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The Hidden Crisis:

Classifying Unmet Healthcare Needs in European Older Adults during COVID-19

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The Hidden Crisis: Classifying Unmet Healthcare Needs in European Older Adults During COVID-19

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Abstract

This study investigates the unmet healthcare needs of older adults during the COVID-19 pandemic, leveraging data from the Survey of Health, Ageing and Retirement in Europe (SHARE) and the two waves of the SHARE Corona Survey (SCS) conducted in 2020 and 2021. Using latent class analysis (LCA) with covariates, we identified distinct groups based on experiences of forgoing medical treatments due to fear of infection, postponed medical appointments, and being denied appointments, and explored socio-demographic, economic, and health-related differences in class membership. The two-wave data provide insights into changes over time, highlighting groups whose needs either improved or deteriorated. Our findings reveal six distinct classes of healthcare needs: no unmet needs, high early postponement with rapid improvement, rising barriers, high early fear-based barriers, high denial with persistent postponement, and persistently high fear-based barriers. Significant disparities in class membership were observed based on age, gender, partnership status, rural/urban residence, education, employment status, financial hardship, self-rated health, changes in health, and the number of chronic conditions. High-risk groups, particularly women, those with lower education, those experiencing financial hardship, and individuals with multiple chronic conditions, were identified as especially vulnerable to unmet healthcare needs during the pandemic. Our findings offer targeted insights for intervention and policy, aiming to address healthcare access disparities among older adults during such crises.

Keywords

Unmet healthcare needs, COVID-19 pandemic, SHARE data, latent class analysis

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1 Introduction

Access to and utilization of healthcare services is considered to be under the influence of different factors that can be grouped into *predisposing* (e.g., education, age, gender, attitudes towards the healthcare system), *enabling* (e.g., income, health insurance, means of access to healthcare) and *need* factors (e.g., subjective and objective health status) (Andersen, 1995). However, when access to healthcare is restricted, it can result in severe and enduring health consequences, diminish the quality of life, lead to poorer overall health, and exacerbate health disparities (Zavras et al., 2016). Numerous studies have shown that unmet healthcare needs among older adults increase their risk of mortality and morbidity (Alonso et al., 1997; Lindström, Rosvall and Lindström, 2020) or lead to a decline in self-reported health (Ko, 2016). According to analyses following the outbreak, the COVID-19 pandemic has become one of the most comprehensive episodes of difficulty accessing healthcare, as access to healthcare for many non-communicable diseases has been significantly limited (WHO, 2020). Health systems focusing on urgent COVID-19 cases led to a decline in the amounts of chronic care supplied, severely affecting those individuals with chronic conditions (Moynihan et al., 2021; Núñez, Sreeganga, & Ramaprasad, 2021), with many older adults being in that group. However, our understanding of the characteristics and effects of the pandemic on healthcare access and unmet healthcare needs of older adults, especially based on SHARE data, remains limited.

Several recent studies using SHARE data identified distinct groups of older adults by analyzing their unmet healthcare needs during the COVID-19 pandemic. Smolić et al. (2022) uncovered the groups of older adults in Europe more likely to report barriers to healthcare access during the pandemic, for example, women, people with higher education and those living in urban areas, those who reported poorer or worsening health status in the outbreak, with two or more chronic conditions, etc. Additionally, Smolić, Blažeski & Fabijančić (2023) confirmed these findings when exploring the characteristics of people aged 50 or older from eight Central Eastern Europe (CEE) countries who reported forgoing healthcare due to fear of COVID-19 infection. Focusing on the effect of economic vulnerability on unmet healthcare needs after the outbreak, Arnault et al. (2022) emphasized that comparatively more of the most economically vulnerable older adults reported having forgone medical care because of the fear of COVID-19 and not being able to obtain a medical appointment when needed. Quintal et al. (2023) singled out individuals who reported subjective unmet healthcare needs in 2020 as those who were more likely to report subjective unmet healthcare needs again in 2021, suggesting some persistence of subjective unmet healthcare needs over time. Likewise, Bergeot & Jusot (2024) argued that unmet specialist care, mainly because medical care was postponed, increases the probability of reporting health issues one year after the pandemic. Smolić, Čipin & Međimurec (2023) also found that over 7% of SHARE respondents from 27 European countries and Israel experienced lasting barriers to healthcare access during the pandemic and that this was more frequent in respondents with poor overall health or among those who had COVID-19-related health symptoms. Moreover, Kanclerė et al. (2024) showed that those whose health status was already poor and those who contracted COVID-19 were most strongly associated with worsened perceptions of general health during the pandemic, which all appear to have exacerbated inequalities in health outcomes.

Considering what was previously mentioned, this study has two main objectives. The first is to identify distinct groups of older adults by analyzing their unmet healthcare needs during the COVID-19 pandemic. Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), and in particular, the two waves of the SHARE Corona Survey (SCS) conducted in 2020 and 2021, we employ latent class analysis (LCA) to uncover a meaningful typology based on experiences of forgoing medical treatments due to fear of coronavirus infection, having medical appointments postponed because of the pandemic, and being denied medical appointments since the outbreak. The second objective is to explore differences in class membership. We apply LCA with covariates to assess how socio-demographic, economic, and health-related variables distinguish the emerging groups.

Previous research used LCA to examine, among others, the effects of the COVID-19 pandemic. With the LCA, Frounfelker et al. (2022) identified subtypes of positive and negative aspects of the experience of COVID-19 social distancing and the association of these subtypes with mental health. Sourial et al. (2023) aimed to detect different profiles of socially isolated community-dwelling older adults in the greater area of Montreal, Quebec, during the first wave of the COVID-19 pandemic, while Kleitman et al. (2021) explored how and why people comply with protective behaviours during COVID-19 by adopting a person-centred approach using Latent Profile Analysis (LPA) to identify clusters/groups of people within the general population who share similar patterns of COVID-19 behaviours and attitudes and determine their situational and psychological profiles.

Although previous research has addressed unmet healthcare needs during the COVID-19 outbreak using SHARE data to the best of our knowledge, our study is the first to longitudinally characterize patterns of unmet healthcare needs among older adults in the pandemic context. Our analysis is primarily exploratory, as we do not test any specific hypotheses about the number, relative size, or profiles of latent classes, nor about the factors that might influence class membership. Nonetheless, the findings offer valuable contributions. By analyzing latent classes and their associated covariates, we aim to determine whether high-risk groups within the older population can be identified – groups who were particularly vulnerable to unmet healthcare needs during the pandemic. Employing LCA with covariates allows us to examine variation in class membership by socio-demographic, economic, and health factors. The two-wave data enable us to capture changes in unmet healthcare needs over time and classify individuals into distinct trajectories, revealing which groups' needs improved or deteriorated. By analyzing the probabilities of unmet needs at each survey wave within each class, this approach identifies changes in risk over time across groups, thereby offering targeted insights for intervention and policy.

2 Methods

2.1 Data

We utilized data collected through SHARE (Börsch-Supan et al., 2013). SHARE is a cross-national longitudinal survey collecting information about older adults' health, socio-economic status, and social and family networks. To date, SHARE has conducted nine regular panel waves. The survey employs probability sampling methods to select its participants. Details about the sampling procedures and survey participation are available in SHARE documentation files (Bergmann et al., 2019). The target population of SHARE comprises non-institutionalized individuals aged 50 and over who regularly reside in their respective survey countries and speak the respective language(s). Partners of target individuals are included in the survey regardless of their age.

In March 2020, the ongoing data collection for Wave 8 was halted due to the outbreak of the COVID-19 pandemic, with about 70% of interviews completed across the participating countries. In response, SHARE implemented the SCS (Scherpenzeel et al., 2020). The two rounds of SCS were conducted: between June and September 2020 (SCS1) and between June and August 2021 (SCS2). Respondents were asked about their health and health behaviours, mental health, COVID-19 infections and healthcare, changes in work and economic situation, and social networks. The SCS1 sample included panel members from Wave 8, irrespective of whether they completed their Wave 8 interview. SCS2 was administered the following year as a follow-up interview. This study leveraged data from the two waves of SCS to investigate the experiences of unmet healthcare needs among older adults throughout the course of the COVID-19 pandemic.

The study sample was restricted to respondents who participated in both waves of SCS, were aged 50 and over in 2020, were not living in nursing homes (based on data from SCS1), and were living in their usual homes (also based on data from SCS1). We combined the SCS data with data from the most recent regular SHARE wave in which respondents participated to obtain the characteristics needed for our study (see Table 1 in Section 2.2 for a complete overview of the variables used in our study and the corresponding SHARE data sources). After excluding cases with missing values in any of the variables of interest (representing 5.8% of the restricted sample), we were left with a workable sample of 44,326 respondents from 27 European countries and Israel.

2.2 Variables

Indicators of unmet healthcare needs. To develop a typology of SHARE respondents based on their experiences of unmet healthcare needs throughout the course of the COVID-19 pandemic, we considered three aspects of barriers to accessing healthcare: first, whether respondents forwent medical treatment due to fear of infection by the coronavirus; second, whether a medical appointment that had been scheduled was postponed by the doctor or medical facility due to the pandemic; and third, whether respondents requested an appointment for medical treatment but could not obtain one. The three indicators were measured across the two waves of SCS. We used a binary variable to identify whether respondents had experienced any of the three situations (yes or no). This generated six separate indicator variables – three measures of unmet healthcare needs across the two SCS waves – for every SHARE respondent. The six indicator variables served as input variables to identify distinct latent classes among the SHARE respondents.

Covariates. We examined the relationships between latent classes and three broad sets of covariates to understand the socio-demographic, economic, and health characteristics associated with each class, aiming to identify any disparities. The first set of covariates included socio-demographic variables: age (50–64, 65–79, and 80+), gender (men or woman), partnership status (partner in the household: yes or no), rural/urban residence (coded as rural = a rural area or village vs. urban = a small town, a large town, the suburbs or outskirts of a big city, or a big city), and educational attainment (three categories based on ISCED1997[1]: low = ISCED0–2, medium = ISCED3–4, and high = ISCED5–6). The second set of covariates included economic variables: employment status at the time when COVID-19 broke out (employed or self-employed: yes or no) and the household's ability to make ends meet since the outbreak[2] (easily, fairly easily, with some difficulty, or with great difficulty). Finally, the third set of covariates included health-related variables: self-rated health before the pandemic (excellent, very good, good, fair, or poor), change in health since the pandemic (health remained about the same, worsened, or improved), and the number of chronic conditions[3] (none, one, two, or three and more).

[1] International Standard Classification of Education (ISCED) is a framework used to categorize and compare education systems across different countries.
[2] In SHARE, one person answers specific questions – including the household's ability to make ends meet – on behalf of the entire household. This person is known as the household respondent. Therefore, the answer to the question about the household's ability to make ends meet is only available for the household respondent. To facilitate data analysis at the individual level, responses given by the household respondent were also assigned to their partner living in the same household.
[3] The number of chronic conditions was derived from the latest data available from regular SHARE waves, using a generated variable that captures the count. This number was updated by adding any new major illnesses or chronic conditions reported in SCS1. The procedure involved summing the illnesses and conditions respondents reported having from a list of seven included in the SCS1.

Table 1 presents SHARE data sources and descriptive statistics for the variables used in our study.

Table 1: Variables and descriptive statistics for the study sample

Variable	Response category	N	%
Forwent healthcare SCS1			
SCS1 (forwent since outbreak)	Yes	5,475	12.35%
	No	38,851	87.65%
Forwent healthcare SCS2			
SCS2 (forwent since last interview)	Yes	3,666	8.27%
	No	40,660	91.73%
Had healthcare postponed SCS1			
SCS1 (postponed since outbreak)	Yes	12,052	27.19%
	No	32,274	72.81%
Had healthcare postponed SCS2			
SCS2 (postponed since last interview)	Yes	5,699	12.86%
	No	38,627	87.14%
Had healthcare denied SCS1			
SCS1 (denied since outbreak)	Yes	2,322	5.24%
	No	42,004	94.76%
Had healthcare denied SCS2			
SCS2 (denied since last interview)	Yes	1,951	4.40%
	No	42,375	95.60%
Age in 2020			
SCS1	50–64	12,769	28.81%
	65–79	24,169	54.53%
	80+	7,388	16.67%
Gender			
SCS1	Men	18,456	41.64%
	Woman	25,870	58.36%
Partner in household			
SCS1	Yes	31,157	70.29%
	No	13,169	29.71%
Area of residence			
Latest data available from regular SHARE Waves 1, 2, 4–8	Rural	15,652	35.31%
	Urban	28,674	64.69%
Education			
Latest data available from regular SHARE Waves 1, 2, 4–8	Low	14,839	33.48%
	Medium	19,216	43.35%
	High	10,271	23.17%
Employed or self-employed when COVID-19 broke out			
SCS1	Yes	9,192	20.74%
	No	35,134	79.26%
Ability to make ends meet since the outbreak			
SCS1	Easily	13,057	29.46%
	Fairly easily	15,722	35.47%
	With some difficulty	11,437	25.8%
	With great difficulty	4,110	9.27%
Self-rated health before the pandemic			
SCS1	Excellent	2,978	6.72%

	Very good	7,383	16.66%
	Good	19,907	44.91%
	Fair	11,365	25.64%
	Poor	2,693	6.08%
Change in health since the pandemic			
SCS1	About the same	39,218	88.48%
	Worsened	3,821	8.62%
	Improved	1,287	2.9%
Number of chronic conditions			
Latest data available from regular SHARE Waves 1, 2, 4–8 updated with data on new conditions from the SCS1	None	8,605	19.41%
	One	11,459	25.85%
	Two	9,596	21.65%
	Three and more	14,666	33.09%

Source: SHARE, release 9.0.0. Notes: Unweighted data. For each variable, the corresponding SHARE data source is indicated below in italics. In drawing data from regular SHARE waves, we did not use Wave 3 (SHARELIFE) because this wave focused on retrospective life histories, lacking socio-demographic and health data comparable to the other regular panel waves.

We prepared data, and descriptive statistics were derived using STATA 18 (StataCorp, 2023).

2.3 Analysis

We applied LCA to identify distinct groups of older adults based on unmet healthcare needs during the COVID-19 pandemic. LCA is an appropriate method when one assumes that the population of interest (in this case, older adults) consists of different groups (classes) that are unobserved (latent) and must be inferred from the data. Our goal was to uncover a meaningful typology to understand barriers to accessing healthcare. Version 6.0 of the Latent GOLD software (Vermunt & Magidson, 2016, 2021) was used to fit a series of latent class models. Parameters were estimated using the maximum likelihood (ML) procedure, implemented via the Expectation-Maximization (EM) algorithm. To minimize the risk of obtaining a local (rather than a global) maximum, we specified 10,000 random starting sets and up to 15,000 iterations for the EM algorithm.

We fitted models with one to eight classes and used multiple statistical criteria to identify the optimal number of classes to retain. We examined the Bayesian Information Criterion (BIC), adjusted BIC (aBIC), Consistent Akaike Information Criterion (CAIC), and Approximate Weight of Evidence (AWE), where lower values indicated better-fitting models. We also considered the Vuong-Lo-Mendell-Rubin (VLMR) and bootstrapped likelihood ratio tests (BLRT) to compare models, using p-values to determine if an additional class significantly improved model fit (a non-significant p-value suggests that the simpler model is preferable). To further refine our selection, we calculated the Bayes Factor (BF) and correct model probability (cmP). The BF provides a pairwise comparison of relative fit between two models (values > 3 are desirable), while the cmP identifies the best model among the models considered, with the highest value indicating the best model. Given that there is often no definitive answer for the optimal number of classes, we relied on these criteria to find candidate solutions and carefully analyzed each by examining the emergent classes, their profiles, and their relative size. We performed secondary model evaluation via classification diagnostics. We looked at entropy and average posterior class probabilities to assess classification accuracy and precision. Entropy, which ranges between 0 and 1 (as implemented in Latent GOLD), measures the uncertainty in class assignments, where higher values indicate clearer classification (values > 0.8 are considered high, and values < 0.5 are considered low). Average posterior class probabilities estimate the likelihood that individuals are correctly classified into their most likely class, with values greater than 0.7 suggesting adequate precision. The final solution was chosen based on a combined consideration of statistical evidence, interpretability, and practical significance. Further details on LCA model fit indices and classification metrics can be found in the literature (e.g., Collins & Lanza, 2010; Masyn, 2013; Nylund-Gibson & Choi, 2018; see Latent GOLD manuals for software implementation).

Once the optimal number of classes was chosen, we examined the latent shared patterns of unmet healthcare needs that defined each group. The groups were then compared based on socio-demographic, economic, and health-related characteristics. We used the three-step ML method to assess the relationships between the emergent latent classes and the covariates (Vermunt, 2010). This approach involves estimating the latent class model in the first step, assigning individuals to their most likely class in the second step based on posterior probabilities, and then using the assigned classes to relate covariates to the latent classes in the third step. The method aims to minimize misclassification biases by accounting for uncertainty in class membership when examining the relationship between latent classes and covariates. We first ran a series of multinomial logistic regression models to explore the bivariate associations between class membership and each socio-demographic, economic, and health-related variable. We then ran a single model to examine the effects of each covariate while controlling for the effects of other covariates. In this model, we included a set of dummy variables representing SHARE countries as covariates (country fixed effects) to account for any country-level differences (e.g., in healthcare systems and policies), allowing us to isolate the effects of socio-demographic, economic, and health-related factors on latent class membership. We relied on Wald statistics to assess the significance of the associations between class membership and the covariates.

3 Results

3.1 Class enumeration

Table 2 presents LCA results for models with one to eight classes. As more classes were added, the log-likelihood (LL) values, which reflect the probability of observing the data given the model parameters, increased. Improvements were significant up to four classes, but the gains slowed down noticeably after six classes. This indicated that the model's ability to effectively explain the data plateaued, suggesting optimal complexity at fewer classes. The BIC, aBIC, and CAIC generally decreased as the number of classes increased from one to six, indicating improved fit. The lowest values for these criteria in six classes suggested that this model offered a balanced description of the data without unnecessary complexity. Indices rose when moving from six to seven classes, implying that additional classes did not substantially enhance model fit and may have introduced undue complexity.

Conversely, the AWE supported a simpler four-class model, considering classification performance. Likelihood ratio tests, including the VLMR and BLRT, showed that increasing the number of classes from one to seven consistently improved fit. Yet, while statistically significant, the transition to an eight-class model indicated reduced certainty in fit improvement, as shown by higher p-values. This pattern suggested that the benefits of additional classes diminished after seven. The BF and cmP for the six-class model further substantiated its advantage, with the cmP indicating the highest likelihood of this model being the correct model among those tested.

Table 2: Model fit summary table for latent class models with one to eight classes

k	LL	Par.	BIC	aBIC	CAIC	AWE	VLMR p	BLMR p	BF	cmP
1	-89.271,3	6	178.606,9	178.587,8	178.612,9	178.689,1	/	/	0,0	0,00
2	-85.532,1	13	171.203,2	171.161,9	171.216,2	202.899,7	0,0000	0,0000	0,0	0,00
3	-85.155,4	20	170.524,9	170.461,3	170.544,9	201.878,1	0,0000	0,0000	0,0	0,00
4	-84.884,7	27	170.058,3	169.972,5	170.085,3	**201.131,0**	0,0000	0,0000	0,0	0,01

5	-84.813,0	34	169.989,8	169.881,7	170.023,8	213.242,5	0,0000	0,0000	0,4	0,24
6	-84.765,8	41	**169.970,3**	**169.840,0**	**170.011,3**	223.206,8	0,0000	0,0000	**6,7**	**0,65**
7	-84.747,4	48	170.008,4	169.855,9	170.056,4	225.409,2	0,0000	0,0000	**21,5**	0,10
8	-84.740,7	55	170.069,8	169.895,1	170.124,8	220.586,6	0,0395	0,0210	/	0,00

Source: Authors' calculations based on SHARE data. Notes: k = number of classes; Par. = number of parameters. Other abbreviations were defined in the text. Values in bold represent the best fit for each statistic.

In summary, although multiple criteria supported the six-class model, including the BIC – the most widely used and trusted statistic for model selection in LCA (e.g., Nylund-Gibson & Choi, 2018) – the fit indices from Table 2 do not conclusively favour any single model. To deepen our understanding, we further explored the sizes, profiles, and classification quality of emergent classes across models with four to eight classes, which appeared to be promising candidates.

Table 3 presents classification diagnostics, including entropy values and average posterior probability (AvePP) for each class across models, used to assess the precision of class assignments. The entropy for the six-class model, being lower than ideal, combined with the presence of some classes with AvePPs below the desired 0.7 threshold, indicated classification uncertainty. The uncertainty increased further for the seven-class model, as evidenced by an entropy value below 0.5. The eight-class model included multiple small classes, all with AvePPs below 0.7.

On the other hand, the four-class model provided a simpler structure and considerably better classification quality. However, it failed to capture some nuanced patterns of unmet healthcare needs observed in more differentiated models. This model seemed to have oversimplified the complexity and diversity of the data, missing important distinctions that were apparent in models with more classes. The five-class solution, with classification diagnostics below the preferred level but workable, seemed like the best contender to the six-class model.

Table 3: Model classification statistics

	k = 4		**k = 5**		**k = 6**		**k = 7**		**k = 8**	
Entropy	0.6601		0.5819		0.5217		0.4938		0.5452	
Class	**Prop.**	**AvePP**	**Prop.**	**AvePP**	**Prop.**	**AvePP**	**Prop.**	**AvePP**	**Prop.**	**AvePP**
1	0.6343	0.9222	0.6061	0.9105	0.5769	0.8912	0.6411	0.8335	0.5984	0.8747
2	0.2021	0.8538	0.1689	0.6869	0.1771	0.6677	0.1062	0.8182	0.1986	0.7776
3	0.0967	0.7355	0.1325	0.7673	0.1156	0.7707	0.0891	0.6561	0.0832	0.6507
4	0.0670	0.8581	0.0552	0.7534	0.0899	0.7390	0.0779	0.5533	0.0663	0.8482
5	/	/	0.0374	0.7404	0.0306	0.6921	0.0570	0.5316	0.0300	0.7257
6	/	/	/	/	0.0098	0.5607	0.0204	0.5964	0.0096	0.6247
7	/	/	/	/	/	/	0.0083	0.6814	0.0073	0.6095
8	/	/	/	/	/	/	/	/	0.0067	0.6770

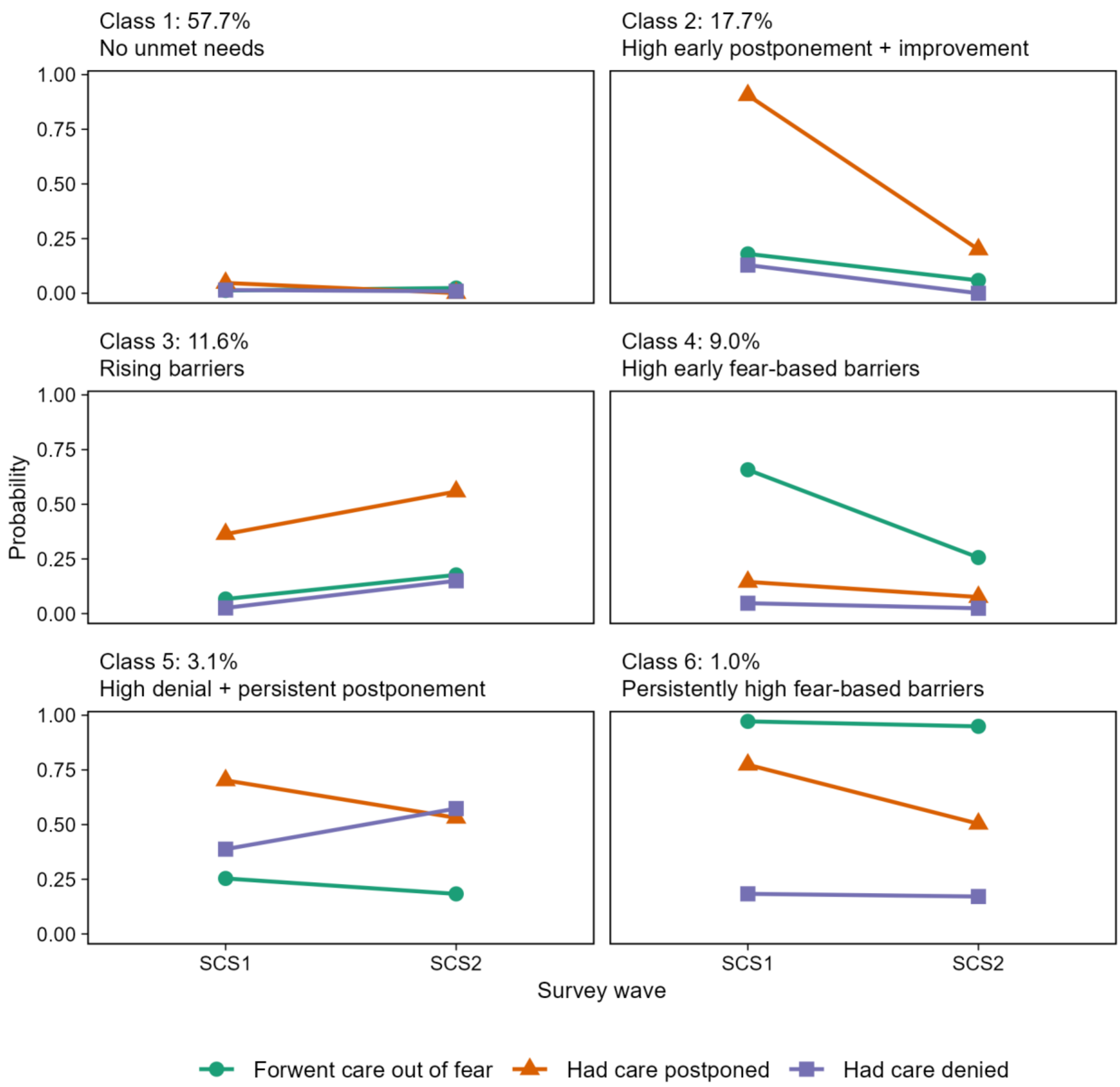
Source: Authors' calculations based on SHARE data. Notes: k = number of classes; Prop. = model estimated proportion for the size of each class; AvePP = average posterior class probability.

Upon closer inspection, it appeared that the six-class model extracted a unique pattern of responses into the smallest class, particularly regarding forgone medical care. More detailed comparisons of class profiles across models are not shown but are available from the authors upon request. The socio-demographic, economic, and health-related differences across the six classes largely aligned with expectations (see Section 3.3). The distinct patterns identified in the six-class solution thus provided useful insights that directly addressed the study objectives of identifying high-risk groups and understanding the factors affecting unmet healthcare needs. Therefore, the six-class model was ultimately selected for its combination of statistical evidence and substantive considerations. However, careful interpretation is necessary due to classification uncertainty, especially in the smallest class, which presented an AvePP notably below satisfactory levels.

3.2 Patterns of unmet healthcare needs throughout the course of the COVID-19 pandemic

Following the enumeration of classes from one to eight, the six-class model was selected as the most appropriate for interpreting unmet healthcare needs during the COVID-19 pandemic. The conditional item probability plot in Figure 1 displays the likelihood of "yes" responses to questions about forgone healthcare due to fear, postponed scheduled medical treatments, and denied healthcare across the two SCS waves. The plot reveals distinct patterns of response probabilities across the six classes, facilitating an interpretation of how different groups experienced barriers to healthcare access during the pandemic. In what follows, we discuss the defining characteristics of each identified class.

Figure 1: Six-class model of unmet healthcare needs during the COVID-19 pandemic



Source: Authors' calculations based on SHARE data. Notes: Results shown are probability estimates of members within each class responding "yes" to each question about having healthcare needs unmet across the two SCS waves. The percentages of *respondents in each class are rounded, and therefore, the sum may not add up to 100%. The figure was created using the ggplot2 package in R (Wickham, 2016).*

Class 1 (N = 25,572; 57.7%) is characterized by low barriers to healthcare access during the COVID-19 pandemic. In both survey waves, this group of older adults exhibited meagre rates of forgone healthcare due to fear, with a slight increase in the second wave, suggesting that fear of infection did not substantially deter their healthcare-seeking behaviour. Similarly, the probabilities of healthcare being postponed or denied were minimal and declining (each below 1% by SCS2), indicating almost non-existent delays or refusals of service from the healthcare system. The negligible rise in forgone care observed in the second wave does little to alter the general trend of stable and reliable access to healthcare for this class. This consistent pattern reflects a group largely unaffected by the disruptions that impacted healthcare systems during the pandemic. We refer to this class as "No unmet needs".

Class 2 (N = 7,851; 17.7%) initially exhibited a notable impact from systemic healthcare delays, particularly through high levels of postponed healthcare in the first survey wave (the probability of having services postponed surpassed 90% in this group in SCS1). This dramatically decreased by the SCS2, indicating a successful adaptation to or mitigation of early pandemic-related healthcare challenges. Initially, a moderate percentage of older adults in this group forwent healthcare out of fear (18%), which significantly decreased as the pandemic progressed (to less than 6%), showing a reduction in fear-based barriers. Similarly, there was a moderate probability of being denied healthcare in the first survey wave (almost 13%), but this became negligible by the second wave, reflecting an overall improvement in accessing required healthcare services. This pattern of high initial postponements followed by substantial improvements highlights Class 2's ability to overcome early supply-side barriers, significantly enhancing their access to scheduled healthcare as the pandemic unfolded. We refer to this class as "High early postponement with rapid improvement".

Class 3 (N = 5,123; 11.6%) is characterized by a rising pattern of healthcare access challenges during the COVID-19 pandemic. Initially, this group of older adults displayed a relatively low rate of forgone healthcare due to fear in SCS1 (below 7%), which increased to a non-negligible level by SCS2 (to almost 18%). This shift suggests a growing trend of fear-based avoidance of healthcare as the pandemic progressed. Regarding postponed healthcare, there was a moderate probability of experiencing delays in SCS1 (around 36%), which further increased in SCS2 (to over 55%). Additionally, the probability of being denied healthcare was very low in SCS1 (below 3%), but a considerable rise was observed in SCS2 (to 15%). This pattern indicates a worsening situation where more members of this class face denials of healthcare services as the pandemic continues. The increasing probabilities of postponements and denials, coupled with a growing reluctance to seek care due to fear, highlight the dual impact of the pandemic on this group's healthcare behaviours, marking an upswing in both supply-side barriers and psychological hesitance to seek care. We refer to this class as "Rising barriers".

Class 4 (N = 3,987; 9.0%) initially demonstrated a significant impact of fear on healthcare decisions during the early stages of the COVID-19 pandemic. In SCS1, there was a high probability of members forgoing healthcare due to fear (almost 66%), which substantially decreased by SCS2 (to just over 25%). This marked reduction suggests a significant alleviation of fear-based barriers over time. Concurrently, the probabilities of postponed healthcare were relatively low in both waves, declining from around 15% in SCS1 to approximately 8% in SCS2, indicating that delays in receiving care were not a major concern for this class. Similarly, the probabilities of being denied healthcare were very low in both survey waves, suggesting that denials of service were rare for these individuals. This class is primarily characterized by a sharp decrease in fear-based healthcare avoidance as the pandemic progressed, with systemic issues such as postponements and denials consistently at relatively low levels and showing further declines. This pattern indicates that while fear significantly influenced healthcare decisions initially, the healthcare system's responsiveness or barriers were not significant factors for this group of older adults, reflecting a group particularly affected by initial fear-based barriers, with a subsequent reduction in such fears or adaptation to the pandemic conditions. We refer to this class as "High early fear-based barriers".

Class 5 (N = 1,358; 3.1%) is characterized by considerable and ongoing issues with healthcare access during the COVID-19 pandemic. This class displayed a moderate rate of individuals forgoing healthcare out of fear, which decreased slightly from SCS1 (25%) to SCS2 (18%). A relatively high probability of postponed healthcare indicates substantial systemic barriers, though this decreased over time (from 70% to 53%). Notably, denied healthcare emerged as a prominent feature, particularly in SCS2 (compared with the SCS1), where more than half of the class (57%) faced healthcare denials, suggesting increasing difficulties in accessing necessary care. The probabilities of having healthcare denied are the highest in this group compared to other groups, at both survey waves. The level of healthcare forgone due to fear is moderate but shows a trend of slight improvement over time. Members of this class face substantial systemic challenges, indicating room for targeted healthcare interventions to address supply barriers more effectively. We refer to this class as "High denial with persistent postponement".

Class 6 (N = 435; 1.0%) is the smallest class, defined by its extremely high fear-based barriers to healthcare. In both survey waves, this class exhibited almost universal rates of forgone healthcare due to fear (97% in SCS1 and 95% in SCS2). Additionally, there were relatively high probabilities of postponed healthcare (77% in SCS1 and 50% in SCS2), alongside notable probabilities of denied healthcare (18% in SCS1 and 17% in SCS2). Members of this class faced fear-based barriers that led them to forego healthcare at very high rates throughout the pandemic, marking them as severely impacted in terms of healthcare access. This class represents those continuously facing high barriers, especially fear-based but also supply-based, primarily manifested through high rates of postponement. This points to a group with substantial and persistent unmet healthcare needs, making them the most vulnerable group during the pandemic. However, it should be noted that there is less certainty about the classification of older adults into this group, as indicated by the entropy and AvePP values presented in Table 2. We refer to this class as "Persistently high fear-based barriers".

3.3 Socio-demographic, economic, and health-related covariates of class membership

In the final part of our analysis, we examined the influences of socio-demographic, economic, and health-related variables on class membership. We began by examining bivariate relationships using multinomial logistic regression models, estimating a series of models with class membership as the outcome variable (with Class 1 as the reference category) and each covariate entered individually. Table 4 presents the estimates from these bivariate models, displaying the coefficients, their standard errors, and the percentual distributions of the covariates given class membership. The coefficients represent the influence of each covariate on the likelihood of class membership relative to the reference class. A positive coefficient indicates an increased likelihood of being in the given class compared to the reference class, while a negative coefficient indicates a decreased likelihood. Standard errors are provided in parentheses.

Additionally, the percentual distributions of covariates given class membership are included to offer a straightforward understanding of the characteristics of each class. This detailed information facilitates a clearer interpretation of how each covariate impacts class membership. We found a highly significant influence of each covariate on class membership.

Table 4: Bivariate relationships between class membership and socio-demographic, economic, and health-related covariates

	Class 1	Class 2		Class 3		Class 4		Class 5		Class 6	
	%	**Coef. (SE)**	**%**	**Coef. (SE)**	**%**	**Coef. (SE)**	**%**	**Coef. (SE)**	**%**	**Coef. (SE)**	**%**
Age in 2020 ***											
50–64	30,1%	Ref.	26,4%	Ref.	27,6%	Ref.	24,7%	Ref.	35,6%	Ref.	24,6%
65–79	52,1%	0.24 (0.04)	57,9%	0.22 (0.06)	59,7%	0.28 (0.06)	56,7%	-0.16 (0.10)	52,6%	0.34 (0.17)	60,1%
80+	17,7%	0.01 (0.05)	15,7%	-0.24 (0.09)	12,7%	0.25 (0.08)	18,6%	-0.57 (0.16)	11,8%	0.05 (0.23)	15,3%
Gender ***											
Men	44,8%	Ref.	40,3%	Ref.	42,4%	Ref.	28,3%	Ref.	30,8%	Ref.	25,9%
Woman	55,2%	0.18 (0.04)	59,7%	0.10 (0.05)	57,6%	0.72 (0.06)	71,7%	0.60 (0.10)	69,2%	0.84 (0.17)	74,1%
Partner in household ***											
Yes	70,8%	Ref.	71,0%	Ref.	71,4%	Ref.	65,7%	Ref.	67,5%	Ref.	66,1%
No	29,2%	-0.01 (0.04)	29,0%	-0.03 (0.06)	28,6%	0.24 (0.05)	34,3%	0.16 (0.10)	32,5%	0.22 (0.15)	33,9%
Area of residence ***											
Rural	36,6%	-0.18 (0.04)	32,5%	0.07 (0.05)	38,2%	-0.30 (0.06)	30,0%	-0.26 (0.10)	30,8%	0.05 (0.14)	37,8%
Urban	63,4%	Ref.	67,5%	Ref.	61,8%	Ref.	70,0%	Ref.	69,2%	Ref.	62,2%
Education ***											
Low	34,5%	-0.03 (0.04)	32,1%	0.06 (0.06)	34,7%	-0.13 (0.06)	28,5%	0.05 (0.11)	31,9%	0.11 (0.16)	35,9%
Medium	44,4%	Ref.	42,7%	Ref.	42,1%	Ref.	41,5%	Ref.	39,2%	Ref.	41,4%
High	21,2%	0.21 (0.04)	25,2%	0.15 (0.07)	23,2%	0.42 (0.06)	30,0%	0.44 (0.11)	28,9%	0.14 (0.19)	22,8%
Employed or self-employed when COVID-19 broke out ***											
Yes	22,2%	Ref.	18,6%	Ref.	18,3%	Ref.	19,5%	Ref.	21,1%	Ref.	13,0%
No	77,8%	0.22 (0.04)	81,4%	0.24 (0.07)	81,7%	0.16 (0.07)	80,5%	0.06 (0.11)	78,9%	0.64 (0.22)	87,0%
Ability to make ends meet since the outbreak ***											
Easily	27,7%	0.23 (0.04)	36,4%	0.04 (0.06)	28,3%	0.34 (0.07)	32,3%	-0.23 (0.14)	20,7%	0.00 (0.22)	20,9%
Fairly easily	36,0%	Ref.	37,4%	Ref.	35,3%	Ref.	30,0%	Ref.	33,8%	Ref.	27,1%
With some difficulty	26,8%	-0.32 (0.05)	20,1%	0.09 (0.07)	28,6%	0.12 (0.07)	25,2%	0.15 (0.12)	29,2%	0.51 (0.18)	33,5%
With great difficulty	9,5%	-0.48 (0.08)	6,1%	-0.18 (0.11)	7,8%	0.46 (0.09)	12,5%	0.60 (0.13)	16,3%	0.96 (0.21)	18,6%
Self-rated health before the pandemic ***											
Excellent	8,0%	-0.40 (0.08)	5,1%	-0.16 (0.10)	6,6%	-0.49 (0.13)	4,4%	-1.12 (0.48)	1,8%	-1.96 (1.27)	0,7%
Very good	18,6%	-0.23 (0.05)	14,2%	-0.23 (0.08)	14,4%	-0.06 (0.08)	16,0%	-0.45 (0.20)	8,1%	-0.68 (0.37)	5,9%

Good	46,4%	Ref.	44,5%	Ref.	45,1%	Ref.	42,4%	Ref.	31,7%	Ref.	29,3%
Fair	22,1%	0.31 (0.04)	28,9%	0.24 (0.06)	27,5%	0.41 (0.06)	30,4%	1.07 (0.11)	44,0%	1.27 (0.17)	49,7%
Poor	5,0%	0.43 (0.07)	7,3%	0.27 (0.12)	6,3%	0.40 (0.11)	6,8%	1.45 (0.14)	14,5%	1.53 (0.22)	14,4%
Change in health since the pandemic * **											
About the same	91,9%	Ref.	84,1%	Ref.	89,6%	Ref.	82,6%	Ref.	69,9%	Ref.	67,3%
Worsened	6,0%	0.77 (0.06)	11,8%	0.18 (0.12)	6,9%	0.91 (0.08)	13,3%	1.75 (0.10)	26,1%	1.92 (0.15)	29,9%
Improved	2,2%	0.73 (0.09)	4,1%	0.51 (0.14)	3,5%	0.76 (0.13)	4,2%	0.90 (0.23)	4,1%	0.57 (0.42)	2,8%
Number of chronic conditions * **											
0	25,1%	Ref.	10,9%	Ref.	13,6%	Ref.	13,0%	Ref.	6,3%	Ref.	7,1%
1	28,3%	0.62 (0.06)	22,8%	0.50 (0.08)	25,2%	0.39 (0.09)	21,6%	0.76 (0.26)	15,1%	0.65 (0.35)	15,2%
2	20,9%	0.91 (0.07)	22,6%	0.71 (0.09)	23,1%	0.78 (0.09)	23,5%	1.36 (0.25)	20,3%	1.09 (0.34)	17,5%
3+	25,6%	1.37 (0.06)	43,7%	1.01 (0.08)	38,1%	1.16 (0.08)	42,0%	2.21 (0.23)	58,3%	2.12 (0.30)	60,2%

*Source: Authors' calculations based on SHARE data. Notes: Coef. = regression coefficient; SE = standard error; Ref. = reference category. The table displays estimates from a series of multinomial logistic regression models for the six latent classes. Each relationship between a covariate and the latent classes was analyzed separately in its own model. Intercepts are not included in this table. Class 1 served as the reference class. In addition to coefficients and their standard errors, the table also shows covariate distributions, expressed as percentages, given class membership. The percentages are rounded; therefore, the sums may not add up to 100%. The estimates were derived using a three-step approach as implemented in Latent GOLD (version 6.0). The significance of the relationships between the covariates and the latent classes was assessed using Wald tests; significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$. Class 1 = No unmet needs; Class 2 = High early postponement with rapid improvement; Class 3 = Rising barriers; Class 4 = High early fear-based barriers; Class 5 = High denial with persistent postponement; Class 6 = Persistently high fear-based barriers.*

We first turn to socio-demographic covariates. The middle age group (65–79), generally the largest (see Table 1), had the highest proportions in Class 6 (Persistently high fear-based barriers) at 60.1%, Class 3 (Rising barriers) at 59.7%, and Class 2 (High early postponement with rapid improvement) at 57.9%. The younger age group (50–64) was notably overrepresented in Class 5 (High denial with persistent postponement) at 35.6%, while the oldest age group (80+) showed a relatively balanced distribution across classes, with slightly higher prevalence in Class 4 (High early fear-based barriers) at 18.6% and Class 1 (No unmet needs) at 17.7%. The results suggest a gender disparity in healthcare access during the pandemic, with women facing greater challenges and exhibiting more early fear-based barriers than men. Women were considerably overrepresented in Class 6 at 74.1%, Class 4 at 71.7%, and Class 5 at 69.2%. These classes were also characterized by the highest proportions of older adults not living with a partner: Class 4 at 34.3%, Class 6 at 33.9%, and Class 5 at 32.5%. Class 4 at 70.0% and Class 5 at 69.2% were most likely to be urban residents. Finally, Class 4 was the best educated (30.0%), followed by Class 5 (28.9%), indicating that older adults with higher education were more likely to experience fear-based barriers early on and continued to report difficulties accessing care throughout the pandemic. Older adults with low education were overrepresented in Class 6 at 35.9%, experiencing persistent fear-based barriers.

Regarding economic covariates, the results in Table 4 show that non-employed individuals faced greater barriers, particularly in Class 6 (87.0%). We found highly significant effects of household financial circumstances, with older adults who reported making ends meet easily or fairly easily more prevalent in Class 2 (36.4% and 37.4%, respectively), suggesting that better financial stability was associated with more quickly resolved barriers to healthcare access. Severe financial hardship was pronouncedly overrepresented in Class 6 at 18.6% and Class 5 at 16.3%, highlighting the strong association between financial difficulties and persistently unmet healthcare needs.

Health-related variables significantly affected healthcare access during the pandemic. Better pre-pandemic health was associated with fewer issues, with those rating their health as good, very good, or excellent more prevalent in Class 1, Class 2, Class 3, and Class 4 at 63% to 73% in total. Fair and poor health were a major characteristic of individuals in Class 5 and Class 6. Those facing a decline in health were more likely to experience high and lasting barriers: older adults whose health worsened since the pandemic were markedly overrepresented in Class 6 at 29.9% and Class 5 at 26.1%. Stable health was more common in Class 1 at 91.9% and Class 3 at 89.6%, indicating no unmet needs or issues emerging later in the course of the pandemic. Improved health, though less common, was highest in Class 4 at 4.2% and Class 2 at 4.1%. Chronic conditions were strongly associated with unmet needs, with three or more conditions overrepresented in Class 6 at 60.2%, Class 5 at 58.3%, and Class 4 at 42.0%. Conversely, those with no chronic conditions were distinctly more prevalent in Class 1 at 25.1%.

Having examined the impact of individual socio-demographic, economic, and health-related covariates, we then turned to the comprehensive model that included all covariates simultaneously. This model controlled for the effects of each covariate while considering the influence of the others, providing a more holistic view of the factors affecting class membership. Additionally, this model incorporated dummy variables for SHARE countries to account for any differences at the country level. The results are shown in Table 5.

Table 5: Adjusted effects of socio-demographic, economic, and health-related covariates on class membership

	Class 1	Class 2		Class 3		Class 4		Class 5		Class 6	
	%	**Coef. (SE)**	**%**	**Coef. (SE)**	**%**	**Coef. (SE)**	**%**	**Coef. (SE)**	**%**	**Coef. (SE)**	**%**
Intercept ***	Ref.	-1.76 (0.11)		-2.95 (0.21)		-2.91 (0.17)		-5.16 (0.52)		-7.08 (0.66)	
Age in 2020 ***											
50–64	30.2%	Ref.	27.5%	Ref.	24.2%	Ref.	25.1%	Ref.	38.8%	Ref.	22.8%
65–79	52.1%	-0.07 (0.05)	57.7%	0.05 (0.09)	61.4%	0.06 (0.08)	55.6%	-0.45 (0.14)	50.7%	0.09 (0.26)	60.6%
80+	17.6%	-0.54 (0.07)	14.7%	-0.48 (0.13)	14.4%	-0.13 (0.10)	19.3%	-1.29 (0.25)	10.5%	-0.61 (0.32)	16.6%
Gender ***											
Men	44.8%	Ref.	39.9%	Ref.	42.7%	Ref.	28.5%	Ref.	31.6%	Ref.	31.8%
Woman	55.2%	0.25 (0.04)	60.1%	0.12 (0.06)	57.3%	0.79 (0.06)	71.5%	0.56 (0.12)	68.4%	0.65 (0.19)	68.2%
Partner in household											
Yes	70.8%	Ref.	71.3%	Ref.	70.0%	Ref.	66.4%	Ref.	70.3%	Ref.	65.0%
No	29.3%	-0.11 (0.04)	28.8%	0.04 (0.07)	30.0%	-0.08 (0.06)	33.7%	-0.23 (0.13)	29.7%	-0.03 (0.17)	35.0%
Area of residence ***											
Rural	36.6%	-0.13 (0.04)	32.6%	0.15 (0.07)	38.5%	-0.06 (0.06)	29.7%	-0.30 (0.13)	29.9%	0.43 (0.16)	42.0%
Urban	63.4%	Ref.	67.4%	Ref.	61.5%	Ref.	70.3%	Ref.	70.2%	Ref.	58.0%
Education ***											
Low	34.4%	-0.23 (0.05)	31.9%	-0.20 (0.08)	35.9%	-0.28 (0.08)	29.0%	-0.34 (0.13)	28.8%	-0.64 (0.20)	37.6%
Medium	44.5%	Ref.	43.2%	Ref.	40.6%	Ref.	40.4%	Ref.	42.0%	Ref.	43.1%
High	21.1%	0.19 (0.05)	24.9%	0.39 (0.08)	23.4%	0.47 (0.07)	30.6%	0.50 (0.13)	29.3%	0.28 (0.24)	19.3%
Employed or self-employed when COVID-19 broke out											
Yes	22.3%	Ref.	19.6%	Ref.	15.3%	Ref.	19.5%	Ref.	24.0%	Ref.	12.6%
No	77.7%	-0.01 (0.06)	80.5%	0.19 (0.11)	84.8%	0.00 (0.08)	80.5%	-0.13 (0.15)	76.0%	0.03 (0.32)	87.4%
Ability to make ends meet since the outbreak ***											
Easily	27.8%	0.13 (0.05)	36.4%	-0.09 (0.09)	27.3%	0.08 (0.08)	32.5%	0.11 (0.17)	22.6%	0.28 (0.23)	21.1%
Fairly easily	36.0%	Ref.	37.2%	Ref.	36.9%	Ref.	29.6%	Ref.	32.0%	Ref.	24.7%
With some difficulty	26.8%	-0.06 (0.05)	20.4%	0.08 (0.08)	28.6%	0.18 (0.08)	24.7%	0.16 (0.14)	28.8%	0.53 (0.23)	33.9%
With great difficulty	9.5%	0.08 (0.09)	6.1%	-0.06 (0.15)	7.3%	0.49 (0.10)	13.2%	0.74 (0.18)	16.6%	1.06 (0.29)	20.4%
Self-rated health before the pandemic ***											
Excellent	8.0%	-0.37 (0.09)	5.5%	-0.26 (0.16)	5.4%	-0.47 (0.14)	4.6%	-0.30 (0.38)	3.3%	-1.86 (1.40)	0.7%

Very good	18.7%	-0.22 (0.06)	14.7%	-0.25 (0.10)	12.9%	-0.15 (0.08)	15.9%	-0.03 (0.20)	11.2%	-1.24 (0.58)	3.3%
Good	46.4%	Ref.	45.1%	Ref.	44.5%	Ref.	41.4%	Ref.	32.3%	Ref.	30.3%
Fair	22.1%	0.27 (0.05)	27.9%	0.41 (0.08)	29.9%	0.31 (0.07)	30.3%	0.78 (0.14)	41.0%	1.26 (0.20)	52.1%
Poor	4.9%	0.28 (0.09)	6.8%	0.51 (0.15)	7.3%	0.37 (0.12)	7.8%	0.87 (0.21)	12.3%	1.31 (0.34)	13.7%
Change in health since the pandemic * **											
About the same	92.0%	Ref.	84.7%	Ref.	88.1%	Ref.	82.0%	Ref.	72.2%	Ref.	70.9%
Worsened	5.9%	0.49 (0.07)	11.3%	0.10 (0.13)	8.3%	0.65 (0.09)	13.8%	1.17 (0.15)	23.9%	1.02 (0.22)	25.9%
Improved	2.2%	0.45 (0.10)	4.0%	0.32 (0.17)	3.6%	0.52 (0.14)	4.2%	0.49 (0.28)	3.9%	0.28 (0.41)	3.3%
Number of chronic conditions * **											
None	25.1%	Ref.	11.8%	Ref.	12.0%	Ref.	13.3%	Ref.	7.6%	Ref.	6.0%
One	28.4%	0.55 (0.06)	23.1%	0.61 (0.12)	24.1%	0.31 (0.10)	21.1%	0.73 (0.28)	17.9%	0.69 (0.43)	15.9%
Two	21.0%	0.83 (0.07)	22.8%	0.83 (0.13)	22.6%	0.65 (0.10)	22.7%	1.18 (0.29)	21.8%	0.97 (0.46)	17.8%
Three or more	25.5%	1.26 (0.07)	42.3%	1.18 (0.14)	41.4%	1.00 (0.10)	43.0%	1.79 (0.29)	52.8%	1.67 (0.45)	60.3%

*Source: Authors' calculations based on SHARE data. Notes: Coef. = regression coefficient; SE = standard error; Ref. = reference category. The table displays estimates from a multinomial logistic regression for the six latent classes with all covariates entered simultaneously, including country dummies. Class 1 served as the reference class. In addition to coefficients and their standard errors, the table also shows covariate distributions, expressed as percentages, given class membership. The percentages are rounded; therefore, the sums may not add up to 100%. The estimates were derived using a three-step approach as implemented in Latent GOLD (version 6.0). The significance of the relationships between the covariates and the latent classes was assessed using Wald tests; significance levels are indicated as follows: *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$. Class 1 = No unmet needs; Class 2 = High early postponement with rapid improvement; Class 3 = Rising barriers; Class 4 = High early fear-based barriers; Class 5 = High denial with persistent postponement; Class 6 = Persistently high fear-based barriers.*

When comparing the adjusted relationships from Table 5 to the bivariate relationships from Table 4, we observed some changes in the strength and significance of certain covariates. Still, the overall findings regarding adjusted covariate effects conveyed similar substantive insights. Concerning age, coefficients for the oldest-old (age 80+) became (more) negative in Table 5, indicating that compared to the youngest group (age 50–64), while keeping other characteristics constant, the oldest-old were less likely to be in any class that experienced some form of unmet healthcare needs rather than in Class 1 with no unmet needs. Nonetheless, adjusted class-specific proportions of the oldest-old slightly increased in Class 3, Class 4, and Class 6. Altogether, with other factors accounted for, the oldest-old were more represented in classes defined by minimal (Class 1) or early fear-based (Class 4) healthcare barriers. Gender differences in Class 5 and Class 6 became slightly less pronounced when controlling for other covariates, but women remained largely predominant in these classes, reinforcing the finding that women were more likely to face high and persistent barriers. For the presence of a partner in the household, the overall effect was no longer statistically significant. We observed less disparity across classes, with a slightly reduced protective effect for those living with a partner, especially notable for Class 4, where the coefficient turned from significant in Table 4 to insignificant in Table 5. The area of residence indicated a notable shift, particularly for Class 6, where rural residents became more prevalent at 42.0%, suggesting that rural living independently contributed to persistent fear-based barriers. Education revealed a consistent pattern, with low education overrepresented in Class 6 (37.6%) and a strong association of high education with Class 4 (30.6%) and Class 5 (29.3%).

For employment status, the adjusted results confirmed that non-employed individuals faced significant barriers, with Class 6 at 87.4%, reinforcing findings from the bivariate analysis. However, the effect of employment status was insignificant overall when adjusted to the influences of other covariates. Regarding household financial circumstances, older adults who reported making ends meet with great difficulty were even more overrepresented in Class 6 (20.4%) and Class 5 (16.6%) in the adjusted model compared to the bivariate results, emphasizing the compounded effect of financial hardship.

The effects of self-rated health before the pandemic and changes in health since the pandemic were consistent across both analyses, but the adjusted results slightly decreased the representation of those with fair or poor self-rated health and worsened health in Class 6 and Class 5. Finally, the number of chronic conditions still showed a strong association with high and persistent barriers after controlling for other variables, with 60.3% of individuals in Class 6 and 52.8% of individuals in Class 5 having three or more chronic conditions.

4 Discussion and conclusions

This paper identified distinct groups of older adults by analyzing their unmet healthcare needs during the COVID-19 pandemic. We utilized data from the SHARE study, particularly the two waves of the SCS conducted in 2020 and 2021. We employed LCA to uncover a meaningful typology based on experiences of forgoing medical treatments due to fear of coronavirus infection, having medical appointments postponed because of the pandemic, and being denied medical appointments since the outbreak. Moreover, we explored the differences in class membership by applying LCA with covariates to assess how socio-demographic, economic, and health-related variables distinguish the emerging groups.

Based on the model that included all covariates, findings suggest that the oldest-old (aged 80+) individuals have avoided significant challenges in healthcare access during the pandemic. Precisely, they were less likely to be in any class that experienced some form of unmet healthcare needs rather than in Class 1 with no unmet needs. On the other hand, this was not the case for women, who were more likely to face high and persistent barriers to accessing healthcare, as represented by membership in Class 5 or Class 6. While women are generally more likely to report unmet healthcare needs (Allin et al., 2010), similar conclusions have been confirmed in studies conducted during the COVID-19 pandemic (e.g., Smolić et al., 2022). Furthermore, we showed that women were more likely to refrain from healthcare utilization due to fear of infection. Our findings corroborate previous studies that found women more concerned about contracting and spreading the virus and perceiving the virus as more prevalent and lethal compared to men (Oreffice & Quintana-Domeque, 2021). Regarding the partnership effects, these diminished once other variables were controlled for, even though bivariate analysis indicated that living with a partner had some protective effects against the most severe and persistent unmet healthcare needs during the pandemic. Living alone, on the other side, has been recognized as a risk factor for the health status decline of older adults, especially for those with unmet healthcare due to COVID-19 (in particular, healthcare forgone and denied) (Smolić, Mudražija, Blaževski & Fabijančić, 2023).

For the impact of the area of residence, we found that urban dwellers were more likely to face early fear-based barriers (Class 4) and to report persistent supply-based barriers (Class 5), perhaps due to higher perceived or actual risk of infection in more populated areas. Although urban areas could benefit from better healthcare access, their high population densities make them highly vulnerable to the spread of diseases in the community, thus increasing the number of infected and deaths (Peters, 2020). This situation, similarly, could have triggered the overcrowding of urban healthcare facilities with COVID-19 patients, reducing the supply for non-covid patients. In addition, one Canadian study on unmet healthcare needs for older adults during the COVID-19 pandemic showed that residents of rural areas were less likely to report any challenges in accessing healthcare (Khattar et al., 2023) while limited access to healthcare after the outbreak was found to be more common for older adults residing in urban areas (Smolić et al., 2022). The fact that rural dwellers are overrepresented in persistent fear-based class could be associated with rural areas being, on average, older than urban areas (Henning-Smith, 2020) and with relatively more older adults with lower education (37.6% in Class 6) and probably fewer resources in grasping the information related to the pandemic. Unlike those with lower education, more educated older adults were notably prevalent in Class 4 (High early fear-based barriers) and Class 5 (High denial with persistent postponement). This indicates that older adults with higher education were more likely to experience fear barriers early on and to report supply-side barriers throughout the pandemic, potentially due to greater awareness of risks or differing healthcare expectations.

Our results also highlight that financial stability significantly affected the type and persistence of unmet healthcare needs, with greater financial difficulties correlating with more severe and ongoing barriers during the pandemic. Arnault, Jusot & Renaud (2022) have presented similar findings for the population aged 50 and over after the outbreak. They showed that most economically vulnerable older adults with poor health before the pandemic were more likely to have faced barriers to accessing healthcare. Similarly, Tavares (2022) confirmed that people with difficulties making ends meet had greater odds to report forgoing healthcare after the outbreak. Pre-pandemic and current health status strongly influenced the type and severity of unmet healthcare needs, with poorer health associated with more significant and enduring barriers during the pandemic. We showed that older adults whose health worsened since the pandemic and those with three or more chronic conditions were predominantly in classes with persistent and significant barriers. This finding should not be disregarded because the health status of older adults declined during the pandemic, leading to increased health inequalities (Lüdecke & von dem Knesebeck, 2023). A decline in health status among older adults can be associated with the reduced use of healthcare services during the pandemic, suggesting that many faced challenges in accessing healthcare (Bíró et al., 2022). In the final model, we could also see that the combination of health variables measuring subjective and objective health status exhibits significant effects. Research showed, for example, that fears of infection were more pronounced among individuals with chronic conditions (Schuster et al., 2021) and that the presence of a chronic disease was correlated with the cancellation of medical care in the UK (Davillas & Jones, 2021). Moreover, Smolić et al. (2022) demonstrated that poorer health status, number of chronic conditions, and healthcare utilization significantly predicted perceived barriers to accessing healthcare among people aged 50 and above.

This study undoubtedly indicated that, with the help of data from the SHARE study, vulnerable groups of older adults can be identified, i.e., those who were most severely affected by the pandemic and who deserve special attention from health policymakers in the post-pandemic period. Furthermore, SHARE data enables the creation of tools that healthcare providers could routinely use to maintain continuity of care for the most vulnerable groups. Above all, our results indicate the existence of gender-based health inequalities (the distribution of health across the population) during the pandemic - women are overrepresented among both those with shorter and longer-term adverse impacts of the pandemic on health utilization - and the greater vulnerability of older adults in poor socio-economic conditions and those in poorer health. Following our findings, Classes 3, 5, and 6 could arguably be considered of primary concern because of the more persistent nature of the adverse impact of the COVID-19 pandemic.

While our study controlled for country differences using fixed effects, future work may consider multilevel LCA to examine both individual and country-level variations in patterns of unmet healthcare needs. This approach would allow for identifying latent classes at multiple levels and understanding contextual influences on class membership. Additionally, future research could use SHARE data collected after the pandemic to explore the impact of belonging to different latent classes (groups identified based on unmet healthcare needs during the pandemic) on later (distal) outcomes, such as post-pandemic health. When interpreting the results, it is important to note that LCA, while useful for uncovering patterns in data, does not provide absolute model fit. While the six-class solution was supported by multiple statistical criteria and provided meaningful insights, other candidate models (e.g., the five-class solution) also showed potential. Classification quality indicated some uncertainty, particularly in the smallest class, suggesting within-class heterogeneity. Furthermore, our findings are specific to older adults in Europe and Israel during the COVID-19 pandemic and may not generalise to other populations or contexts. Future research could test these typologies in different populations to assess their robustness.

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