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Exploring the most important factors related to self-perceived health among older men in Sweden: a cross-sectional study using machine learning

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ABSTRACT

Objective To evaluate which factors are the most strongly related to self-perceived health among older men and describe the shape of the association between the related factors and self-perceived health using machine learning.

Design and setting This is a cross-sectional study within the population-based VAScular and Chronic Obstructive Lung disease study (VASCOL) conducted in southern Sweden in 2019.

Participants A total of 475 older men aged 73 years from the VASCOL dataset.

Measures Self-perceived health was measured using the first item of the Short Form 12. An extreme gradient-boosting model was trained to classify self-perceived health as better (rated: *excellent* or *very good*) or worse (rated: *fair* or *poor*) using self-reported data on 19 prevalent physician-diagnosed *health conditions*, intensity of 9 *symptoms* and 9 *demographic and lifestyle factors*. Importance of factors was measured in SHapley Additive exPlanations absolute mean and higher scores correspond to greater importance.

Results The most important factors for classifying self-perceived health were: pain (0.629), sleep quality (0.595), breathlessness (0.549), fatigue (0.542) and depression (0.526). *Health conditions* ranked well below *symptoms* and *lifestyle variables*. Low levels of symptoms, good sleep quality, regular exercise, alcohol consumption and a body mass index between 22 and 28 were associated with better self-perceived health.

Conclusions *Symptoms* are more strongly related to self-perceived health than *health conditions*, which suggests that the impacts of *health conditions* are mediated through *symptoms*, which could be important targets to improve self-perceived health. Machine learning offers a new way to assess composite constructs such as well-being or quality of life.

STRENGTHS AND LIMITATIONS OF THIS STUDY

- ⇒ The study used a novel machine learning approach to evaluate factors related to self-perceived health.
- ⇒ The included factors cover many aspects of older adults' lives regarding health.
- ⇒ The symptoms scales used in this study are validated, widely used and easy to compare.
- ⇒ We cannot generalise these results to women or younger individuals.
- ⇒ The study sample was relatively small and a larger sample could increase the generalisability for older men in the population.

INTRODUCTION

Health comprises multiple domains and is defined by WHO as '*a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity*'.[1] Physical health can be described more *objectively*, for example, through clinical examinations by healthcare staff, and *subjectively* through self-report by individuals in the form of self-perceived health (SPH). SPH is often measured on a single Likert scale[2] or a visual analogue scale (VAS)[3] and is used to compare health status between groups in economic and sociological health studies and as an important outcome measure in clinical trials.[4] External information on health, such as a diagnosis by a medical practitioner, can influence the individuals' perception of their health. Furthermore, SPH may vary between age, social and cultural groups.[4] Epidemiological studies have shown SPH as an important predictor of future health events, prognosis and mortality, although these findings can vary between groups.[4–7]

Healthy ageing is a prioritised area for public health and includes ageing that minimises troublesome health conditions and symptoms and the ability to actively participate in activities in advance age.[8] As people age, chronic symptoms and health conditions become more prevalent and a majority of adults over 65 years suffer from multimorbidity[9] that can cause an array of symptoms that risk lowering the SPH and impairing well-being among the older population.[10]Among the oldest old, health conditions' effects on SPH are mediated though the consequences of the health conditions, such as symptoms and impaired mobility and less directly by the health conditions itself.[10]

In contrast, clinical guidelines rarely encompass multimorbidity[9] and the interaction between symptoms and health conditions is not fully understood.

There are few studies evaluating the importance of health-related factors such as health conditions, physical activity, social life and sleep quality to SPH among older adults. Previous studies have mainly analysed single factors associated with SPH using standard statistical methods.[11–13] In the presence of multiple factors related to SPH, understanding the complex interaction between the factors and SPH is important for preventative care, clinical evaluation and treatment to optimise well-being in older adults. The few studies that compared multiple factors found physical activity, chronic disease, dizziness, fatigue, depression, limitations in daily life and social factors to be relevant for SPH among older adults.[10 14 15] A study evaluating functioning, disease, pain, mental health and behaviour domains among adults 50 years or older found pain and mental health as the most important factors for SPH.[16] However, without comparing multiple factors such as symptoms, lifestyle and health conditions it is, to date, unknown which factors are the most strongly associated with SPH. However, to date, it is unknown which factors are the most strongly related to SPH. Innovative methods are required to take these next important steps in developing an understanding of SPH.

Machine learning and the use of SHapley Additive exPlanations (SHAP)[17] may offer new opportunities to analyse the importance and the shapes of associations among multiple factors in a way not feasible with standard statistical methods.[18] Machine learning can be used from a more explorative perspective to identify important factors and complex interactions.[17] A previous study[14] used machine learning to identify factors related to SPH while using standard statistical methods to evaluate the associations between the identified factors and SPH. A later study[19] used machine learning to explore the interaction between four health indicators and SPH among different age groups in the population. Both studies[14 19] defined associations between the factors and SPH, without quantifying the magnitude. Using a machine learning approach to evaluate the associations of multiple factors with SPH among older adults can contribute to the knowledge of how health is perceived among older adults and identify targets for improving health in this group.

The primary aim of this study was to evaluate which factors are most strongly related to SPH among older men using an explorative machine learning approach. The secondary aim was to describe the shapes of the associations between the related factors and SPH.

METHODS

Study design and population

This was a cross-sectional study of men aged 73 years enrolled in the population-based VAScular and Chronic Obstructive Lung disease study (VASCOL).[20] This is an ongoing study of older men's health that started in 2010 as part of a screening campaign for abdominal aortic aneurysms (AAAs) offered to all men aged 65 years in Blekinge, Sweden. The screening campaign of AAA was not offered to women. The men attending the screening were asked to participate in the VASCOL study. In 2019, when the participants were approximately 73 years old (n=1193), a follow-up postal survey study was conducted with a focus on lifestyle, symptoms, health conditions and well-being and 907 of the men participated. The VASCOL study includes multiple overall aims and the present study is a secondary analysis of this longitudinal study. Data collection and the variables of the VASCOL study have been described in detail previously.[20] All variables used in the present analyses are from the 2019 follow-up, with the exception of education level, which was collected at baseline (2010). The inclusion criteria for this study were participants in the 2019 VASCOL study with available data on SPH. Exclusion criteria was missing data on SPH outcome variable (but not the independent variables). This report complies with the Reporting of Observational Studies in Epidemiology[21] guidelines.

Assessments

SPH was measured with the first item in the Swedish version of the SF-12v2: "*In general, would you say your health is:*". with the possible answers: *excellent*, *very good*, *good*, *fair* or *poor*. The timeframe for SPH was during the last 4weeks, which is the original timeframe for SF-12v2.

Participants also self-reported 19 common health conditions diagnosed by medical practitioners, including cardiovascular and respiratory diseases and cancer (online supplemental text); intensity of 8 symptoms (anxiety, appetite, breathlessness, depression, drowsiness, fatigue, nausea and pain) on numerical rating scales (NRSs) from 0 (*none*) to 10 (*worst possible intensity*) using the revised Edmonton Symptom Assessment System[22] and 8 demographic and lifestyle factors (table 1). The focal period for the symptoms and lifestyle factors was during the last 2weeks.

Machine learning

Supervised machine learning which is used in the present study aims to learn to see patterns in data to classify an outcome. The data are often split into a training and test set to be able to evaluate the model's ability to generalise for new, unseen data. First, the model is trained to classify the outcome on the training set. During the training, so-called hyperparameters are tuned and evaluated on the training set. Hyperparameters can be seen as different settings of the model that can be changed to improve classification accuracy. Finally, the model is evaluated on the test set which is kept isolated from the model during the training to prevent overfit. Overfit occurs when a model is too adjusted to the training data and cannot generalise for

Table 1 Characteristics of 475 men aged 73 years in the study population

	Self-perceived health		
Factors (% missing values)	**Total n=475**	**Better n=193**	**Worse n=282**
Anthropometrics, lifestyle and demographic factors			
Body mass index (1.1%)	27.07 (4.1)	25.77 (2.8)	27.96 (4.5)
University degree (0%)	96 (20.2%)	57 (29.5%)	39 (13.8%)
Ever smoker (1.9%)	313 (65.9%)	113 (58.5%)	200 (70.9%)
Pack-years of smoking (9.7%)	8.84 (16.6)	10.06 (21.6)	8.00 (11.9)
Exercise frequency (1.7%)			
Less than once a week	82 (17.3%)	10 (5.2%)	72 (25.5%)
1–3 times a week	134 (28.2%)	42 (21.8%)	92 (32.6%)
3–6 times a week	146 (30.7%)	79 (40.9%)	67 (23.8%)
Everyday	113 (23.8%)	62 (32.1%)	51 (18.1%)
Standard units of alcohol (15.8%)	6.43 (6.3)	6.88 (5.8)	6.13 (6.6)
Sleep quality (0.6%)			
Very bad	65 (13.7%)	4 (2.1%)	61 (21.6%)
Bad	159 (33.5%)	36 (18.7%)	123 (43.6%)
Quite good	137 (28.8%)	80 (41.5%)	57 (20.2%)
Good	5 (1.1%)	0 (0.0%)	5 (1.8%)
Very good	109 (22.9%)	73 (37.8%)	36 (12.8%)
Sleep duration (0.6%)			
4 hours or less	43 (9.1%)	8 (4.1%)	35 (12.4%)
5 hours	77 (16.2%)	21 (10.9%)	56 (19.9%)
6 hours	177 (37.3%)	80 (41.5%)	97 (34.4%)
7 hours	130 (27.4%)	68 (35.2%)	62 (22.0%)
8 hours	32 (6.7%)	14 (7.3%)	18 (6.4%)
9 hours	5 (1.1%)	1 (0.5%)	4 (1.4%)
10 hours or more	11 (2.3%)	1 (0.5%)	10 (3.5%)
Symptoms			
Anxiety (2.9%)	1.03 (2.0)	0.12 (0.4)	1.65 (2.4)
Appetite (2.5%)	0.71 (1.7)	0.05 (0.4)	1.16 (2.1)
Breathlessness (2.9%)	2.08 (2.6)	0.50 (1.0)	3.16 (2.8)
Depression (3.2%)	1.48 (2.2)	0.25 (0.6)	2.32 (2.5)
Drowsiness (4.0%)	2.35 (2.4)	0.73 (0.9)	3.46 (2.5)
Fatigue (3.2%)	2.76 (2.6)	0.90 (1.2)	4.03 (2.5)
Nausea (2.9%)	0.60 (1.5)	0.09 (0.5)	0.95 (1.8)
Pain (2.7%)	2.84 (2.6)	1.05 (1.4)	4.07 (2.5)
Health conditions (4.2%)			
Cancer	89 (18.7%)	33 (17.1%)	56 (19.9%)
Cardiovascular disease	179 (37.7%)	48 (24.9%)	131 (46.5%)
Diabetes	79 (16.6%)	18 (9.3%)	61 (21.6%)
Hypertension	275 (57.9%)	91 (47.2%)	184 (65.2%)
Hyperlipidaemia	127 (26.7%)	36 (18.7%)	91 (32.3%)
Respiratory disease	85 (17.9%)	17 (8.8%)	68 (24.1%)
Rheumatological disease	30 (6.3%)	9 (4.7%)	21 (7.4%)

All values are presented as the mean (SD) or frequency (%). Values in the table correspond to the values after imputation of missing values by median for continuous variables and mode for categorical variables.

previously unseen data. For a comprehensive paper on how to understand and interpret machine learning studies, see Liu *et al.*[18]

Data handling

The analyses were conducted using R software, V.4.03 (R Foundation for Statistical Computing). SPH was dichotomised as either *better* (rating their health as *excellent* or *very good*) or *worse* (rating their health as *fair* or *poor*). Participants rating their health as the middle score (*good*) were excluded from the dataset to create a clear difference between better and worse SPH. For details on handling and deriving new variables, see online supplemental text.

Participants' characteristics were tabulated descriptively. Missing values of the independent variables (table 1) were assumed to be missing at random and were imputed with the median for continuous and mode for categorical independent variables.[23] The dataset was randomly split into a training (80%) and validation (20%) set and to validate the randomisation of the split, χ^2 tests were used and a two-tailed p value of <0.05 was considered statistically significant.

Model training and validation

We used the supervised machine learning algorithm extreme gradient boosting (XGBoost)[24] to binarily classify SPH as either worse or better using all factors in the dataset as predictor variables (table 1). XGBoost is a gradient boosting, tree-based model, meaning that it uses multiple decision trees to classify an outcome and the model boosts the worst-performing decision trees while learning. Overfit is a common problem in machine learning studies and occurs when a model is too adjusted to the training data which lowers the external validity of the model for unseen data. XGBoost uses regularisation to prevent overfit and to be more generalisable for new, unseen data.[24]

To find the optimal hyperparameters, grid searches were performed with fivefold cross-validation on the training set and the model with the highest area under the curve (AUC) of the receiver operating characteristic was selected for evaluation. The final model's performance was evaluated by classifying SPH in the validation set and assessing AUC, sensitivity and specificity.

Associations of factors

The associations of factors with SPH among the individual participants were explained by SHAP[17] values. SHAP values can be interpreted as log-odds, a positive SHAP value corresponds to an increased probability of worse SPH and a negative SHAP value corresponds to an increased probability of better SPH. The average importance of each factor for SPH among the participants was presented by the SHAP absolute mean values. An increased SHAP absolute mean represents increased importance (prediction power) of the factor when the model classifies SPH as either better or worse.

Shapes of associations

The shape of the association between the intensity of a factor and SPH was evaluated for the top 10 most important variables for SPH by plotting the log-odds for predicting SPH against the values of the factor with a locally estimated scatterplot smoothing line. This represents the change in association with worse (positive log-odds) or better (negative log-odds) SPH by the intensity of the factor. SHAP has emerged as a robust measurement for explaining factors of importance in machine learning studies and can be used to identify complex, non-linear relationships between factors but at the same time remain interpretable.[17]

Sensitivity analysis

To account for a possible bias by excluding participants rating their health as 'good', a sensitivity analysis was performed by including participants rating their health as 'good' in the *better* SPH category and performing the same training and evaluation procedure.

Patient and public involvement

The survey was piloted on 10 people of similar age to the VASCOL study which gave feedback on the survey. Minor layout changes were done to the survey questions to fit the specific study participants.[20]

RESULTS

Participant characteristics

After the exclusion of 10 men with missing data on SPH and 422 men reporting a middle SPH score (good), 475 men were included in the analyses (online supplemental figure S1). Characteristics of the included men are shown in table 1. A total of 193 (41%) men rated their health as better (rated: *excellent* or *very good*) and 282 (59%) men rated their health as worse (rated: *fair* or *poor*). The majority of the participants were ever-smokers (65.9%), and among them, the mean pack-years of smoking was 8.84 (SD 16.6). Almost one-fifth (17.3%) exercised less than once a week, the mean body mass index (BMI) was 27.07 (SD 4.1) and the mean standard units of alcohol consumed per week was 6.43 (SD 6.3). Cardiovascular disease was present among more than a third of the participants (37.3%) and approximately one-fifth of the participants had respiratory disease (17.9%), diabetes (16.6%) and/or cancer (18.7%). Characteristics were similar between participants in the training and validation sets, which supports the validity of the randomisation (online supplemental material table S1).

Model performance

The final XGBoost model had high accuracy, with an AUC of 0.897 (95% CI 0.837 to 0.957), a sensitivity of 0.941 and specificity of 0.852 when evaluated in the validation set, which supports the high generalisability of the model. The final model hyperparameters are presented in online supplemental material table S2.

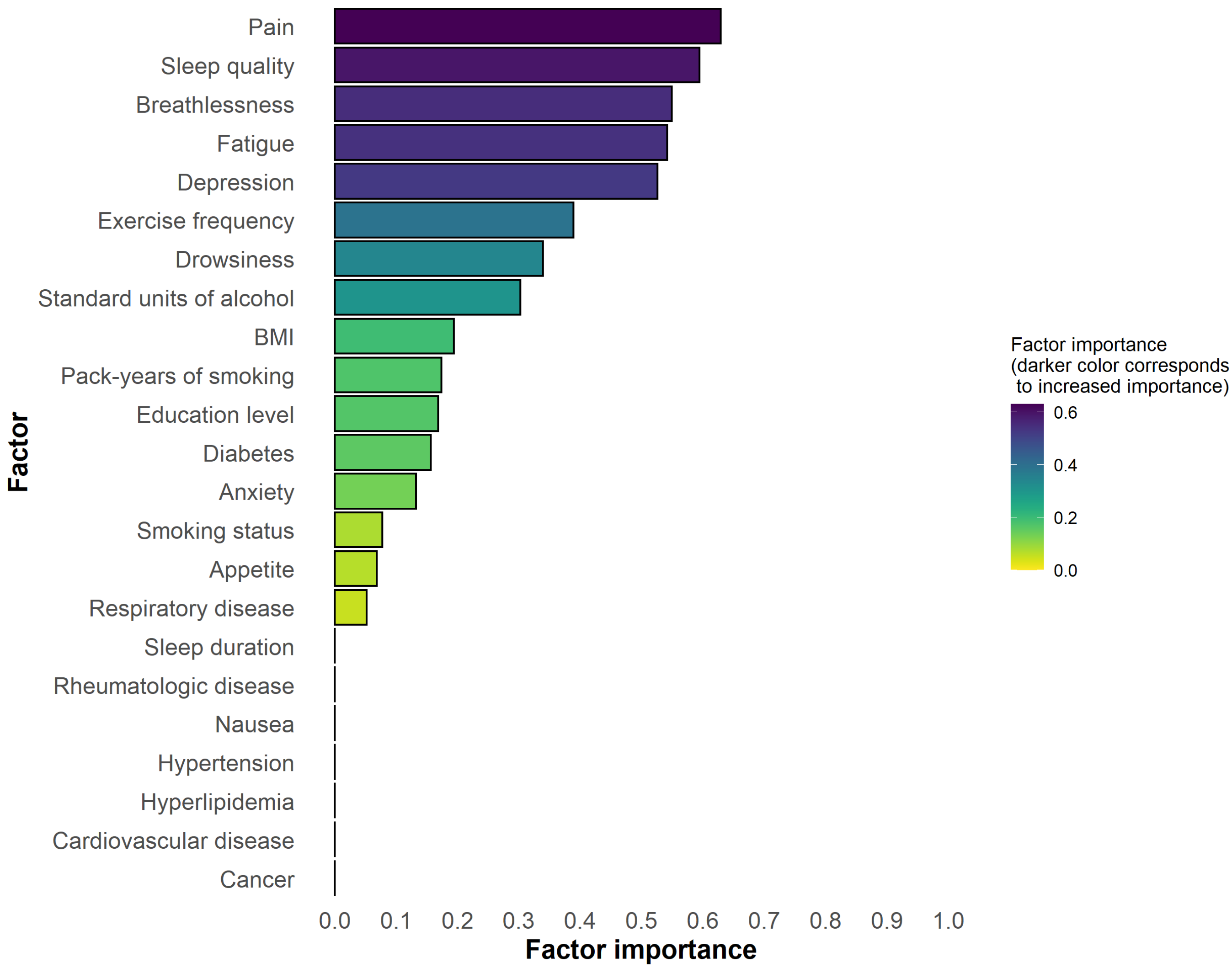

Figure 1 Importance of factors for self-perceived health. Ranking of variables for predicting better (excellent/very good) or worse (fair/poor) self-perceived health is measured in SHapley Additive exPlanations (SHAP) absolute mean values and is calculated on the participants in the validation set. A higher SHAP absolute mean value corresponds to greater importance for predicting self-perceived health as better or worse. The variable importance is multivariate and is calculated in relation to all other factors in the dataset. BMI, body mass index.

Factor importance for SPH

The factors with the highest SHAP absolute mean and greatest importance for the classification of SPH were *symptoms*: pain (0.629), sleep quality (0.595), breathlessness (0.549), fatigue (0.542) and depression (0.526; figure 1). Other important factors were exercise frequency (0.389), drowsiness (0.340) and standard units of alcohol consumption (0.303). BMI (0.194) and education level (0.169) were not as important as most symptoms. Diabetes (0.157) and respiratory diseases (0.052) were the most important *health conditions*, but overall, health conditions were less important than most symptoms and lifestyle variables. Hypertension, hyperlipidaemia, cancer and rheumatological and cardiovascular diseases had a SHAP absolute mean of zero for SPH.

Shapes of associations with SPH

The shapes of the relationships of the top 10 important factors and their intensities with SPH can be seen in detail in figure 2 and online supplemental figure S2. For most of the *symptoms,* a total absence or a very low intensity was associated with *better* SPH. A pain score of 0/10 or 1/10 had a weaker association with *worse* SPH, while a pain score of ≥2/10 had a stronger association with *worse* SPH until a ceiling effect was reached around a score of 4. A similar pattern was seen for fatigue, depression and drowsiness, all with a ceiling effect at a score of approximately 3–4. Having only a score of ≥1/10 on the breathlessness scale markedly increased the association with *worse* SPH, but still a ceiling effect was seen for scores ≥4.

The relationship between BMI and SPH was U-shaped; having a BMI of <22 or >28 was associated with *worse* SPH compared with having a BMI of 22–28. Good sleep quality and regular exercise were associated with *better* SPH and drinking no alcohol was associated with *worse* SPH.

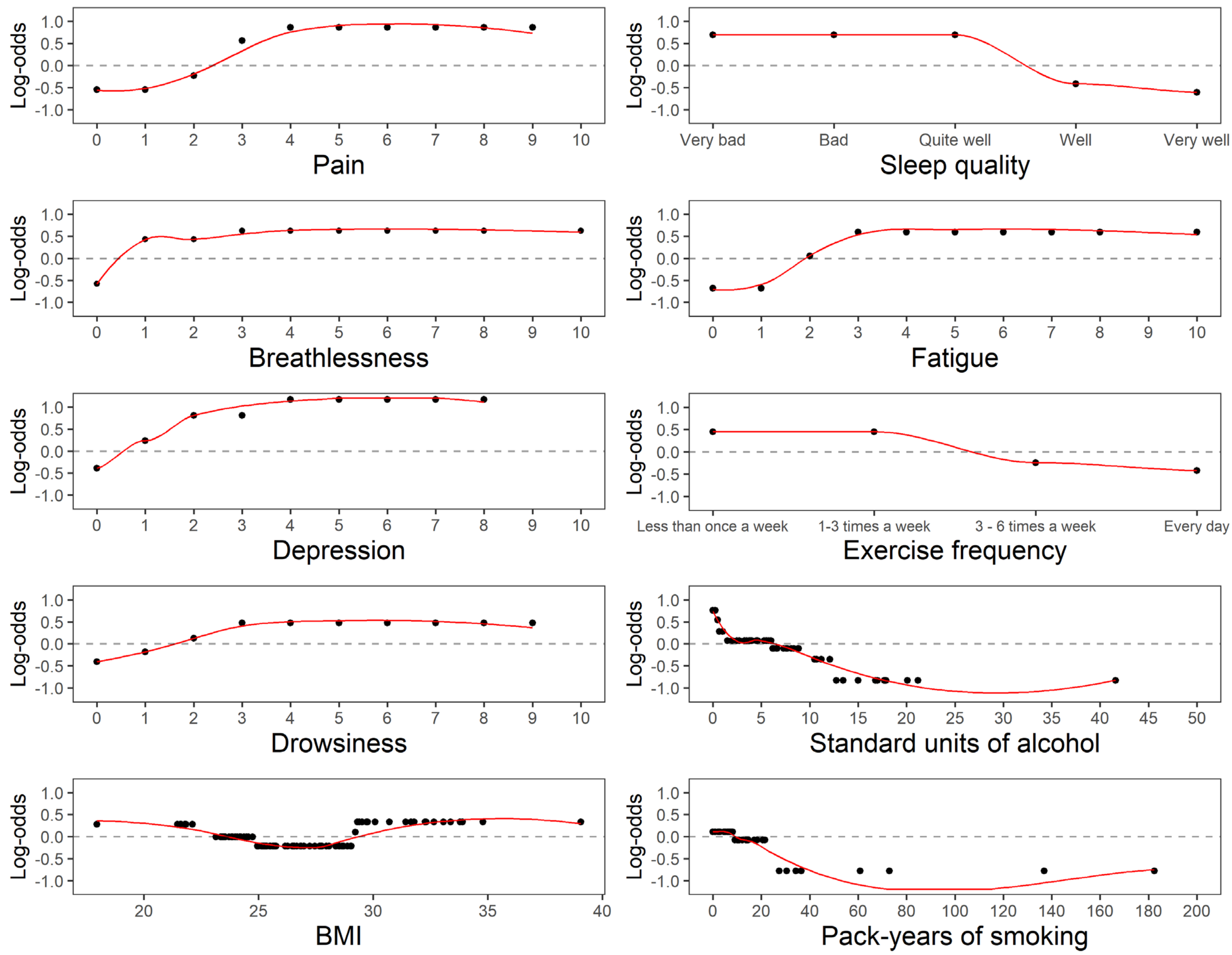

Figure 2 Variable impact on log-odds for self-perceived health. Each dot represents a participant in the validation set. X-axes represent the participants' scores for the factor. Y-axes represent the change in log-odds of rating self-perceived health as either worse (positive logodds) or better (negative log-odds). The red line is a locally estimated scatterplot smoothing line (LOESS) that represents a summarized value of the participant's log-odds. The dashed line marks a log-odds of zero. The symptoms are reported using a numerical rating scale (NRS) from 0 (none) to 10 (worst possible intensity of the symptom). Standard units of alcohol correspond to weekly average. BMI, body mass index.

Sensitivity analysis

Including participants reporting a middle SPH score (good) in the *better* SPH category resulted in a major drop of classification accuracy (AUC: 0.758; 95% CI 0.692 to 0.823), supporting the first model's ability to explain differences in factors related to SPH between the participants. The factor importance rankings and shapes of associations were similar for both models.

DISCUSSION

Main findings

Factors including pain, sleep quality, breathlessness, fatigue and depression were the most important factors for classifying a dichotomised rating of SPH among older men, with each factor's importance being similar. Diabetes and respiratory diseases were the most important *health conditions*, but overall, the presence of *health conditions* was not as important as almost all *symptoms*. The absence or very low level of symptoms, good sleep quality and regular exercise were associated with better SPH. Low or high BMI was associated with worse SPH as well as not drinking alcohol.

What this study adds

This is the first study using machine learning techniques to explore the importance of multiple concurrent factors for SPH. The study used a hypothesis-free exploration of the data and factor importance was estimated in relation to all other factors in the dataset, whereas previous studies in most cases only adjusted for a few variables selected based on previous knowledge.[11 12] Our study is one of the first to use machine learning to explore factors related to SPH.[14 19] Our study extends previous observations, as we included more detailed symptom data and were able to explore the shapes of the associations between factors and SPH among older men—findings that have clinical and research implications

A major finding in the present analysis is that the total absence of symptoms is more important for classifying SPH than the presence of health conditions and it reflects the WHO's definition of health: '*a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity*'.[1] Previous studies have identified an association between health conditions and lower SPH[4 13] and also show that health conditions have an indirect effect on SPH by the consequences of health conditions rather than a direct effect on SPH by health conditions.[10] The present analysis extends this line of research as it evaluates the classification importance between *health conditions* and *symptoms* concurrently with a more detailed focus on symptoms. An interpretation is that diagnosed conditions can be seen as *external information of our health from an authority* (medical practitioners)[4] and symptoms can reflect the *direct lived experienced*, which suggests why symptoms were more important since they can have stronger presence in the participant's everyday life and mind. When rating health, individuals often compare their health in relation to others or how their own health was before.[4] Our study also suggests that the important factors when individuals are comparing their health with others or how their own health was before are not conditions but symptoms. Symptoms reflects the immediate state of the individual and should be a clearer comparable reference of well-being than health conditions. The conditions should still have a univariate association with SPH.[4 13] Our interpretation is that the conditions are mediated by the symptoms, which could explain why health conditions were less important than symptoms for SPH. Symptoms should therefore be important targets to improve SPH among older adults with chronic health conditions. The present finding of a stronger association of physical activity with SPH compared with health conditions is in line with a previous study.[15] The result of the study also shows the importance of physical activity for SPH among older adults, as suggested before.[25] Exercising three to six times a week was similarly associated with SPH as exercising daily. This suggest that WHO's recommended weekly exercise frequency of 150–300 min[26] should be enough to optimise SPH among older men. Furthermore, we cannot evaluate any casual effect of physical activity from the present study, but the health benefits of regular exercise among older individuals are well documented.[27] The increased importance of symptoms and lifestyle factors for SPH can be important in clinical practice, as it shows the value of a holistic view of the patient's health in all clinical settings instead of only focusing on the underlying condition(s).

The shape of association with SPH differed between symptoms in relation to SPH among older men. Having a very low level of pain, fatigue or drowsiness was not associated with worse SPH. This was in comparison with breathlessness, which reached a peak of association with worse SPH at a score of one and depression, which was positively associated with worse SPH at a score of ≥1 and continued to increase until a ceiling was reached. This shows that breathlessness and depression are perceived differently than pain, fatigue or drowsiness. This suggests that a minor intensity of pain, fatigue or drowsiness can be seen as more 'acceptable' by the individual in comparison to a minor intensity of breathlessness or depression. As previously shown,[15] limitations in daily life are associated with worse SPH and breathlessness is highly associated with physical limitations and impaired mental well-being,[28 29] which can explain the clear association with SPH in our study.

A novel finding of our study is that BMI had a U-shaped relationship with SPH and being underweight or overweight was associated with *worse* SPH. Health conditions and limitations associated with underweight and overweight can play a role in the individual's perception of their health. Depression and mortality have previously been suggested to have a similar shaped association with BMI.[30 31] We also believe that BMI's relationship to SPH can be addressed by *external information* such as expectations on what a *healthy* BMI is. In the present study, this is reinforced by the shape of the association between BMI and SPH. Participants considered as obese (BMI ≥30) had a much increased probability of worse SPH. Drinking no alcohol or having no pack-years of smoking were associated with *worse* SPH and we suggest *reverse causality*[32] as an explanation for this result. Individuals could change their lifestyle because of deteriorating health after recommendation by their evaluating clinician, which could explain the association in our study. Additionally, drinking alcohol can be associated with an active social life, which has been shown to be associated with better SPH.[33] Our study shows that sleep quality and exercise frequency are related to SPH among older adults, confirming the findings of previous studies.[11 12 34] However, as our study was cross-sectional, we cannot evaluate a causal effect and symptoms and health conditions are likely associated with inactive lifestyle and impaired sleep quality among older adults.

The increased importance of symptoms can explain why SPH is related to mortality. Pain,[35] sleep quality,[36] breathlessness[37 38] and fatigue[39] were the most important factors for SPH in our study and their presence was each associated with increased mortality.[35–39] SPH has previously been explained as the current state of humans[4] and has been suggested to be the reason why SPH is such a strong predictor of mortality. Our result strengthens this concept[4] of SPH, with the symptoms being the warning signs of mortality. This could explain a biological pattern or sequence among symptoms, SPH and death. This again emphasises the importance of clinicians actively assessing the symptom burden experienced by older adults at each clinical encounter; the importance of symptom burden should also be understood by caregivers, family members and the individuals themselves.

Pain, sleep quality, breathlessness, fatigue and depression are all factors that should be assessed and addressed to improve SPH among older men. Optimising functional well-being and independence as well as minimising the experience and impact of symptoms are two key clinical goals, especially as people age. Future research should therefore focus on interventions for improved symptom relief and assessment and management of sleep problems among older men.

Strengths and limitations

The machine learning model had excellent performance when classifying SPH, which strengthens the generalisability of the study. The included factors cover many aspects of older adults' lives regarding health. The symptoms scales used in this study are validated, widely used and easy to compare due to all symptoms using an NRS 0–10. The study's results build on findings from previous studies, strengthening the validity of our study. The participants were of the same age and sex and these factors have been shown to be relevant for SPH as a predictor of mortality.[6 7] Overall, the participants are representative regarding health data for other men of a similar age in Sweden.[20] However, we cannot generalise the results to women or younger individuals. Factors' effect on SPH has previously shown to be similar among adults aged 65–74 years[19] and also among men and women in the oldest old age group with the exception of fatigue.[10] We suggest that future studies should use more detailed data than previous studies to compare sex differences of factors' effect on SPH among the older population. Limitations include that the study sample was relatively small, included males of the same age and included few participants with high symptom scores. A larger sample could increase the generalisability for older men in the population and increase the validity of the shape of the association for participants with high symptom scores. Last, excluding the participants who scored the middle score of the SPH item has some drawbacks, as we did not evaluate these participants, which resulted in a smaller sample size. The included study population could therefore be seen as representative of two polarised sides of SPH.

CONCLUSION

When compared with multiple other factors, pain, sleep quality, breathlessness, fatigue and depression were the most important factors when classifying SPH among older men. Diabetes and respiratory diseases were the most important *health conditions*, but overall, *symptoms* were more important than the presence of *health conditions,* which suggests that the conditions are mediated through the symptoms. The absence or very low level of symptoms, good sleep quality and regular exercise were associated with better SPH and a low or high BMI, as well as not drinking alcohol, was associated with *worse* SPH. Machine learning offers a new way to explore composite constructs such as well-being or quality of life and enables the identification of factors to target for improving SPH among older adults.

Contributors MPE designed the study and is guarantor. MO and MPE conducted the data collection. MO performed the data analysis. MO and MPE wrote the first draft of this paper. DCC contributed substantially with his medical knowledge. All authors contributed to the interpretation of the results, helped revise the manuscript and approved the final version. The

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Competing interests None declared.

Patient and public involvement Patients and/or the public were involved in the design, or conduct, or reporting, or dissemination plans of this research. Refer to the 'Methods' section for further details.

Patient consent for publication Not applicable.

Ethics approval This study was approved by the Swedish Ethical Review Authority (reference number: 2019-00134). Informed written consent was obtained from all participants.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available on reasonable request. The VASCOL research group will consider requests for using de-identified data from the VASCOL study by external collaborators. Also, all requests must be approved by the Sweden's national ethical review board.

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REFERENCES

1 World Health Organization. *Basic documents*. 48th edn. World Health Organization, 2014.
2 Brazier JE, Harper R, Jones NM, *et al*. Validating the SF-36 health survey questionnaire: new outcome measure for primary care. *BMJ* 1992;305:160–4.
3 Burström K, Sun S, Gerdtham U-G, *et al*. Swedish experience-based value sets for EQ-5D health states. *Qual Life Res* 2014;23:431–42.
4 Jylhä M. What is self-rated health and why does it predict mortality? towards a unified conceptual model. *Soc Sci Med* 2009;69:307–16.
5 Ryou I, Cho Y, Yoon H-J, *et al*. Gender differences in the effect of self-rated health (SRH) on all-cause mortality and specific causes of mortality among individuals aged 50 years and older. *PLoS One* 2019;14:e0225732.
6 Franks P, Gold MR, Fiscella K. Sociodemographics, self-rated health, and mortality in the US. *Soc Sci Med* 2003;56:2505–14.
7 Benjamins MR, Hummer RA, Eberstein IW, *et al*. Self-reported health and adult mortality risk: an analysis of cause-specific mortality. *Soc Sci Med* 2004;59:1297–306.
8 World Health Organization. *World report on ageing and health*. World Health Organization, 2015.
9 Barnett K, Mercer SW, Norbury M, *et al*. Epidemiology of multimorbidity and implications for health care, research, and medical education: a cross-sectional study. *Lancet* 2012;380:37–43.

10 Lisko I, Törmäkangas T, Jylhä M. Structure of self-rated health among the oldest old: analyses in the total population and those living with dementia. *SSM Popul Health* 2020;11:100567.
11 Zhao J, Chhetri JK, Ji S, *et al*. Poor self-perceived health is associated with frailty and prefrailty in urban living older adults: a cross-sectional analysis. *Geriatr Nurs* 2020;41:754–60.
12 Machón M, Vergara I, Dorronsoro M, *et al*. Self-perceived health in functionally independent older people: associated factors. *BMC Geriatr* 2016;16:66.
13 Fernandez-Martinez B, Prieto-Flores M-E, Forjaz MJ, *et al*. Self-perceived health status in older adults: regional and sociodemographic inequalities in Spain. *Rev Saude Publica* 2012;46:310–9.
14 Clark CR, Ommerborn MJ, Moran K, *et al*. Predicting self-rated health across the life course: health equity insights from machine learning models. *J Gen Intern Med* 2021;36:1181–8.
15 Maniscalco L, Miceli S, Bono F, *et al*. Self-Perceived health, objective health, and quality of life among people aged 50 and over: interrelationship among health indicators in Italy, Spain, and Greece. *Int J Environ Res Public Health* 2020;17. doi:10.3390/ijerph17072414. [Epub ahead of print: 02 04 2020].
16 Lazarevič P, Brandt M. Diverging ideas of health? comparing the basis of health ratings across gender, age, and country. *Soc Sci Med* 2020;267:112913. doi:10.1016/j.socscimed.2020.112913
17 Lundberg SM, Erion G, Chen H, *et al*. From local explanations to global understanding with Explainable AI for trees. *Nat Mach Intell* 2020;2:56–67.
18 Liu Y, Chen P-HC, Krause J, *et al*. How to read articles that use machine learning: users' guides to the medical literature. *JAMA* 2019;322:1806–16.
19 Gumà J. What influences individual perception of health? using machine learning to disentangle self-perceived health. *SSM Popul Health* 2021;16:100996. doi:10.1016/j.ssmph.2021.100996
20 Olsson M, Engström G, Currow DC, *et al*. Vascular and chronic obstructive lung disease (VASCOL): a longitudinal study on morbidity, symptoms and quality of life among older men in Blekinge County, Sweden. *BMJ Open* 2021;11:e046473.
21 von Elm E, Altman DG, Egger M, *et al*. The strengthening the reporting of observational studies in epidemiology (STROBE) statement: guidelines for reporting observational studies. *Lancet* 2007;370:1453–7.
22 Lundh Hagelin C, Klarare A, Fürst CJ. The applicability of the translated Edmonton Symptom Assessment System: revised [ESAS-r] in Swedish palliative care. *Acta Oncol* 2018;57:560–2.
23 Berkelmans GFN, Read SH, Gudbjörnsdottir S, *et al*. Population median imputation was noninferior to complex approaches for imputing missing values in cardiovascular prediction models in clinical practice. *J Clin Epidemiol* 2022;145:70–80.
24 Chen T, Guestrin C. XGBoost: a scalable tree boosting system, 2016. Available: https://ui.adsabs.harvard.edu/abs/2016arXiv160302754C [Accessed 01 Mar 2016].
25 Sebastião E, Henert S, Siqueira VAAA. Physical activity and physical function in older adults living in a retirement community: a cross-sectional analysis focusing on self-rated health. *Am J Lifestyle Med* 2021;15:279–85.
26 World Health Organization. Physical activity: World Health organization, 2020. Available: https://www.who.int/news-room/fact-sheets/detail/physical-activity
27 Fanning J, Walkup MP, Ambrosius WT, *et al*. Change in health-related quality of life and social cognitive outcomes in obese, older adults in a randomized controlled weight loss trial: does physical activity behavior matter? *J Behav Med* 2018;41:299–308. doi:10.1007/s10865-017-9903-6
28 Parshall MB, Schwartzstein RM, Adams L, *et al*. An official American thoracic Society statement: update on the mechanisms, assessment, and management of dyspnea. *Am J Respir Crit Care Med* 2012;185:435–52.
29 Currow DC, Dal Grande E, Ferreira D, *et al*. Chronic breathlessness associated with poorer physical and mental health-related quality of life (SF-12) across all adult age groups. *Thorax* 2017;72:1151–3.
30 de Wit LM, van Straten A, van Herten M, *et al*. Depression and body mass index, a U-shaped association. *BMC Public Health* 2009;9:14.
31 Bhaskaran K, Dos-Santos-Silva I, Leon DA, *et al*. Association of BMI with overall and cause-specific mortality: a population-based cohort study of 3·6 million adults in the UK. *Lancet Diabetes Endocrinol* 2018;6:944–53.
32 Sattar N, Preiss D. Reverse causality in cardiovascular epidemiological research: more common than imagined? *Circulation* 2017;135:2369–72.
33 Saravanakumar P, Garrett NKG, Van Wissen K, *et al*. Social connectedness and self-perceived health of older adults in New Zealand. *Health Soc Care Community* 2022;30:e647–56.
34 Clark AJ, Dong N, Roth T, *et al*. Factors associated with asthma diagnosis within five years of a bronchiolitis hospitalization: a retrospective cohort study in a high asthma prevalence population. *Hosp Pediatr* 2019;9:794–800.
35 Smith D, Wilkie R, Uthman O, *et al*. Chronic pain and mortality: a systematic review. *PLoS One* 2014;9:e99048.
36 Garfield V, Joshi R, Garcia-Hernandez J, *et al*. The relationship between sleep quality and all-cause, CVD and cancer mortality: the Southall and Brent revisited study (SABRE). *Sleep Med* 2019;60:230–5.
37 Nishimura K, Izumi T, Tsukino M, *et al*. Dyspnea is a better predictor of 5-year survival than airway obstruction in patients with COPD. *Chest* 2002;121:1434–40.
38 Moll M, Qiao D, Regan EA, *et al*. Machine learning and prediction of all-cause mortality in COPD. *Chest* 2020;158:952–64.
39 Basu N, Yang X, Luben RN, *et al*. Fatigue is associated with excess mortality in the general population: results from the EPIC-Norfolk study. *BMC Med* 2016;14:122.