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Trajectories of homelessness and association with mental health and substance use disorders among young people transitioning from out-of-home care in Australia

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ABSTRACT

Background: Researchers have examined sub-groups that may exist among young people transitioning from out-of-home care (OHC) using various theoretical models. However, this population group has not been examined for trajectories of homelessness risk.
Objectives: To examine whether different subtypes of homelessness risk exist among young people transitioning from care and whether these trajectories of homelessness are associated with mental health and substance use disorders.
Participants and setting: A retrospective population-based cohort study was conducted from a population of 1018 young people (aged 15–18 years) who transitioned from out-of-home in 2013 to 2014 in the state of Victoria, Australia, with follow-up to 2018.
Methods: Latent Class Growth Analysis was conducted using linked data from homelessness data collections, child protection, mental health information systems, alcohol and drug use, and youth justice information systems.
Results: Three sub-groups of young people were identified. The *'moving on'* group (88 %) had the lowest levels of homelessness, with the slope of this trajectory remaining almost stable. The '*survivors*' (7 %) group started off with a high risk of homelessness, followed by a sharp decrease in homelessness risk over time. The '*complex*' (5 %) group started off with a low risk of homelessness but faced sharp increases in the risk of homelessness over time.
Conclusions: Our study demonstrates that subgroups of young people transitioning from care exist with distinct longitudinal trajectories of homelessness, and these classes are associated with different risk factors. Early intervention and different approaches to tackling homelessness should be considered for these three distinct groups before transitioning from care and during the first few years after leaving care.

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1. Introduction

Out-of-home care (OHC) involves placing children and young people with foster or kinship caregivers due to abuse, neglect, or receiving inadequate care from their primary carers (AIHW, 2022; Department of Education, 2020). In 2021, 46,200 children were in OHC in Australia, and the rate has remained relatively stable at 8 per 1000 children over the past five years. The discharge rate from OHC was highest for young people aged 15–17 years at 4 per 1000 children (AIHW, 2022). Young people in OHC often face quicker and unplanned transitions to adulthood compared with their peers in the general population (Mendes, 2022; OECD, 2022).

Young people often lack the emotional and/or financial support to transition smoothly from out-of-home care (OHC) to adulthood (Courtney & Heuring, 2005; Mendes et al., 2011). This lack of support results in significant challenges such as homelessness, housing instability, substance misuse, and poor mental health (Brackertz et al., 2018). The transition to adulthood presents psychological stress, risk, and uncertainty about what the future holds for these young people. Despite this understanding, little is known about the trajectory of housing instability or homelessness, how it varies across individuals, and how it interacts with mental health issues and substance misuse.

Young people transitioning from OHC experience homelessness at a higher rate compared with young people in the general population (AIHW, 2020; Fowler et al., 2017; Harris & Udry, 2022). The rate of young people transitioning from OHC accessing homelessness services in the state of Victoria was 3.6 per 10,000 compared with 2.5 per 10,000 people for the general population across Australia (AIHW, 2020). Globally, some studies have reported homelessness rates of between 26 % to 36 % among young people leaving out-of-home care compared to rates of <10 % of young people in the general population (Bender et al., 2015; Dworsky et al., 2013; Kelly, 2020; Sanders et al., 2021). Due to high homelessness rates among young people transitioning from care, research is required to understand the different patterns of homelessness, how young people go through the various pathways, their experiences of homelessness and, ultimately, the factors contributing to these pathways over time.

1.1. Definition of homelessness

Homelessness or housing instability is a much broader concept than just visible homelessness or rooflessness (Brändle & García, 2015; Fitzgerald et al., 2001). However, many studies on homelessness frequently do not offer a more nuanced definition of homelessness and thus potentially underestimate the prevalence of homelessness among OHC young people (Fowler et al., 2017). In addition, some authors acknowledge that census estimates on homelessness may potentially exclude young people who may be "couch surfing" on census night (Australian Bureau of Statistics, 2018). The European Typology of Homelessness and Housing Exclusion framework (ETHOS) overcomes some of these issues and provides a more nuanced definition of homelessness (Brändle & García, 2015; Busch-Geertsema et al., 2016). The framework has four conceptual and thirteen operational definitions which encompass visible homelessness, lack of tenure, housing insecurity, housing inadequacy, and housing instability.

1.2. Predictors of homelessness

Risk factors for homelessness among young people transitioning from care are a mix of pre-care and in-care experiences. These include being male (Dworsky et al., 2013), Indigenous (AIHW, 2020; Martin et al., 2021), experiencing family violence (Sznajder-Murray et al., 2015), child maltreatment (Kelly, 2020), poor parenting relationships (Van den Bree et al., 2009), and mental health and substance abuse problems (Chikwava et al., 2022; Martin et al., 2021). In-care experiences include placement instability (Fowler et al., 2009), living in residential settings (Fowler et al., 2009) and criminal justice involvement (Shah et al., 2017). Factors such as having good relationships with a carer (Sznajder-Murray et al., 2015), receiving leaving care support until the age of 21 years (Mendes, 2022), high school completion, and access to various supports (Courtney et al., 2019) reduce the odds of being homelessness.

1.3. Relationship between mental health and homelessness

Mental health issues and substance misuse have been shown to be highest among people with chronic housing instability or those who are homeless compared with those who are housed (Bevitt Andrew et al., 2014; Mallett et al., 2005). A long history of research has identified mental health and substance misuse as some of the strongest predictors of homelessness (Giano et al., 2020). Young people in OHC who end up homeless often have histories of mental health issues or substance use dependence (Greeno et al., 2019; Hodgson et al., 2013; Lippert & Lee, 2015; Martijn & Sharpe, 2006; Pumarino et al., 2017). Moreover, young people experiencing homelessness are exposed to an accumulation of risk factors such as worsening mental health issues compared with young people with stable housing (Adair et al., 2017; Dworsky et al., 2013; Spicer et al., 2015). A history of poor mental health not only increases a young person's likelihood of experiencing homelessness but can also reinforce and lengthen their episodes of homelessness (C M. T. Chu et al., 2020; Fowler et al., 2009, 2011).

Regarding trajectory analysis, previous studies have not examined the association between homelessness and the dual diagnosis of mental health and substance misuse. Some studies identified mental health (Courtney et al., 2012; Fowler et al., 2011) and substance misuse problems (Courtney et al., 2012; Hernandez & Lee, 2020; Keller et al., 2007) in describing various latent classes; however, there is no evidence of associations between homelessness and the dual diagnosis of mental health and substance misuse. As such, there is a need to understand the extent to which dual diagnosis of mental health and substance misuse increases the risk of homelessness among this population group.

1.4. Person-centred and variable-centred techniques

Our study takes an integrative approach that combines both person-centred and variable-centred approaches to understanding the trajectories of sub-groups of homelessness experienced by young people transitioning from care and the factors associated with these trajectories. These approaches will allow us to identify sub-groups of individuals who share similar characteristics (Courtney et al., 2012; Keller et al., 2007; Laursen & Hoff, 2006) and how they differ based on their patterns of homelessness risk.

The theory of resilience of OHC youth developed by Stein (Stein, 2008) provides the framework for our study. The framework is based on research studies on the resilience of OHC youth spanning 25 years (1983–2008). Stein's framework posits three distinct groups of young people leaving OHC: a *'moving on'* group, a *'survivors'* group, and a *'struggling'* group. Stein mentions homelessness as one of the negative outcomes experienced by young people in the *'survivors'* and *'struggling'* groups. However, given that the term *'struggling'* may be deemed inappropriate, this term will be referred to as *'complex'* from hence forward (Munro et al., 2022). Several authors who have conducted fixed mixture modelling among young people transitioning or those who have left OHC have found evidence of similar groups of young people as reflected in Stein's work (Fowler et al., 2011; Keller et al., 2007; Miller et al., 2017; Rebbe et al., 2017).

These works provide a framework for understanding the trajectories of young people transitioning from out-of-home care. In addition, the framework applies to this study since homelessness is one of the factors contributing to the resilience of young people and leading to the identification of the three distinct groups of young people as they transition to adulthood. The largest group identified by these authors was the '*moving on*' group (>35 %). By and large, these young people achieved better outcomes when they transitioned from care and had better in-care experiences than other groups. They successfully transitioned from care with less housing instability (Fowler et al., 2011; Hernandez & Lee, 2020; Keller et al., 2007). The second group, '*survivors',* faced some challenges during care, and experienced more instability compared to the *'moving on'* group. They relied on government assistance for housing, financial, and personal support (Hernandez & Lee, 2020; Stein, 2008). The third group, '*complex*', faced the most instability while in care, often experienced multiple mental health and substance misuse challenges, and faced homelessness or housing instability when they left OHC (Fowler et al., 2011; Hernandez & Lee, 2020; Stein, 2008).

Although these studies provide evidence of heterogeneity in describing young people transitioning from care, they have several limitations which our study aims to address. For example, most of the studies only focussed on young people who stayed in foster care (Fowler et al., 2011; Keller et al., 2007; Miller et al., 2017; Rebbe et al., 2017), yet outcomes experienced by young people leaving care may be influenced by different types of living arrangements they had while in care. Additionally, the studies focused primarily on measurements at one specific time point (Courtney et al., 2012; Miller et al., 2017), thus limiting our understanding of the influence of covariances on changes in outcomes over time. Furthermore, retrospective self-reporting of life events, such as adverse childhood events, may introduce recall bias (Fowler et al., 2011; Keller et al., 2007; Rebbe et al., 2017). This can be overcome by utilising administrative data from child protection records. Another limitation was the definition of homelessness used in some of these studies, which was restricted to rooflessness or houselessness and did not consider broader experiences of homelessness over time (Courtney et al., 2012; Fowler et al., 2017). Our study offers a more nuanced categorisation of homelessness, encompassing all forms of homelessness, from the most severe form of rough sleeping to the less severe form of extreme overcrowding (Brändle & García, 2015; Busch-Geertsema et al., 2016). In addition, another strength of our study is that the data has five years follow-up time post young people leaving care, which offers a better understanding of trajectories after leaving care.

1.5. Latent class growth modelling

A longitudinal study design is necessary to determine causality and the trajectories experienced by sub-groups of young people to inform the timing, type, and extent of support and interventions for young people transitioning from care and entering adulthood. While latent class growth modelling has gained popularity for longitudinal studies (Muthén & Muthén, 2000; Nagin, 1999), there is a lack of studies examining the trajectories of homelessness among young people transitioning from OHC and how mental health and dual diagnosis of mental health and substance misuse are associated with different trajectories (Fowler et al., 2011).

1.6. Purpose of study

There is limited evidence to determine the trajectories of homelessness risk that may exist among the population of young people transitioning from OHC. Our study adds to the knowledge around trajectories of homelessness, by introducing dual diagnosis of mental health and substance use disorders, which has not been investigated in previous studies. While previous research has determined various characteristics associated with homelessness, our analysis will add to the current understanding of resilience pathways of young people and the impact of mental health and substance use on the homelessness trajectories for young people transitioning from care.

The period when young people immediately transition from care is a very critical time since most supports start to diminish from that point forward. To address these gaps in the literature, the present study aims to address the following research questions:

1. What is the evidence for, and characteristics of, subgroups of young people that follow distinct trajectories of homelessness risk from the time when young people transition from OHC to early adulthood (RQ1)?
2. To what extent is a history of mental health or substance misuse (prior leaving care) and dual diagnosis of mental health and substance misuse associated with the latent class trajectories of young people transitioning from OHC (RQ2)?

2. Methodology

2.1. Procedure

We conducted a retrospective population-based cohort study using linked records from administrative datasets of the state of Victoria, Australia. Data linkage was undertaken by the Centre for Victorian Data Linkage using secure, high-quality data linkage infrastructure (Flack & Smith, 2019). De-identified datasets with a unique identification number for each study participant were provided to the researchers.

2.2. Participants

The study comprised a retrospective cohort of 1848 young people aged 15–18 years who left the Victorian OHC system in 2013–2014, with follow-up until the end of 2018. Out of the 1848 young people, 1547 participants had records of homelessness data from the Victorian Homelessness data collection. The analysis was conducted among 1018 participants with at least three of the five-year follow-up data, which is a key requirement when conducting growth mixture modelling (Wickrama et al., 2016).

2.3. Measures

2.3.1. Socio-demographic characteristics

These were obtained from child protection data, and they included participants' age of leaving care, gender, Indigenous status, and geographical location classified as either regional or urban area.

2.3.2. Homelessness status

A continuous housing status dataset was created by integrating data from the homelessness data collection (AIHW, 2020), hospital patient data, emergency department, and alcohol and drug use data collections (Centre for Victoria Data Linkage, 2009). The homelessness risk variable was derived using the ETHOS framework (Busch-Geertsema et al., 2016). The ETHOS framework is comprised of four conceptual definitions ("rooflessness", "houselessness", "insecure housing" and "inadequate housing"), each of which was expanded to 13 operational definitions ranging from the most severe to the least severe form of homelessness. The variables from our study that mapped to these 13 operational definitions included housing situation at present, residential type, tenure type and reasons for seeking homelessness services (Supplementary Table 1).

The homelessness risk score was calculated based on the level of severity of homelessness experienced in a 60-day period. We then assigned a risk score for each level of homelessness based on their ETHOS category (i.e., a score of 13 for rough sleeping, a score of 12 for emergency housing, all the way through to the least severe form of housing (i.e., a score of 1 for overcrowding). We then added up the total number of episodes experienced by each homeless category and multiplied this by its risk score. The final homelessness risk score for each year was then added up to obtain a continuous homelessness risk score, whereby the higher the score, the higher the risk profile of homelessness (see Supplementary Table 2). Chronic homelessness was defined as homelessness experienced in two of the five follow-up times. A detailed mapping of the homelessness data using the ETHOS framework is described in a recent article (Chikwava et al., 2022).

2.3.3. Mental health disorders

Information about mental health disorders were obtained from inpatient and outpatient records from the Victorian Admitted Episodes (hospital admissions) data, the Victorian Emergency Department data, and the Clinical Mental Health data (Centre for Victoria Data Linkage, 2009). The data do not include private outpatient records. These sources contain diagnostic information based on the WHO International Classification of Diseases (ICD 10), recorded for each episode of care (Supplementary Table 3). Mental health disorders were determined prior to leaving OHC to determine a history of mental health before leaving OHC (4 years before leaving OHC). The variables were coded as either Yes (having any mental health disorder) or No (not having any mental health disorder).

2.3.4. Child protection involvement

The data included information on the last placement type, allegations, substantiations, and information on care placements for all closed cases. Substantiated child maltreatment allegations (any harm) included physical, sexual, psychological, and neglect. Placement types included kinship care, residential care, general home-based care, complex or intensive home-based care, and permanent care. In Australia, residential care involves a child placed into a home staffed by carers, while kinship care refers to the placement of a child with relatives (kin). Home-based care refers to care provided for a child placed in the home of a carer, who is reimbursed for that child's care cost. The difference between general and complex home-based care is that complex placements are highly resourced, consisting of specific service responses and individualised interventions. Following amendments to the Children, Youth and Families Act in 2014, permanency in OHC through permanent care orders was established to facilitate pro-activeness about future care arrangements for children in OHC and to promote permanency of those arrangements beyond 18 years of age (Victoria State Government, 2022). The difference between permanent care and kinship care or foster care is that permanent care provides long-term security for the child, whereas with kinship or foster care, the child may move from one placement type to another, and permanency is not guaranteed (Victoria State Government, 2022).

2.3.5. Substance misuse

The data for substance misuse was obtained from four data sources i.e. the Victorian Admitted Episodes (hospital admissions) data, the Victorian Emergency Department data, the Clinical Mental Health data (Centre for Victoria Data Linkage, 2009) and the Victorian Alcohol and Drug Information System (ADIS) (Victoria State Government, 2018). The ADIS data contains data on assessment, treatment and support services provided to adults and young people who have alcohol and/or drug use problems. Two variables were constructed from these data sources based on a diagnosis using the ICD10 classification and use of ADIS services to determine substance misuse i.e. (i) a history of substance misuse, which involved use of substances prior to leaving care (4 years before leaving OHC). The variable was coded as either Yes (having any substance misuse) or No (not having any substance misuse). (ii) a dual mental health and substance misuse variable was constructed to determine chronic mental health and substance misuse for the total follow-up time after leaving OHC: chronic = 2 to 5 years; not chronic = 0 to 1 year.

2.3.6. Youth justice

The youth justice dataset contains information on all criminal court orders in the youth justice system in Victoria. Variables extracted and used were custodial or community justice involvement prior to leaving care. Any recorded instance of youth justice involvement from this data was coded as one and zero if there was no recorded instance.

2.4. Statistical analysis

Due to selection of a sub-sample of 1018 participants with at least three of the five-year follow out of a population of 1800 participants, we had to assess any potential bias and ensure that this sub-sample was still representative of the total population, by conducting chi-square tests to determine differences in key socio-demographic characteristics among our sample and that of the total population. A probability-based weighting method was applied to the data to remove any bias that might result from having different kinds of people represented in the wrong proportion. This method involves weighting each case by the inverse of its probability of selection, which would remove any bias that might occur from having different kinds of people represented in the wrong proportion. The method also ensured that the sample was representative of the total population of young people in out-of-home care in Victoria (Richiardi & Pizzi, 2015). We then analysed the data in two stages. *First*, we conducted growth mixture modelling to identify groups of young people with similar risk trajectories of homelessness over the study's five years. *Second*, we evaluated participant demographic characteristics, social and environmental risk factors, and mental health diagnosis as potential predictors of group membership.

2.4.1. RQ1

Heterogeneity was initially checked in the data by conducting Latent Growth Curve Modelling (LGCM). Exploratory analysis was then conducted to determine the best model fit to our data by examining the Latent Class Growth Analysis (LCGA), Growth Mixture Model with class-invariant (constrained) variances and covariances (GMM-CI), and the Growth Mixture Model with class-varying (free estimation) variances and covariances (GMM-CV) (Feldman et al., 2009; Nagin, 2014; Wickrama et al., 2016). Latent class growth analysis (LCGA) was then selected as the best-fitting approach and was used to identify sub-groups of individuals who had a homogeneous trajectory. Bivariate analyses were then conducted using chi-square tests of association to determine associations of covariates with latent class membership. Post-hoc analysis was conducted using the Bonferroni correction to limit the possibility of getting a statistically significant result, where more than two groups are being compared. LCGA analysis was conducted to test for the presence of distinct longitudinal patterns of homelessness risk. LCGA has been used in the homelessness or housing instability literature to examine trajectories of homelessness over time (Fowler et al., 2009; Tevendale et al., 2011).

Four criteria were evaluated to determine the ideal number of latent classes to include in our models (Muthén & Muthén, 2000). The sample size adjusted Bayesian information criterion (SSABIC) was used to determine the relative fit across models; a low value indicates a well-fitting model (Nylund et al., 2007; Wickrama et al., 2016). The classification quality ("entropy") was examined by reviewing posterior probabilities of class membership; these estimates reflect the average likelihood of membership in the determined latent class. A value closer to one indicates a good fit. The Lo-Mendell-Rubin likelihood ratio test (LMR-RT*)* and the Bootstrapped likelihood ratio test (BLRT) were conducted to assess whether the fit of a given model was significantly better than the fit of an identical model with one less class (Lo et al., 2001; Muthén & Muthén, 2000; Nylund et al., 2007; Wickrama et al., 2016). Next, we considered the usefulness and interpretability of our latent classes. Models were tested, and absolute and relative fit indices were compared to choose the most parsimonious and conceptually and empirically valid and well-differentiated model (Nylund et al., 2007).

2.4.2. RQ2

In the second stage, we conducted a multinomial logistic regression analysis and the likelihood ratio test to choose the most parsimonious model in the conditional models (El-Habil, 2012). We controlled for the following covariates: gender, region, age of leaving care, involvement with the criminal justice system, history of psychological harm and out-of-home care placement type. We also tested if placement type modified the association between chronic mental health and substance misuse and class membership. The four criteria were utilised to determine the best-fitting model. We used Full Information Maximum Likelihood (FIML) in *Mplus* Version 8.8 which allows cases with missing values on some variables (Muthén & Muthén, 2000).

2.5. Ethics

Ethical approval for this study was granted by the Curtin Human Research Ethics Committee (Ethics number HRE2021-0151), and as per usual practice with linked datasets, the need for consent was waived by the ethics committee because of the anonymised nature of the linked administrative data used.

3. Results

In total 1018 participants out of 1800 study participants were eligible for the LCGA since they had homelessness data for at least three of the five data points, which is a key requirement for conducting LCGA. There were 58 % females and 42 % males who were included in the dataset, and this distribution had a borderline significant difference from the total population of young people who exited the out-of-home care system. ($\chi2 = 3.76$; $p = 0.05$). The dataset consisted of 23 % Indigenous young people compared with 77 % non-Indigenous young people, and the distribution was significantly different to that of the total young people who left the OHC system ($\chi2 = 11.4$; $p = 0.001$). As a result of this imbalance, we used a sample size adjusted weight based on gender and Indigenous status for the descriptive analysis and latent class growth analysis.

3.1. Unconditional growth models

Initially, the adequacy of fit of a one-class latent growth model with both a linear and quadratic growth factor was tested. Fit indices

Table 1
Characteristics of study population and class membership.

Characteristic	Class 1: *Moving on* (N = 895)		Class 2: *Survivors* (N = 67)		Class 3: *Complex* (N = 56)		Total (N = 1018)		Chi Square test/ Fischer Exact Test (*p-value*)[a]	Bonferroni post-hoc test adjustment[b]		
	N	`%	N	%	N	%	N	%		Class 1 vs. Class 2 test (*p-value*)[a]	Class 1 vs. Class 3 test (*p-value*)[a]	Class 2 vs. Class 3 test (*p-value*)[a]
Gender												
Male	373	41.7	33	49.3	19	33.9	425	41.8	2.96	1.47	1.31	2.93
Female	522	58.3	34	50.8	37	66.1	593	58.3				
Indigenous status												
Not indigenous	698	78.0	48	71.6	35	62.5	781	76.7	8.11*	1.44	7.16*	1.16
Indigenous	197	22.0	19	28.4	21	37.5	237	23.3				
Geographic location												
Major cities	536	59.9	42	62.7	40	71.4	618	60.7	3.06	0.20	2.94	1.05
Regional/remote	359	40.1	25	37.3	16	28.6	400	39.3				
Age of leaving care												
15–16 years	527	58.9	27	40.3	35	62.5	589	57.9	9.35**	8.81*	0.29	6.01*
17–18 years	368	41.1	40	59.7	21	37.5	429	42.1				
Youth justice involvement												
No	654	73.1	37	55.2	36	64.3	727	71.4	11.20**	9.81*	2.04	1.04
Yes	241	26.9	30	44.8	20	35.7	291	28.6				
History of any harm												
No	57	6.4	1	1.5	3	5.4	61	6.0	0.32	2.62	0.09	1.45
Yes	838	93.6	66	98.5	53	94.6	957	94.0				
History of psychological harm												
No	353	39.4	23	34.3	14	25.0	390	38.3	5.13	0.68	4.64	1.26
Yes	542	60.6	44	65.7	42	75.0	628	61.7				
History of mental health disorders												
No	503	56.2	24	35.8	23	41.1	550	54.0	14.43**	10.45*	4.88	0.36
Yes	392	43.8	43	64.2	33	58.9	468	46.0				
History of substance misuse												
No	634	70.8	28	41.8	29	51.8	691	67.9	31.16***	24.51**	9.06*	1.23
Yes	261	29.2	39	58.2	27	48.2	327	32.1				
Chronic mental health and substance misuse disorders												
0–1 year	801	89.5	52	77.6	34	60.7	887	87.1	44.74***	8.76*	40.77**	4.14
2–5 years	94	10.5	15	22.4	22	39.3	131	12.9				
Most recent placement												
Kinship care	284	31.7	7	10.5	10	17.9	301	29.6	17.46***	13.38**	4.75	1.41
Home based care or permanent care	283	31.6	19	28.4	13	23.2	315	30.9	1.97	0.31	1.74	0.41
Residential care	328	36.7	41	61.2	33	58.9	402	39.5	25.09***	15.89**	11.11*	0.06

OHC = out-of-home care.
[a] Chi-square test for significant difference among the 3 latent class groups; significance level: *$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.001$.
[b] Post-hoc comparisons using chi-square tests of the three groups based on an alpha of $0.05/3 = 0.0167$: *$p \leq 0.0167$; **$p \leq 0.001$.

improved after the addition of the quadratic term, though there were still some statistically significant variances of growth factors. The latent growth curve model performed poorly on relative fit indices, indicating that more than one class was present, thus necessitating the use of growth mixture modelling ($\chi 2 = 20.49$, $p < 0.001$, CFI = 0.94, TLI = 0.90, RMSEA = 0.05, SRMR = 0.04). Exploratory analysis was conducted for the unconditional models to determine the most parsimonious model with fewer convergence issues among the LCGA, the GMM-CI and the GMM-CV models.

The LCGA was selected as the best approach since it had less convergent issues and no class had <1 % minimum sample size for each of the classes. The entropy values were consistent and high for the 2-, 3-, and 4- class models (0.87–0.91), indicating high classification accuracy across all models (Bakk & Kuha, 2021). In comparison, the GMM-CI and GMM-CV models had lower entropy values compared to the LCGA models (S2 Table). The 4- and 5- class models of the GMM-CV model failed to converge even after increasing the number of random starting values and constraining the negative variances to be zero (Ram & Grimm, 2009). For each of the three approaches, we evaluated fits of 2-, 3-, 4-, and 5-class models, and determined that the 3-class solution provided the best fit to the data (Supplementary Table 4). While the 4-class model had the lowest AIC and SSABIC values, we opted for the 3-class model since it had a higher entropy value (0.904) and higher classification probabilities compared to the 4-class model (0.871). In addition, the 3-class model was selected because graphically, it had clear class separations compared to the 4-class model. Lastly, based on theory and previous literature, the 3-class model provided a better fit to the data.

Consistent with Stein's resilience theory (Stein, 2008), the three groups of young people that were determined from the LCGA were (C1: *'moving on'*; 88 %), (C2: *'survivors'*; 7 %), and (C3: *'complex'*; 5 %) group. The main characteristics used to describe the three groups were demographic characteristics and risk factors of homelessness, which included youth justice involvement, history of abuse and maltreatment, history of alcohol or drug use, history of any mental health disorder, most recent placement type and chronic mental health and substance misuse.

In the bivariate analysis using chi-square test of association, the *'complex'* group had a significantly higher proportion of Indigenous young people (38 %) compared to the *'survivors'* (28 %) and *'moving on'* groups (22 %). Overall, there were a greater number of young people aged 17 to 18 years old in the *'moving on'* group (86 %) compared to the other two groups. Other significant covariates included involvement with the criminal justice system, out-of-home care placement type, history of substance misuse involvement, history of mental health, chronic mental health, and substance misuse (see Table 1). In addition, mental health, and substance misuse across the five time periods significantly differed across the three groups, with the highest rates reported among the *'complex'* group.

Post-hoc comparisons revealed statistically similar proportions in indigenous status, involvement with justice, history of mental health, history of substance misuse, chronic mental health and substance misuse, kinship care and residential care among the *'survivors'* and *'complex'* groups of young persons. Similar proportions were also found in the age of leaving care, involvement with justice,

Table 2
Fit Indices of trajectory classes for conditional LCGA model.

Model fit statistics	2 classes	3 classes	4 classes	5 classes
AIC	32,286.10	31,987.92	31,902.25	31,840.60
BIC	32,581.64	32,446.01	32,522.88	32,623.77
SSABIC	32,391.08	32,150.63	32,122.69	32,118.77
LL (no. of parameters)	16,083.05 (60)	−15,900.96 (93)	−15,825.12 (126)	−15,761.30 (159)
Adj. LMR − LRT (*p*)	601.33 (*0.006*)	376.55 (*0.04*)	171.73 (*0.367*)	−1.377 (*0.103*)
BLRT (*p*)	603.96 *(<0.001)*	378.20 *(<0.001)*	172.48 *(<0.001)*	190 *(<0.001)*
Entropy	0.912	0.904	0.886	0.928
Group size (%)				
C1	923 (91 %)	895 (88 %)	834 (82 %)	856 (84 %)
C2	95 (9 %)	67 (7 %)	100 (10 %)	53 (5 %)
C3	–	56 (5 %)	43 (4 %)	44 (4 %)
C4	–	–	41 (4 %)	41 (4 %)
C5	–	–	–	24 (2 %)

Parameter estimates for 3-class model.

Mean of growth factors	Class 1 (n = *895)*	Class 2 (n = *67)*	Class 3 (n = *56)*
Intercept factor	1.331	1.242	−5.520
Linear factor	−0.128	−2.681	8.880

LCGA = Latent Class Growth Analysis.
LL = Log-Likelihood value.
No. of Parameters = Number of estimated (freed) parameters.
AIC = Akaike Information Criteria.
BIC = Bayesian Information Criteria.
SSABIC = Sample Size Adjusted BIC.
LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio Test.
Adj. LMR-LRT = Adjusted Lo-Mendell-Rubin Likelihood Ratio Test.
BLRT = Bootstrap Likelihood Ratio Test.
p = *p*-value.

history of mental health problems, and kinship care among the *'moving on'* and *'complex'* groups of young persons. The *'moving on'* and *'survivors'* groups had similar proportions of indigenous status.

3.2. Conditional growth models

The conditional growth model was run using LCGA and included the covariates that were identified in the bivariate analysis. The LMR-LRT indicated that the two- and three- class models were preferable to the baseline and two-class models respectively (see Table 2). To distinguish between 2-, 3-, 4- class models, AIC and SSABIC indices were used. The AIC and SSABIC values were smaller for the 4- class model compared to the 3- class model. The BLRT was significant for all classes and therefore was not used to determine the best fitting class. Fig. 1 shows clear class separations for the 3-class model compared to the 4-class model. In addition, the 3-class model had classes which were clearly interpretable and consistent with theory (Stein, 2006, 2008). Thus the 3-class model was accepted as the best fitting model.

As shown in Fig. 1, the largest group (C1: *'moving on'*) included those who had the lowest homelessness risk when they left care and gradually faced increases in homelessness risk, with the slope of this trajectory remaining almost stable across 5 years (mean homelessness risk from 3.3 to 7.0). The second group (C2: '*survivors*') started off with a high risk of homelessness and the homelessness risk sharply decrease over time (mean homelessness risk from 31.5 to 10.3). The third group (C3: '*complex*'), started off with low risk of homelessness but faced sharp increases in the risk of homelessness over time (mean homelessness risk from 7.2 to 47.3). A subsequent analysis comparing trajectories of young people who left care at 15–16 years and those who left care at 17–18 years showed a similar number of latent classes, further supporting the claim of three distinct subgroups; however, there was delayed homelessness risk for those aged 15–16 years. During the first year of leaving care, young people aged 17–18 years had a significantly higher mean homelessness risk score compared to young people who left care at 15–16 years old (Mean score 7.03 vs 4.51 respectively, $t = 4.05$; $p = 0.0001$; see Supplementary Table 5 and Figs. 2 and 3). This finding might be explained by those leaving care at a younger age being re-unified with their parents (Delfabbro et al., 2015); however, we do not have the data to substantiate this as a possible explanation.

The adjusted associations (adjusted risk ratio: ARR) between baseline participants' characteristics and the probability of following each homelessness risk-trajectory profile are presented in Table 3: The *c1: 'moving on'* homelessness risk profile was the reference group for the model. In the analysis, young people who left care at an older age (ARR: 1.83; 95%CI: 1.07–3.14), or those who lived in home-based or permanent care (ARR: 2.39; 95%CI: 0.98–5.87), or stayed in residential care (ARR: 3.55; 95%CI: 1.52–8.30) or had a history of substance misuse (ARR: 2.13; 95%CI: 1.19–3.82) were more likely to be members of the *'survivors'* group than the *'moving on'* group. While age of leaving care explains the trajectories of young people up to 4 or 5 years after leaving care, these trajectories may change, say 7 to 10 years later, due to other factors.

In addition, young people who were Indigenous (ARR: 2.13: 95%CI: 1.17–3.87) or stayed in residential care (ARR: 2.41; 95%CI: 1.11–5.23), or who had chronic mental health and substance misuse after leaving care (ARR: 4.17; 95%CI: 2.21–7.87) were more likely to be members of the *'complex'* group than the *'moving on'* group. Further sensitivity analysis to explore predictors of group membership (multivariate analysis) for the two age groups, showed similar results from the original model with all young people (Supplementary Table 6). Placement type did not modify the association between chronic mental health and substance misuse and class membership (Supplementary Table 6). While our study did not investigate all in-care experiences that may be associated with homelessness trajectories, some in-care experiences are shown to be significantly associated with class membership i.e., criminal justice involvement, placement type and mental health or substance misuse prior leaving care.

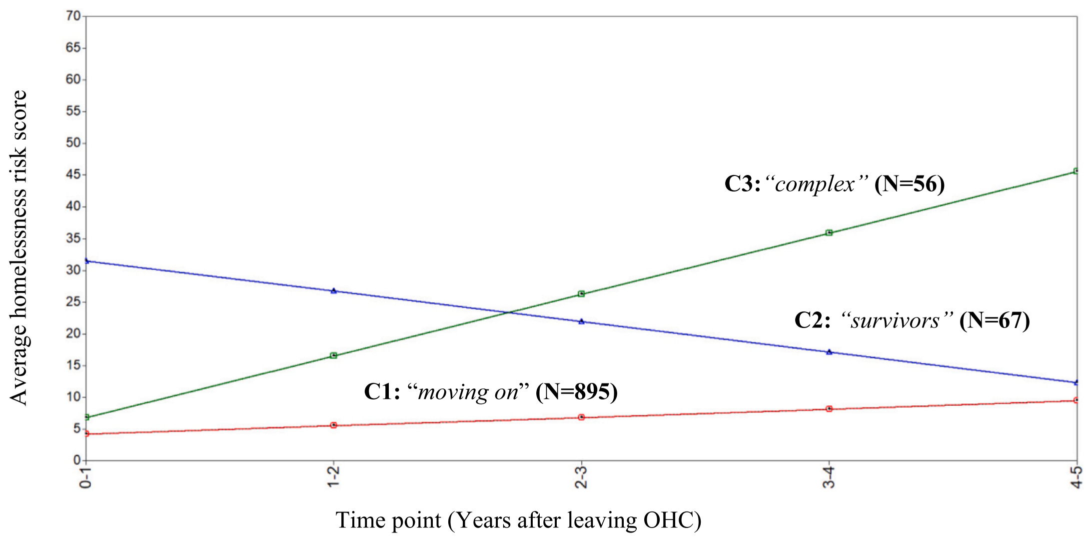

Fig. 1. Latent class growth trajectories.

Table 3
Adjusted associations (Relative-risk ratio RR) of mental health and substance use with homelessness risk trajectory group profiles for OHC study participants over 5 years follow-up.

Characteristic	Class 2: *'Survivors'* (N = 67)		Class 3: *'Complex'* (N = 56)	
	RR (95 % CI)	*p-value*	RR (95 % CI)	*p-value*
Gender				
Male	*Reference*		*Reference*	
Female	0.91 (0.53–1.56)		1.63 (0.88–3.04)	
Indigenous Status				
Not Indigenous	*Reference*		*Reference*	
Indigenous	1.29 (0.72–3.21)		2.13 (1.17–3.87)	*
Location				
Major Cities	*Reference*		*Reference*	
Regional/remote	1.01 (0.59–1.73)		0.62 (0.33–1.16)	
Age of leaving care				
15–16 years	*Reference*		*Reference*	
17–18 years	1.83 (1.07–3.14)	*	0.84 (0.46–1.54)	
Criminal justice involvement	1.04 (0.58–1.88)		1.12 (0.57–2.20)	
Psychological harm victim	1.11 (0.64–1.93)		1.56 (0.81–2.99)	
History of substance misuse	2.13 (1.19–3.82)	*	1.57 (0.83–2.98)	
History of mental health disorders	1.41 (0.80–2.48)		0.91 (0.49–1.71)	
Chronic mental health and substance misuse	1.84 (0.95–3.55)		4.17 (2.21–7.87)	***
Recent placement type				
Kinship care	*Reference*		*Reference*	
Home based/permanent care	2.39 (0.98–5.87)	*	1.48 (0.62–3.52)	
Residential care	3.55 (1.52–8.30)	**	2.41 (1.11–5.23)	*

Multinomial logistic regression significance level: $^{*}p \leq 0.05$; $^{**}p \leq 0.01$; $^{***}p \leq 0.001$.
Reference group: Class 1 *'Moving on'* group.

4. Discussion

4.1. Trajectories of homelessness among sub-groups of young people

Previous studies utilising growth mixture models have tested the hypothesis that sub-groups may exist among young people transitioning from OHC; however, to date, the trajectories of homelessness risk have not been examined in this population group. In this retrospective longitudinal study, we examined trajectories of homelessness risk of young people (15–18 years) over a five-year period after leaving OHC. Overall, findings suggest that there are three distinct groups with different trajectories of homelessness risk. The findings are consistent with prior research indicating that young people transitioning from OHC may comprise three distinct sub-group populations; the *'moving on'*, '*survivors'*, and *'complex'* groups (Bengtsson et al., 2020; Stein, 2008). We also examined factors associated with the various trajectories of these young people.

The largest group, the *'moving on'* group (88 %), had the lowest levels of homelessness risk. This group initially faced low levels of homelessness risk, but the risk gradually increased over time. The group had a significantly higher proportion of young people who were non-Indigenous, those not involved in the criminal justice system, and those who resided in kinship or home-based care. This group also had the lowest proportion of young people with a history of mental health or substance misuse and the lowest rates of chronic mental health and substance misuse disorders compared to the other groups. A similar profile was found in other studies (Courtney et al., 2012; Fowler et al., 2011; Hernandez & Lee, 2020; Keller et al., 2007). While this group had the lowest rates of homelessness, the trajectory suggests gradual increases of homelessness risk within five years, and previous research determines that if young people do not get the necessary supports post leaving care (Bengtsson et al., 2020), the homelessness trajectory could change with sharp increases over time.

The second group, the *'survivors'* group (7 %), initially started with high levels of homelessness risk, which declined significantly over time. This group was associated with having a history of substance misuse disorders and staying in residential or home-based care compared to the *'moving on'* group. This could explain the initial high levels of homelessness risk the first year after leaving care. A history of substance misuse and mental health difficulties has also been shown to elevate levels of homelessness during the first few years after young people leave care (Courtney et al., 2012; Keller et al., 2007). The risk of homelessness among young people aged 17–18 years was higher in this group compared to the *'moving on'* group. This is because of the high initial levels of homelessness risk experienced by young people aged 17–18 years during the first year of leaving care, compared to young people aged 15–16 years. Young people who leave care at a young age (15–16 years) may have re-united with their families or carers, hence the reason why they faced lower rates of homelessness compared to older youth (17–18 years old) in the first few years after leaving care. Previous studies have shown that re-unification usually occurs during the first year after leaving care, with declining re-unification rates over time (Delfabbro et al., 2015; Hines et al., 2007). This is an important finding, given ongoing campaigns to extend the age of leaving care from 18 to 21 years among young people in OHC (Mendes & Rogers, 2020).

The third group, the *'complex'* group (5 %), started with low homelessness risk but faced sharp increases in homelessness risk over time. While this group had the lowest proportion of young people leaving care, the sharp increase in rates of homelessness risk over time is concerning. The increase in homelessness risk may be the result of a lack of support provided to this group of young people. The risk of homelessness among Indigenous young people was higher in this group compared to the *'moving on'* group. This finding is consistent with previous literature where young people of indigenous background are over-represented in the OHC system and have poorer outcomes, regardless of care experience (AIHW, 2020). In addition, the risk was higher among young people who stayed in residential care compared to those in the *'moving on'* group, an indication of inconsistent support offered to young people when they leave care (Miller et al., 2017). Prior research has shown that young people with a history of staying in residential care settings have poorer outcomes, such as mental health difficulties and homelessness, when they exit care (Kelly, 2020). The study has also shown that chronic mental health and substance misuse increases the risk of homelessness over time, particularly for this group.

This result shows that providing integrated mental health and substance misuse services is crucial for this high-risk group who faces increased homelessness risk over time. Policies alone aimed at improving homelessness may be insufficient to significantly reduce homelessness in this group. Further support may be required, such as giving young people opportunities to further their studies or training, ultimately leading to better employment prospects and the ability to secure stable accommodation (Stein, 2006).

4.2. Support for Stein's Theory

The findings from our study provide strong support for Stein's Theory, elucidating three distinct groups based on homelessness and housing instability patterns over time and how certain factors contribute to these. While the *'moving on'* group had the lowest levels of homelessness, the upward trajectory is of concern, especially if there is a lack of extended care and housing support. Consistent with Stein's Theory, the *'survivors'* group were more likely to experience instability, including periods of homelessness after leaving care. We could speculate that the declining homelessness trajectory could be because of a higher proportion of young people leaving care at an older age and possible support they received while leaving care.

Our findings support the notion that mental health and substance misuse interventions could contribute to reducing the trajectory of homelessness among this group since this group was associated with higher levels of substance misuse problems prior to leaving care. The *'complex'* group showed steep increases in homelessness over time, which was mostly associated with chronic mental health and substance misuse problems. This shows that further support should include programs focussing on dual mental health and substance misuse diagnosis. While our study supports Stein's theory, more information may be required on in-care and pre-care experiences to understand the different trajectories of young people leaving care. These may include relationships and support from carers, placement stability, age of entry into care, education, planning for leaving care, and supports received while in and after having left care (Courtney & Heuring, 2005; McGuire et al., 2018; Stein, 2008). This theory should be tested in future research.

4.3. Implications for practice, legislation, and policy

The findings provide evidence for developing a more nuanced approach to interventions for people leaving OHC. The results suggest that policymakers may need to have different approaches for each of these three groups. The low levels of homelessness among the *'moving on'* group could represent the impact of engaging with services or supports on homelessness. Slight adjustments are required for the *'moving on'* group, given that homelessness is slightly increased over time. In addition, given that this is the largest group, and they start from a very low level of risk, it likely does not warrant large amounts of resources.

Given the downward trajectory of homelessness over time, some lessons could be learnt from the *'survivors'* group. Clearly, some interventions seemed to have worked for this group that started off with the highest levels of homelessness with a steep decline over time. This group may require resources and support for the first two years after leaving care, after which fewer resources may be needed to maintain the downward trajectory of homelessness.

New approaches to interventions may be needed for the *'complex'* group. We need to learn from the *'moving on'* group, combined with new innovative ways to reduce homelessness risk for the *'complex'* group, which may involve trauma-informed care and culturally sensitive programs responsive to the needs of Indigenous young people (Mayer, 2019). The interventions have to focus on creating safe spaces for young people to access services without fear of being judged and to build trust and relationships with indigenous young people, acknowledging the trauma that these young people have experienced in their lives (Brooks et al., 2018; Van den Bree et al., 2009).

The low level of homelessness in the *'moving on'* group is reassuring; however, it is clear for the other two groups, the high rate of homelessness could be reduced post leaving care. Evidence has shown that extending support for care leavers could reduce homelessness rates (Mendes & Rogers, 2020). This could potentially result in halving the rate of homelessness among young people leaving care (Mendes & Rogers, 2020). If partnership agreements are to be fulfilled and targets to reduce homelessness and housing stress are to be met in Australia, policymakers would need to have an integrated and coordinated effort in tackling homelessness among the diverse groups of young people in OHC (Johnson et al., 2015).

4.4. Recommendations for future research

This study has identified distinct homelessness and housing instability trajectories among young people leaving care and the factors associated with these. Chronic mental health and substance misuse emerged as a significant predictor of increasing homelessness rates, pointing to a potential bidirectional association between mental health and homelessness, which should be explored in future research.

Future studies should collectively and, perhaps, cumulatively determine which factors (before and during placement in OHC) are strong predictors in identifying future homelessness trajectory group membership. These factors may include in-care characteristics such as the age of entry into care, the type of OHC placement with the most extended duration, placement instability, planning for independent living, carer and agency supports and cumulative abuse (Courtney & Heuring, 2005; McGuire et al., 2018; Stein, 2008). This study showed strong predictors of homelessness trajectories, such as comorbid mental health and substance use after leaving care; however, it is critical to explore how comorbid mental health and substance use before leaving care would influence homelessness trajectories.

In addition, future research could explore how other resilience factors, such as life course agency, could help young people plan for the future (Bengtsson et al., 2020), including planning for independent living (Hojer & Sjoblom, 2014). Other factors include having positive and lasting relationships with carers (Mendes & Purtell, 2020) or exposure to various housing support programs (Tsemberis, 2011), which could further enhance our understanding of the three trajectories that were identified in this study.

Previous studies have shown strong associations between homelessness and employment status and education (Fowler et al., 2011; Hernandez & Lee, 2020) for young people in OHC, which should be explored in future research. The attribution of various housing or mental health interventions on the trajectories of homelessness warrants further research. While this study showed distinct trajectories among the OHC group, it would be valuable to have comparison groups at a population level to determine the type of trajectories that exist among young people who had child protection contact but never lived in OHC or among those who never had contact with the child protection system. All these variables are important in longitudinal research as they may potentially influence how young people adapt to changing situations and functioning over time. The three groups are complex, and there is a need for further research to improve data collection and reporting in child protection systems.

4.5. Limitations

Linked administrative data contain measures used for administrative purposes and may therefore lack outcome data for research (Johnson & Nelson, 2013). The data may therefore need to be augmented with self-reported data. However, the benefits of using administrative data are well documented and outweigh the limitations, particularly for research among hard-to-reach population groups such as young people transitioning from out-of-home care (Hurren et al., 2017; Tew et al., 2017).

As discussed in previous research (Chikwava et al., 2022), the homelessness data from the Victorian homelessness collection only identifies young people who were referred to or attended homelessness services, thus potentially underestimating the true prevalence of homelessness. Further, those who are chronically homeless may not use homelessness services due to stigma or barriers to accessing these services (Randolph et al., 2002). However, by using a more nuanced measure of homelessness in this study, we have tried to capture all forms of homelessness from the least to the most severe.

The mental health and substance misuse measures reported in this study are from public inpatient and outpatient records, and they exclude private outpatient records, thus potentially excluding the less severe forms of mental health disorders. This information may be captured in community-based settings or through interviews with young people who do not access healthcare. Some in-care and pre-care variables that could predict homelessness risk, such as the age of entry into care and placement type with the most extended duration, were unavailable in these datasets.

4.6. Conclusions

Our findings are consistent with previous studies on sub-groups of young people leaving care (Fowler et al., 2011; Keller et al., 2007; Stein, 2008); however, our study demonstrates that subgroups of young people transitioning from care exist with distinct longitudinal trajectories of homelessness, and these classes are associated with different risk factors. The multiple linked datasets used in this study provided a comprehensive set of variables that were used to determine the homelessness trajectories among a group of young people leaving care in one part of Australia. We examined the factors contributing to the homelessness trajectories, including chronic mental health and substance misuse disorders.

While the study showed that not all young people transitioning from OHC are at increased risk of homelessness, the increased risk among the '*complex*' group is a notable finding and worthy of consideration as the basis for targeted interventions. It is critical that policymakers and service providers provide early intervention and different approaches to tackling homelessness for these three distinct groups before transitioning from care and during the first few years after leaving care to improve trajectories and promote positive outcomes (Healey & Fisher, 2011).

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chiabu.2024.106643.

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