Examining the impact of an Accommodation and Support Intervention in reducing homelessness amongst Care Leavers in Australia: A hybrid type-1 Implementation-Effectiveness Study using Propensity Score methods

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Background: Young people transitioning from out-of-home care (OOHC) face elevated risks of adverse outcomes across multiple domains. Existing interventions have shown small or null effects when rigorously evaluated, highlighting the need to identify effective approaches to supporting care leavers.
Objective: Evaluate the impact of the Premier's Youth Initiative (PYI), an accommodation and support intervention, on homelessness outcomes for care leavers and explore its implementation.
Participants and setting: 295 eligible care leavers who received PYI in New South Wales, Australia between 2017-2020 and a matched comparison group drawn from locations where PYI was unavailable.
Methods: We undertook a hybrid type-1 implementation-effectiveness study that used linked administrative data from child welfare and homelessness services. Propensity score methods were applied to estimate the average treatment effect on the treated on ten measures of homelessness between ages 18-19. Implementation was explored through focus groups with participants, service providers and the funder to explore intervention acceptability as well as barriers and facilitators.
Results: Overall PYI had no impact on any of assessed homelessness measures—with treatment effects consistently near zero. Subgroup analyses showed that Aboriginal participants experienced worse outcomes than non-Aboriginal peers. Participants who experienced homelessness during OOHC appeared to benefit more from PYI, relative to those who didn't, but estimates were inconsistent. Implementation analysis identified high acceptability among participants but revealed substantial barriers, particularly inadequate leaving care planning.
Conclusions: Interventions like PYI may need to commence earlier, be provided at greater intensity, or be targeted more effectively to the most vulnerable care leavers.

Keywords: foster care, emerging adulthood, child welfare, homeless, quasi experimental methods, program evaluation

Introduction

Background

Children and adolescents who experience abuse or neglect by their parents or carers can be removed from their families and placed in out-of-home care (OOHC) arrangements to protect their safety and wellbeing. If they are not restored to their families, young people will remain in OOHC until formal support ceases; the timing of which varies between and within countries but typically ends between the ages of 18 and 21 (Strahl, van Breda, Mann-Feder, & Schröer, 2021). These youth have often experienced significant trauma and disruption before, and during, their time in OOHC through multiple placements, changes in schools, and irregular family contact (Sanders, Jones, & Whelan, 2021). These compounding disruptions can exacerbate difficulties in forming stable relationships, maintaining educational continuity, and developing key life skills (Nuñez, Beal, & Jacquez, 2022). Once young people 'age out' of OOHC, they become care leavers. Many care leavers lack the material resources, social networks, and independent living skills needed to thrive (Courtney & Dworsky, 2006). Consequently, care leavers tend to have lower educational attainment and higher rates of unemployment, homelessness, criminal behaviour, financial stress, and physical and mental health challenges (Gypen, Vanderfaeillie, De Maeyer, Belenger, & Van Holen, 2017;

Petäjä, Terkamo-Moisio, Karki, & Häggman-Laitila, 2022) relative to peers without care experience. Moreover, the assistance they receive before or after leaving OOHC frequently proves insufficient to prevent these adverse outcomes (Taylor et al., 2024).

In Australia, findings from the Australian Institute of Health and Welfare (AIHW) highlight challenges faced by care-experienced young people (CEYP). Using linked data from state and national sources, the AIHW (2021, 2022, 2023) reported that CEYP between 18 and 30 years of age were 9-10 times more likely to access Specialist Homelessness Services (SHS) compared to peers in the general population. This peaked at age 18, with 21% of CEYP requiring SHS. CEYP were also three times more likely to receive income support payments between the ages of 16 and 30. Nearly half (46%) of CEYP received both income support and SHS, compared to 5.7% of non-care peers—an 8.1-fold difference. The use of both services was 1.6 times higher among CEYP with experience of residential care (66%) compared to foster care (41%). Aboriginal CEYP (59%) were 1.4 times more likely than their non-Aboriginal counterparts (41%) to access both forms of support (AIHW, 2023).

Cashmore and Paxman (2007) found New South Wales (NSW) care leavers experienced high rates of homelessness (39%), housing instability poor educational and employment outcomes—with only 42% completing secondary school and 25% in full-time work or study—and widespread mental health problems affecting nearly half of respondents.

Policy and practice context

Since this study was conducted, NSW has expanded support for care leavers. Until age 21 they can now receive either a) a financial allowance to remain with their carer, or b) a payment to help cover accommodation and living expenses for those living independently (DCJ, 2025). These supports are typically characterised as extended care in the literature (Mendes et al., 2025), however the NSW Department of Communities and Justice (DCJ) does not use or endorse this term to describe this support. We adopt it in this paper for consistency with the literature. In addition to these supports, the Specialist Aftercare Program provides intensive casework, mentoring, and tailored support for care leavers with moderate to high needs (DCJ, 2025).

Existing evidence

A recent systematic review by Taylor et al. (2024) found limited evidence for transition support programs (TSPs), with most showing small or null effects when synthesised in a meta-analysis. The review examined the impact of two broad categories of support provided to care leavers: TSPs and extended care. The review identified only 14 studies that used experimental or observation methods of sufficient methodological quality to make causal claims about effectiveness, with all but one conducted in the United States. Independent Living Programs (ILPs), the most common type of TSP, showed no meaningful impact across housing, education, employment and life skills outcomes. Although some individual studies showed promising results, these effects were modest.

The review found extended care policies appear more promising, though evidence was limited to two observational studies from the United States. In Washington, extended care led to substantial reductions in homelessness and improved educational outcomes (Miller, Bales, & Hirsh, 2020). Similarly, in Illinois, extended care led to small improvements in educational attainment and reduced criminal justice involvement, although these effects diminished over time (Courtney & Hook, 2017). Overall, the review identified that while some interventions showed promise, particularly extended care, the scope and strength of included evidence is insufficient to strongly recommend any included approach.

Subsequent to the completion of the aforementioned systematic review, two recent studies have examined the impact of extended care in the United Kingdom (Picker, Hirneis, & Sanders, 2024) and the United States (Spindle-Jackson,

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Data availability statement: The administrative data used in this study cannot be shared publicly as they remain the property of DCJ. Access to these data requires formal permission from the data custodians. The analytic code used to produce the findings reported in this paper is available in our public GitHub repository https://github.com/davetayl-r/pyi-impact-study **Conflicts of interest:** All authors declare they have no conflicts of interest. DCJ reviewed and provided comment on a draft version of this manuscript. The views expressed in this report are the views of the authors and do not necessarily reflect those of DCJ. **Grant numbers and/or funding information:** This evaluation was funded by the NSW Department of Communities and Justice (DCJ). **Acknowledgments and credits:** We acknowledge Robyn Mildon, Bianca Albers, Arno Parolini, Min-Taec Kim, Jonathan Ng and Susy Harrigan for their valuable contributions to this evaluation. We are especially thankful to the young people who generously shared their experiences with us. We thank DCJ, particularly FACS Insights, Analysis and Research (FACSIAR) for their support in undertaking and publishing this work and for reviewing a draft manuscript. Author roles were classified using the Contributor Role Taxonomy (CRediT; https://credit.niso.org/) as follows: David Taylor: formal analysis, writing, visualisation, conceptualisation, methodology, project administration; Jessica Roberts: data curation, conceptualisation, methodology, editing; Vanessa Rose: conceptualisation, methodology, funding acquisition, project administration, editing; Alex Gyani: conceptualisation, editing, methodology; Aron Shlonsky: conceptualisation, editing, methodology, supervision, editing

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Byrne, & Collins, 2024): both found persistent reductions in homelessness among care leavers. Another recent study of a TSP from the UK, Lifelong Links, also showed a reduction in homelessness amongst care leavers (Sanders & Picker, 2023). These findings add to the growing, though still limited, evidence suggesting that both extended care policies and targeted TSPs can potentially help reduce homelessness among care leavers.

Rationale

We used a hybrid Type-1 implementation-effectiveness study design to assess the effectiveness of the intervention, while also collecting information about its implementation (Curran, Bauer, Mittman, Pyne, & Stetler, 2012). Our rationale for this is twofold. Firstly, the use of causal methods to assess the intervention's impact is crucial given that the intervention is novel and that evidence on the effectiveness of interventions for care leavers remains limited (Taylor et al., 2024). Secondly, the intervention had multiple active components and was delivered to a vulnerable population within a complex service system where a wide range of implementation barriers could have potentially affected outcomes (Fixsen, Naoom, Blase, Friedman, & Wallace, 2005). By collecting information about the intervention's implementation, we can understand not just whether the intervention works, but also what factors may have influenced its success.

Objectives

This study aims to estimate the impact of the Premier's Youth Initiative (PYI) on homelessness outcomes among youth leaving OOHC at age 18, while examining aspects of its implementation. The primary objective is to estimate the average treatment effect on the treated (ATT) by comparing utilisation of SHS in the 12 months post-OOHC between PYI participants and a statistically-matched comparison group that received usual services. A secondary objective is to assess intervention acceptability among PYI recipients and identify of barriers and facilitators to implementation from the perspectives of service providers and the funder.

Methodology

Study design and setting

This study used propensity score methods to examine intervention effectiveness. Additional aspects of the intervention's implementation were explored through focus groups and interviews with service providers, the funder and participants.

An evaluation of PYI was completed by the authors in 2020 and was published previously as a technical report (Taylor et al., 2020). That report relied on data with variable, and limited, follow-up periods after participants left OOHC—necessitating the use of time-to-event modelling. This study utilises an updated administrative data extract that allows assessment of homelessness outcomes for all participants 12 months after leaving OOHC at age 18.

We followed the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines (Elm et al., 2007) and the RECORD (REporting of studies Conducted using Observational Routinely-collected Data) extension (Benchimol et al., 2015). A completed STROBE-RECORD checklist is provided in the supplementary material (Table S1) (Taylor, Roberts, Rose, Gyani, & Shlonsky, 2025). Additionally, we adhered to Thoemmes and Kim's Thoemmes and Kim (2011) reporting guidance for studies using propensity score methods (Table S2).

Intervention description and implementation

PYI was developed and funded by DCJ. PYI was delivered by seven consortia of non-government agencies (NGOs) that provided either support services, housing services, or both. During the evaluation period (2017-2020) PYI was available in ten administrative districts used by DCJ: Central Coast, Hunter, Illawarra Shoalhaven, Mid-North Coast, Nepean Blue Mountains, New England, Northern NSW, Southern NSW, South-Western Sydney, and Western NSW.

The PYI intervention featured four core components: (1) leaving care planning; (2) prosocial network development; (3) education and employment mentoring; and (4) transitional support. These components are delivered through the provision of personal advice, education and employment mentoring, housing, transitional support and brokerage for additional supports.

Three key worker roles—Personal Advisor (PA), Education and Employment Mentor (EEM), and Transition Support Worker (TSW)—collaborate to provide support services tailored to the needs of care leavers. While all participants received access to a PA and EEM, access to TSW and/or housing was rationed based on need—additional information regarding this is available in the technical report (Taylor et al., 2020).

Service providers had significant latitude in the way they implemented PYI. All intervention components could be provided by a single agency, or in consortia with others providing specialist services (e.g., housing providers). Sites had the freedom to assign roles and responsibilities across the PA, EEW and TSW roles in any manner they saw fit. Client facing staff were expected to have completed training in motivational interviewing, trauma and addictions and trauma-informed practice (Taylor et al., 2020).

As of 2025, the intervention is provided in the same catchments under the name Youth Initiative (Homes NSW, 2025).

Participants and recruitment

Intervention inclusion and exclusion criteria

To be eligible, young people must be aged between 16 years, 9 months and 17 years, 6 months and meet at least one of the following four inclusion criteria: a) they must either be in residential OOHC, b) have a history of placement instability, c) be in a permanent OOHC placement, or e) have been in care for 12 months or longer (see Table S3). Young people who are incapable of living independently due to support needs were excluded.

Intervention recruitment

Young people who met one or more of these criteria were identified through DCJ's administrative data systems, with PYI providers then approaching them directly to invite them to participate in the intervention. No other referral pathways existed.

Evaluation recruitment

Care leavers who commenced PYI between 1 July 2017 and 30 March 2020 were included in the quantitative analysis. A convenience sample of PYI participants, PYI service providers and DCJ stakeholders were invited to participate in interviews or focus groups to understand the intervention's implementation. Detailed information about recruitment and consent procedures is available in the supplementary material (sections S3.2-S3.4).

Ethical approval

All research activities were approved by the Monash University Human Research Ethics Committee (MUHREC: #18216). All participants who participated in primary data collection provided their informed consent. This work was conducted under a Research Agreement with DCJ, who retain ownership of unit-record data used in this analysis. Unit-record data was stored and analysed within Monash University's Secure Research Platform. Quantitative analysis was undertaken using R version 4.3.3 (R Core Team, 2024).

Data and measures

This study used linked unit-record administrative data from two DCJ-held data assets: ChildStory — which captures child and family interactions with the child protection (1 January 1998 to 30 June 2021) and OOHC systems (1 January 1998 to 30 June 2021), and the Client Information Management System (CIMS) — which records interactions with SHS (1 July 2015 to 30 June 2021). Individual records across data assets were linked using a statistical linkage key generated by DCJ. No records were excluded due to concerns about data quality. All PYI participants were identified in ChildStory.

The primary goal of PYI was to reduce homelessness amongst care leavers after exiting OOHC at age 18. Accordingly, the key outcome interest was homelessness—as measured by the use of SHS for housing-related reasons. SHS use was tracked between ages 18 and 19, with outcomes including SHS use on 18th and 19th birthdays, new (i.e., commencing after age 18) and ongoing (i.e., commenced before age 18) homelessness spells, unsheltered homelessness episodes, and need for short-term accommodation (all binary measures). Given the low frequency of such events, we also measured duration of SHS spell (continuous measure) and the number of distinct SHS spells (count measure).

Data on the use of SHS for housing-related reasons was sourced from CIMS. Given the nature of service provision—where individuals may be referred between SHS providers within a continuous support episode—we aggregated service interactions across providers into 'spells' to reflect uninterrupted periods of homelessness assistance. A 'housing-related' spell was defined as meeting any of the following criteria: (1) current or previous week residential dwelling was a tent, improvised dwelling, no dwelling (in the open), or motor vehicle, OR (2) sleeping rough or in non-conventional accommodation in the last week, OR (3) in short-term or emergency accommodation in the last week, OR (4) requiring short-term accommodation. Demographic characteristics and details of an individual's OOHC history were sourced from ChildStory.

Identification and Estimation Strategy

Our identification strategy capitalises on two key features of the intervention's implementation. Firstly, PYI was a pilot offered exclusively in distinct geographical catchments within NSW. This spatial restriction provides a natural comparison pool — care leavers in similar policy and administrative contexts but without access to the intervention. Secondly, the study was initially envisioned to be a randomised controlled trial (RCT) with eligibility determined by four explicit criteria recorded in administrative data. Although the RCT design did not proceed, the four intervention eligibility criteria (denoted as X_i) were retained to form a well-defined assignment mechanism. An individual was assigned to treatment if, and only if, they met one of the four eligibility criteria and resided in a location where PYI was offered. The transparent, administratively determined selection process provides a rare opportunity to credibly invoke a selection-on-observables assumption.

We use the potential outcomes framework (Rubin, 1974) to specify our causal question. Let $Y_i(1)$ and $Y_i(0)$ denote individual (i)'s potential outcomes under intervention ($D_i = 1$) and comparison ($D_i = 0$) conditions, respectively. The observed outcome is therefore:

$$Y_i = D_i Y_i(1) + (1 - D_i) Y_i(0)$$

Our estimand of interest is the average treatment effect on the treated (ATT):

$$ATT = E\left[Y_i(1) - Y_i(0) \mid D_i = 1\right]$$

Identification of the ATT requires satisfying the selection-on-observables assumption:

$$Y_i(1), Y_i(0) \perp D_i \mid X_i$$

which states that, conditional on X_i, potential outcomes are independent of treatment assignment. Given the explicitly defined selection criteria and the use of detailed administrative data, we argue that this assumption is plausible.

To test this assumption, we developed a directed acyclic graph (DAG) that models the data generating process for this study (Figure 1). The DAG was refined during a three-round Delphi process with a panel of experts (n=20) with content and technical expertise (Taylor, Roberts, & Shlonsky, 2025). The minimal adjustment set derived from this DAG using the backdoor criterion aligned exactly with the intervention's eligibility criteria X_i. This means that conditioning on the intervention criteria is theoretically sufficient to block all confounding relationships between the treatment and outcome of interest.

Propensity Score Matching Specification

We implemented propensity score matching using a series of iterative specifications to achieve covariate balance. Propensity scores were estimated using a generalised additive model (GAM) with a probit link function using the `MatchIt` package (Ho, Imai, King, & Stuart, 2011). The model included both our minimal adjustment set X_i derived from our DAG and four additional pre-treatment covariates Z_i that improved balance without introducing confounding or collider bias (see Figure S1).

We applied two matching approaches: 1) 1:1 Nearest Neighbour, where each treated unit was matched to a single comparison unit with the closest propensity score, and 2) full matching, which optimally partitions the full sample into matched sets containing one treated unit and a variable number of weighted comparison units. In both specifications, matching was done without replacement and comparison units outside the region of common support were trimmed. No treated units were excluded.

Treatment Effect Estimation

Treatment effects were estimated for binary, count, and continuous outcome measures using logistic, Poisson, and linear regression models respectively. Each model included the minimal adjustment set of covariates derived from our DAG X_i, as it has been shown to reduce dependence on the specification of the matching model, while potentially increasing precision and reducing bias from any residual imbalance (Ho, Imai, King, & Stuart, 2007). We do not include the additional covariates Z_i in our model since X_i is sufficient for identification.

Our general regression model specification took the form:

$$g(E[Y_i]) = \beta_0 + \beta_1 D_i + X_i' \beta$$

where Y_i is the outcome for individual i, D_i is the treatment indicator, X_i is the vector of covariates representing our minimal adjustment set, and $g(.)$ is the appropriate link function (identity for continuous outcomes, log for count outcomes, and logit for binary outcomes).

The ATT was estimated using g-computation (Snowden, Rose, & Mortimer, 2011) using the `marginaleffects` package (Arel-Bundock, Greifer, & Heiss, 2024). Standard errors (SE) and confidence intervals (CI) were estimated using cluster-robust methods that account for dependence between matched sets (Abadie & Spiess, 2022). For non-linear models, where the delta method provides only approximate standard errors, we used a cluster bootstrap with 4,999 replications (Austin & Small, 2014).

Treatment Effect Heterogeneity

To test for treatment effect heterogeneity, we plotted individual treatment effect estimates against their propensity scores, following Rosenbaum and Rubin (1983). We examined these plots to see if the fitted lines for the treatment and comparison groups visibly differed across the range of the propensity score and thus reveal potential effect moderators.

Subgroup Analysis

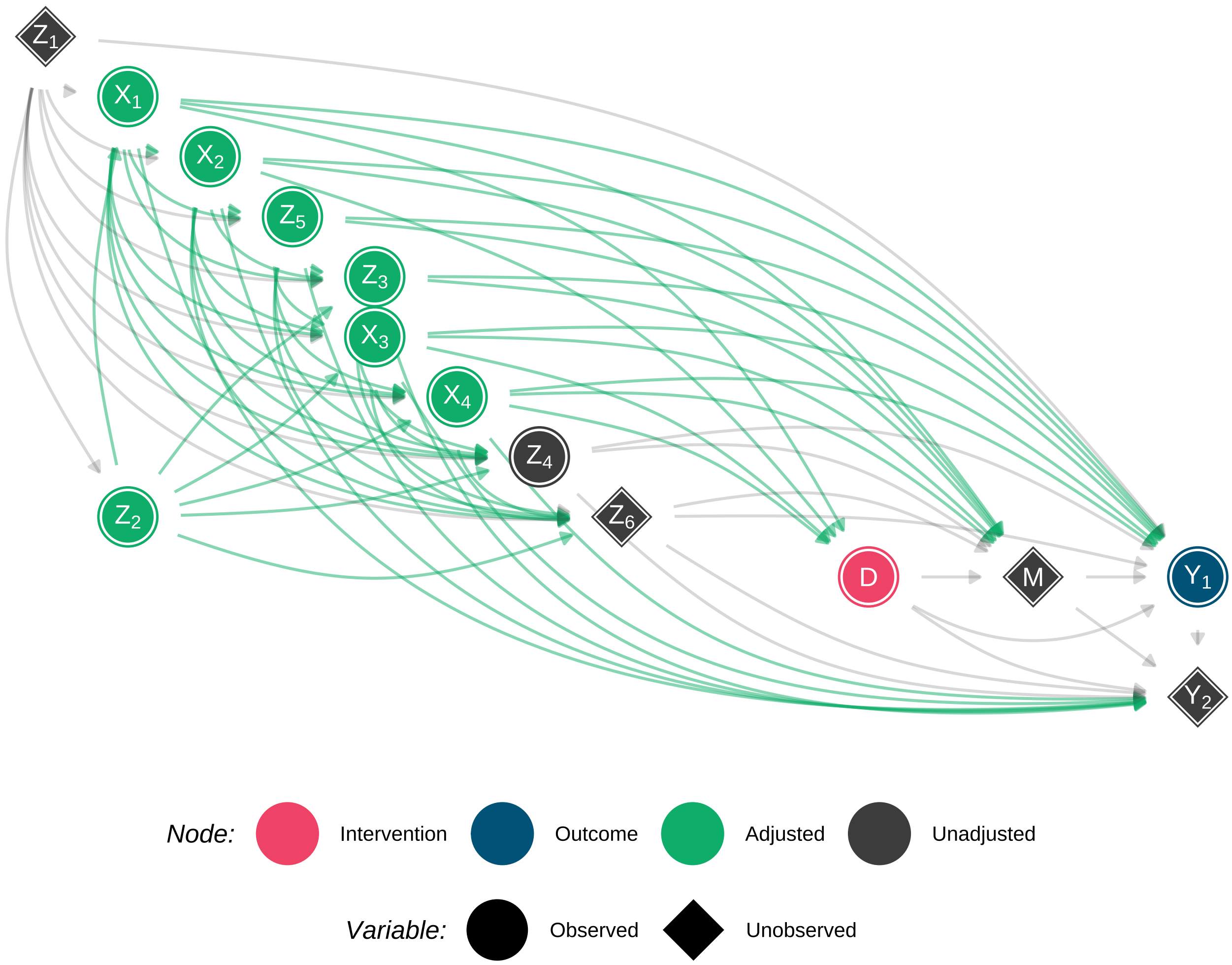
Conditional average treatment effects (CATTs) were estimated for two pre-specified subgroups: Sex and Aboriginal and Torres Strait Islander status. Subgroup analyses were also undertaken for variables where the heterogeneity diagnostics suggested the potential for meaningful effect modification. All CATTs were estimated with the full sample using subgroup-treatment interaction terms. Given the small samples and rare outcomes, we used parsimonious specifications without additional covariates. For binary outcomes, we applied maximum penalised likelihood with powers of the Jeffreys prior as penalty to reduce bias using the `brglm2` package (Kosmidis & Firth, 2021).

Sensitivity Analysis

We assessed sensitivity to unmeasured confounding using tipping point analysis (McGowan, 2022) to determine the strength of confounding required to nullify our findings.

Figure 1

Directed Acyclic Graph of the data generating process for this study



Key:
Y_1: Use of SHS after age 18, Y_2: Other (unobserved) outcomes, D: Intervention (PYI), M: Mediators, X_1: 12 months or more in OOHC,
X_2: History of placement instability, X_3: In residential care placement during eligibility period, X_4: In permanent care placement during eligibility period,
Z_1: Factors that occured before or during OOHC, Z_2: Parental responsibility of the Minister during eligibility period,
Z_3: In kinship care placement during eligibility period, Z_4: Self-placed from placement after age 16, Z_5: Use of SHS between age 16 and 18,
Z_6: Factors that occured before 18

Implementation Analysis

Data Collection

We examined implementation through focus groups and interviews with key stakeholders (October 2019-August 2020): PYI participants (8 focus groups, n=36), PYI service and housing providers (8 focus groups and 6 interviews, n=42 participants), and funder representatives (5 focus groups, n=15). Data collection protocols were informed by the Consolidated Framework for Implementation Research (CFIR) (Damschroder et al., 2009). Participant characteristics and data collection protocols are provided in the supplementary material (sections S3.2-S3.4).

Qualitative analysis framework

A modified version of the CFIR framework was used to examine implementation barriers and facilitators at four critical junctures in the client journey: intervention entry, pre-leaving care, transition period, and independent living. Analysis followed a four-step process: data familiarisation, application of both CFIR-derived and emergent codes, categorisation of themes into barriers and facilitators, and synthesis across stakeholder perspectives. We used data convergence to triangulate findings across stakeholder groups to determine

(Figure S1) and common support (Figure S2) for both specifications are available in the supplementary material.

Effectiveness results

Overall results

Table 3 reports the ATT for each of the ten outcomes, under both full and nearest-neighbour matching specifications. As recommended by Westreich and Greenland (2013), we did not interpret (or report) the individual regression coefficients, which lack meaningful causal interpretation given our goal is to estimate the treatment effect.

All outcomes represent negative events (e.g., entry into a SHS spell), therefore a negative ATT estimate favours PYI. However, the observed estimates typically centre near zero, with confidence intervals comfortably spanning no effect, suggesting that on average, PYI does not meaningfully shift the likelihood or magnitude of these outcomes relative to the comparison group. Given that these events occur in only approximately five percent of the sample, their rarity, along with the relatively small sample size, may hinder detection of small or subtle effects. Notably, the results are highly consistent across both matching specifications, reinforcing the conclusion that there is no large or systematic difference attributable to PYI.

To facilitate interpretation and synthesis, we have reported results in multiple formats—for both full (Table S8) and nearest neighbour (Table S9) specifications in the supplementary material. For binary outcomes, we report risk differences (RD), relative risks (RR), and odds ratios (OR). For count outcomes, we present both the raw mean difference and its standardised form (Cohen's *d*). For continuous outcomes, we report mean differences in the natural units as well as Cohen's *d*. We have opted to provide this range of effect measures as a) it allows readers to interpret results in their preferred metric, and b) it may support including this study in future meta-analyses work. In Figure 2, we present a complete summary of our results, including both matching specifications and all or our subgroup analyses, with results visualised using Cohen's *d* to place them on a common scale.

Treatment Effect Heterogenity. We tested for treatment-effect heterogeneity in the ATT model and in six additional conditional ATT analyses stratified by binary variables included in the matching model (see Figures S3–S12). Across all ten outcomes, heterogeneity emerged specifically for individuals who had been homeless between ages 16 and 18 (hereafter 'housing vulnerability'). This pattern was observed in both matching specifications, although it was more pronounced under full matching. These findings suggest that housing vulnerability is a potential moderator, warranting further examination through subgroup analysis.

Subgroup Analyses

Subgroup analysis was undertaken to estimate the conditional ATT (CATT) on being male, Aboriginal or Torres Strait Islander or experiencing housing vulnerability.

No difference was detected for the existence of moderation by sex (see Tables S10 and S11) for results for both specifications.

We found that Aboriginal status moderates the treatment effect in four of the ten examined outcomes in our full matching specification. For the outcome in SHS on 18th birthday, Aboriginal participants experienced an increased risk (CATT: 0.068, 95% CI: [0.024, 0.126]), while non-Aboriginal participants experienced a decrease (CATT: -0.057, 95% CI: [-0.126, -0.012]). The difference in risk differences (-0.125, 95% CI: [-0.201, -0.049], p = 0.001) provides some evidence of a negative moderation effect. Similar patterns were observed for new or ongoing SHS spell between 18th and 19th birthday (-0.164, 95% CI: [-0.308, -0.020], p = 0.026), new or ongoing SHS spell requiring short-term accommodation (-0.164, 95% CI: [-0.308, -0.020], p = 0.026), and days in SHS spell between 18th and 19th birthday (-29.651, [-49.273, -10.029], p = 0.003). In each of these cases, Aboriginal participants experienced less favourable treatment effects compared to their non-Aboriginal counterparts.

To put these results into context, for results reported as a risk difference (RD), we can calculate the Number Needed to Treat (NNT) or Number Needed to Harm (NNH) by taking the inverse of the point estimate of the CATT (1/RD) (Laupacis, Sackett, & Roberts, 1988). For Aboriginal participants, an NNH of ~15 (1/0.068 = 14.71) indicates that for every 15 youth who received PYI, one additional youth will be in SHS on their 18th birthday. Conversely, for non-Aboriginal participants, an NNT of ~18 (1/-0.057 = -17.54) means that 18 youth must receive the intervention to prevent one additional youth from being in an SHS on their 18th birthday. Results from the Nearest Neighbour specification corroborated these results and identified similar moderation effects in two additional outcomes (see Tables S12 and S13).

Moderation findings for housing vulnerability varied by matching specification. Results from the nearest neighbour estimates suggest that prior homelessness moderates the treatment effect in seven out of ten outcomes (Table S14). Young people without prior homelessness experienced a higher risk (CATT: 0.045, 95% CI: [0.012, 0.088]; NNH: ~22) of being in an SHS spell on their 19th birthday. Whereas, those with prior homelessness were all at a lower risk of experiencing a new or ongoing SHS spell between 18th and 19th birthday (CATT: -0.173, 95% CI: [-0.313, -0.018]; NNT: ~6), days in SHS spell between 18th and 19th birthday (CATT: -34.535, 95% CI: [-62.702, -6.368]), number of distinct SHS spells between 18th and 19th birthday (CATT: -0.399, 95% CI: [-0.754, -0.044]), a new or ongoing SHS spell that requires short term accommodation (CATT: -0.173, 95%

Figure 2

Treatment effect results for overall (ATT) and subgroup analysis (CATT) presented as SMD for both matching specifications

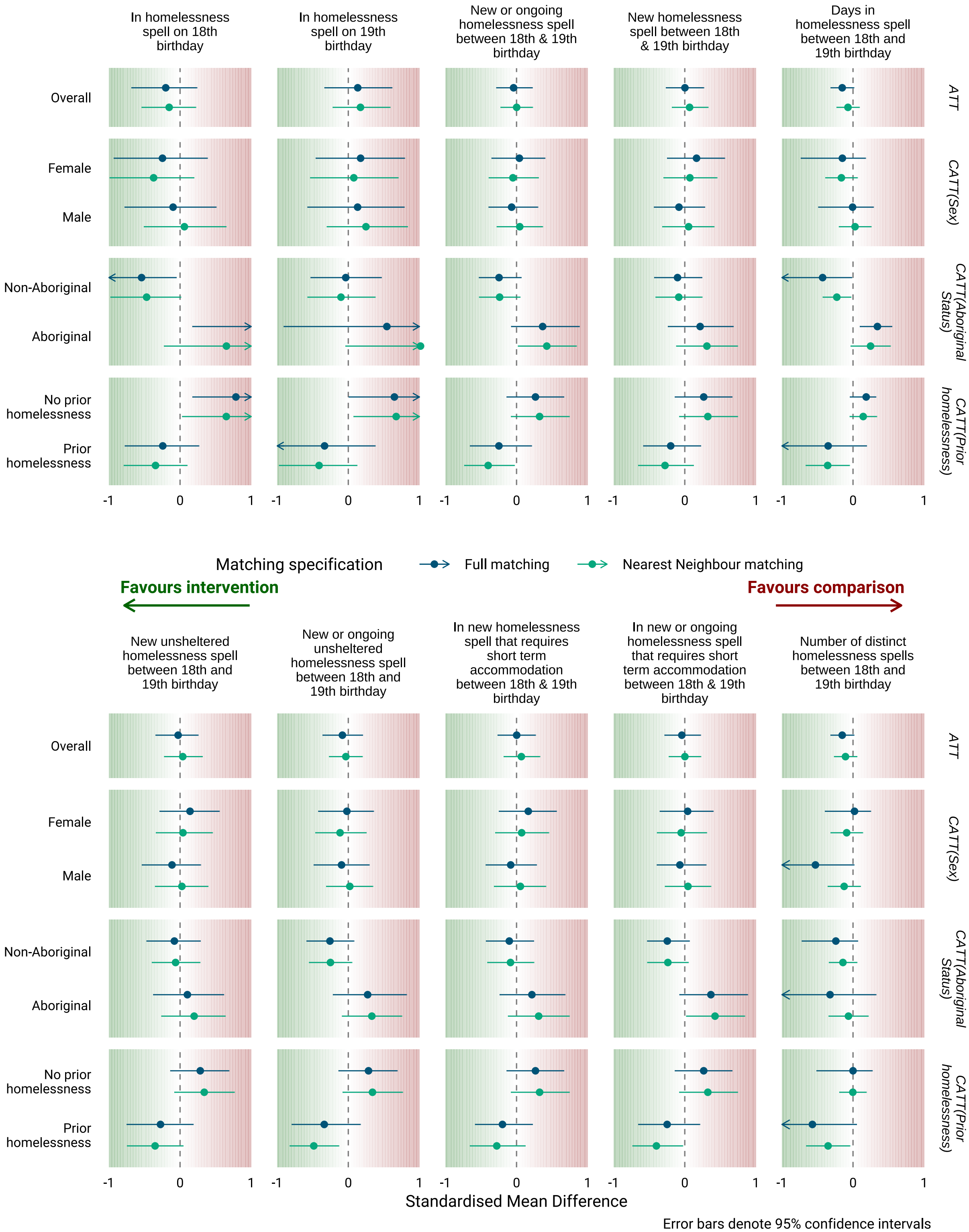


Table 1

Baseline characteristics of intervention group

Characteristic	Value
Sample size (n)	295
Demographics:	
Male	145 (49.15)*
Female	150 (50.85)*
Aboriginal or Torres Strait Islander	97 (32.88)*
Non-Aboriginal or Torres Strait Islander	198 (67.12)*
Eligibility criteria for intervention:	
Residential care placement	61 (20.68)*
Foster care placement	127 (43.05)*
Kinship care placement	92 (31.19)*
Permanent placement	218 (73.9)*
Other variables of interest:	
Parental responsibility of the Minister	287 (97.29)*
Twelve months or more in out-of-home care	292 (98.98)*
History of out-of-home care placement instability	292 (98.98)*
Months spent in care at point at which eligible for intervention	107.36 (54.6)^
Placement breakdown	65 (22.03)*
Placement ended due to disruptive behaviour	107 (36.27)*
Self-placed, missing or absent from placement	54 (18.31)*
Independent living placement	59 (20)*
Spell in homelessness services	91 (30.85)*

Note:
* N (%), ^ Mean (SD)

Table 2

Results from two selected matching specifications

	Intervention		Comparison				
Specification	PYI sample	PYI matched	Sample	Matched	ESS	Unmatched	Discarded
Nearest Neighbour	295	295	422	295	-	127	0
Full matching	295	295	422	406	196.8	0	16

CI: [-0.313, -0.018]; NNT: ~6), or new or ongoing unsheltered homelessness spell (CATT: -0.203, 95% CI: [-0.340, -0.059]; NNT: ~5).

The full matching estimates pointed in the same direction (see Figure 2), however they were subject to wider confidence intervals that encompassed the null (Table S15). In other words, the nearest neighbour results suggest potential heterogeneity in treatment effects by housing vulnerability and the full matching results are consistent with this possibility, however they are not detected at conventional levels of statistical significance.

Sensitivity Analyses

Since we did not detect any precise ATT estimates, we have included results of our tipping point analysis in section S4.3 of the supplementary material.

Table 3

ATT results for both matching specifications

Outcome	Estimated Potential Outcomes		Treatment Effect		
	Intervention group	Comparison group	ATT	SE	95% CI
Full matching:					
In SHS spell on 18th birthday	0.047	0.067	-0.02	(0.022)	[-0.068, 0.019]
In SHS spell on 19th birthday	0.064	0.051	0.013	(0.022)	[-0.032, 0.055]
New SHS spell between 18th & 19th birthday	0.142	0.142	0	(0.03)	[-0.06, 0.055]
New or ongoing SHS spell between 18th & 19th birthday	0.169	0.18	-0.011	(0.034)	[-0.076, 0.056]
New unsheltered homelessness episode between 18th & 19th birthday	0.129	0.134	-0.006	(0.031)	[-0.074, 0.049]
New or ongoing unsheltered homelessness episode between 18th & 19th birthday	0.153	0.173	-0.02	(0.035)	[-0.09, 0.046]
In new SHS spell that requires short term accommodation between 18th & 19th birthday	0.142	0.142	0	(0.03)	[-0.06, 0.055]
In new or ongoing SHS spell that requires short term accommodation between 18th & 19th birthday	0.169	0.18	-0.011	(0.034)	[-0.076, 0.056]
Number of distinct SHS spells between 18th & 19th birthday	0.227	0.351	-0.124	(0.079)	[-0.279, 0.031]
Days in SHS spell between 18th & 19th birthday	15.427	18.725	-3.298	(4.931)	[-12.963, 6.368]
Nearest Neighbour matching:					
In SHS spell on 18th birthday	0.047	0.062	-0.014	(0.017)	[-0.049, 0.019]
In SHS spell on 19th birthday	0.064	0.048	0.016	(0.018)	[-0.02, 0.053]
New SHS spell between 18th & 19th birthday	0.142	0.128	0.014	(0.027)	[-0.038, 0.068]
New or ongoing SHS spell between 18th & 19th birthday	0.169	0.169	0	(0.029)	[-0.057, 0.057]
New unsheltered homelessness episode between 18th & 19th birthday	0.129	0.121	0.008	(0.026)	[-0.043, 0.061]
New or ongoing unsheltered homelessness episode between 18th & 19th birthday	0.153	0.161	-0.008	(0.028)	[-0.063, 0.047]
In new SHS spell that requires short term accommodation between 18th & 19th birthday	0.142	0.128	0.014	(0.027)	[-0.038, 0.068]
In new or ongoing SHS spell that requires short term accommodation between 18th & 19th birthday	0.169	0.169	0	(0.029)	[-0.057, 0.057]
Number of distinct SHS spells between 18th & 19th birthday	0.227	0.307	-0.08	(0.059)	[-0.196, 0.036]
Days in SHS spell between 18th & 19th birthday	15.427	19.667	-4.24	(4.458)	[-12.979, 4.498]

Note. For binary outcomes, potential outcomes represent the estimated predicted probability of experiencing the outcome in each group (ranging from 0 to 1). The ATT represents the difference in these probabilities between groups (risk difference). For continuous and count outcomes, potential outcomes represent the estimated mean value in each group. The ATT represents the mean difference between groups.

Implementation results

Intervention acceptability

Intervention acceptability—defined as the perception among stakeholders that an intervention is agreeable, palatable, or satisfactory (Proctor et al., 2011)—was examined through focus groups with participants. Thematic analysis revealed that participants' perceptions of acceptability were largely shaped by four interconnected domains: relationships with workers, effectiveness of support, appropriateness of services, and peer relationships. Firstly, participants often highlighted the importance of strong, trusting connections with frontline staff. Many felt that workers' empathy, consistency, and willingness to listen were central to the intervention's overall value, particularly during critical junctures like entry into the intervention and preparation for leaving care. As one participant shared *"They listen more than they talk… and they ask us what we want… we have a choice about what we want to do…"*. Secondly, views on the intervention's effectiveness centered on whether the support provided aligned with participants' self-identified needs. They often contrasted the way in which PYI providers supported them with negative experiences from OOHC. As one participant noted: *"My [OOHC] case worker changed so many times, these guys [PYI] really make things happen"*. While some described the assistance as timely and well-tailored—particularly around housing navigation and life skills—others expressed a desire for broader or more intensive resources in areas such as mental health and longer-term stability. Thirdly, participants commented on the appropriateness of services, noting that a flexible, person-centered approach helped them feel respected and acknowledged. At the same time, some participants wanted clearer communication about eligibility, referrals, and ongoing support options, underscoring the need for transparent and consistent processes. Lastly, participants' interactions with one another were seen as an influential factor. Positive peer relationships often reinforced feelings of shared experience and mutual support. As one participant observed *"We have a group chat where we can chat and swap tips… it's really helpful"*.

Barriers and Facilitators

Implementation barriers and facilitators were thematically explored around four time points, reflecting a clients experience of the intervention: a) engaging with PYI; b) in PYI and before they left OOHC; c) as they transitioned from OOHC; and d) living independently in the community.

Several barriers were identified during engagement with PYI. Firstly, as a pilot, PYI and its providers were unfamiliar to many OOHC caseworkers, leading to inconsistent engagement and delays in connecting eligible youth to services. As one PYI provider shared *"If they [case worker] didn't think their client needed PYI, or would benefit from it, they wouldn't prioritise engaging with us… it was really frustrating"*. Secondly, while young people with significant disabilities that prevented them from living independently were ineligible for PYI, this information was not captured in administrative data, requiring time-consuming manual screening by PYI providers. Finally, the closed referral pathway and the initial evaluation design (RCT) initially created some suspicion at multiple levels of the OOHC system in sites where PYI was provided. However, the structured eligibility criteria and use of administrative data to identify eligible young people was also identified as facilitating the identification of at-risk youth—particularly those who self-placed— who might have been overlooked through standard referral channels. As one PYI provider noted: *"Without it some of these kids would have fallen through the cracks… they didn't have a caseworker, they needed us to go hunting for them."*

While young people were still in OOHC, the major barrier faced by PYI providers was that many clients lacked basic aftercare preparation like leaving care plans, identification documents, and access to financial services — despite statutory requirements for this to occur. As one representative from DCJ noted *"DCJ has made it really difficult to get 'sign off' to leaving care plans… PYI has helped us show this"*. This required PYI staff to divert time and resources toward securing these basic entitlements rather than focusing on goal-setting and attainment. Providers felt that engaging with care leavers at an earlier age provided them with more time to build relationships and advocate for aftercare support.

As they transitioned from OOHC, several structural barriers impacted service delivery. Limited employment opportunities and appropriate housing stock in regional areas made it difficult to support care leavers to find either employment or housing. PYI's emphasis on private rental market placements created implementation challenges, as providers felt that this option wasn't suitable for all participants. As one PYI housing provider explained, *"It's tough because kids don't normally move out of home at 18 and here we have these kids, that are coming straight out of care and into a private rental without knowing what's normal functioning in a house."* While accommodation was available through PYI, providers reported underutilisation of allocated housing slots despite perceived scarcity, suggesting a misalignment between intervention design and local implementation contexts. Implementation facilitators emerged through providers' adaptive responses. Success in housing placement was achieved through developing relationships with real estate agents and property owners. Providers enhanced service integration by connecting participants with complementary supports through vocational educational institutions that structured the delivery of practical skill-building activities, particularly around budgeting and tenancy management.

After young people left care the reliance on private rental markets continued to be a barrier, where limited affordable housing stock constrained providers' placement options. While shared housing was utilised to address this barrier, implementation success varied based on whether participants had choice in these arrangements. Service delivery was further complicated by property management issues, particularly around visitor-related damages, which strained provider relationships with real estate agents. The absence of clear operational definitions for "success" created implementation uncertainty, affecting both service boundaries and exit planning. Implementation facilitators centred on sustained worker engagement and ongoing flexible support. Providers identified that young people required approximately 12 months post-care to develop adequate support networks. Finally, providers observed that they required 12-18 months to codify and deliver services they perceived to be effective, highlighting the substantial time investment needed to achieve stable intervention delivery.

Discussion

Key results

On average, the PYI intervention did not meaningfully alter the likelihood or magnitude of homelessness-related outcomes for care leavers between their 18th and 19th birthdays. Across ten measures of the homelessness, point estimates were near zero, and confidence intervals comfortably encompassed no effect. The rarity of these events likely limited power to detect smaller effects, yet the consistency of findings under both full and nearest-neighbour matching reinforces the absence of any large or systematic impact. While this suggests that PYI may not dramatically shift short-term housing trajectories, it does not categorically exclude more nuanced or longer-run effects.

The effectiveness of PYI differs meaningfully across participant subgroups with evidence of treatment-effect heterogeneity emerged in two substantively important domains. First, we observed that PYI's impact may differ for those with a history of homelessness between ages 16 and 18 (i.e., housing vulnerability). Under nearest-neighbour matching, these individuals appeared to benefit more from PYI compared with their peers without such histories, although the confidence intervals for the full matching specification crossed the null, signaling that we cannot we confident about this result. Second, Aboriginal participants exhibited less favourable responses to PYI relative to non-Aboriginal participants. This pattern was evident under both matching approaches and persisted across multiple measures. Our confidence in this finding is limited by the uncertainty in the estimates, but even with this uncertainty, we believe this pattern warrants highlighting.

Implementation of PYI was characterised by significant system-level barriers despite strong acceptability among stakeholders and identifiable facilitators of success. Thematic analysis reveals that acceptability of the intervention was driven chiefly by strong worker-participant relationships, perceived effectiveness of support, appropriate service alignment with participants' needs, and the potential for peer relationships to bolster mutual support. However, intervention implementation encountered substantial barriers across four key phases of engagement: from initial referral through to the transition from OOHC and into independent living. Poor aftercare planning and limited housing options—particularly within private rental markets—were recurrent challenges that providers sought to mitigate. Facilitators included the use of eligibility criteria and administrative data to identify at-risk youth, developing relationships with key stakeholders (e.g., real estate agents), and providing ongoing support in a flexible manner.

Interpretation

Consistent with other impact evaluations, it may be that interventions like PYI are delivered at the wrong time, to the wrong population, or are not delivered at an intensity sufficient to help care leavers with the many complex challenges that they face. In the case of PYI, the fact that 31% of those who received the intervention already had at least one spell in SHS before turning 18 suggests that the intervention may have been delivered too late to change their trajectory—at least in the first 12 months post-exit. Assisting care leavers in their transition to independence is a challenging area of practice, we know that most TSP for care leavers have null effects, and if they do have an impact, they tend to be small (Taylor et al., 2024). By focusing the intervention on those care leavers who were at the highest risk, e.g., those who had previously self-placed or used SHS, it is possible that PYI may have been able to be provided at a higher intensity.

It is promising that care leavers find PYI highly acceptable, suggesting that they welcome the provision of supportive interventions like PYI. In focus groups, participants often contrasted the perceived effectiveness of the support they received through PYI relative to leaving care planning they received from their OOHC caseworkers. Furthermore, anecdotes from participants suggest that those who had self-placed were more likely to engage with PYI.

The insufficient and/or poor leaving care planning identified by PYI providers raises concerns, as these deficiencies crowded out the delivery of core components of the intervention. Notably, these shortcomings in leaving care planning by OOHC providers are consistent with reviews by NSW Office of the Children's Guardian (2022) and Victorian Commission for Children and Young People (2020).

Limitations

Several limitations must be acknowledged. Firstly, the scope of our outcome data was limited to SHS use, which may overlook other relevant outcomes such as employment, income support, arrests, convictions, incarceration, unplanned pregnancies, and emergency department presentations. Furthermore, we were only able to observe outcomes between the ages of 18 (when participants left OOHC) and 19, a relatively short window during which the trajectories of those receiving PYI may not have fully diverged from their counterfactual. Additionally, the use of administrative data captures only individuals who engage with SHS, thus failing to account for those experiencing hidden homelessness (e.g., couch surfing), potentially underestimating the true incidence of housing instability (Metraux & Tseng, 2017). Finally, as with any study relying on selection-on-observables, the potential for unmeasured confounding must be acknowledged. Whilst we are confident in our ability to account for the intervention's selection criteria, we lack sufficient information to identify individuals in the comparison group who are not capable of living independently. Young people with health conditions or disabilities that prevent them from living independently would have been ineligible for PYI. These individuals were likely supported by a different system that includes accommodation and would thus, comparatively, have a lower likelihood of homelessness. Our inability to identify and exclude these individuals from our comparison pool potentially biases our estimates toward services as usual.

Implications for practice and policy

With nearly one-third of PYI participants accessing SHS before leaving care, interventions such as PYI—that are specifically designed to prevent homelessness among care leavers—must begin earlier and be more precisely targeted. Since PYI's inception, NSW has introduced extended care until age 21, a scalable initiative appealing as a broad policy option (Mendes et al., 2025). Some evidence suggests extended care can reduce homelessness among care leavers, but the evidence in favour is not conclusive, especially with respect to heterogenous treatment effects (Taylor et al., 2024). Meanwhile, interventions like PYI pose scaling challenges and may not be suited for broad adoption as a first-line strategy.

Poor aftercare planning has been identified as a practice issue in NSW (Office of the Children's Guardian, 2022; Taylor et al., 2020). Quality improvement methods such as audit and feedback, which can pinpoint and rectify deficiencies in service delivery, may be a viable option to improve practice (Grimshaw et al., 2019). Care leavers are not a monolithic group. While extended care could help some achieve a more stable transition to independent living, it likely will not benefit others, particularly those already disengaged from their placements. The use of predictive modelling with administrative data could help identify high-risk care leavers earlier, enabling more targeted, preemptive responses (Cuccaro-Alamin, Foust, Vaithianathan, & Putnam-Hornstein, 2017).

Implications for research

Selection-on-observables approaches, such as matching, are widely used in program evaluations, but the strong assumptions they require—namely that all relevant confounders have been observed—often receive insufficient scrutiny. To address this, we employed a DAG to make our assumptions explicit. Use of a DAG does not guarantee freedom from unmeasured confounding. However, it clarifies the causal pathways that we hypothesise are present and enables others to assess potential biases in our analysis, and we recommend their use. Likewise, we also recommend application of the potential outcomes framework as it supplies a transparent and formal means of framing a causal question. Finally, the use of *g*-computation can then help avoid the pitfalls of misinterpreting regression coefficients, commonly known as the Table 2 fallacy (Westreich & Greenland, 2013). Huntington-Klein (2022) and Cunningham (2021) provide detailed, accessible and practical resources for practitioners interested in applying such methods.

Looking ahead, there remains a pressing need to improve our understanding of how care leavers and CEYP fare across critical domains—such as education, employment, mental health, and housing stability—at different ages so that we can develop policies and/or interventions that provide appropriate support at the right time. Linked administrative data offers excellent opportunities to undertake this important epidemiological work. While administrative data may lack the granular detail of surveys (or other qualitative approaches), the ability to use it to follow an entire cohort makes it uniquely suited for tracking care leavers, who can be hard-to-reach.

Conclusion

PYI did not significantly reduce homelessness for most participants. The intervention was markedly less effective for Aboriginal young people, although it did potentially benefit those with prior experience of homelessness. We cannot definitively determine whether PYI's limited impact stems from issues with the intervention's design, if it was delivered at the wrong time or not implemented well.

Evaluating interventions like PYI is essential for advancing our understanding of 'what works', even (and perhaps especially) when results show limited or no effect. In the absence of experimental studies, careful application of observational methods, such as those employed in this paper, can play a crucial role in building the evidence base. By illuminating both the strengths and weaknesses of current approaches, such work helps practitioners to refine future services and ensures that support for care leavers is guided by the best available evidence.

References

Abadie, A., & Spiess, J. (2022). Robust Post-Matching Inference. *Journal of the American Statistical Association*, *117*(538), 983–995. https://doi.org/10.1080/01621459.2020.1840383

ABS. (2023). *Population estimates by age and sex, by SA2, 2023*. Canberra: Australian Bureau of Statistics.

ABS. (2024). *Estimated resident population, Aboriginal and Torres Strait Islander Australians, sex and age groups by states and territories and Australia—2011 to 2021*. Canberra: Australian Bureau of Statistics.

AIHW. (2021). *Income support receipt for young people transitioning from out-of-home care*. Canberra: Australian Institute of Health and Welfare.

AIHW. (2022). *Income support receipt for young people transitioning from out-of-home care 2022*. Canberra: Australian Institute of Health and Welfare.

AIHW. (2023). *Specialist homelessness service usage and receipt of income support for people transitioning from out-of-home care*. Canberra: Australian Institute of Health and Welfare.

Arel-Bundock, V., Greifer, N., & Heiss, A. (2024). How to Interpret Statistical Models Using marginaleffects for R and Python. *Journal of Statistical Software*, *111*, 1–32. https://doi.org/10.18637/jss.v111.i09

Austin, P. C., & Small, D. S. (2014). The use of bootstrapping when using propensity-score matching without replacement: A simulation study. *Statistics in Medicine*, *33*(24), 4306–4319. https://doi.org/10.1002/sim.6276

Benchimol, E. I., Smeeth, L., Guttmann, A., Harron, K., Moher, D., Petersen, I., … Committee, R. W. (2015). The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD) Statement. *PLOS Medicine*, *12*(10), e1001885. https://doi.org/10.1371/journal.pmed.1001885

Cashmore, J., & Paxman, M. (2007). *Longitudinal study of wards leaving care: Four to five years on*. Sydney: Social Policy Research Centre, University of New South Wales.

Commission for Children and Young People. (2020). *Keep caring: Systemic inquiry into services for young people transitioning from out-of-home care*. Melbourne: Commission for Children and Young People.

Courtney, M. E., & Dworsky, A. (2006). Early outcomes for young adults transitioning from out-of-home care in the USA. *Child and Family Social Work*, *11*(3), 209–219. https://doi.org/10.1111/j.1365-2206.2006.00433.x

Courtney, M. E., & Hook, J. L. (2017). The potential educational benefits of extending foster care to young adults: Findings from a natural experiment. *Children and Youth Services Review*, *72*, 124–132. https://doi.org/10.1016/j.childyouth.2016.09.030

Cuccaro-Alamin, S., Foust, R., Vaithianathan, R., & Putnam-Hornstein, E. (2017). Risk assessment and decision making in child protective services: Predictive risk modeling in context. *Children and Youth Services Review*, *79*, 291–298. https://doi.org/10.1016/j.childyouth.2017.06.027

Cunningham, S. (2021). *Causal Inference: The Mixtape*. New Haven, CT: Yale University Press.

Curran, G. M., Bauer, M., Mittman, B., Pyne, J. M., & Stetler, C. (2012). Effectiveness-implementation Hybrid Designs: Combining Elements of Clinical Effectiveness and Implementation Research to Enhance Public Health Impact. *Medical Care*, *50*(3), 217–226. https://doi.org/10.1097/MLR.0b013e3182408812

Damschroder, L. J., Aron, D. C., Keith, R. E., Kirsh, S. R., Alexander, J. A., & Lowery, J. C. (2009). Fostering implementation of health services research findings into practice: A consolidated framework for advancing implementation science. *Implementation Science*, *4*(50). https://doi.org/10.1186/1748-5908-4-50

DCJ. (2025). Your Choice, Your Future – new aftercare supports for carers. https://dcj.nsw.gov.au/dcj/children-and-families/out-of-home-care/children-in-out-of-home-care/planning-for-your-future-and-support-after-care/your-choice-your-future.html; NSW Government.

Elm, E. von, Altman, D. G., Egger, M., Pocock, S. J., Gøtzsche, P. C., & Vandenbroucke, J. P. (2007). The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: Guidelines for reporting observational studies. *The Lancet*, *370*(9596), 1453–1457. https://doi.org/10.1016/S0140-6736(07)61602-X

Fixsen, D. L., Naoom, S. F., Blase, K. A., Friedman, R. M., & Wallace, F. (2005). *Implementation Research: A Synthesis of the Literature* (The {{National Implementation Research Network}} No. FMHJ Publication #231). Tampa FL: University of South Florida, Louis de la Parte Florida Mental Health Institute.

Grimshaw, J. M., Ivers, N., Linklater, S., Foy, R., Francis, J. J., Gude, W. T., & Hysong, S. J. (2019). Reinvigorating stagnant science: Implementation laboratories and a meta-laboratory to efficiently advance the science of audit and feedback. *BMJ Quality & Safety*, *28*(5), 416–423. https://doi.org/10.1136/bmjqs-2018-008355

Gypen, L., Vanderfaeillie, J., De Maeyer, S., Belenger, L., & Van Holen, F. (2017). Outcomes of children who grew up in foster care: Systematic-review. *Children and Youth Services Review*, *76*, 74–83. https://doi.org/10.1016/j.childyouth.2017.02.035

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. *Political Analysis*, *15*(3), 199–236. https://doi.org/10.1093/pan/mpl013

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2011). MatchIt: Nonparametric Preprocessing for Parametric

Causal Inference. *Journal of Statistical Software*, *42*(8), 1–28.

Homes NSW. (2025). Youth Initiative. https://www.nsw.gov.au/departments-and-agencies/homes-nsw/housing-reforms-and-initiatives/youth-initiatives-housing-and-homelessness/youth-initiative; NSW Government.

Huntington-Klein, N. (2022). *The Effect: An Introduction to Research Design and Causality*. Chapman & Hall.

Kosmidis, I., & Firth, D. (2021). Jeffreys-prior penalty, finiteness and shrinkage in binomial-response generalized linear models. *Biometrika*, *108*(1), 71–82. https://doi.org/10.1093/biomet/asaa052

Laupacis, A., Sackett, D. L., & Roberts, R. S. (1988). An Assessment of Clinically Useful Measures of the Consequences of Treatment. *New England Journal of Medicine*, *318*(26), 1728–1733. https://doi.org/10.1056/NEJM198806303182605

McGowan, L. D. (2022). Tipr: An R package for sensitivity analyses for unmeasured confounders. *Journal of Open Source Software*, *7*(77), 4495. https://doi.org/10.21105/joss.04495

Mendes, P., Roche, S., Kristo, I., O'Donnell, M., Moore, T., Malvaso, C., … McDowall, J. J. (2025). The Introduction of Extended Out-of-Home Care (OOHC) Until 21 Years in Australia: A Mapping of Policy, Legislation and Programs in Each Jurisdiction. *Australian Journal of Social Issues*, 1–12. https://doi.org/10.1002/ajs4.389

Metraux, S., & Tseng, Y.-P. (2017). Using Administrative Data for Research on Homelessness: Applying a US Framework to Australia. *Australian Economic Review*, *50*(2), 205–213. https://doi.org/10.1111/1467-8462.12216

Miller, M., Bales, D., & Hirsh, M. (2020). *Extended Foster Care in Washington State: Final Report* [Document {{Number}} 20-05-3201]. Olympia, WA: Washington State Institute for Public Policy.

Nuñez, M., Beal, S. J., & Jacquez, F. (2022). Resilience factors in youth transitioning out of foster care: A systematic review. *Psychological Trauma: Theory, Research, Practice, and Policy*, *14*(S1), S72–S81. https://doi.org/10.1037/tra0001096

Office of the Children's Guardian. (2022). *Report on leaving care monitoring program 2020-21*. Sydney: Office of the Children's Guardian.

Palinkas, L. A., Aarons, G. A., Horwitz, S., Chamberlain, P., Hurlburt, M., & Landsverk, J. (2011). Mixed Method Designs in Implementation Research. *Administration and Policy in Mental Health and Mental Health Services Research*, *38*(1), 44–53. https://doi.org/10.1007/s10488-010-0314-z

Petäjä, U.-K., Terkamo-Moisio, A., Karki, S., & Häggman-Laitila, A. (2022). The Prevalence of High-Risk Behavior Among Adolescents in Aftercare Services and Transitioning from Out-of-home Care: A Systematic Review. *Adolescent Research Review*. https://doi.org/10.1007/s40894-022-00198-1

Picker, V., Hirneis, V., & Sanders, M. (2024). A Quasi-Experimental Evaluation of the Staying Put Intervention for Reducing Homelessness Among Care Leavers. *European Journal of Homelessness*, *18*(1).

Proctor, E., Silmere, H., Raghavan, R., Hovmand, P., Aarons, G., Bunger, A., … Hensley, M. (2011). Outcomes for Implementation Research: Conceptual Distinctions, Measurement Challenges, and Research Agenda. *Administration and Policy in Mental Health and Mental Health Services Research*, *38*(2), 65–76. https://doi.org/10.1007/s10488-010-0319-7

R Core Team. (2024). *R: A language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing.

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.2307/2335942

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, *66*(5), 688–701. https://doi.org/10.1037/h0037350

Sanders, M., Jones, L., & Whelan, E. (2021). Homelessness and Children's Social Care in England. *European Journal of Homelessness*, *15*(3), 129–141.

Sanders, M., & Picker, V. (2023). *The Impacts of Lifelong Links on Housing Outcomes for Young People Leaving Care: An evaluation using matching*. London: Centre for Homelessness Impact.

Snowden, J. M., Rose, S., & Mortimer, K. M. (2011). Implementation of G-Computation on a Simulated Data Set: Demonstration of a Causal Inference Technique. *American Journal of Epidemiology*, *173*(7), 731–738. https://doi.org/10.1093/aje/kwq472

Spindle-Jackson, A., Byrne, T., & Collins, M. E. (2024). Extended foster care and homelessness: Assessing the impact of the fostering connections to success and increasing adoptions act on rates of homelessness among youth. *Children and Youth Services Review*, 107820. https://doi.org/10.1016/j.childyouth.2024.107820

Strahl, B., van Breda, A. D., Mann-Feder, V., & Schröer, W. (2021). A multinational comparison of care-leaving policy and legislation. *Journal of International and Comparative Social Policy*, 1–16. https://doi.org/10.1017/ics.2020.26

Taylor, D., Albers, B., Mann, G., Lewis, J., Taylor, R., Mendes, P., … Shlonsky, A. (2024). Systematic Review and Meta-Analysis of Policies and Interventions that Improve Health, Psychosocial, and Economic Outcomes for Young People Leaving the Out-of-Home Care System. *Trauma, Violence, & Abuse*, *25*(5), 3534–3554. https://doi.org/10.1177/15248380241253041

Taylor, D., Roberts, J., Rose, V., Gyani, A., Harrigan, S., & Shlonsky, A. (2020). *Evaluation of the Premier's Youth Initiative: Final Report*. Sydney: Centre for Evidence and Implementation.

Taylor, D., Roberts, J., Rose, V., Gyani, A., & Shlonsky, A. (2025). Examining the impact of an Accommodation and Support Intervention in reducing homelessness amongst Care Leavers in Australia: A hybrid type-1 Implementation-Effectiveness Study using Propensity Score methods - supplementary material.

Taylor, D., Roberts, J., & Shlonsky, A. (2025). *Connecting the Dots: Using a Modified Delphi Method to Develop a Directed Acyclic Graph to evaluate the effectiveness of an Accommodation and Support Intervention for Care Leavers*. Unpublished Manuscript, Data Matters, Monash University, Melbourne.

Thoemmes, F. J., & Kim, E. S. (2011). A Systematic Review of Propensity Score Methods in the Social Sciences. *Multivariate Behavioral Research*, *46*(1), 90–118. https://doi.org/10.1080/00273171.2011.540475

Westreich, D., & Greenland, S. (2013). The Table 2 Fallacy: Presenting and Interpreting Confounder and Modifier Coefficients. *American Journal of Epidemiology*, *177*(4), 292–298. https://doi.org/10.1093/aje/kws412