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Labour market trajectory clusters and utilisation of healthcare and benefits among the long-term unemployed: a Finnish population-based study

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Abstract

Background There exists limited knowledge regarding the utilisation of services and benefits associated with long-term unemployment. In this study, our objective is to identify distinct pathways into long-term unemployment by analysing patterns of healthcare and social benefit utilisation in relation to individuals' prior labour market positions. This research aims to generate insights that facilitate the early identification and implementation of supportive measures for individuals experiencing or at risk of long-term unemployment.

Methods Within the Finnish working-age population, individuals predominantly unemployed during the years 2020 and 2021, and for whom labour market position data for 2013–2021 was available, were identified ($n = 72{,}485$). The analysis utilised register data from Statistics Finland and the Finnish Institute for Welfare and Health. To identify distinct pathways based on labour market history, sequence analysis was employed. Variations in healthcare and social benefit utilisation across the identified clusters were examined using linear regression models, with adjustments made for potential confounders age, sex, education, living situation, migrant background, and low income.

Results Five distinct clusters were identified based on labour market status during years 2013–2021: unemployed (54%), students (3%), employed (23%), inactive (10%), and those with unstable labour market positions (10%). Healthcare utilisation was most prevalent among individuals who were inactive or unemployed. These clusters also had the highest proportions of individuals with mental and musculoskeletal disorders, as well as elevated rates of sickness absence and recipients of basic social assistance. In the associations between healthcare utilisation and benefit use across clusters, confounding from sociodemographic factors appeared to be minimal, except among students, who showed reduced risk of mental health diagnoses compared to the unemployed after adjusting for age and sex. At the beginning of the observation period, income disparities between clusters were pronounced. By the end, income levels among the unemployed, inactive, and students had converged, while those employed or with unstable employment history had higher income levels.

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Conclusions In planning preventive measures and developing individualised multisectoral services and social security systems for individuals at risk of labour market marginalisation, it is essential to consider their previous labour market positions.

Keywords Unemployment, Health services, Social security

Background

In the European Union, approximately 20% of unemployed individuals have experienced unemployment for a duration of at least two years, whereas an average of 65% have been unemployed for less than one year. In Finland, these proportions are 12% and 80% in the year 2023 [1]. Long-term unemployment is frequently associated with poor health and limited work capacity. Previous literature suggests a bidirectional relationship: individuals with health conditions are often observed to be selected into unemployment [2–4], while prolonged unemployment itself is argued to contribute to health deterioration, for instance, through the loss of social status [5, 6]. Furthermore, low income and wealth have been found to correlate with poor mental health [7, 8], which may partially explain the negative association between unemployment and health. However, studies utilising exogenous variation in unemployment indicate that this association is primarily driven by the selection of unhealthy individuals into unemployment [9, 10]. Nonetheless, long-term unemployment can be preceded by various distinct patterns that differ in terms of health and work capacity. Identifying the diverse backgrounds among the unemployed is crucial for developing suitable and well-targeted services.

Long-term unemployment may be associated with healthcare utilisation in various ways. Nordic studies have demonstrated that health issues during unemployment increase the need for healthcare services [11–13]. Additionally, there are indications of unmet healthcare service needs; individuals who become unemployed may be unable to access services or may choose not to seek care despite the need [11, 13, 14]. Notably, low income and mental health disorders have been found to predict unmet healthcare needs among unemployed individuals [11, 14]. Furthermore, a Finnish study found that individuals with longer durations of unemployment are less likely to have public healthcare visits, whereas no such difference was observed in the use of specialised healthcare [15]. Another Finnish study examining the use of occupational, private, and public healthcare within a 12-month observation period found that overall healthcare visits declined already at the transition to unemployment. However, during the period of unemployment, the use of public primary care was slightly higher among the unemployed compared to their matched controls [12].

In addition to healthcare services, various social benefit patterns may be associated with unemployment, contingent upon work capacity and the duration of unemployment. In Finland, jobseekers who have contributed to an unemployment fund and meet the requisite employment conditions are entitled to an earnings-related unemployment allowance for a maximum of 500 days. In other circumstances, a basic unemployment allowance or labour market subsidy may be applicable. The last-resort financial support, intended for basic living needs, is social assistance. In cases of impaired work capacity, an individual may apply for sickness allowance (SA). According to a Finnish study, unemployed individuals are at an increased risk of SA due to musculoskeletal or mental health diagnoses, both in terms of the incidence and duration of SA spells, compared to upper non-manual workers [16]. When accounting for sociodemographic factors and income, an increased risk was observed for both the incidence and duration of sickness absence due to musculoskeletal diagnoses. For mental disorders or any diagnosis, the increased risk was limited to the duration of sickness absence [16].

Studying healthcare services and benefits in conjunction is essential as they are closely interconnected: The use of disability benefits, unemployment benefits, and social assistance has been found to be associated with increased healthcare service use [17–19]. In high-income countries, access to healthcare has been observed to be related to work capacity, particularly among individuals with chronic diseases [20–22]. Benefits use, on the other hand, reflects underlying health and social needs, shaping incentives and barriers to employment [20–22]. Examining these aspects together enables the identification of service gaps, unmet needs, and interactions between health and financial support systems, facilitating the design of comprehensive, targeted interventions to address vulnerabilities.

In this study, we conduct sequence analysis to identify distinct groups of long-term unemployed individuals based on their labour market information from 2013 to 2021. As our primary interest lies in the most vulnerable individuals in the labour market, we focus on individuals who have been consistently unemployed in 2020 and 2021. Within the identified clusters, we examine the development of healthcare and social benefit use during the observation years from 2013 to 2021. We additionally explore the annual prevalence of mental health and musculoskeletal diagnoses among the identified groups.

Our results reveal diverse health, healthcare, and benefits use patterns that may precede long-term

unemployment and are instrumental in identifying groups that are most vulnerable in the labour market. These findings are significant for planning supportive efforts to reduce long-term unemployment.

Methods

Data

This study utilises register data encompassing the entire working-age population of Finland from 2013 to 2021 (n = 3,223,578 in 2021, age 18 to 64 years). We acquired data on sociodemographics, income, employment status and services, and benefits utilisation from the FOLK modules of Statistics Finland. Information on healthcare utilisation and diagnoses was sourced from the Care Register for Health Care and the Register of Primary Health Care Visits of the Finnish Institute for Health and Welfare). In this retrospective analysis, we initially identified individuals who experienced long-term unemployment during 2020 and 2021, subsequently examining their prior labour market positions from 2013 onwards, including also the years mainly unemployed. The data was limited to those at least 26 years in year 2021 since only those with full information during follow-up time (at least 18 years of age in year 2013) were analysed.

From the individual-level data, we identified those who had been consistently unemployed for a minimum of two years by 2021. Initially, the study population was confined to individuals aged 26 to 64 in 2021 who had been unemployed for at least 22 months during 2020–2021 (11 to 12 months per year) (N = 79,700). Alternatively, individuals were included in the target population if they had been employed for no more than two months during 2020–2021, corresponding to 45–74 days according to Statistics Finland (N = 82,202 after the alternative criterion). The objective of applying these criteria was to capture a comprehensive view of individuals vulnerable in the labour market, including those not necessarily classified as active jobseekers.

Each individual was assigned to one labour market state per year. These states were constructed by utilising two complementary datasets from Statistics Finland—one providing basic information on the labour market situation at the end of each year (unemployment, work, student, other) and the other offering further details on employment service type based on information at the start of each year. Since these two datasets are based on information from slightly different points in a year, we prioritised the categorisation of the labour market states in the following order:

1) Unemployment (UE)
2) UE in employment-promoting activities
3) UE in employment-promoting education
4) Work
5) Student
6) Other (conscripts, parental leave, other)

The sample was restricted to the years 2013–2021, as data on employment services was only available from 2013 onwards. Additionally, only individuals with labour market state information for each year were included (n = 75,319 after exclusion). These constructions limit our study to adults below retirement age who have resided in Finland throughout the entire observation period. Moreover, we excluded individuals who had been on disability pension during the observation years to homogenise the study population to those without permanent work disabilities. The final study population comprised 72,485 individuals, aged 26–64 in the year 2021.

Variables

Healthcare attendance and diagnoses

Primary and specialised healthcare attendance was defined based on the number of days visited within a year. Each visit included ICD-10 diagnostic codes (https://icd.who.int/browse10/2019/en, accessed 10th Dec 2024), indicating either a pre-existing or newly diagnosed condition. These ICD codes were utilised to categorise annual mental (F00–F99) and musculoskeletal (M00–M99) diagnoses in primary or specialised healthcare as binary variables. We combined data from primary and specialised healthcare to determine, on an annual basis, the proportion of participants with a diagnosis (yes/no). The diagnostic categories of mental and musculoskeletal disorders were selected for this study due to their prevalence as the two most common causes of temporary work disability among the working-age population [16]. In the Finnish healthcare system, occupational healthcare (not observed in this study) is available for employed individuals, and student healthcare is available for those in tertiary education. Access to specialised care requires a referral from primary, occupational, or student healthcare in non-emergency situations.

Sickness allowance

Sickness allowance (SA) serves as compensation for income loss due to work incapacity lasting less than one year. Typically, SA is granted following a 10-day waiting period, commencing from the initial day of illness. Consequently, the receipt of SA generally signifies a work incapacity of at least 10 days [23]. However, the waiting period is reduced to one day if the sickness absence is attributed to a previously recognised illness (e.g., recent SA for the same illness or SA commencing post-rehabilitation). Full SA is also extended to non-working groups, including students and the unemployed [24]. Partial SA is available for employed individuals. In this study, SA was classified as a binary variable, indicating whether an

individual received it within a year. The dataset included information on SA disbursed to the insured individual.

Basic social assistance

Basic social assistance (BSA) is provided when a household is unable to fulfil its fundamental needs, such as housing and food. Since this benefit is assessed at the household level, an individual is considered to be receiving BSA if either they or their spouse (an adult residing in the same household) is a beneficiary of BSA. BSA was categorised as a binary variable accordingly.

Unemployment benefits

In Finland, there exist three categories of unemployment benefits. Individuals who are registered with a union and possess a sufficient wage-earning history—defined as having been employed for at least 26 weeks within the 28 months preceding unemployment—are eligible for an earnings-based allowance until they have utilised 300, 400, or 500 days of unemployment benefits. The maximum number of days is contingent upon the individual's age and length of employment history [25]. For those not affiliated with a union but otherwise meeting similar criteria, a basic unemployment allowance, disbursed by the Social Insurance Institution of Finland, is available, amounting to 33.78 euros per day in 2021. In other circumstances, a labour market subsidy, also provided by the Social Insurance Institution of Finland, is accessible. It is important to note that the accumulation of unemployment days (300/400/500 thresholds) is suspended while an individual is receiving a sickness allowance.

Sociodemographic information

We acquired various sociodemographic variables from the FOLK modules of Statistics Finland. Gender was utilised as a binary variable (men/women). Age was considered a discrete variable with 39 levels. Educational attainment was categorised into three levels: basic (nine years of schooling in Finland), upper secondary (general or vocational), and tertiary education (university or university of applied sciences). Marital status was classified into groups of unmarried, married, and divorced or widowed. Household type was divided into four categories: living alone, cohabiting couples, families with children under 18 years of age, and other. The urbanicity of the residential area was defined as a binary variable, indicating whether an individual resides in urban areas or other are. Similarly, migrant background was coded as a binary variable based on the individual's and their parental background. The region of residence was treated as a discrete variable with 21 levels. Additionally, low income was defined as a binary variable, taking the value of one if an individual's disposable income was less than 60% of the median disposable income in Finland [26].

Analytical approach

We conducted a sequence analysis to examine the patterns of social benefit and healthcare service utilisation among the study population within similar clusters, both prior to and during periods of long-term exclusion from the workforce. The sequences were derived from data on the annual labour market status for the years 2013 to 2021. To evaluate the distances between these sequences, we employed the Dynamic Hamming algorithm [27]. Specifically, this algorithm substitutes elements of individual sequences until they achieve complete similarity. The minimum number of substitutions required reflects the degree of similarity between two sequences. Each substitution is weighted by certain cost. In the Dynamic Hamming approach, substitution costs are time-varying and derived in relation to transition matrices from a broader set of sequences observed in the sample. Consequently, higher transition levels between two states at a given time point result in a lower cost for transitions between these states. This process generates a distance matrix that illustrates the similarities between individual-level sequences.

The distance matrix generated by Dynamic Hamming was employed for clustering similar sequences. Specifically, Ward's method was utilised as the clustering solution [28]. To determine the optimal number of clusters, three cluster validation metrics were evaluated: ASWw, HG, and PBC (Supplemental Figure S1).

Subsequently, we analysed sociodemographic factors and the frequency of healthcare and benefit use within each cluster. For categorical variables, *p*-values were calculated using chi-square and Fisher's exact tests. To further assess differences between clusters, effect sizes were calculated using Cramer's V for categorical variables. For continuous variables, *p*-values and effect sizes with 95% confidence intervals were obtained from analysis of variance (ANOVA) using eta-square (η^2). No strong associations were observed between sociodemographic factors, based on correlation coefficients. In the final step, we examined the longitudinal development of healthcare and social benefit use by focusing on the beginning and end of the observation period (years 2013 and 2021). Ordinary least squares (OLS) regression was employed in all analyses [29]. For binary outcomes, a linear probability model was used, as all control variables were categorical [29]. In such cases, the results from the linear probability model are typically comparable to the marginal effects derived from nonlinear models such as logit or probit [30]. Two models were investigated: Model (1), which controls for year of birth fixed effect and sex, and Model (2), which adds fixed effects for education level, household type, civil status, region of residence, urbanicity of residence, migrant background, and low-income status. The cluster 'Unemployed' was used as the reference since

it was the largest cluster in the data, providing a stable baseline for comparison. Additionally, this cluster was the only one in which individuals primarily remained unemployed throughout the entire follow-up period (Fig. 1), thus serving as a meaningful reference point for examining how healthcare and benefit use evolve in other clusters that were in different states prior to unemployment, in comparison to individuals who were consistently unemployed.

This study was conducted using Stata statistical software, version 17.0 (StataCorp. 2021, Stata Statistical Software: Release 17. College Station, TX: StataCorp LLC.) and R version 4.0.5 (https://www.r-project.org/), utilising the packages TraMineR, WeightedCluster, plm, ggeffects, and ggplot2 for the main analyses [31–34]. The analyses were conducted in Statistics Finland's remote working environment, providing access to readily pseudonymised register data.

Results

Five distinct clusters were identified based on individuals' previous labour market positions, who had been out of the labour market for at least two years. These clusters were categorised as unemployed (54%), students (3%), employed (23%), inactive (10%), and unstable (10%) (Fig. 1). To determine the optimal number of clusters, based on validation metrics, we considered four or five clusters as optimal. We selected the five-cluster solution as it identified the group of individuals who had returned to unemployment after temporary participation in the workforce (cluster `Unstable´).

All clusters comprised fewer women than men (34–45%), with an average age of 49 ± 11 years (Table 1). Those previously employed were, on average, older (53 ± 11 years), while students were younger (34 ± 8 years) compared to other clusters. Across all clusters, secondary education, urban living, and low income were prevalent. Apart from the employed cluster, the majority in all other clusters lived alone, whereas living as a couple was more common among the employed. In 2021, over half of the individuals utilised primary healthcare, and nearly one-third accessed specialised healthcare (Supplemental Table S1). Sickness allowance and basic social assistance were most prevalent among individuals in the inactive cluster (8% SA, 58% BSA) (Supplemental Table S2).

Initially, we examined crude estimates of healthcare visits, diagnoses, benefits, and disposable income without adjusting for sociodemographic factors (Figs. 2 and

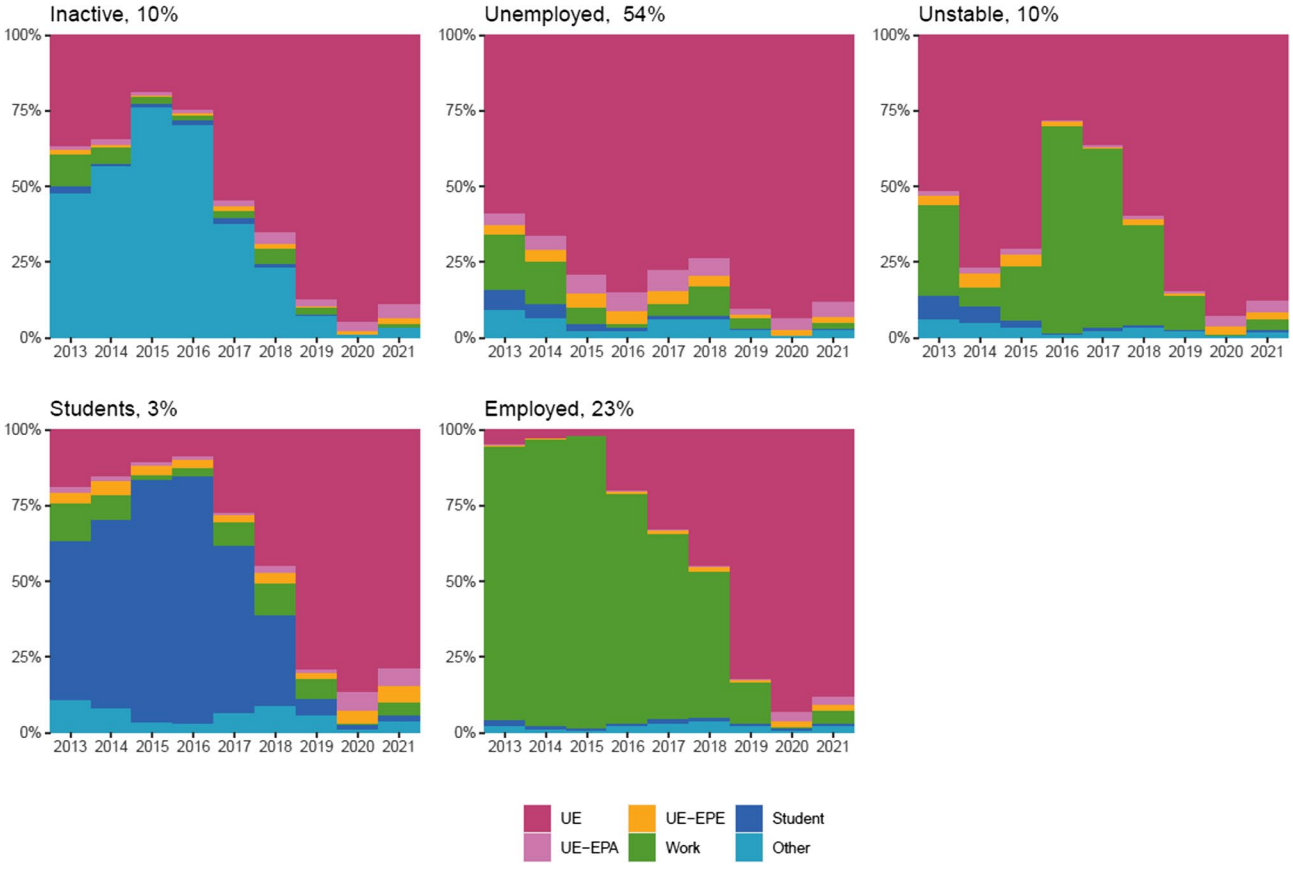

Fig. 1 Five distinct clusters of long-term unemployed individuals, based on labour market history during 2013–2021; UE: unemployment; UE-EPA: UE in employment-promoting activities; UE-EPE: UE in employment-promoting education

Table 1 Descriptive statistics of those individuals unemployed in years 2020 and 2021, age 26–64 years.

Variable	All (*n* = 72,458)	Employed (*n* = 16,995)	Inactive (*n* = 7,026)	Unstable (*n* = 7,237)	Students (*n* = 1916)	Unemployed (*n* = 39,311)	Effect size (eta-square with 95% CI/ Cramer's Vs)
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	
Age	49.3 (11.35)	53.0 (10.53)	45.7 (10.75)	49.7 (11.91)	33.6 (8,15)	49.1 (10.93)	0.09(0.08–0.09)
Disposable income	15,359 (15093)	19,176 (24696)	14,280 (7738)	15,828 (19116)	13,044 (8316)	13,928 (8135)	0.02(0.02–0.02)
	n (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	
Sex							0.07
Women	27,565 (38.0)	7117 (41.9)	3166 (45.1)	2694 (37.2)	643 (33.6)	13,945 (35.5)	
Age categories							0.18
26–35	11,769 (16.2)	1623 (9.5)	1501 (21.4)	1243 (17.2)	1372 (71.6)	6030 (15.3)	
36–45	14,925 (20.6)	2627 (15.5)	2049 (29.2)	1398 (19.3)	347 (18.1)	8504 (21.6)	
46–55	17,355 (23.9)	3586 (21.1)	1779 (25.3)	1509 (20.9)	139 (7.3)	10,342 (26.3)	
56–64	28,436 (39.2)	9159 (53.9)	1697 (24.2)	3087 (42.7)	58 (3.0)	14,435 (36.7)	
Education							0.16
Tertiary	16,421 (22.7)	5573 (32.8)	839 (11.9)	1689 (23.3)	655 (34,2)	7665 (19.5)	
Secondary	34,996 (48.3)	8236 (48.5)	2713 (38.6)	3959 (54.7)	930 (48.5)	19,158 (48.7)	
Basic	21,068 (29.1)	3186 (18.7)	3474 (49.4)	1589 (22.0)	331 (17.3)	12,488 (31.8)	
Civil status							0.14
Unmarried	35,307 (48.7)	5994 (35.3)	3689 (52.5)	3346 (46.2)	1542 (80.5)	20,736 (52.7)	
Married	21,050 (29.0)	7188 (42.3)	1734 (24.7)	2257 (31.2)	248 (12.9)	9623 (24.5)	
Divorced or widowed	16,128 (22.3)	3813 (22.4)	1603 (22.8)	1624 (22.6)	126 (6.6)	8952 (22.8)	
Household type							0.12
Living alone	32,266 (44.5)	5619 (33.1)	3101 (44.1)	2961 (40.9)	975 (50.9)	19,610 (49.9)	
Couples	16,787 (23.2)	6070 (35.7)	882 (12.6)	1906 (26.3)	260 (13.6)	7669 (19.5)	
Family with children	10,901 (15.0)	2437 (14.3)	1710 (24.3)	1054 (14.6)	265 (13.8)	5435 (13.8)	
Other	12,531 (17.3)	2869 (16.9)	1333 (19.0)	1316 (18.2)	416 (21.7)	6597 (16.8)	
Urbanicity							0.07
Urban	55,575 (76.7)	12,705 (74.8)	5448 (77.5)	5180 (71.6)	1672 (87.3)	30,570 (77.8)	
Rural	14,527 (20.0)	3870 (22.8)	1178 (16.8)	1825 (25.2)	187 (9.8)	7467 (19.0)	
Migrant background							0.06
Yes	8686 (12.0)	1551 (9.1)	1048 (14.9)	848 (11.7)	163 (8.5)	5076 (12.9)	
Low income							0.24
Yes	54,521 (75.2)	9700 (57.1)	5586 (79.5)	5230 (72.3)	1645 (85.9)	32,360 (82.3)	

For continuous variables *p*-values and effect sizes from analysis of variance (ANOVA) using eta-square(η^2). For eta-square results, 95% confidence intervals are shown. The cut-off values: $\eta^2 = 0.01$, small effect; $\eta^2 = 0.06$, medium effect; and $\eta^2 = 0.14$, large effect. For categorical variables, *p*-values with chi-square and Fisher's exact tests, effect sizes from Cramer's V. The cut-off values V = 0.1 small; V = 0.3 medium; V = 0.5 large effect. All basic character variables had *p*-value < 0.001

3). When considering average trends in healthcare and social benefit use, as well as annual mental health and musculoskeletal disease diagnoses, healthcare utilisation was most common among those primarily inactive prior to long-term unemployment (Fig. 2). The proportion of mental health diagnoses increased most within the students (year 2013: 14%, year 2021: 24%) and employed (year 2013: 5%, year 2021: 13%) clusters (Fig. 2, Supplemental Table S1). In musculoskeletal diagnoses, the increase was most notable within the employed cluster (year 2013: 10%, year 2021: 19%). In social benefits use, the differences between clusters decreased over time, except for BSA (Fig. 3, Supplemental Table S2). In BSA, the highest share was observed among the inactive (year 2013: 52%, year 2021: 58%) and the lowest in the employed cluster (year 2013: 6%, year 2021: 18%) (Fig. 3, Supplemental Table S2).

The regression analysis, which examined the initial and final years of the observation period while controlling for specific sociodemographic factors, identified statistically significant variations in healthcare outcomes across different clusters compared to the unemployed (Table 2). Individuals who were employed or in unstable labour market conditions consistently exhibited lower rates of both primary and specialised care visits, as well as mental health diagnoses, relative to the unemployed cluster. For students, primary care utilisation was also reduced compared to the unemployed, although no notable differences were observed in specialised care visits. In contrast to unadjusted results (Fig. 2), students demonstrated a reduced probability of mental health diagnoses compared to the unemployed in 2013 (fully adjusted model, Table 3), with no significant difference observed in 2021. Those who were inactive prior to long-term

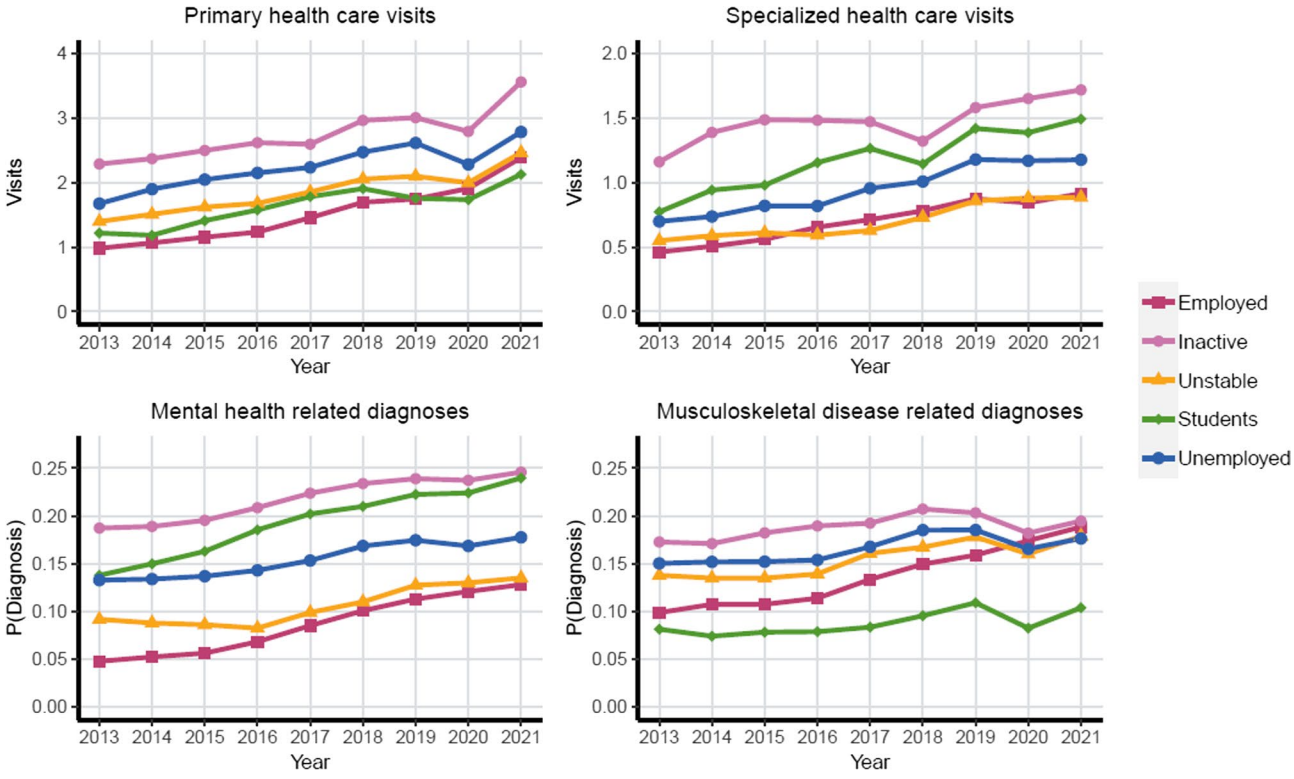

Fig. 2 Health care visits and diagnosis information by clusters identified among those unemployed during years 2020–2021

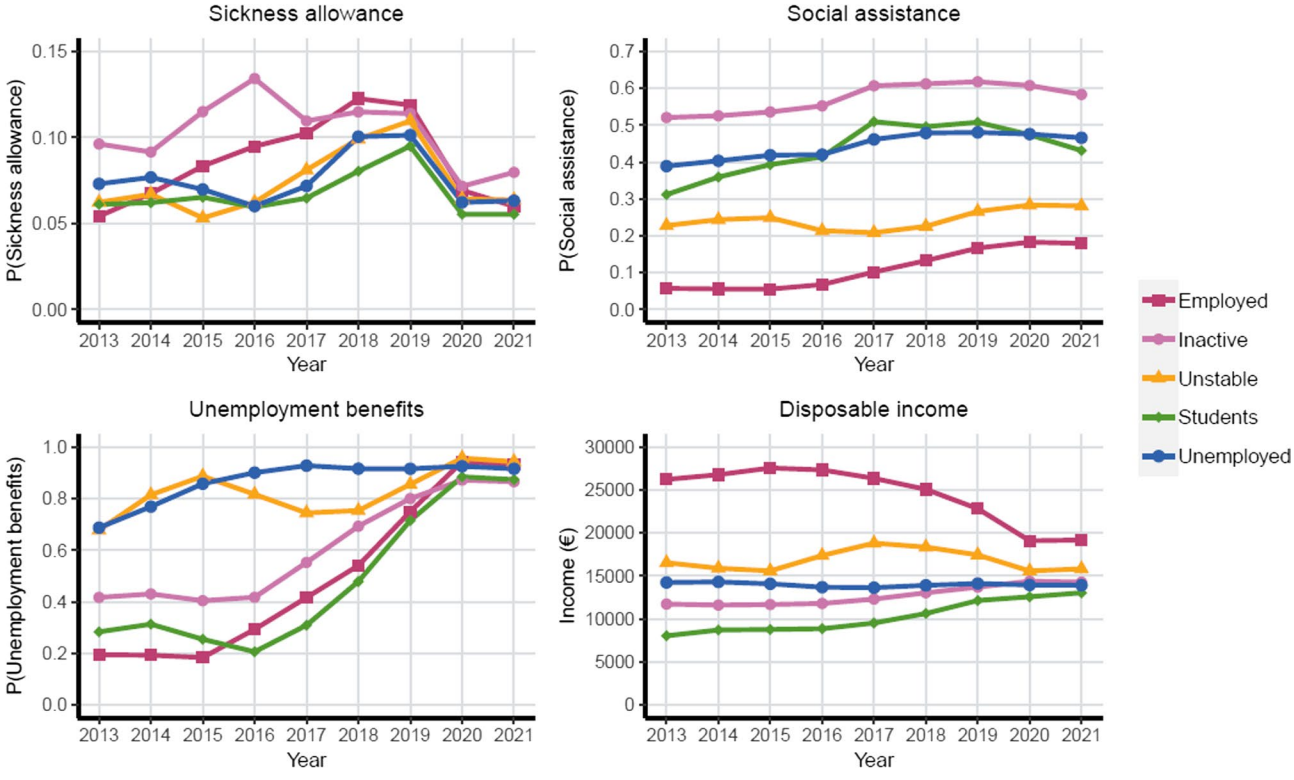

Fig. 3 Social benefit use and disposable income by clusters identified among those unemployed during years 2020–2021

Table 2 Health care visits and probability of mental health and musculoskeletal disorder diagnoses by clusters based on labour market information in years 2013 to 2021 for those 26–64 years in year 2021 and mainly unemployed both in year 2020 and 2021. The reference group is cluster 'unemployed"

Model specification	Model (1)		Model (2)	
	2013	2021	2013	2021
Primary care visits				
Employed	−0.660***	−0.281***	−0.656***	−0.425***
	(0.032)	(0.077)	(0.035)	(0.08)
Inactive	0.517***	0.588***	0.369***	0.507***
	(0.045)	(0.108)	(0.045)	(0.108)
Returned to UE	−0.236***	−0.281***	−0.198***	−0.318***
	(0.044)	(0.106)	(0.044)	(0.106)
Students	−0.395***	−0.918***	−0.319***	−0.729***
	(0.084)	(0.202)	(0.084)	(0.202)
Specialized care visits				
Employed	−0.193***	−0.147***	−0.245***	−0.156***
	(0.028)	(0.043)	(0.031)	(0.045)
Inactive	0.372***	0.398***	0.368***	0.392***
	(0.039)	(0.06)	(0.04)	(0.061)
Returned to UE	−0.133***	−0.266***	−0.129***	−0.238***
	(0.039)	(0.06)	(0.039)	(0.059)
Students	0.006	−0.046	0.015	0.05
	(0.074)	(0.114)	(0.074)	(0.114)
P(Mental health diagnosis)				
Employed	−0.070***	−0.021***	−0.064***	−0.022***
	(0.003)	(0.003)	(0.003)	(0.004)
Inactive	0.040***	0.042***	0.033***	0.039***
	(0.004)	(0.005)	(0.004)	(0.005)
Returned to UE	−0.036***	−0.034***	−0.030***	−0.032***
	(0.004)	(0.005)	(0.004)	(0.005)
Students	−0.030***	−0.024***	−0.025***	−0.014
	(0.008)	(0.009)	(0.008)	(0.009)
P(Musculoskeletal disease diagnosis)				
Employed	−0.057***	0.006	−0.060***	−0.007*
	(0.003)	(0.004)	(0.003)	(0.004)
Inactive	0.022***	0.017***	0.013***	0.013***
	(0.004)	(0.005)	(0.004)	(0.005)
Returned to UE	−0.010**	0.006	−0.010**	−0.0005
	(0.004)	(0.005)	(0.004)	(0.005)
Students	−0.029***	−0.025***	−0.022***	−0.01
	(0.008)	(0.009)	(0.008)	(0.009)
Controlling for:				
Birth year + gender	X	X	X	X
Additional sociodemographics			X	X
Observations	72 485	72 485	72 485	72 485

The estimates are presented for the first and last years of the follow-up period, indicating years 2013 and 2021. Model (1) controls for year of birth fixed effects and sex. Additional sociodemographics controlled for in Model (2) include fixed effects for education level, household type, civil status, region of residence, and indicators for urbanicity of residence, migrant background, and low income -status. Standard errors are shown in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. UE = unemployment

unemployment showed higher utilisation of both healthcare services and a greater likelihood of mental health and musculoskeletal disease diagnoses than unemployed individuals.

Employed individuals had a lower probability of receiving social benefits at both the beginning and end of the observation period compared to the unemployed (Table 3). Inactive individuals consistently exhibited a higher likelihood of receiving sickness allowance and social assistance than the unemployed. Those with unstable unemployment were less likely to receive social assistance throughout the observation years but were more likely to receive unemployment benefits. Students did not differ from the unemployed in their use of sickness allowance at either the beginning or end of the observation period.

Regarding disposable income, significant differences were observed in 2013, particularly between employed and unemployed individuals (10,936.320€, standard error [SE] 121.13, p-value < 0.001). By the end of the observation period, those who had been employed or in unstable labour market conditions prior to unemployment had higher disposable income compared to the 'unemployed' cluster, whereas those who had been inactive or in studies did not exhibit statistically significant differences compared to the unemployed.

In this study, data from both men and women were pooled as the results of the sequence analysis, when conducted separately for each gender, were similar. Additionally, descriptive statistics revealed comparable results for both men and women (data not shown). In terms of sociodemographics, only a few sex differences were identified: tertiary education (29% vs. 19%), being married (38% vs. 24%), and migrant background (16% vs. 10%) were more prevalent among women than men. Furthermore, the proportion of individuals with mental health diagnoses was similar for men and women across clusters, except among students, where women had a higher share of those with mental or musculoskeletal diagnoses compared to men. In terms of healthcare visits, both in primary and specialised care, women had a higher proportion of individuals with any visits compared to men.

Discussion

In this study, we identified five distinct clusters among individuals who were long-term unemployedin both 2020 and 2021, based on their labour market positions from 2013 to 2021. These clusters exhibited variations in their utilisation of healthcare services and social benefits, as well as in their sociodemographic characteristics. Across all clusters, the proportion of individuals with mental health diagnoses increased from 2013 to 2021. Regarding health service and benefit utilisation, individuals who were out of the labour market for unspecified

Table 3 Sickness allowance, social assistance and unemployment benefits, and disposable income by clusters based on labour market information in years 2013 to 2021 for those 26–64 years in year 2021 and mainly unemployed both in year 2020 and 2021. The reference group is cluster 'unemployed"

Model specification	Model (1)		Model (2)	
	2013	2021	2013	2021
P(Sickness allowance)				
Employed	−0.020***	0.003	−0.026***	−0.001
	(0.002)	(0.002)	(0.003)	(0.002)
Inactive	0.022***	0.013***	0.024***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
Returned to UE	−0.009***	0.006*	−0.012***	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Students	0.008	−0.007	0.01	−0.001
	(0.006)	(0.006)	(0.006)	(0.006)
P(Social assistance)				
Employed	−0.295***	−0.228***	−0.221***	−0.158***
	(0.004)	(0.004)	(0.004)	(0.004)
Inactive	0.115***	0.086***	0.088***	0.059***
	(0.006)	(0.006)	(0.005)	(0.005)
Returned to UE	−0.149***	−0.163***	−0.108***	−0.121***
	(0.005)	(0.006)	(0.005)	(0.005)
Students	−0.157***	−0.174***	−0.119***	−0.100***
	(0.01)	(0.011)	(0.01)	(0.01)
P(Unemployment benefits)				
Employed	−0.500***	0.000	−0.410***	0.001
	(0.004)	(0.003)	(0.004)	(0.003)
Inactive	−0.259***	−0.041***	−0.247***	−0.032***
	(0.006)	(0.004)	(0.006)	(0.004)
Returned to UE	0.000	0.025***	0.015***	0.023***
	(0.006)	(0.004)	(0.006)	(0.004)
Students	−0.259***	0.022***	−0.262***	0.016**
	(0.011)	(0.007)	(0.011)	(0.007)
Disposable income				
Employed	10,936.320***	4,659.602***	9,824.712***	4,087.251***
	(121.13)	(139.058)	(120.124)	(140.178)
Inactive	−1,600.850***	560.926***	−1,612.429***	242.477
	(168.783)	(193.764)	(164.901)	(192.73)
Returned to UE	2,165.482***	1,548.080***	1,893.984***	1,446.611***
	(166.287)	(190.899)	(161.84)	(188.706)
Students	−877.559***	130.399	−1,166.730***	−561.06
	(317.331)	(364.299)	(308.336)	(360.748)
Controlling for:				
Birth year + gender	X	X	X	X
Additional sociodemographics			X	X
Observations	72 485	72 485	72 485	72 485

The estimates are presented for the first and last years of the follow-up period, indicating years 2013 and 2021. Model (1) controls for birth year fixed effects and sex. Additional sociodemographics controlled for in Model (2) include fixed effects for education level, household type, civil status, region of residence, and indicators for urbanicity of residence, migrant background, and low income -status. In the estimation of disposable income, indicator for low income status was excluded. Standard errors are shown in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

reasons (denoted as 'inactive') consistently demonstrated the highest levels of use compared to other clusters throughout the observation period. These results corroborate previous research findings that have identified an interconnection between healthcare service utilisation and benefits use [18–22, 35]. Our findings contribute to existing knowledge by highlighting labour market background as a key indicator of diverse patterns in healthcare and benefit use.

Generally, prolonged unemployment is considered to be associated with poor health [2–6, 36], which is also reflected in our research: the proportion of individuals

with diagnoses (mental or musculoskeletal) and the number of healthcare visits increased during the observation period across all clusters. This occurred even during the last two observation years when participants were unemployed. Previous studies have shown that the association between unemployment and health may depend on age [36, 37]. Our results did not confirm an increased mental health risk among the youngest cluster (students) [36], but they support the notion that older individuals may be at greater risk for overall health issues [37]. An US study focusing on health at age 50 found that mid-career and persistently high unemployment were associated with worse mental and physical health [38]. This aligns with our findings, which indicate that individuals in the inactive and unemployed clusters were most likely to have mental health and musculoskeletal disease diagnoses. Moreover, based on previous knowledge which have shown declined or stable health care use in event of unemployment [11, 12, 14, 15], we anticipated a decrease in service use among those in unemployment throughout the follow-up period. However, our findings showed increased service use over time. Additionally, the findings revealed that the identified clusters differed from each other in their service use already at the beginning of the observation period, with those inactive being most active in attendance.

Despite strong evidence on link between UE and health, and our findings being in line with those, there exists studies that have not confirmed this link. In a German study with 2,400 participants, 31–60 years, and a 5-year follow-up, decreased work ability was shown to contribute to non-employment, measured as combination of information on SA, UE, and disability pension but not when considering work ability and UE alone [39]. In a study showing worsening health in the transition from employment to unemployment, no effect on health in relation to the length of the unemployment spell was found [37]. This controversy warrants more investigation.

In addition to examining healthcare visits and diagnostic information, our research focused on the utilisation of social benefits. Generally, the granting of SA is indicative of health issues that impede work participation, whereas receiving BSA can be considered an additional life stressor [40]. Similar to healthcare data, we observed early differentiation among clusters based on their social benefits profiles. Both for SA and BSA, those inactive had highest proportions. For UE benefits, those unemployed through follow-up time and with unstable employment, had high proportions through follow-up time on UE utilisation, while the other clusters had increased use over time. For SA, there was a clear decline during the last two years of observation which warrants further investigation to determine whether it is related to unemployment or the impact of the COVID-19 pandemic, latter which may have affected healthcare access [41].

Across all our measures (service and benefits utilisation), individuals inactive in the labour market exhibited the highest healthcare visits, the highest proportions of mental or musculoskeletal diagnoses, and the highest receipt of BSA. Overall, the findings on healthcare and benefits utilisation support the notion that work incapacity is a significant factor contributing to prolonged exclusion from the labour market [8–10, 36].

Furthermore, unemployment, along with the often-consequent low income and loss of social status, is considered a stressful event with potential negative health consequences [2–8]. We considered low income as a potential confounder in our analysis; however, in most cases, confounding due to sociodemographic factors was not evident. An exception was observed among students, who were at the same or lower risk for mental health diagnoses compared to the unemployed in models adjusted for sex, age, and additional characteristics, while unadjusted results suggested a greater risk for students.

This study aimed to provide a comprehensive overview of long-term unemployment by examining both healthcare service and benefits utilisation both before and during unemployment. Our findings support previous reports indicating a linkage between healthcare utilisation and BSA receipt [18] and introduce the component of previous labour market position as a predictor of healthcare and benefits utilisation. While our results do not directly address unmet health needs, they suggest that BSA receipt, rather than SA, aligns more closely with healthcare visits. When comparing healthcare visit data with SA, these results may indicate an underutilisation of SA by the unemployed, consistent with earlier Finnish population-based studies [16].

Practical implications

In examining the demographics of individuals experiencing long-term unemployment, it is imperative to emphasise preventive measures early in their working lives. Our findings reveal that a significant number of those in long-term unemployment encounter health-related issues. Consequently, healthcare systems must ensure accessibility for unemployed individuals. In addition, interaction between health and financial support systems need to be developed in order to recognise unmet service needs and service gaps. Furthermore, given that our results indicate a minimal influence of sociodemographic factors as confounding variables, we posit that labour market history serves as a robust predictor of service and benefits utilisation. This should be considered when developing services for individuals facing long-term unemployment.

Strengths and limitations

The strengths of this study include the comprehensive data encompassing the entire Finnish working-age population, with complete registry information available throughout the observation period. This comprehensive dataset facilitated the inclusion of individuals experiencing long-term unemployment, a demographic typically challenging to access at this scale. Notably, during the observation years, there were no significant legislative changes that could have influenced our findings. Although several governmental initiatives aim to enhance healthcare access for the unemployed, we consider their impact on our results to be minimal.

The limitations of this study primarily stem from the exclusive reliance on register-based data. The absence of self-reported health information constrains our ability to assess unmet healthcare needs or identify service gaps. Furthermore, regarding the 'other' labour market state, the available data did not permit further differentiation of the reasons for this classification, as factors such as parental leave or entrepreneurship accounted for only a portion of this group. Our analyses were aggregated for both men and women, as no significant differences were observed in cluster analysis or sociodemographic factors. In contrast to a Norwegian study on post-unemployment events, which reported increased healthcare utilisation among men compared to women [42], our findings indicated that women had a similar or higher proportion of individuals with diagnoses and healthcare visits (data not shown).

The descriptive statistics for the study population suggest that clustering by labour market history effectively delineated distinct types of individuals. Variations in education, household type, and urban versus rural residence further substantiate this division, providing a credible foundation for examining the relationship between labour market history and healthcare service and benefit utilisation prior to and during ongoing unemployment. Future research should aim to integrate information on perceived work capacity and functional limitations to enhance understanding of barriers to work participation among the long-term unemployed and their relation to service and benefit utilisation. We consider these findings to be applicable to Nordic countries with similar welfare and labour market structures.

Conclusions

In this study, we identified five distinct clusters among individuals experiencing long-term unemployment, categorised according to their previous positions in the labour market. These clusters demonstrated significant variations in their utilisation of healthcare services and benefits, with those inactive in the labour market exhibiting the highest usage of healthcare services. Overall, we contend that our findings offer valuable insights into individuals vulnerable within the labour market. This information can facilitate the development of targeted, integrated multisectoral services designed to address the needs of individuals excluded from the workforce.

Abbreviations

BSA	Basic social assistance
SA	Sickness absence
UE	Unemployment
UE-EPA	Unemployed in employment-promoting activities
UE-EPE	Unemployed in employment-promoting education

Supplementary Information

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Supplementary Material 1.

Authors' contributions

SK, JL, MM, PS were all part of planning the study concept and design and interpreting the results. SK and JL conducted the data analysis and wrote the original draft. MM, PS revised and edited the draft. All authors have read and approved the final version of this manuscript.

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Data availability

The data for this study are available from Statistics of Finland and the Finnish Institute for Health and Welfare. Restrictions apply to the availability of the data, which were used under license for this study (data permissions: THL/4830/6.02.00/2022, TK/476/07.03.00/2023). The permission for the secondary use of the data can be applied from Finnish Social and Health Data Permit Authority Findata. Instructions for applying are available at Findata website: https://findata.fi/en/permits. Contact information for guidance and advice is info@findata.fi.

Declarations

Ethics approval and consent to participate

This research is based on register data and has been conducted according to ethical principles of Declaration of Helsinki. For this project, consent to participate and assessment in ethics committee was waived by the Finnish Institute for Health and Welfare Ethics committee as not applicable conforming to Finnish legislation (Data Protection Act, Finland, 1050/2018, available at: https://www.finlex.fi/en/laki/kaannokset/2018/en20181050.pdf). Authors had access to pseudonymized data in secure remote environment provided by Statistics of Finland.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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