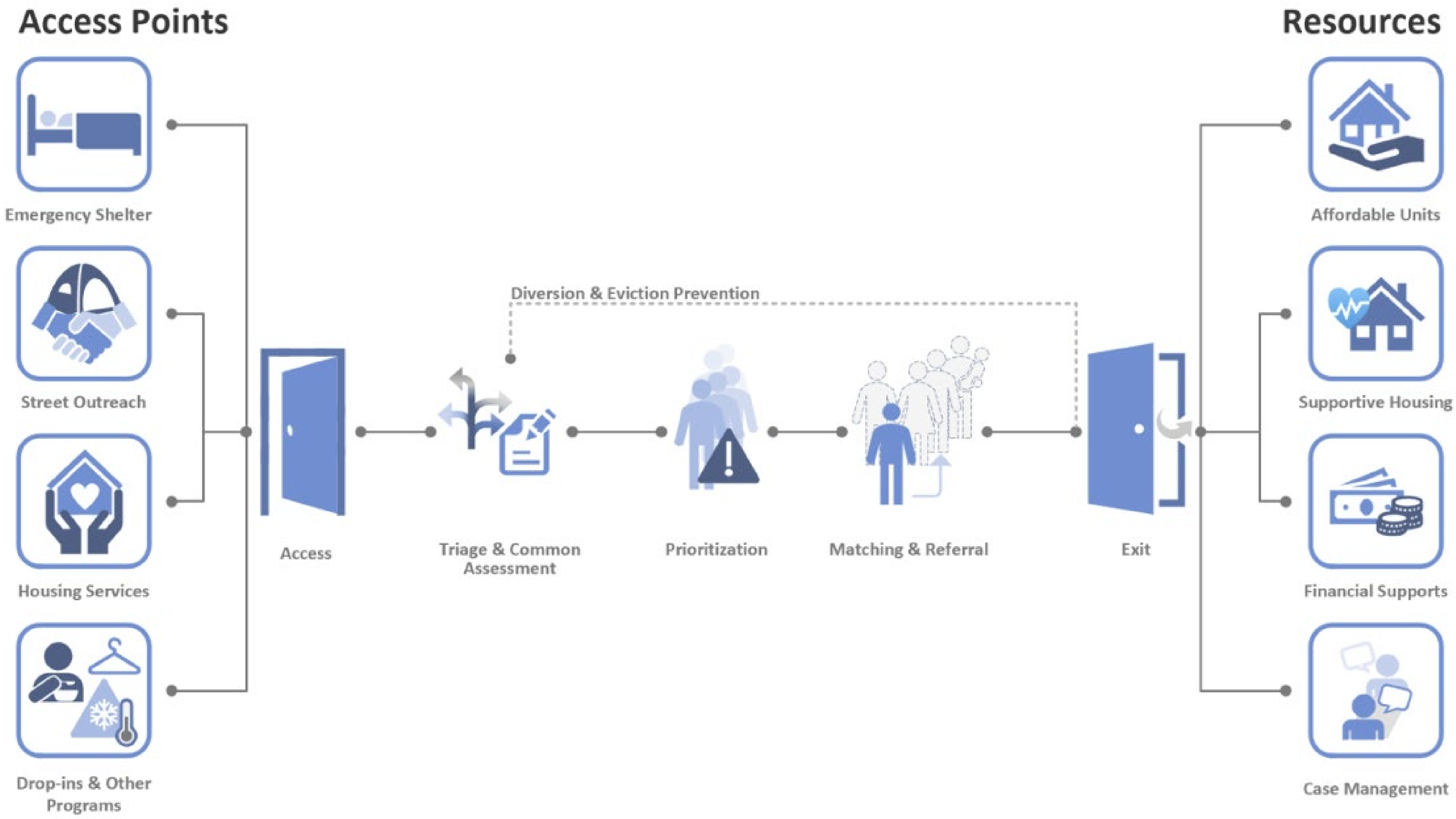
Subsidy will cover the difference between client's income and up to 150% AMR according to the bedroom size they are eligible for which is based on household composition

Eligibility Requirements

Category	Guidelines
Residency	• Must reside in Peel to provide immediate support to current residents • Secured housing must be within Peel to receive subsidy
Status	Canadian citizen or landed immigrant
Coordinated Access	To receive subsidy: clients must be on the By-Name List, experiencing homelessness, and not currently have a lease agreement. Homeless may include households that are: emergency sheltered, unsheltered (makeshift/street, vehicle, campsite, public space, squatting), provisionally accommodated (staying with friends, family, strangers).
Income	The existing household income limits as per O. Reg. 370/11 based on current year
Assets	• Agree to sell any home or land that client owns (or share ownership of) within 6 months of accepting an offer • Not have cash, investments, or property worth more than $50,000 (or $75,000 if applying with someone)
Community/Social Housing Provider	Arrears: May be required to arrange a repayment agreement and demonstrate that the repayment obligations are being met as part of the case plan Units: Clients that are searching for accommodations cannot receive a portable subsidy if the new accommodation is a social housing provider unit.
Centralized Waitlist	If client is currently on the Centralized Waitlist, they will be removed if they accept the offer for a needs-based portable subsidy. Removal from the wait list will not occur until housing is secured.

Peel Residents Experiencing Homelessness Stream

By-Name List and Coordinated Access



A Phased Approach for NBPS

Pilot - Aug 8, 2023

Wave 1- 3 – October 31, 2023– May 2, 2024

Wave 4 (current) - Intensive Housing Case Managers

Documentation

Timelines

Housing Availability

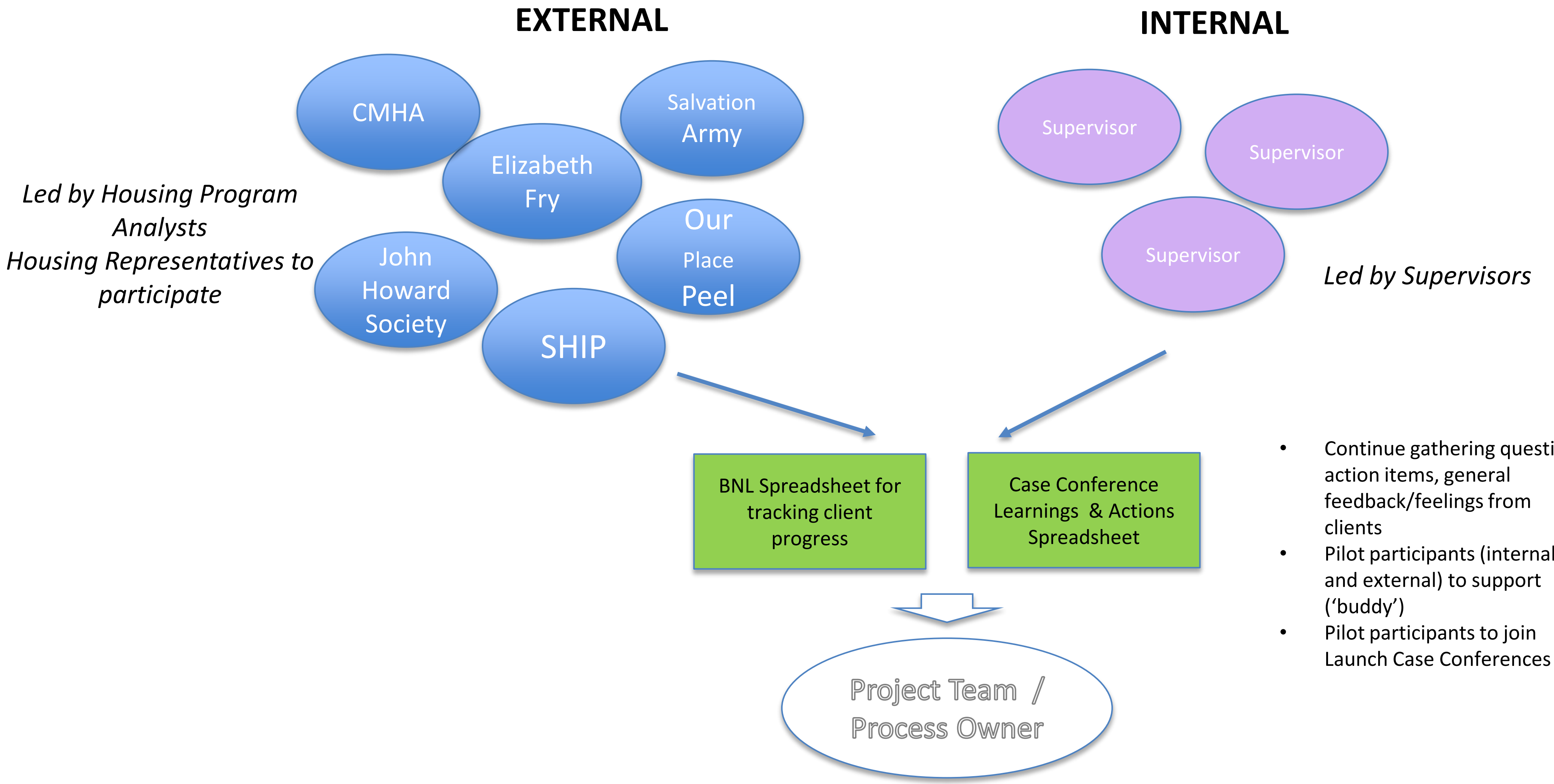
Creativity

Collaboration

Needs Based Portable Subsidy Process

1. Determine Subsidy Allocation
2. Access BNL & Prioritize Clients
3. Contact Clients
4. Determine Eligibility & Extensions
5. Conduct Housing Search & Finalize Lease
6. Complete Unit Set-up & Obtain Agreement
7. Set-up Payments & Issue Subsidy
8. Provide Ongoing Monitoring & Management of Subsidy

Launch Case Conferences & Learnings



- Continue gathering questions, action items, general feedback/feelings from clients
- Pilot participants (internal and external) to support ('buddy')
- Pilot participants to join Launch Case Conferences

Client’s Summary & Experience to Date

Last updated: Oct 21, 2024

Client emotions/feedback captured is as assessed by internal HSWs and external case managers and shared at Case Conferences

Client	Details	CONTACT CIENTS	DETERMINE ELIGIBILTY/EXTENSIONS	CONDUCT HOUSING SEARCH	UNIT SET UP/AGREEMENT	SET UP PAYTS/ISSUE SUBSIDY	ONGOING MONITORING/SUPPT	Status
1A	From Shelter to hospital; Referred by Salvation Army							Not able to contact.
1B	Male; Previously housed May 2023; incarcerated		Docs					**Moved in: Sept 11, 2023!**
1C	Male; Not in Shelter; living in his car		Lost contact					Not able to contact
1D	Couple; Pregnant; Not in Shelter; VOFV; OW							**Moved In: Nov 8, 2023!**
2A	Shelter - Peel Family with partner; ODSP		Stressed about deadline					**Moved in: Oct 2, 2023!**
2B	Male; Shelter; Country Inn New to Canada; Employed; OW ended Sept 2023	Guilt, why chosen		1 bdrm				**Moved in: Oct 24, 2023!**
3A	Male; Not in Shelter (tent in Malton) Chronically homeless; OW		Docs	Max rent confusion; No call backs				Lost contact due to hospitalization; New Housing Search created Oct 2024
3B	Chronically homeless last 4 years; Couple; Substance use; ODSP		Docs. for Female					**Moved in Oct 1, 2023!**
4A	CMHA; Male; Not in Shelter							Not able to contact
4B	CMHA; Couple; chronically homeless 2 years; Not in Shelter; Regeneneration; ODSP			Distracted				**Moved in: June 1st, 2024!**
4C	CMHA; Male. Not in Shelter; chronically homeless 10 years; Family support (mother); ODSP		Feels safer on the street					**Move In: Nov 24, 2023!**
5A	OPP; Female; Youth; chronically homeless 2 yrs; ODSP	Mix of emotions	Discouraged Hesitation; timeline anxiety	Frustrated				**Moved In: Nov 6, 2023!**
5B	OPP; international student							Not eligible
5C	OPP; Male; Youth; Homeless 8 mths; OW			Not motivated				**Moved In: Nov 1, 2023!**
6A	Salvation Army; Male; Senior; Shelter; Medical; OW							**Moved In: Nov 1, 2023!**
6B	Salvation Army; Female; Shelter; OW							**Moved In: Oct 18,2023!**

Tracking Progress:
Needs Based Portable Subsidy & Client Outcomes

- **Clients Prioritized:** **478** households selected from the By Name List
- **Housing Secured:** **235** households have successfully moved into house since the program's implementation on August 8, 2023
- **Remaining Goal:** **31** more move-ins are needed to meet the allocation target for this stream
- **Current Status:** Households in the housing search stage are actively working with Housing Support Workers and external Case Managers to find rental units

Takeaways & Findings

By-Name List & Coordinated Access

- By-Name List Data Quality
- Unsheltered vs Emergency Sheltered Clients

NBPS Process & Procedure

- Vulnerable population
- Lack of available ID on hand
- Housing Availability
- Landlord hesitation

Outcomes to Present Date

1. Streamlined the process
2. Improved collaboration with other departments and community services
3. Launched the Needs Based Prevention Subsidy July 2024 to help client who are precariously housed, and possibly facing homelessness

NBPS Prevention Stream

Overview

1. To assist Peel residents who spend more than the CMHC recommended guideline of 30% income on housing costs
2. **308** Prevention subsidies to be issued which started in July 2024
3. Prioritized clients will work with our internal staff (Housing Representatives and Housing Support Workers) to move through the process towards an eligibility decision

Tracking Progress:
NBPS PREVENTION & Client Outcomes

- **Clients Prioritized:** 1626 households selected from Housing files and our Centralized Wait List
- **Subsidy Secured:** 104 households are successfully receiving a subsidy
- **Remaining Goal:** 204 more clients are needed to meet the allocation target for this stream
- **Current Status:** Staff working to contact pre-selected households and actively working to submit the necessary documents for eligibility.

How to Allocate Housing Supports?

- Region of Peel has > 37, 200 households on the Centralized Waitlist

- Roughly 2% of these households have Housing Support Worker assigned

- Potential methods of allocation:
  1. Random
  2. Chronological
  3. Qualitative
  4. Quantitative

- Allocation should be "needs-based"

Criteria for Allocation Model

- Transparent
  - Random ✓, Chronological ✓, Qualitative ✕, Quantitative **?**
- Uniform
  - Random ✓, Chronological ✓, Qualitative ✕, Quantitative ✓
- Fair/Equitable (should be based on need)
  - Random ✕, Chronological ✕, Qualitative **?**, Quantitative **?**
- Empirical
  - Random ✕, Chronological ✕, Qualitative ✕, Quantitative ✓/ **?**
- How do we define need? How do we measure it? What do we do with the Measure?

Piloting a Quantitative Method for Allocation

- Definition of ‘need’ operationalized as Core Housing Need (CHN)
  - A household is in CHN **if (**STIR **>** 30% **|** unit unsuitable **|** unit inadequate**) &** median local acceptable unit requires STIR **>** 30%*

- CHN is reported in Census data by Statistics Canada

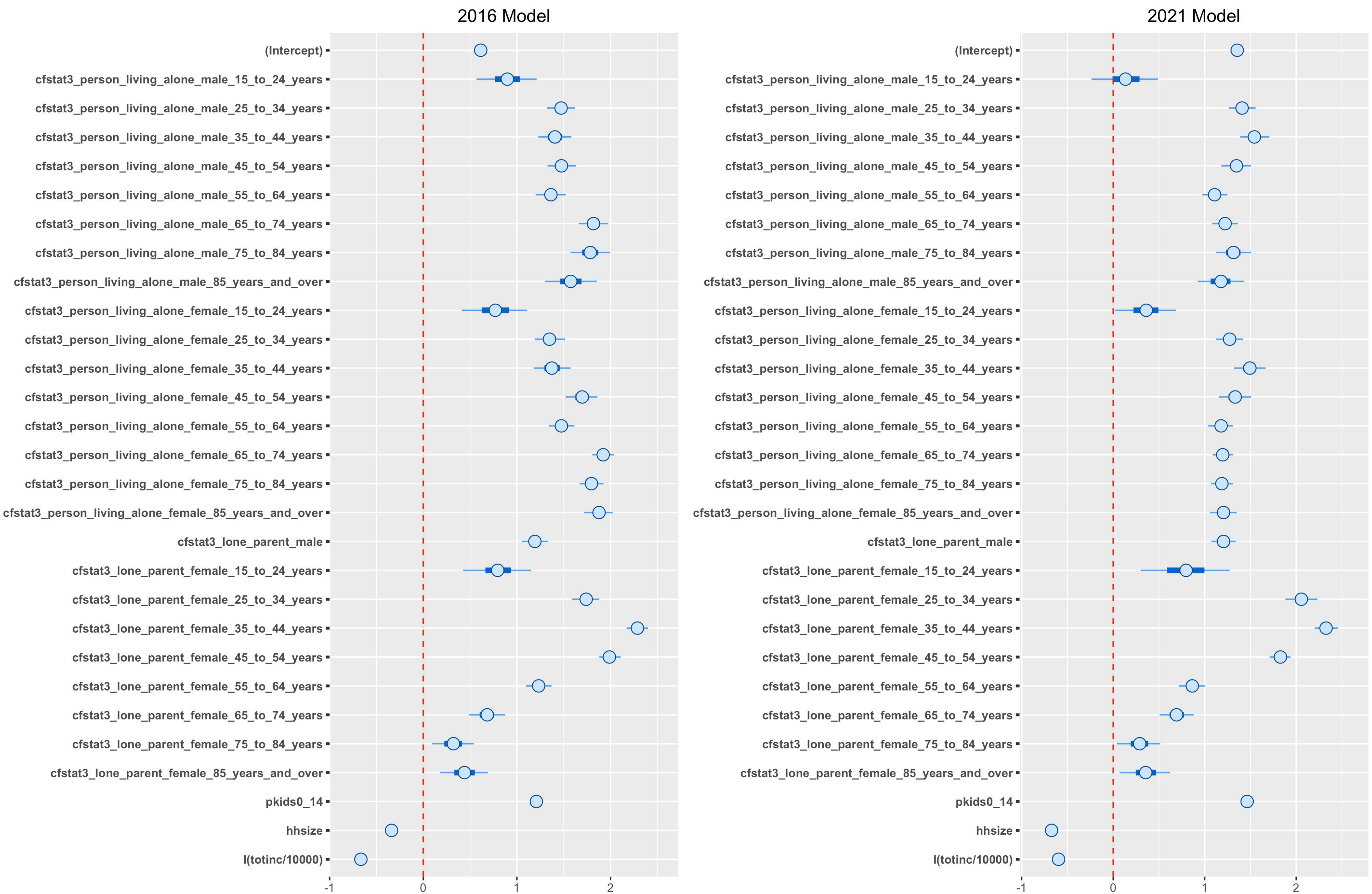
- Use Census public-use microdata files (PUMFs) to model CHN as a function of other variables in the PUMF

- Certain types of models can produce probabilities that an individual/household is in CHN – probabilities provide common scale for comparing units (a “housing stress point”)

Piloting a Quantitative Method for Allocation

- Census data used to generate model coefficients(weights) which are then be applied to each unit in our waitlist population
- Variables used in this model must be common to the census and administrative data routinely collected by the Region of Peel
  - Reasonable proxies and transformation can be applied to variables when there isn't exact concordance between census and administrative variables.
- Census variables employed were
  - 1) *Simplified census-family structure (CFSTAT)*, 2) *Household Size (HHSIZE)*, 3) *Total income (TOTINC)*, 4) *Presence children < 15 y/o: if (PKID0_1 ==1 | PKID2_5 ==1 | PKID6_14 ==1) = 1 else = 0*, 5) *Age (AGEGRP) [for single households]*, 6) *Gender (Gender/SEX) [for single households]*
- Used Logistic Regression:

$$p(CHN)_i = \text{logit}^{-1}(\mu_i)$$
$$\mu_i = \alpha + \boldsymbol{\beta}^T \mathbf{X}_i$$


2016 Model
(Intercept)
cfstat3_person_living_alone_male_15_to_24_years
cfstat3_person_living_alone_male_25_to_34_years
cfstat3_person_living_alone_male_35_to_44_years
cfstat3_person_living_alone_male_45_to_54_years
cfstat3_person_living_alone_male_55_to_64_years
cfstat3_person_living_alone_male_65_to_74_years
cfstat3_person_living_alone_male_75_to_84_years
cfstat3_person_living_alone_male_85_years_and_over
cfstat3_person_living_alone_female_15_to_24_years
cfstat3_person_living_alone_female_25_to_34_years
cfstat3_person_living_alone_female_35_to_44_years
cfstat3_person_living_alone_female_45_to_54_years
cfstat3_person_living_alone_female_55_to_64_years
cfstat3_person_living_alone_female_65_to_74_years
cfstat3_person_living_alone_female_75_to_84_years
cfstat3_person_living_alone_female_85_years_and_over
cfstat3_lone_parent_male
cfstat3_lone_parent_female_15_to_24_years
cfstat3_lone_parent_female_25_to_34_years
cfstat3_lone_parent_female_35_to_44_years
cfstat3_lone_parent_female_45_to_54_years
cfstat3_lone_parent_female_55_to_64_years
cfstat3_lone_parent_female_65_to_74_years
cfstat3_lone_parent_female_75_to_84_years
cfstat3_lone_parent_female_85_years_and_over
pkids0_14
hhsize
I(totinc/10000)
-1
0
1
2
2021 Model
(Intercept)
cfstat3_person_living_alone_male_15_to_24_years
cfstat3_person_living_alone_male_25_to_34_years
cfstat3_person_living_alone_male_35_to_44_years
cfstat3_person_living_alone_male_45_to_54_years
cfstat3_person_living_alone_male_55_to_64_years
cfstat3_person_living_alone_male_65_to_74_years
cfstat3_person_living_alone_male_75_to_84_years
cfstat3_person_living_alone_male_85_years_and_over
cfstat3_person_living_alone_female_15_to_24_years
cfstat3_person_living_alone_female_25_to_34_years
cfstat3_person_living_alone_female_35_to_44_years
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cfstat3_person_living_alone_female_55_to_64_years
cfstat3_person_living_alone_female_65_to_74_years
cfstat3_person_living_alone_female_75_to_84_years
cfstat3_person_living_alone_female_85_years_and_over
cfstat3_lone_parent_male
cfstat3_lone_parent_female_15_to_24_years
cfstat3_lone_parent_female_25_to_34_years
cfstat3_lone_parent_female_35_to_44_years
cfstat3_lone_parent_female_45_to_54_years
cfstat3_lone_parent_female_55_to_64_years
cfstat3_lone_parent_female_65_to_74_years
cfstat3_lone_parent_female_75_to_84_years
cfstat3_lone_parent_female_85_years_and_over
pkids0_14
hhsize
I(totinc/10000)
-1
0
1
2

Predictive Algorithms: Rationales

- Predictive algorithms are often contrasted with the following traditional methods for decision-making

1. Bureaucratic rules
    a. Goals are often vague
    b. Attributes often selected based on intuition about their relevance to decision
    c. Attributes discretized into categories
    d. Categories are combined using Boolean logic to make decisions
2. Human Judgement
    a. Inaccurate, potentially biased and/or arbitrary
    b. Costly

- Using predictive algorithms often based on claims of improved:

    1) Accuracy, 2) Fairness (reduce bias), and 3) Efficiency

Predictive Algorithms: Cautionary Tales

- Dutch Child-Benefit Scandal
  - Fraud detection system erroneously identified tens of thousands of cases - at least 38,000 recognized victims of 69,000 complainants. (see Amnesty International's 2021 report *Xenophobic Machines: Discrimination Through Unregulated Use of Algorithm's in the Dutch Childcare Benefits Scandal)*
- Australian 'Robotdebt' scheme
  - Automated system to recover welfare overpayments with 470,000 erroneous penalties
- British Post Office Scandal
- COMPAS
- Alleghany Family Screening Tool

- CHN allocation model differs because intervention is not punitive
  - COHB subsidies delivered in standard way using HSW discretion. Serves as 'failsafe', over 550 new applications this year.

Bill 194: ENHANCING DIGITAL SECURITY AND TRUST ACT, 2024

- Bill 194 (EDST Act) set to regulate the use of “AI” by PSEs in Ontario
  - General Use (Section 5)
    - Provide information to the public (Section 5(2))
    - Develop and implement an accountability framework (Section 5(3))
    - Manage risks with prescribed steps (Section 5(4))
    - Use AI systems in accordance with prescribed requirements (Section 5(5))
    - Not use an AI system if it is explicitly proscribed (Section 5(6))
  - Specific uses (Section 6, relating to prescribed circumstances)
    - Disclose information regarding the use of the AI system (in accordance with regulations). (Section 6(2)(a))
    - Ensure an individual exercises oversight over the AI system's use and provides additional information (as per regulations) (Section 6(2)(b))
    - Comply with technical standards for AI use defined in regulation (Section 8)
  - No specifics yet, will be defined by regulation

What is ‘AI’?

- ‘AI’ defined in the EDST Act:
  - “An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments...”
- ‘Algorithm’ defined in the OED:
  - “A procedure or set of rules used in calculation and problem-solving; a precisely defined set of mathematical or logical operations for the performance of a particular task”
- ‘Machine Learning’ (my own definition)
  - Refers to a family of statistical tools designed to maximize predictive accuracy, but which generally do not provide interpretable model parameters. ML contrasts with standard ‘inferential’ statistics. (ML tools often described as ‘black-box’ models)
- CHN model uses very standard method, most examples on previous slide use ML.

Evaluating Predictive Algorithms Used in Decision-Making

- *Against Predictive Optimization: On the Legitimacy of Decision-Making Algorithms that Optimize Predictive Accuracy* (Wang et al. 2024)
  - https://predictive-optimization.cs.princeton.edu/

- APO defines "*predictive optimization*" as an *ideal-type* of decision-making algorithm that predicts future outcomes of interest about individuals
- Identifies *categories of recurrent problems* that may apply to models beyond the ideal-type described; *provide framework for evaluation* of the suitability of decision-making algorithms.
- *Presumptive Illegitimacy*: "The burden of evidence for justifying why the deployment of predictive optimization is not harmful should rest with the developers of the tools"

Recurrent Flaws Identified in APO

1. Intervention vs. Prediction: Good predictions may not lead to good decisions
   - *Interventions based on predictions might affect the outcomes being predicted* (e.g. setting loan premiums)
   - CHN Model: Intervention can only be beneficial; relevant comparison is against alternative allocation methods or other candidate models.
2. Target-Construct Mismatch: It is hard to measure what we truly care about
   - The *subject of intervention is usually unobservable (construct)*, so it is proxied by something that can be measured. The construct may be abstract so any proxy could be insufficient (e.g. job performance by sales, teacher effectiveness by pupil rating)
   - CHN proxies 'housing stress' or, more concretely, risk of eviction/homelessness which we can't measure. CHN does not exist and hasn't been validated as a predictor of realized outcomes.* (Also, many problematic exclusions)

Recurrent Flaws Identified in APO Continued

3. Distribution Shifts: The data used to train the model often differs significantly from the population where it is deployed
   - ML methods often suffer from degradation of predictive performance with even minor changes in the distribution.
   - CHN model: Model is fit to representative census data so would generally be less problematic. However, 2021 CHN estimates affected by COVID benefits so we used 2016 CHN estimate as well
4. Limits to prediction: Social outcomes are fundamentally unpredictable
   - COMPAS no more accurate or fair than predictions made by humans with no criminal justice expertise. Simple 2 variables model nearly as predictive as 137 variable COMPAS model
   - CHN model: Prediction of CHN less important than producing set of empirically justifiable parameters to rank eligible population. High prediction accuracy will not necessarily be produced by model which fully describes population parameters*

Recurrent Flaws Identified in APO Continued

5. Disparate Performance: Demographic group will experience disparate treatment by predictive models
    - Fairness impossibility theorems hold that when two groups have different base rates, any calibrated algorithm cannot ensure equal false-positive rates for both groups.
    - "We interpret these impossibility theorems as formalizing the well-known fact that a decision-making system that only considers people's current degree of similarities and differences, without accounting for the reasons behind those differences or histories of prejudice, will, in turn, be unjust".
    - CHN Model: TBD – Exclusions for STIR > 100% should be addressed by treatment of income variable in the model. Other excluded categories are not represented by explicit variables in the model so there is no direct impact, but disparate performance could result from correlations between unobserved categories and included variables, although disparate performance may not be confined to excluded categories

Recurrent Flaws Identified in APO Continued

6. Contestability: Mistakes are inevitable
   - Errors can arise at every step; data pre-processing, modeling, evaluation, and deployment so model outputs should be explicable and contestable
   - The previous cautionary examples either denied individuals the right to know what data had been used to generate decisions, had methods that were proprietary, or had uninterpretable parameters (e.g. COMPAS methods were not understood even by experts and used incorrect data for an undetermined number of subjects, who could not challenge what data had been used in the decision).
   - CHN Model: Our model is relatively good on this issue as we used a simple model with transparent parameters. A household's score is just the sum of the coefficients for each predictor variable.
7. Goodhart's Law: No accounting for strategic behaviour
   - Well-known examples are 'teaching to the test' and the 'cobra effect'.
   - Unclear how this would manifest in CHN model

APO Potential Solutions and CHN Model Updates

- Categorical Prioritization
  - Already done for VOFV and VOHT in housing system
- Hybridizing categorical and predictive optimization
  - Using predictive techniques to prioritize population categories
  - Example: Rationing COVID-19 vaccines. Categorical prioritization was informed by predictive considerations (age and potential exposure). These prioritizations were accessible to the public so debate about moral dimensions of policy were informed.
- Data limitations and HSW feedback have led us to employ a hybrid categorical approach where eligible population is stratified according to subjective assessment, CHN model then ranks within strata
  - 1) 65% seniors, 2) 25% lone parent families, 3) 10% youth 15-24 single or lone parents
  - Data is 'coarse' and scaling to large population results in many ties and obvious pattern of sorting

Takeaways and Next Steps

- Simple method provides transparency about contribution of specific client attributes to priority
- Model has been complemented by qualitative judgements rather than replacing them
- Data issues abound!
- Bill 194 (EDST Act) will likely impact this and similar programs

- Next steps:
  - Thorough evaluation
  - Improve data quality and coverage in our internal systems

Region of Peel
working with you

Contact Details

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Peel Region

Thank You!

An ML model of Homelessness Prevention

- Homelessness Prevention Unit (HPU) in Los Angeles County
- Used linked-data from 11 County Agencies (health and social services, police, etc.)
- Eligible population: Used county medical services within prior six months and have a social services benefit record but not currently
- Used an ML model with 580 features on population of ~95,000 which achieved precision of 24% among the highest-risk population sub-group
  - They observed the thing they were trying to prevent, important difference!
- Only 1 in 5 selected individuals were enrolled, with about 50% were unreachable
- Construction of linked-dataset began in 2006!

Limits to Prediction Demonstrated

- Future of Families and Child Wellbeing Study
  - Study of cohort of US children and their families (4,242 families) born in large cities between 1998-2000 with follow-up at ages 1, 3, 5, 9, and 15
- Salganik et al. (2020) *Measuring the predictability of life outcomes with a scientific mass collaboration*
  - Recruited 160 research teams to predict 6 outcomes for half of the study population at wave 6, using the remainder of the data for wave six and all data from waves 1-5 (nearly 13,000 variables available).

Outcome_Variable	R^2_Holdout
Material Hardship (Scale)	0.23
GPA	0.19
Grit (Scale)	0.06
Eviction	0.05
Job Training (caregiver)	0.05
Layoff (caregiver)	0.03