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Patterns and correlates of sickness absence before and during the COVID-19 pandemic in a cohort of Finnish public sector employees

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Abstract

Background As a global health crisis, the COVID-19 pandemic offered a unique opportunity to identify sickness absence (SA) patterns consisting of long and short episodes and total number of SA days in a cohort of Finnish public sector employees while comparing to pre-pandemic timepoint.

Methods Survey data from 39,791 employees in four Finnish cities in 2020 were linked to SA records between Jan-1 and Dec-31, 2021. We used K-means modelling on short (1–9 days) and long (10–365 days) episodes and total numbers of SA days. For comparison, we analysed 2019 (pre-pandemic) SA records. Employee and work characteristics associated with SA patterns were analysed using multinomial regression.

Results Four distinct SA patterns during COVID-19 were identified: Low SA ($n=31,320$, 79%), repeated short episodes ($n=5149$, 13%), repeated long episodes ($n=2964$, 7%), and very high SA ($n=358$, 1%). Compared to others, employees with low SA were less likely to have had a first-wave COVID-19 infection, more frequently worked from home, were more often men in higher occupational positions, had lower body mass index, lower smoking and higher alcohol abstinence rates. Repeated short episodes were associated with younger age and team reorganization, whereas repeated long episodes and very high SA were linked to older age. Except for fewer overall SA days, the pre-pandemic SA pattern structure was similar.

Conclusions We identified four distinct SA patterns with different employee correlates during the COVID-19 pandemic. These patterns appeared stable over time, as similar profiles – albeit with lower overall SA rates – were evident before the pandemic.

Keywords Sick leave, Absenteeism, Long-term, Short-term, Clustering, COVID-19

1 Introduction

Sickness absence (SA) has significant costs for the employees, employers, and societies in terms of income and productivity losses and workers' compensations [1, 2]. In European countries, the number of workers absent from work due to illness or disability

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increased from 3.6 million in 2006 to 5.2 million in 2020, the absence rate being approximately 3% for working men and 4% for women in 2020 [1].

SA is a complex and multidimensional phenomenon and can be viewed from several different perspectives and disciplines [1, 3, 4]. Individual and work-related factors are associated with the causes, frequency, and duration of SA [1, 4, 5]. Repeated, or long absence episodes, for example, have been linked to older age and increased risk of disability retirement [6–8], unemployment [6, 9], and mortality [10, 11].The global COVID-19 pandemic had a significant impact on workers, workplaces, and work practices [12], including higher rates of SA among employees who contracted COVID-19 infection [13]. However, few studies have examined the clustering of episode length and total absent days, or the factors associated with these patterns during the pandemic.

As a global health crisis affecting the whole workforce, the pandemic offers a unique opportunity to identify distinct SA patterns and explore their employee- and work-related correlates. Understanding the factors that contributed to SA during the COVID-19 pandemic can guide the development of targeted strategies to prepare for future pandemics. Identifying these correlates also support evidence-informed resource allocation, including adequate staffing, occupational health services, and the creation of supportive work environments. Recognizing possible distinct SA patterns and identifying risk groups is important for work disability management. Furthermore, understanding factors associated with SA during a pandemic may also inform strategies to reduce work loss in a non-pandemic context, as many of these factors influence SA independently of pandemic conditions.

To interpret the SA patterns, the Work Ability model [14] provides a useful theoretical framework. This model emphasizes the dynamic balance between an individual's characteristics—such as health, functional capacities, and skills—and the demands of work. When this balance is disrupted, for example due to increased workload, uncertainty, or pandemic, work ability may decline, potentially leading to SA.

The aim of this study was to identify patterns of SA based on total SA days and the number of short and long episodes among Finnish public sector employees during the COVID-19 pandemic in 2021. To ensure the correct temporal relationships, we examined individual and work-related correlates in 2020, preceding the SA patterns. To assess whether these patterns were unique to the pandemic, we also analysed SA patterns from 2019, prior to the pandemic.

2 Methods

2.1 Participants and setting

This is a nested cohort study within the ongoing Finnish Public Sector study (FPS) [15]. The FPS survey is distributed online by the Finnish Institute of Occupational Health (FIOH). In the current study, we used data gathered from employees of four large Finnish cities ($N = 58{,}971$). No financial incentives were provided for respondents by FIOH. Participating organizations have participated in FPS study for 10 to 20 years (depending on organization). Thus, FIOH has long history in cooperating with them. As the organizations are highly committed, they try their best to make sure people respond to this survey. Some organizations have lotteries with small prizes (cinema tickets etc.) to encourage participation. The employees in these cities cover a wide range of occupations, from administrative positions to manual work. The most common occupations are

in social and health care and education, which represent nearly 50% of all occupational groups [15, 16]. For those participants who gave consent to link their survey responses with register data (no consent, $n = 3490$), the survey data gathered in September-October 2020 (response rate 73%) were linked with SA data from January 1 to December 31, 2021, retrieved from employer registers ($n = 39{,}731$). This sample was used to create SA patterns, i.e., clusters. For regression modelling, the final analytic sample consisted of 34,394 participants with complete data on all relevant variables (Fig. 1). The FPS study was approved by the Ethical Committee of the Helsinki and Uusimaa Hospital district (HUS/1210/2016). All methods were carried out in accordance with relevant guidelines and regulations.

In Finland, the first coronavirus case was diagnosed for a Chinese tourist on January 29th, 2020. COVID-19 was classified as a generally hazardous communicable disease on February 13, 2020, and the spread of the virus began to escalate in early March, influenced by travel to the Alps during February's winter holidays. The epidemic was considered to have started in mid-March, shortly after the WHO declared COVID-19

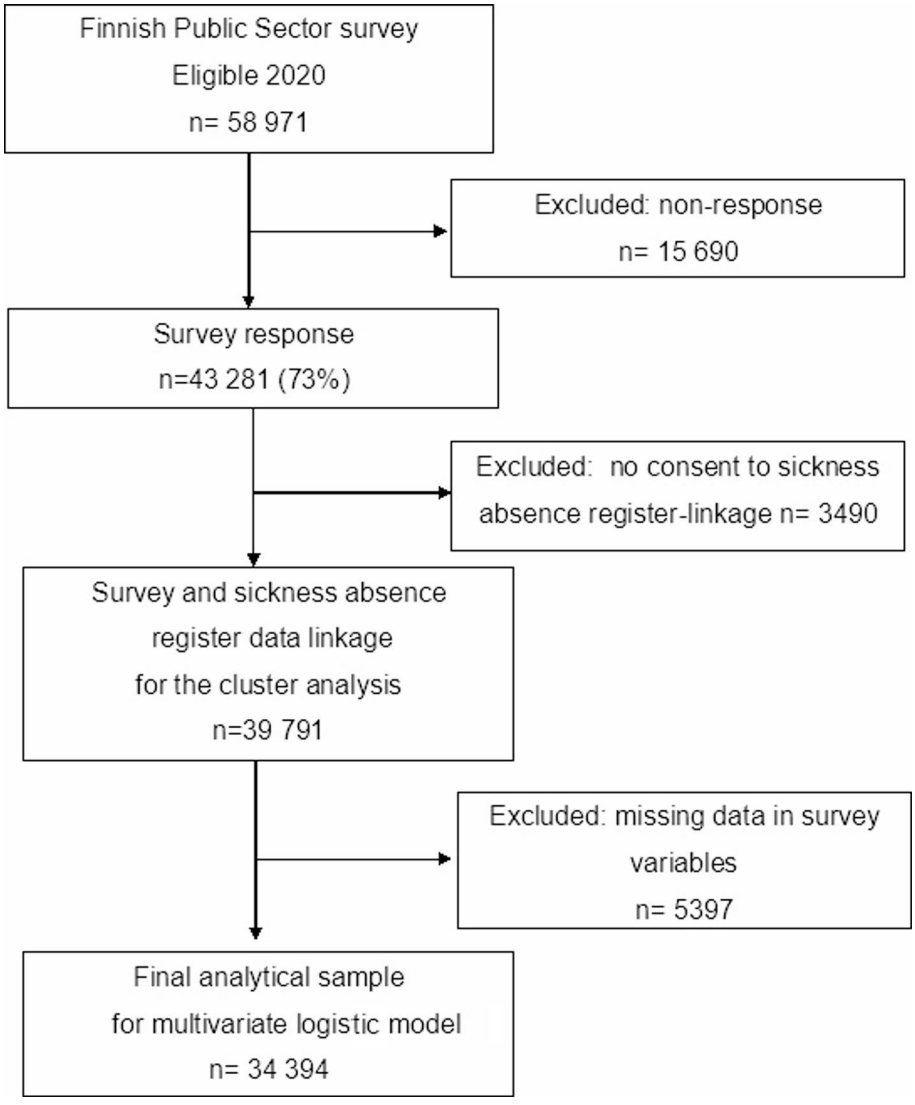

Fig. 1 Flowchart of the study participants

a pandemic. On March 16, 2020, the Finnish Government declared a state of emergency and implemented physical distancing measures to slow the spread and protect risk groups and mandated the closing of schools, restaurants, and other public places and implemented working from home policy for workplaces [16, 17]. Across the Nordic countries, Finland had the lowest incidence rate, with 1.4 COVID-19 cases per 1000 population 4–6 months after the start of the pandemic, compared with 1.7 in Norway, 2.4 in Denmark, and 7.8 per 1000 population in Sweden. Mortality rates showed a similar pattern: Norway and Finland had the lowest levels (0.05 and 0.06 deaths per 1000), clearly lower than in Denmark (0.10) and especially Sweden (0.54) [16, 18]. Compared to many other countries, Finland experienced the onset of pandemic later. This delay allowed Finnish authorities to implement preventive restrictions—such as closing schools, limiting public gatherings, and encouraging remote work—before widespread community transmission occurred. These early measures helped mitigate and postpone the impact of the pandemic compared to countries where restrictions were introduced only after significant spread. Finland acted proactively, which contributed to a slower initial infection rate and reduced pressure on the healthcare system, which enabled governmental recommendations and restrictions early on [17]. Together with a high testing rate, this possibly contributed to the relatively low number of COVID-19 infections and mortality [16–18].

2.2 Sickness absence

SA information from the period before the COVID-19 pandemic (1.1.–31.12.2019) and during the pandemic (1.1.–31.12. 2021) were retrieved from employers' registers. Employers are legally required to record all SA along with other absence from work to ensure salary or sickness allowance paid by Social Insurance Institution of Finland during SA [19] but they are not allowed to record SA diagnosis [20]. Depending on employer, short SA can be based on self-certification, but all episodes lasting for 10 days or more require medical certificate. If the SA lasts for more than 30 days, the employer must inform its occupational health care service provider to ensure that sufficient actions are taken to support work ability. The maximum days of sickness allowance is 300 days for the same illness, after which, if the disability continues, other social security benefits are possible. For these reasons, these data include all SA days from the first day onwards without information on diagnosis behind SA. The data are reliable, as they are based on salary data on working times with interruptions (including SA). Previous research has shown register-based SA, and long-term episodes in particular, to be a valid measure of health and to accurately predict mortality [10, 11]. Data on SA were measured as the total annual number of (1) SA days (2) of short (1–9 days) SA episodes, and (3) of long (10–365 days) SA episodes.

2.3 Employee and work-related correlates

The following potential determinants of SA patterns were retrieved from the 2020 online survey.

Employee characteristics: sex, age (continuous), marital status (married/cohabiting, single, divorced/widowed), body mass index calculated using self-reported height and weight and expressed as kg/m^2 (continuous). Smoking was classified as never, ex-, or current smoking, and alcohol use as no, moderate (1–12 weekly units for women, 1–24

weekly units for men), or at-risk use (> 12 weekly units for women, > 24 weekly units for men) cut points based on Finnish Current Care Guidelines [21].

Commute mode was defined as weekly days of commuting by 1) walking, 2) cycling, 3) public transport with ≥ 1 km walking or cycling 4) public transport with < 1 km walking or cycling, and 5) car. The scale was from daily to never, where "daily" was converted to 5 days per week, "a few times a week" to 3 days, "about once a week" to 1 day, "less than once a week" to 0.5 day, and "never" to 0. Weekly commute with each mode were asked separately for winter and summer weather. These were summed and resulting weekly days were divided by two [22, 23].

First-wave COVID- 19 infection (before Oct 2020; yes vs. no) was based on self-report of own or physician's estimation or confirmation by laboratory test.

Information on self-rated health and work ability was gathered using following validated single-item questions: "How do you rate your health?" (1 = poor,…,5 = good) [24] and "Let's assume that your work ability at its all-time best would be given 10 points, and 0 points would indicate that you are completely unable to work. How would you score your current work ability? " [25]. Both these items were treated as continuous in the analyses.

Work characteristics: job contract (temporary vs. permanent), working time mode (shift work vs. no shift work), occupation -based socioeconomic status (SES) categorization based on the 2001 International Standard Classification of Occupations (ISCO) [26] codes as high (managers and senior specialists, such as physicians and teachers), intermediate (specialists, office workers, customer service, and health and social care workers), and low (manual workers, including construction and cleaning services workers, and practical nurses).The consequences of COVID-19 pandemic were asked in relation to transfer to working from home (yes vs. no), transfer into new tasks (yes vs. no), and team reorganization (yes vs. no) due to COVID-19 pandemic [15].

2.4 Statistical analysis

To identify different patterns of SA behaviour, we performed clustering with k-means model by SAS FastClus procedure intended for use in large data sets [27, 28]. The procedure uses Euclidean distances where cluster centres are based on least squares estimation. The clustering variables were total number of SA days, of short (1–9 days), and of long (10–365 days) SA episodes in 2021. Prior to clustering we used standardization to mitigate the influence of variables with larger scales from dominating how clusters are defined. Standardisation rescales the variables to conform to a standard normal distribution with a mean of 0 and standard deviation of 1, thereby ensuring equal weight for all variables during the clustering process [28, 29]. Total number of SA days correlated strongly with long SA episodes (r=.77), and moderately with short SA episodes (r =.30). The correlation between long and short SA episodes was rather low (r=.21).

K-means cluster analysis requires determining the number of clusters [27, 29]. We tested solutions involving 3–5 clusters and chose the optimal number based on cluster metrics (Supplementary Table 1). We started with a 5-cluster solution, which was rejected as it produced two very small clusters. The 4-cluster solution was selected, as despite producing one small cluster, it was more meaningful than 3-cluster solution where the ratio of between-cluster variance to within-cluster variance decreased to below 1 for SA episodes. Pseudo-F value was also largest for the 4-cluster solution. In

addition to statistical criteria, this solution provided clearest conceptual distinctions and best reflected the occurrence of SA within each cluster.

We described the different SA behaviour patterns (clusters) by means and range of number of SA days and of short and long SA episodes. We used multinomial logistic regression analysis to examine the associations between employee and work characteristics in 2020 and SA patterns in 2021. The estimates are presented as odds ratios (OR) with 95% confidence intervals (CI) using the low SA pattern as the reference category. Municipality was treated as a confounder in the analysis.

To examine whether the SA clusters were unique to pandemic year 2021, we performed k-means modelling to identify SA patterns before the pandemic in 2019 as additional analysis. The SA clusters from 2019 were compared to SA clusters from 2021. Sensitivity analyses included separate negative binomial regression models to examine the relationship between employee and work characteristics with separate count outcome variables of total SA days, short SA episodes, and long SA episodes in 2021. With this analysis, we wanted to study if SA patterns as an outcome offered new insights compared to separate outcome measures. Additionally, since the total number of SA days highly correlated with long SA episodes, we also conducted a cluster analysis using only short and long SA episodes as clustering variables.

Finally, means and standard deviations of self-rated health and work ability stratified by SA patterns were calculated to examine how survey-based measures of health and work ability aligned with the SA patterns. All analyses were conducted using SAS version 9.4.

3 Results

3.1 Sickness absence patterns in 2021

Based on the k-mean cluster analysis and cluster metrics (Supplementary Table 1), the 4-cluster solution distinguished between clear cluster identities and produced meaningfully interpretable clusters. These different SA patterns were named based on the mean and range of number of SA days and of short and long SA episodes as follows (Table 1):

Table 1 Clustering variables of sickness absences (SA) in 2021 among 39,791 Finnish public sector employees

	Sickness absence patterns			
	Low SA (*n* = 31320)	**Repeated short SA episodes (*n* = 5149)**	**Repeated long SA episodes (*n* = 2964)**	**Very high SA, long episodes (*n* = 358)**
Number of SA days in 2021				
Mean (SD)[a]	4.4 (6.5)	23.9 (14.1)	66.6 (31.6)	238.8 (71.7)
Range	0–41	1–137	1–192	94–365
Number of short (1–9 days) SA episodes in 2021				
Mean (SD)[a]	1.1(1.2)	7.0 (2.9)	2.9 (2.7)	2.6 (3.0)
Range	0–4	4–35	0–21	0–16
Number of long (10–365 days) SA episodes in 2021				
Mean (SD)[a]	0.1 (0.3)	0.3 (0.5)	1.7 (0.8)	3.7 (2.5)
Range	0–1	0–3	1–6	1–16

[a]SD, standard deviation

1) Lowest SA pattern: Employees in this most common SA pattern ($n = 31320$, 79%) had the lowest total number of SA days (mean 4.4, range 0–41) and the fewest short (mean 1.1, range 0–4) and long (mean 0.1, range 0–1) SA episodes.
2) Repeated short SA episodes: This second most common pattern ($n = 5149$, 13%) involved the second lowest total number of SA days (mean 23.9, range 1–137), the highest number of short SA episodes (mean 7.0, range 4–35), and the second lowest long SA episodes (mean 0.3, range 0–3).
3) Repeated long SA episodes: In this pattern ($n = 2964$, 7%), employees had an average 66.6 SA days (range 1–192), 2.9 (range 0–21) short episodes, and 1.7 (range 1–6) long episodes, all being the second highest compared to other SA patterns.
4) Very high SA, long episodes: This pattern had the fewest employees ($n = 358$, 1%), but they experienced the most SA days (mean 238.8, range 94–365) and had an average 2.6 (range 0–21) short, and 3.7 (range 1–16) long SA episodes.

Table 2 shows the employee and work characteristics of the total sample and by SA patterns. At baseline, 78% of the study participants were women, the mean age was 46 years, and 69% were married or cohabiting. The average body mass index was 26.4, indicating higher than a healthy (≤ 25) weight. A total of 11% were current smokers, and 4% were at-risk alcohol users. Only 3% of the employees reported having had a COVID-19 infection. Driving was the most common commute mode, while walking was the least common.

Regarding work characteristics, 52% of the employees were in a high occupational socioeconomic position and 84% had a permanent job contract. Only 2% were in shift work. Due to COVID-19 pandemic, 44% had worked from home in 2020, 8% were transferred to new tasks in 2020, and 5% experienced a team reorganization in 2020.

3.2 Employee and work characteristics in 2020 associated with the 2021 sickness absence patterns

Several employee and work characteristics measured in 2020 were associated with the SA patterns in 2021 (Fig. 2). Compared to others, employees with low SA were less likely to have had a first-wave COVID-19 infection, more frequently worked from home during COVID-19, and had a profile linked also previously to lower risk of SA (more men in higher occupational positions, lower body mass index, lower smoking and higher alcohol abstinence rates). Repeated short SA episodes were associated with younger age and team reorganization during COVID-19, whereas repeated long episodes and very high SA were linked to older age.

The strongest associations, when compared to the low SA pattern were:

1) Repeated short SA episodes: female sex (OR 2.00, 95% CI 1.82–2.20), low SES (OR 1.50, 95% CI 1.37–1.65), first-wave COVID-19 infection (OR 1.44, 95% CI 1.22–1.70), and not having transferred to working from home during the pandemic (OR 0.45, 95% CI 0.42–0.49). This pattern was also more likely in younger, single and divorced/widowed employees, employees with temporary job contracts, current smokers, those using passive commute modes like private car or public transport, and those who had experienced team reorganization due to COVID-19 pandemic. Shift workers were less likely to belong to repeated short SA episodes pattern than to the lowest SA pattern.

Table 2 Sample characteristics overall and by sickness absence (SA) patterns in 2021 among Finnish public sector employees

Variables (2020)	Sickness absence patterns 2021				
	Total sample (*n* = 39791)	**Low SA (*n* = 31320)**	**Repeated short SA episodes (*n* = 5149)**	**Repeated long SA episodes (*n* = 2964)**	**Very high SA, long episodes (*n* = 358)**
Employee characteristics					
Sex (n, %)					
Men	8637 (21.7)	7491 (23.9)	634 (12.3)	453 (15.3)	59 (16.5)
Women	31,154 (78.3)	23,829 (76.1)	4515 (87.7)	2511 (84.7)	299 (83.5)
Age (mean, SD[a])	45.8 (10.9)	46.1 (10.9)	43.2 (11.0)	46.8 (11.0)	48.6 (10.4)
Marital status (n, %)					
Married/cohabiting	27,252 (69.2)	21,853 (70.5)	3232 (63.4)	1953 (66.6)	219 (61.9)
Single	7241 (18.4)	5512 (17.8)	1117 (21.9)	533 (18.2)	79 (22.3)
Divorced/widowed	4872 (12.4)	3618 (11.7)	751 (14.7)	447 (15.2)	56 (15.8)
Body mass index (mean, SD[a])	26.4 (4.9)	26.2 (4.8)	27.1 (5.4)	27.4 (5.5)	27.9 (5.9)
Smoking (n, %)					
Never	26,819 (67.9)	21,690 (69.8)	3206 (62.7)	1714 (58.5)	209 (59.5)
Ex-smoker	8148 (20.6)	6228 (20.0)	1106 (21.6)	729 (24.9)	85 (24.2)
Current smoker	4510 (11.4)	3164 (10.2)	801 (15.7)	488 (16.6)	57 (16.2)
Alcohol use (n, %)					
No	9034 (22.9)	6709 (21.6)	1419 (27.7)	795 (27.1)	111 (31.2)
Moderate	28,774 (72.9)	23,041 (74.2)	3499 (68.3)	2009 (68.4)	225 (63.2)
At-risk use	1677 (4.2)	1321 (4.2)	202 (4.0)	134 (4.5)	20 (5.6)
First-wave COVID-19 (n, %)					
No	38,482 (96.7)	30,389 (97.0)	4919 (95.5)	2838 (95.7)	336 (93.9)
Yes	1309 (3.3)	931 (3.0)	230 (4.5)	126 (4.3)	22 (6.1)
Commute mode (weekly days; mean, SD [a])					
Walking	0.8 (1.6)	0.8 (1.6)	0.9 (1.8)	0.8 (1.6)	0.9 (1.7)
Cycling	1.3 (2.0)	1.3 (2.0)	1.2 (2.0)	1.1 (1.9)	0.9 (1.8)
Public transport with active element	1.2 (2.0)	1.2 (2.0)	1.4 (2.0)	1.2 (1.9)	1.1 (1.9)
Public transport without active element	0.9 (1.8)	0.9 (1.8)	1.0 (1.8)	0.9 (1.8)	0.9 (1.8)
Car	2.4 (2.3)	2.4 (2.3)	2.3 (2.3)	2.6 (2.4)	2.7 (2.4)
Work characteristics					
Socioeconomic status (n, %)					
High	18,813 (51.5)	16,007 (55.0)	1700 (38.7)	1008 (37.5)	98 (32.8)
Intermediate	9995 (27.4)	7782 (26.7)	1289 (29.3)	833 (31.1)	91 (30.4)
Low	7684 (21.1)	5323 (18.3)	1410 (32.0)	841 (31.4)	110 (36.8)
Job contract (n, %)					
Permanent	33,111 (83.7)	26,194 (83.6)	4214 (81.8)	2585 (87.2)	318 (88.8)
Temporary	6480 (16.3)	5126 (16.4)	935 (18.2)	379 (12.8)	40 (11.2)
Working time mode (n, %)					
No shift work	38,844 (98.1)	30,580 (98.1)	5036 (98.2)	2883 (97.8)	345 (97.5)
Shift work	754 (1.9)	587 (1.9)	94 (1.8)	64 (2.2)	9 (2.5)
Remote work due to COVID-19 (n, %)					
No	22,152 (55.7)	15,934 (50.9)	3935 (76.4)	2012 (67.9)	271 (75.7)
Yes	17,639 (44.3)	15,386 (49.1)	1214 (23.6)	952 (32.1)	87 (24.3)
Transfer into new tasks due to COVID-19 (n, %)					
No	36,679 (92.2)	29,040 (92.7)	4623 (89.8)	2692 (90.8)	324 (90.5)
Yes	3112 (7.8)	2280 (7.3)	526 (10.2)	272 (9.2)	34 (9.5)
Team reorganisation due to COVID-19 (n, %)					

Table 2 (continued)

Variables (2020)	Sickness absence patterns 2021				
	Total sample (*n* = 39791)	**Low SA (*n* = 31320)**	**Repeated short SA episodes (*n* = 5149)**	**Repeated long SA episodes (*n* = 2964)**	**Very high SA, long episodes (*n* = 358)**
No	37,923 (95.3)	29,960 (95.7)	4830 (93.8)	2801 (94.5)	332 (92.7)
Yes	1868 (4.7)	1360 (4.3)	319 (6.2)	163 (5.5)	26 (7.3)

[a]SD, standard deviation

2) Repeated long SA episodes: female sex (OR 1.69, 95% CI 1.51–1.89), low SES (OR 1.66, 95% CI 1.48–1.87), and smoking (OR 1.60, 95% CI 1.41–1.80).
3) Very high SA: first-wave COVID-19 infection (OR 2.46, 95% CI 1.50–4.02), low SES (OR 2.08, 95% CI 1.49–2.91), and not having transferred to working from home during the pandemic (OR 0.49, 95% CI 0.37–0.67).

Older age predicted repeated long and very high SA patterns, while cycling to work was protective for these patterns.

3.3 Comparison of the pandemic and pre-pandemic SA patterns

As in SA patterns of 2021, also for SA patterns of 2019, the optimal number of four clusters was chosen based on cluster metrics (Supplementary Table 2) and different SA behaviour patterns were named accordingly, corresponding the names of the patterns in 2021. The low SA pattern was the most common ($n = 29{,}608$, 74%), followed by the repeated short SA episodes ($n = 4931$, 12%), repeated long SA episodes ($n = 4484$, 11%), and very high SA, long episodes ($n = 768$, 2%).

Supplementary Table 3 shows descriptive results for the SA patterns in 2019. When comparing these descriptive statistics to those for the SA patterns in 2021 (Table 1), notable differences were observed. Total SA days across all four distinct SA patterns were lower in 2019. Additionally, in 2019, employees in the repeated long and very high SA patterns had less long SA episodes than in 2021.

3.4 Sensitivity analyses

Supplementary Table 4 presents the results of separate negative binomial regression models that examine the associations between employee and work characteristics and the total number of SA days, as well as short and long SA episodes in 2021. These findings were consistent with the results of regression models that analysed these associations across the four distinct SA patterns.

Cluster analysis using only short and long SA episodes as clustering variables, yielded a three-cluster solution as the optimal choice, as the four- to- five cluster solutions included at least one cluster that was too small (Supplementary Table 5).

The three clusters were:1) low SA, 2) repeated short SA episodes, and 3) repeated long SA episodes (Supplementary Table 6). This analysis did not add much to the results from the analysis of these two outcomes separately.

Supplementary Table 7 describes the means and standard deviations of self-rated health and work ability in 2020 among employees across different SA patterns in 2021. Both self-rated health and work ability had lower mean values in the most adverse SA patterns than in the most optimal SA pattern.

	Sickness absence patterns		
	Repeated short SA episodes (n=4119)	Repeated long SA episodes (n=2510)	Very high SA long episodes (n=277)
	OR 95% CI	OR 95% CI	OR 95% CI
Employee characteristics			
Sex			
Men	1	1	1
Women	2.00 1.82-2.20	1.69 1.51-1.89	1.44 1.05-1.97
Age	0.98 0.97-0.98	1.00 1.00-1.01	1.03 1.02-1.05
Marital status			
Married/cohabiting	1	1	1
Single	1.05 1.00-1.15	1.02 0.91-1.15	1.61 1.18-2.19
Divorced/widowed	1.36 1.23-1.50	1.18 1.04-1.33	1.22 0.87-1.71
Body mass index	1.03 1.03-1.04	1.04 1.03-1.04	1.04 1.02-1.06
Smoking			
Never	1	1	1
Ex-smoker	1.14 1.05-1.25	1.34 1.21-1.49	1.29 1.00-1.72
Current smoker	1.34 1.21-1.48	1.60 1.41-1.80	1.32 0.93-1.89
Alcohol use			
Moderate	1	1	1
No	1.11 1.03-1.21	1.20 1.09-1.32	1.49 1.14-1.94
At-risk use	1.04 0.87-1.24	1.12 0.92-1.36	1.27 0.74-2.18
First-wave COVID-19			
No	1	1	1
Yes	1.44 1.22-1.70	1.37 1.11-1.69	2.46 1.50-4.02
Commute mode			
Walking	1.04 1.02-1.07	0.99 0.96-1.02	0.98 0.90-1.08
Cycling	0.99 0.97-1.01	0.97 0.95-0.99	0.91 0.84-0.98
Public transport with active element	1.04 1.01-1.06	0.98 0.96-1.01	0.98 0.91-1.06
Public transport without active element	1.02 1.00-1.04	1.00 0.97-1.02	1.00 0.92-1.09
Car	1.03 1.01-1.05	1.00 0.98-1.03	0.98 0.90-1.06
Work characteristics			
SES			
High	1	1	1
Intermediate	1.19 1.09-1.30	1.34 1.20-1.48	1.46 1.06-2.02
Low	1.50 1.37-1.65	1.66 1.48-1.87	2.08 1.49-2.91
Job contract			
Permanent	1	1	1
Temporary	1.10 1.00-1.20	0.89 0.79-1.01	0.84 0.57-1.26
Working time mode			
No shift work	1	1	1
Shift work	0.73 0.57-0.92	1.03 0.78-1.36	0.79 0.32-1.94
Remote work due to COVID-19			
No	1	1	1
Yes	0.45 0.42-0.49	0.68 0.62-0.75	0.49 0.37-0.67
Transfer into new tasks due to COVID-19			
No	1	1	1
Yes	1.04 0.93-1.17	1.05 0.90-1.21	0.86 0.55-1.35
Team reorganisation due to COVID-19			
No	1	1	1
Yes	1.27 1.10-1.46	1.12 0.93-1.34	1.52 0.96-2.40

Fig. 2 Associations between employee and work characteristics and sickness absence (SA) patterns (multinomial logistic regression). Participants with low SA pattern are the reference ($n = 27488$). Red indicates higher risk of cluster membership, green indicates lower risk of cluster membership. Stronger shade indicates stronger effect size. Only statistically significant estimates are highlighted. OR: odds ratio, CI: confidence interval

4 Discussion

Among Finnish public sector workers, we observed four distinct SA patterns during the COVID-19 year of 2021. While most employees (79%) had a low level of SA, with an average of four annual SA days (i.e., the optimal SA pattern), 13% had a pattern of repeated short SA episodes and 7% pattern of repeated long SA episodes. The rarest

pattern, observed only in 1% of the employees, was characterised by very high levels of SA days and long episodes, with an average of 239 days absent from work due to own illness.

We observed characteristics common to all three adverse SA patterns: lower occupational socioeconomic position, on-site work and team reorganizations during the pandemic, and higher likelihood of reporting first-wave COVID-19 infection. These characteristics have been linked to higher risk of SA and declining work ability also in previous studies [13, 30] and are more likely attributes of specific occupations rather than attributes of individuals. However, we also observed differences between the three patterns. The pattern of repeated short SA episodes was more common among younger employees, whereas the patterns of repeated long episodes and very high SA were more likely among older employees. While female sex was associated with all these patterns, the strongest association was observed for the repeated short episodes. Moreover, while poor lifestyle was associated with all three patterns, smoking was most strongly associated with repeated long episodes. Abstinence from alcohol, which can be an indicator of health problems leading to quitting drinking, was most strongly associated with the pattern of very high SA.

When comparing the SA patterns before the COVID-19 pandemic to those observed in 2021, we observed that SA days were lower across all adverse SA patterns pre-pandemic. Although overall SA was more common during the pandemic, the pattern structure remained similar before and during the pandemic. Thus, we were able to demonstrate that the observed pattern holds irrespective of COVID-19.

We are not aware of other studies focusing on the SA patterns during the pandemic. We used cluster analysis which helps to identify patterns and similarities within data that would not be evident when studying separate outcomes. In previous studies, SA has often been modelled as a univariate outcome, considering only the duration or frequency of SA. The use of approaches where both can be jointly considered, has recently been emphasized [3]. By examining both dimensions as separate but related outcomes, a more comprehensive understanding of SA patterns and the factors associated with them can be gained [3]. Analysing SA days and episodes of both short and long absences simultaneously also provides more accurate insights into different SA patterns and may help to target measures to manage SA rates.

Our findings are consistent with previous studies that have utilised trajectory analysis to identify different developmental pathways of SA. While most of the employed population has low levels of SA, various patterns of SA behaviour exist. Finnish nationally representative studies [31, 32], as well as studies among municipal employees [33, 34], have identified 3 to 4 distinct SA trajectories, i.e. different latent groups of employees that tend to have a similar SA profile over time. Studies of Danish blue- and white-collar workers in sectors such as cleaning, manufacturing and transportation [35], and studies of Swedish white-collar workers in the trade and retail industry [36], have identified similar trajectories. In all these studies, the largest groups consist of employees with minimal or no SA, while the smallest groups comprise individuals with a high number of SA occurrences over the study period. Additionally, Virtanen et al. [37] estimated six-year-level counts of SA spells and days based on employers' registers. More than half of the employees belonged to the low-level group, averaging about five SA days and one spell annually over the study period. The smallest high-range group consisted of individuals

with a high number of days (60–100) and spells (six to eight). These previous findings, along with the findings of our study, underscore the variability in SA patterns among individuals and the potential for fluctuations over time.

Our results regarding employee and work characteristics align with previous findings on the associations between female gender [38–40], higher body mass index [41, 42], and lower occupational socioeconomic status with SA [34, 43, 44]. Women typically have higher rates of SA than men [38–40]. In our study, this difference was partly explained by women's greater number of short SA episodes [38]. Female excess in short-term SA has been linked to the gender composition of occupations and workplaces [45]. Men and women are often employed in different jobs and sectors, each with distinct working conditions; for example, social and health care and education are female-dominated sectors with high physical and mental workloads, which may contribute to higher absence rates [46]. For longer SA spells, the excess among females has been attributed to factors such as poorer physical functioning, self-reported chronic conditions, higher physical work demands, and work fatigue [36]. Women may also have a slower recovery rates leading to longer absences [40].

Compared to the most optimal, that is, the lowest SA pattern, a higher body mass index was equally associated with all other SA patterns. Low occupational socioeconomic status had the strongest link to very high SA pattern. In previous studies of SA trajectories, a higher body mass index [31, 33, 34], and low occupational class [34], were associated with a higher likelihood of belonging specifically to a high SA trajectory [31, 33, 34]. The observed associations between abstinence from alcohol and former smoking with SA is plausibly a result of reverse causation, where illness causing SA leads individuals to abstain from alcohol and quit smoking, rather than these quitting the behaviours directly causing SA.

COVID-19 infection and on-site work during the pandemic were linked to SA patterns, with the greatest impact on very high SA pattern. Infected individuals were 2.5 times more likely to have very high levels of SA suggesting that although few employees reported a COVID-19 infection in 2020, they may have had longer recovery, or other underlying health issues. The employees in the very high SA pattern also seemed to have fewer opportunities to work from home during the pandemic. At the end of 2021, 63% of the Finnish social and health care employees, largely working on-site, were in the public sector [47], increasing the risk of infection exposure. Employees who reported having had COVID-19 infection in 2020 experienced higher rates of SA in 2021. This increased risk was most consistently observed among those with an intermediate occupational socioeconomic status, such as social workers and registered nurses [13]. During the pandemic, quarantine requirements and remote work policies may have influenced how SA was documented. For instance, employees in mandatory quarantine or working remotely might not have been recorded as absent in the same way as in non-pandemic times. These policies may have reduced the number of documented SA episodes, particularly for mild illnesses.

Flexible remote work is applicable only to work that is possible to do off-site. However, when possible, working from home may decrease the risk of communicable disease also in non-pandemic times.

The pattern of very high SA, long episodes were less common among those who cycled to work. This aligns with previous findings that commuting by bicycle is associated with

lower SA [48, 49]. Additionally, we have observed that increased active commuting, whether by walking or cycling, may improve self-rated health [22], and work ability [23]. However, the association was of small magnitude and could also be a case of reverse causality, where healthier individuals are more likely to cycle. Additionally, those who have cycled to work may have avoided exposure to COVID-19 infection in crowded public transportation, thereby staying healthier.

The second most common SA pattern was characterized by repeated short SA episodes. This group of employees is worth noting because repeated or prolonged SA may lead to adverse consequences, such as increased risk of disability retirement [6–8]. Factors like younger age, being single or divorced/widowed, current smoking, passive commuting, temporary employment, and team reorganization during the pandemic were associated with the patterns of repeated short SA episodes. These factors are important to consider if proactive measures are planned to prevent SA.

The study's strengths include its large sample size, which consists of nearly 40,000 employees from various public sector occupations. The high response rate (73%) in the employee survey and the use of linked register-based SA data further enhance the study's robustness. No financial incentives were provided for respondents by FIOH. Instead, the high response rate is achieved by sustained collaboration between FIOH and participating organizations as the study has lasted for more than 25 years to date. As the organizations are highly committed, they try their best to make sure people respond to this survey. Some organizations have lotteries with small prizes (cinema tickets etc.) to encourage participation. Moreover, in the final multivariate modelling, several employee and work-related characteristics were comprehensively considered, with complete data on associations with the SA patterns.

Instead of focusing solely on the duration or frequency of SA, we extensively utilized employers' SA register data, including the total number of SA days, and both short- and long-term SA episodes, to identify patterns of SA behaviour. We employed a widely used, methodologically efficient, and swift k-means cluster analysis, which is suitable for large datasets containing numerous variables [27–29].

There were also limitations. The sample was exclusively public sector employees, predominantly female (78%), reflecting the Finnish public sector workforce in general. However, this limits generalizability to the broader Finnish working population and to the private sector. Furthermore, the study was conducted within the context of Finland's robust social security system, where employees have guaranteed rights to paid sick leave and employment benefits are protected. These conditions may influence SA behaviour compared to settings with less comprehensive benefits. Therefore, caution is warranted when extrapolating these findings to countries or sectors with different labour market structures and social security systems.

We lacked information on the specific diagnoses related to SA. Employee and work characteristics were self-reported, potentially introducing reporting bias. Social desirability bias might have led over- or underreporting, as employees may answer in ways they perceived as favourable. However, as the survey was conducted online and distributed by an independent research organization rather than internally by the employer, the risk of social desirability bias was reduced. Respondents were less likely to feel direct pressure to provide socially desirable answers. Nevertheless, this bias cannot be entirely ruled out, as individuals may still choose to present themselves in a favourable light.

Employees who were able to work from home during the pandemic may differ in health status and job characteristics from those who could not, which may have influenced the observed SA patterns reflecting health-selection bias. For example, employees with lower occupational socioeconomic status, more often in physically demanding jobs were probably less likely to have the option to work from home than employees with higher occupational status. From earlier research, we know that higher occupational socioeconomic status is linked with better health and work ability [50, 51]. Also, although cluster analysis identified distinct patterns of SA, heterogeneity within clusters is possible. Employees grouped in the same cluster may differ in underlying health conditions, reasons for absence, and work context, which should be considered when interpreting the findings and designing interventions. Lastly, although the total sample was large (nearly 40 000 participants), the rarest SA pattern, very high SA, included only 358 participants. This led to few observations for rare exposures, such as alcohol risk use, COVID-19 infection, and shift work. For shift work in particular, the sample size was insufficient to detect small or even moderate size differences between employees with very high SA and those with other SA patterns.

5 Conclusions and practical implications

We identified four distinct patterns characterising SA behaviours among Finnish public sector employees. Most of the employees had a pattern with low occurrence of SA, but three other SA patterns emerged: very high levels and long episodes of SA, repeated long episodes, and repeated short SA episodes. Compared to the most optimal pattern of low SA, female sex and unhealthy weight and lifestyle were associated with all three more adverse SA patterns. The indicators of first-line work during the pandemic, including lower socioeconomic occupational position, on-site work, and perhaps subsequent first-wave COVID-19 infection were all associated with all the adverse SA patterns. Clustering provided new insights into SA patterns and their characteristics, which is important for SA assessment and preventive planning.

For work ability management within work ability model [14], these findings have practical implications for occupational health and organizational policy. Recognizing different SA patterns offers more nuanced information than single SA indicators considered in isolation and can inform targeted interventions and preventive measures. For example, employees with repeated short-term SA may benefit from early support to prevent progression to long-term SA, while those in high-risk patterns could be prioritized for work disability prevention and rehabilitation programs. Cluster-based risk profiles could also be integrated into work disability management information systems, and they could be used to anticipate staffing needs and guide occupational health services. Furthermore, knowledge of risk groups during the pandemic highlights preparedness strategies for future health crises, including flexible remote work policies where feasible and interventions addressing health behaviours, obesity in particular, as it is linked to severe consequences of several infections [52]. These approaches can help reduce overall absence rates and maintain work ability.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12982-026-01886-2.

Supplementary Material 1.

Author contributions
EH: conceptualization; writing-original draft preparation; writing - review & editing. MJ: writing - review & editing. JK: writing - review & editing. TO: writing - review & editing. JV: writing - review & editing. MK: writing - review & editing. JE: conceptualization; methodology; formal analysis; writing - review & editing; supervision; funding acquisition.

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Data availability
Anonymised subset of survey dataset used and analysed during the current study is available from the last author (JE, firstname.lastname@ttl.fi) upon reasonable request. Register data is not publicly available due to legislation on secondary use of health and social data (the Ministry of Social Affairs and Health, https://stm.fi/en/secondary-use-of-health-and-social-data).

Declarations

Ethics approval and consent to participate
The Ethical Committee of the Helsinki and Uusimaa hospital approved the Finnish Public Sector study (HUS/1210/2016) in accordance with the Declaration of Helsinki. In the Finnish Public Sector study informed consent is received from the participant by informing them in the cover letter of the questionnaire that the responses would be used in scientific research and answering the questionnaire is voluntary and if one does not wish to participate in the study, to ignore the questionnaire or notify the researchers of refusal. At the end of the questionnaire, a specific informed consent is asked to link survey data with register data. The full information to the participants describing informed consent can be found online at: https://www.ttl.fi/en/tutkimus/hankkeet/kunta-ja-hyvinvointialan-henkiloston-seurantatutkimus-fps/kunta10-tiedote-tutkittavalle. The description of data privacy and data protection policy for this study is available at https://www.ttl.fi/tietosuoja/hankkeiden-ja-tutkimusten-tietosuoja/tietosuojailmoitus-kuntasektorin-henkiloston-seurantatutkimus-fps (in Finnish only).

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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