Detecting Disabilities in Everyday Life: Evidence from a Geriatric Assessment

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RESEARCH

Detecting Disabilities in Everyday Life: Evidence from a Geriatric Assessment

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Abstract

Background: The Activities of Daily Living score (ADL) is a widely used index to establish the degree of independence from any help in everyday life situations. Measuring the ADL accurately is time-consuming and costly. This paper presents a framework to approximate the ADL via variables usually collected in standard geriatric assessments. We showed that the selected variables serve as good indicators in explaining the physical disabilities of older and frail patients.

Methods: Our sample included information from a geriatric assessment of 326 patients aged between 64 and 99 years in a hospital in Tyrol, Austria. In addition to the ADL, 23 variables reflecting the physical and mental status of these patients were recorded during the assessment. We performed LASSO to determine which of these variables had the highest impact on explaining the ADL. Then, we used ROC analysis and logistic regression techniques to validate our model performance. Finally, we calculated cut-off points for each of the selected variables, showing at which values the ADL falls below a certain threshold.

Results: Mobility, urinary incontinence, nutritional status and cognitive function were closest related to the ADL and, therefore, to a geriatric patient's functional limitations. Jointly, the selected variables were able to predict neediness with high accuracy (AUC $= 0.89$ and 0.91, respectively). If a patient had a limitation in one of these variables, the probability of everyday life disability increased with a statistically significant factor between 2.4 (nutritional status, 95%-CI $1.5-3.9$) and 15.1 (urinary incontinence, 95%-CI $3.6-63.4$).

Conclusions: Our study highlighted the most important impairments of everyday live, facilitating a more efficient use of clinical resources which, in turn, allows for a more targeted treatment of geriatric patients. At the patient level, our approach enables early detection of functional limitations and timely indications of a possible need for assistance in everyday life.

Keywords: Geriatric assessment; Functional limitations; Activities of Daily Living (ADL); Variable selection; LASSO; ROC analysis

Background

Many countries in the world are faced with fast ageing societies. This demographic shift not only poses capacity problems for healthcare providers, but also changes the quality-related requirements on health services. Early detection of diseases and impairments of everyday life is therefore an indispensable task to maintain the healthcare system sustainable.

This study addressed the mental and physical impairments of older and frail people who underwent geriatric screening to assess their health status and potential limitations to participate in daily life. Such assessments typically rely on formal tools such as questionnaires and tests to evaluate physical and mental dimensions of an older adult's health [1–3]. A key issue is the measurement of functional impairments, i.e., a person's inability to perform activities needed in everyday life. In clinical practice, the Activities of Daily Living score (ADL) is used to measure such limitations. The ADL is part of the geriatric assessment and represents a compound index of different everyday tasks, such as the ability of toileting, bathing or dressing. The collection of these components requires an ongoing inpatient observation, queries to the referring physician and often lots of bureaucratic work. Providing an accurate and comprehensive measure of the ADL is therefore a time-consuming and costly task [4, 5]. Hence, using more easily available information also collected in the geriatric assessment to approximate the ADL may facilitate a more efficient use of clinical resources which,

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in turn, may improve the treatment of geriatric patients.

Previous research took three major approaches to approximate the ADL [5]. A first strand of literature used sensor data from wearable devices or smart home environments to obtain information on functional limitations [6, 7]. Although these studies provided accurate results, they are faced with very specific problems, especially in the elder and frail population. For example, not everyone in this age cohort is able to operate electronic devices properly. A second line of research relied on large scale data and machine learning algorithms to predict the ADL. For example, Wojtusiak et al. used patient records of about 200,000 patients in the US and identified 578 patient characteristics to explain the ADL [5]. Apart from the fact that comparable datasets are not easily available, such a large number of explanatory variables is hardly suitable for daily clinical use, particularly in the outpatient sector. Therefore, a third approach referred to clinical data (e.g., from patient admissions), which are more easily available and also have a high degree of accuracy. For instance, Guralnik et al. and Prasitsiriphon and Weber utilized large-scale clinical studies from the US and Thailand and identified mainly physical performance measures influencing the ADL [8, 9]. In a similar vein, Jonkman et al. provided a cohort study on patients aged between 65 and 75 years in four countries (Germany, UK, Italy and the Netherlands) and identified ten out of 22 potential covariates to predict the ADL. A large portion in the sample did not suffer from functional impairments in the ADL, which was explained by the fact that only participants below 75 years were included in the study. The authors concluded that additional research for adults above 75 years is requested [10].

This paper is related to the third strand of literature and extends the existing research in two regards. First, using clinical data from a standardized assessment of 326 geriatric patents we focused on the age group between 64 and 99 years. Hence, we were particularly able to predict the ADL for old aged and frail patients. Second, we propose a framework that allowed to identify not only the most important predictors of the ADL but also to estimate the cut-off values at which the ADL falls below a certain threshold.

Our results suggested that mobility, urinary incontinence, nutritional status, and cognitive function were able to predict the ADL and, therefore, neediness in everyday life with high accuracy. Monitoring these variables together with the derived cut-off values could be interesting from a clinical perspective, as it supports a more efficient use of medical resources, which in turn allows for a more targeted treatment of geriatric patients. In addition, it facilitates an early detection of functional limitations and a potential need for daily assistance, which particularly might be useful in outpatient care.

Methods

To explain the ADL of elder and frail patients we conducted a cross-sectional study in the Geriatric Center of Hochzirl, Tyrol (Austria). This hospital is specialised in the care of geriatric patients. On admission, patients underwent a standard geriatric assessment. Further on, the ADL was collected for each patient.

Data

Our sample included 326 patients aged between 64 and 99 years, who underwent the geriatric assessment between July 2019 and February 2020. Information on the patients and their general health status was extracted from the medical history, which was collected by a doctor in the course of admission according to a specific procedure. Within the first three days after admission, every patient older than 64 years was assigned to the geriatric assessment by the doctor in charge. The assessment was waived if a patient had the following contra-indications: (i) lack of consent, (ii) complete independence and no need for assistance in daily living, (iii) stable need for assistance with no prospect of rehabilitation, (iv) terminal illness, (v) severe dementia, and (vi) the current report was not older than 12 weeks.

The assessment took about 30 to 60 minutes and was performed by a trained graduated nurse following a pre-specified procedure (more details are provided in the results section below). A test could be skipped if the patient was not able to perform it due to a physical or a mental dysfunction. In addition, further information was gathered from the nurse team on the ward in form of a patient related questionnaire to collect all the necessary information for the ADL. Finally, a document with the results of the geriatric assessment (including the ADL) was handed over to the attending physician. The results of the geriatric assessment were gathered by the doctors team and data was collected manually on Microsoft, Excel.

Outcome Variable

Our main variable of interest was the ADL, which measures in a standardized way physical independence and, hence, a patient's need for assistance in everyday life [11]. In particular, the ADL index consists of ten different everyday tasks: Presence/absence of fecal incontinence, presence/absence of urinary incontinence and help needed with grooming, toileting, feeding, transferring (e.g. from chair to bed), walking, dressing, climbing stairs and bathing. Each performance item is rated on a scale with 0, 5, 10 or 15 points, leading to a total score between 0 and 100, with a lower score indicating greater disability [11]. Previous research distinguished between patients who require help in everyday life and those who do not [8, 9, 12, 13]. We followed this approach and created an indicator variable ADL*, which equals 1 if a patient scores less than or equal to 80 points and zero otherwise [14–16].

Explanatory Variables

To determine the driving impairments behind the ADL, we relied on all test procedures of the geriatric assessment. These included the general health status (i.e., the clinical admission) of the patients as well as information on their mobility, cognitive abilities, nutritional status, urinary incontinence, sensory functions and general psychological situation. In total, our sample included 23 geriatric variables which we divided into *seven categories* (number of variables in parentheses):[1]

- *Mobility (3):* Falls are often caused by mobility problems [3]. To identify the corresponding impairments we used the Tinetti Mobility test (TMT) [17, 18], the Timed Up and Go test (TUG) [19], and a patient's hand force (HF) [20].
- *Cognitive function (3):* Recognition and information processing issues may indicate dementia or need for assistance. In geriatric assessments, cognitive performance was measured with the Mini Mental State Examination (MMSE) [21], the Clock Completion test (CC) [22], and the Money Counting test (MC) [23].
- *Nutritional status (3):* Elderly people often suffer from vitamin and mineral deficiencies [3]. Therefore, as part of geriatric assessments, nutritional status was evaluated by the Mini Nutritional Assessmen (MNA) [24], the Body Mass Index (BMI) [25] and the fat mass (FM) [26].
- *Incontinence Screening (4):* Urinary incontinence not only has a negative impact on physical health due to an increased risk of infections, falls and death, but also on mental health as self-esteem suffers and affected people isolate themselves more often [3, 27]. In geriatric assessments, urinary incontinence was recorded by the urinary incontinence score (ICS), the urinary incontinence diagnosis (ICD) and by information on a permanent catheter (PC) [28]. Further, we included an urinary incontinence indicator (ICI) variable to indicate whether information on ICS was available or not.
- *Sensory function (2):* Carabellese et al. showed that sensory impairments in older people have a negative impact on their social relationships and self-sufficiency [29]. To capture sensory functions, our geriatric assessment incorporated an indicator variable on hypacousia (HC) (hearing abilities) and a categorical variable capturing pain (PAIN) [30].
- *Psychological situation (1):* The most common psychological illness in older people is depression. We used the Geriatric Depression Scale (GDS) which has been developed to identify such psychological situations [31].
- *Clinical admission status (7):* To account for a patient's general health status we included a patient's age (AGE) and sex (SEX), whether and which type of diabetes mellitus (DM) was diagnosed, whether medication for diabetes mellitus therapy (DMT), arterial hypertension (AH) or cerebrovascular diseases (CVD) were prescribed prior to the assessment or polypharmacy (PP) occurred.

Table A.1 of the Additional file 1 provides a summary over all variables included in the study along with a description of the units of measurement.

Descriptive Statistics

Our sample included information on assessments of 326 geriatric patients. It contains the ADL along with 23 covariates collected in these assessments (see Table A.1 of the Additional file 1). Table 1 reports the corresponding descriptive statistics. Accordingly, our sample consisted of 74% females. The age of the patients was 80.6 ± 7.4 years and varied between 64 and 99 years. The ADL for all patients in the sample was 70.2 ± 20.3 points, with a minimum of 10 and a maximum of 100. Further, and according to the 80%-threshold of the ADL defined above (i.e., ADL*), we observed that around 69% of all patients needed assistance in everyday life. Regarding other geriatric covariates, we observed a body strength (HF) of 38.9 ± 15.8 kPa, a fall risk score (TMT) of 16.7 ± 2.3 and a mobility impairment test (TUG) of 35.8 ± 9.8 seconds. The BMI was 26.7 ± 6.3.

Generally, our sample characteristics were comparable to the ones of previous clinical studies [32, 33]. Bahat et al., for instance, was the most related study with regard to the clinical setting. They used a sample of 406 patients between 65 and 99 years and observed an average age of 76.6 ± 7.7 years, a female share of 69.7% and a BMI of 29.7 ± 5.4 [33].

Column 2 of Table 1 informs about the number of missing values per variable. It shows that missing entries were unevenly distributed across our variables.

[1] For the sake of brevity, we henceforth refer to these variables as "explanatory variables" or "geriatric covariates".

Table 1: Descriptive statistics ($N = 326$)

Variable	**Missing**		**Statistics**		**Range**	
	N	Ind.	Mean	s.d.	Min.	Max.
ADL	0		70.17	20.27	10	100
ADL*	0		0.69	0.46	0	1
HF	7	✓	38.87	15.75	0	85
TMT	36	✓	16.71	2.27	1	27
TUG	38	✓	35.76	9.80	7	110
CC	9	✓	2.73	2.93	0	7
MC	75	✓	55.09	30.57	18	183
MMSE	10	✓	25.38	3.93	5	30
BMI	9	✓	26.67	6.26	13.50	59.20
FM	83	✓	36.78	7.42	4.20	49.90
MNA	10	✓	19.51	2.98	9	25
ICD_1	9	✓	0.38	0.49	0	1
ICD_2			0.04	0.21	0	1
ICD_3			0.17	0.38	0	1
ICD_4			0.17	0.38	0	1
ICS	8	✓	1.70	1.35	0	5
PC	9	✓	0.14	0.34	0	1
IC	8	✓	0.13	0.33	0	1
HC	11	✓	0.50	0.50	0	1
PAIN	7	✓	5.21	1.93	0	10
GDS	11	✓	6.13	2.04	0	12
AGE	8	✓	80.64	7.37	64	99
AH	0		0.69	0.46	0	1
CVD	3	✓	0.16	0.37	0	1
DM_1	0		0.01	0.10	0	1
DM_2			0.22	0.41	0	1
DMTH_1	0		0.08	0.28	0	1
DMTH_2			0.07	0.26	0	1
PP	3	✓	0.82	0.38	0	1
SEX	0		0.74	0.44	0	1

Notes: The subscript informs about the type of impairment. For example, ICD_1 denotes urge urinary incontinence, ICD_2 stress urinary incontinence, ICD_3 mixed urinary incontinence, and ICD_4 denotes uncertainty about the presence of an urinary incontinence. A detailed variable description is reported in Table A.1 of the Additional file 1.

While we had no missings for ADL, AH, DM, DMT and SEX, we observed a much larger share of missings for TMT (36), TUG (38), MC (75), and FM (83). As described above, missing entries were not completely at random. For instance, it was clear from the outset that some patients were not able to take the TUG or the MC. To account for this non-randomness, we added an indicator variable with entry 1 if we observed at least one missing for a variable, and zero else. In the table, these variables are indicated by ✓, subsequently they are denoted by 1_x where "x" indicates a particular variable in the dataset. Further, we applied a standard imputation approach and replaced the missing entries with the mean of the associated variable. In this way, our approach ensured an easy interpretation of our parameter estimates and a clear identification of missings in our dataset.

Statistical Analysis

For variable selection and model evaluation we proceeded in a two-step approach. In the variable selection process, the Least Absolute Shrinkage and Selection Operator (LASSO) was applied to identify the most influential geriatric covariates on the numeric ADL. In the second step, and as we were solely interested in whether a person was independent from everyday assistance or not, we transformed the ADL to a binary variable and performed logistic regression techniques and Receiver Operating Characteristic (ROC) analysis to evaluate the variable selection of the first step. More specifically, we calculated the Area Under the ROC-Curve (AUC) as a measure of discriminatory power. In addition, and to identify easily patients with a potential ADL disability, we derived optimal cut-off values for the selected geriatric variables. To test their strength we used odds-ratios.

Variable Selection

To identify the most relevant geriatric covariates driving the ADL, we applied LASSO [34]. This method is applicable for high-dimensional data reduction and feature selection as it performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the resulting model. The basic intuition behind LASSO is that it forces the sum of the absolute value of the regression coefficients to be less than a fixed value (known as regularization parameter, henceforth λ). As a result, less important coefficients are shrinked to zero, i.e., are excluded from impacting the model. Since optimal selection of the regularization parameter is critical, we took a 100 fold cross validation to detect optimal values of λ based on resulting regression errors. Following Friedman et al., we chose two different λ-specifications in the variable selection process [35]. The first one leads to the minimum mean cross-validated error (λ_{min}), and the second one is the largest value of λ such that the error is within one standard error of the cross-validated errors for λ_{min}. We refer to this as λ_{1se}.

Model Evaluation

Based on our definition of neediness in everyday life, we examined to what extent our geriatric covariates were able to explain our indicator variable ADL* [8, 9, 12, 13]. For this purpose, we used a logistic regression framework and ROC analysis for both λ-specifications.

Further, one might be interested in the univariate effects of the selected variables on ADL* and, even more, in the cut-off values of these geriatric covariates, as they are essential for clinical decision-making. In medical practice, for example, cut-off values support the diagnosis of an impairment and thus the initiation of appropriate therapies or assistance [36]. Out of the standard approaches to estimate those cut-off values [36, 37], we used the Youden index, which defines the optimal cut-off as the point maximizing the Youden function, which is the difference between true positive rate and false positive rate over all possible cut-off values [38–40]. To assess the strength of each optimal cut-off value, we reclassified the geriatric covariate into a binary variable taking entry 1 if an ADL disability was indicated and 0 otherwise. Then we used the binary covariate as an explanatory variable for ADL* in a logistic regression to determine its odds ratio, i.e., the factor by which the probability of an ADL disability is greater when the binary covariate under consideration indicates such a disability than when it does not.

Software and Computational Details

The statistical analysis was carried out with R version 4.1.1 [41]. For the LASSO variable selection we used the package `glmnet` [42], for the ROC analysis the package `ROCit` [43], and for the logistic regressions the package `car` [44].

Results

In this section, we firstly describe which variables were selected to explain the ADL. Then, we derive the underlying cut-off values and present the evaluation of the selected variables based on their predictive accuracy.

Variable Selection

We applied LASSO to detect those geriatric covariates which serve as appropriate explanatory variables to describe the ADL and cross-validation to estimate the penalty term λ.

Using λ_{1se}, nine variables: TUG, TMT, MMSE, MNA, ICD_4, ICS and the dummy variables for missing values on TUG (1_{TUG}), TMT (1_{TMT}), and MC (1_{MC}), were selected to explain the ADL. In case of λ_{min}, five additional geriatric covariates entered the model: ICD_3, PC, GDS, AGE and 1_{HF}. Hence, we included 14 variables to explain the ADL in this specification (Table 2).

TUG and TMT are mobility measures. TUG is a quick test to assess basic functional mobility. At the sign of a supervisor, using everyday walking aids and

Table 2: Joint prediction accuracy of the data-driven selected explanatory variables

Specification	**AUC**	K	**Variables**				
λ_{1se}	0.89	9	TUG	TMT	1_{TUG}	1_{TMT}	MMSE
			1_{MC}	MNA	ICD_4	ICS	
λ_{min}	0.91	14	9 variables from $\lambda_{1se}+$				
			1_{HF}	ICD_3	PC	GDS	AGE

Notes: AUC denotes the Area Under the (ROC) Curve and measures the prediction accuracy towards ADL*; K denotes the number of selected variables.

wearing shoes, a participant has to stand up from an armchair, to walk three meters, to turn around, to walk back to the armchair and to sit down again. The supervisor stops time during this process [19]. TMT consists of a balance and a gait test in which 28 points can be achieved [18]. Different manoeuvres and assessment criteria allow early detection of mobility disorders and their underlying limitations. The tasks correspond to movements of daily living and the treatment of impairments is intended to increase mobility and thus reduce the risk of falls [17].

The MMSE is a test consisting of eleven questions that distinguish people with cognitive impairment from people without cognitive impairment. The procedure only takes between five to ten minutes and is therefore also suitable for older people suffering from (weak) dementia. In the first part of the test, orientation, memory, and attention are assessed verbally. In the second part, the ability to name and execute verbal and written commands is measured [21].

Malnutrition is a frequently unrecognised problem in the elderly and affects mortality, risk of infection, and quality of life. To better perceive this issue, Guigoz et al. developed the MNA, a 15-minute questionnaire. It records anthropometric parameters such as the BMI or upper arm circumference, general condition in terms of housing situation or skin problems, nutritional habits such as the number of daily meals or food choices, and a self-assessment of malnutrition and health status [24].

Urinary incontinence is often not mentioned by the patients, so that it is necessary to observe this impairment directly. The ICS is a five-question survey that asks about the situations in which urine is lost in an uncontrolled way. One point is awarded for each question answered with "yes". This questionnaire is also used to specify the type of urinary incontinence. Depending on which question is answered positively, the ICD registers urge (captured by dummy variable ICD_1), stress (ICD_2) or mixed urinary incontinence (ICD_3). ICD_4 indicates uncertainty about the presence of urinary incontinence, and ICD_0 suggests no urinary incontinence [28]. ICD_4 and ICD_3 point to a need for assistance in daily life. The same applies if a patient had a permanent catheter (captured by PC).

The GDS informs about a possible depression of the patient. This survey consists of 15 simple questions and due to the short form little concentration and administration time is required. For example, it is asked whether many activities and interests have been dropped or whether it is wonderful to be alive now [31].

Model evaluation and cut-off values

To assess the effectiveness of the data-driven selected variables in identifying the need for assistance in everyday life, we applied logistic regression techniques and ROC analysis. We were interested in the predictive accuracy as well as the optimal cut-off values of the explanatory variables and their strength to indicate ADL disability.

Table 2 reports the prediction accuracy of the jointly used explanatory variables per λ-specification. If the nine variables, selected under λ_{1se}, were used jointly to explain ADL*, the need for assistance was recognized with good accuracy (AUC = 0.89). Using the 14 explanatory variables, selected under λ_{min}, a functional limitation in everyday life was identified with high accuracy (AUC = 0.91). Thereby, the potential of the joint use of the data-driven selected variables to capture ADL disability was supported by these higher predictive accuracies compared to previous literature [8–10, 13, 33, 45] when no prior observed ADL was taken into account [5].

Nevertheless, we were also interested in the univariate performance of the variables selected under λ_{1se}, since in the case of Guralnik et al. or Prasitsiriphon and Weber the joint use of variables was only partially able to outperform individual explanatory variables [8, 9]. Further, we calculated cut-off values for each of the selected variables, which serve as thresholds to indicate ADL impairment. Therefore, these thresholds might be very important for clinical purposes [36]. We compared these values with the ones from previous

Table 3: Univariate evaluation of the data-driven selected explanatory variables

Variable	AUC	CV	Interpretation	OR	95%-CI
TUG	0.85	36	$\leq$10: mobility normal	13.36	7.35 - 24.3
			11-19: little mobility		
			20-29: limited mobility		
			$\geq$30: mobility impairment		
TMT	0.82	17	<20: increased falling risk	13.96	6.89 - 28.3
1_{TUG}	0.57	1	$= 1$: missing TUG	9.57	2.26 - 40.6
1_{TMT}	0.57	1	$= 1$: missing TMT	8.95	2.11 - 38.0
MMSE	0.66	27	$\leq$17: severe cognitive deficit	2.75	1.69 - 4.47
			$\leq$24: cognitive deficit		
1_{MC}	0.59	1	$= 1$: missing MC	3.31	1.66 - 6.59
MNA	0.63	21	$\geq$24: satisfactory	2.38	1.47 - 3.85
			17-23.5: malnutrition risk		
			<17: poor nutritional status		
ICD_4	0.61	1	$= 1$: urinary incontinence unclear	15.12	3.61 - 63.4
ICS	0.59	1.70	$\geq$1: incontinence probable	2.57	1.59 - 4.15

Notes: AUC denotes the Area Under the (ROC) curve and measures the prediction accuracy towards ADL*; CV denotes the cut-off value at which the explanatory variable has to be split to explain the ADL*; OR denotes the odds ratio; 95%-CI indicates the 95% confidence interval of the odds ratio.

studies, which were either derived only for mobility measures [9, 12, 13] or are mentioned in the literature without reference to ADL.

Table 3 reports the AUC for each selected variable along with the corresponding cut-off value (CV), the classification commonly used in the literature and the strength of the cut-off value, measured as odds ratio (OR) with its 95% confidence interval (95%-CI). For example, TUG was able to identify an ADL disability with good accuracy (AUC = 0.85). If patients took 36 seconds or more to complete the TUG, they were significantly 13.4 times more likely to need assistance in daily living than patients who completed the test in less than 36 seconds. This finding was in line with the literature, which assumes mobility impairment from 30 seconds onwards [19].

Overall, on a univariate level, the AUC varied between 0.57 (1_{TUG} and 1_{TMT}) and 0.85 (TUG). As expected, the cut-off values of the dummy variables were 1, so it was assumed that patients who were unable to perform the corresponding tests (1_{TUG}, 1_{TMT}, 1_{MC}) or whose incontinence status was unclear (ICD_4) needed help in everyday life. The cut-off values we calculated for the metric variables were also supported by the literature, as patients who were indicated to have a ADL disability also had an impairment in the respective geriatric covariate. The only exception was the cut-off value of the MMSE, according to which patients with a score below 27 already needed help in everyday life, whereas in the literature a cognitive deficit is only assumed at less than 25 points [46–48].

The odds ratios quantify the strength of these cut-off values, which showed that for a patient with a limitation in one of these explanatory variables, the probability of needing assistance in daily living increased by a statistically significant factor between 2.4 (MNA, 95%-CI 1.5 – 3.9) and 15.1 (ICD_4, 95%-CI 3.6 – 63.4). None of the estimated CI intervals overlapped with the null value (OR=1). This can be used as a proxy of statistical significance of the estimated cut-off values.

Discussion

Focusing on single dimensions of the ADL, Gobbens and van Assen, Duchowny et al. and Prasitsiriphon and Weber used a test of balance, usual walking speed, grip strength, physical activity, BMI or fatigue to explain functional limitations [9, 12, 13]. A common characteristic of those works was that the selection of the relevant variables had to be made a priori. In contrast, Jonkman et al. and our approach enabled to examine the effect of geriatric variables on the ADL simultaneously which, in turn, allowed to distinguish between more and less influential dimensions of functional limitations. They found that ten variables associated with mobility (handgrip strength, gait speed, five-repeated chair stands time), nutritional situation (BMI), psychological situation (depressive symptoms) and the general health status (AGE, CVD, DM, chronic obstructive pulmonary disease, arthritis) were critical for the development of an ADL disability in young older people (65 − 75 years) who had no impairment at baseline [10]. In our clinical setting, we focused on older and frail patients for whom nine geriatric covariates are critical for an ADL impairment. These can be categorised into the four health domains of mobility (TUG, TMT, 1_{TUG}, 1_{TMT}), cognitive function (MMSE, 1_{MC}), nutritional status (MNA) and urinary incontinence (ICS, ICD_4). Wojtusiak et al., though relying on a different methodological approach and using large-scale rather than clinical data, came up with a very similar variable choice, i.e., emphasizing the role of cognitive functions, age and urinary incontinence for the ADL [5]. Despite broad agreement, these results showed that different variables are required for targeted ADL prediction depending on the research goal and clinical setting.

Evaluating the selected variables for their ability to detect an ADL disability, the highest accuracy was achieved when our selected variables were used jointly (AUC = 0.89 and 0.91, respectively). Regarding the predictive power of single influencing dimensions, only the mobility measures (TUG and TMT) indicated functional limitations with good accuracy. This is in line with Guralnik et al. and Jonkman et al., who also examined the predictive accuracy of a joint rather than a univariate use of their explanatory variables [8, 10]. However, compared to previous literature that used geriatric covariates univariately or jointly [8–10, 13, 33, 45], we found a higher predictive accuracy, which clearly supports our data-driven variable selection approach.

The cut-off values we obtained from our analysis were broadly in line with the existing literature. One notable exception was the MMSE, for which previous papers suggested a cognitive deficit at scores below 25 [46–48], while our study found that scores below 27 already indicated a functional impairment. However, Perneczky et al. used a more detailed classification of the MMSE, arguing that a cognitive deficit could be excluded for scores of 30, and was doubtful for scores between 26-29 points [49]. According to this classification, our finding with regard to the MMSE seemed plausible.

Conclusions

We used data from a standardized geriatric assessment to explain the Activities of Daily Living (ADL) index, which is used to measure functional impairments and an older patient's need for assistance in everyday life. Empirically, we proposed a data-driven approach which allowed to employ all patient-related information typically recorded in a geriatric assessment. In particular, we identified nine variables belonging to four groups of impairments that are most influential for the ADL: Mobility, urinary incontinence, nutritional status and cognitive function. For each of the underlying variables, we derived cut-off values indicating functional impairment and the need for support in everyday tasks. Jointly, these selected variables were able to indicate ADL disability with high accuracy.

Our findings might be of interest for clinical practice. First, determining the ADL requires a comprehensive observation of the patients. In some cases, additional information has to be obtained from the referring physicians, and also the writing of test protocols is time consuming and causes high administrative costs. Our study proposes a method of approximating the ADL based on a limited patient information that is typically easy to obtain. Using this information rather than the ADL may lead to significant cost savings for a hospital. Second, and perhaps more important, ongoing monitoring of the main drivers of the ADL allows for early detection of limitations in daily living. This seems particularly interesting for general practitioners and physicians in outpatient care, where the ADL is usually not collected.

Abbreviations

ADL: Activities of Daily Living; AGE: Age; AH: Arterial hypertension; AUC: Area Under the (ROC) Curve; BMI: Body Mass Index; CC: Clock Completion test; CVD: Cerebrovascular diseases; DM: Diabetes mellitus; DMT: Diabetes mellitus therapy; FM: Fat mass; GDS: Geriatric Depression Scale; HC: Hypacousia; HF: Hand force; ICD: Urinary incontinence diagnosis; ICS: Urinary incontinence score; ICI: Urinary incontinence indicator; LASSO: Least Absolute Shrinkage and Selection Operator; MC: Money Counting test; MMSE: Mini Mental State Examination; MNA: Mini Nutritional Assessment; PAIN: Pain; PC: Permanent catheter; PP: Polypharmacy; ROC: Receiver Operating Characteristic; SEX: Sex; TMT: Tinetti Mobility test; TUG: Timed Up and Go test

Ethical approval

This study involving human participants was in accordance with the ethical standards of the institutional and national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. In view of the retrospective nature of the study, where all procedures performed were part of the routine geriatric assessment of the hospital, informed consent of the study participants was waived. The study has been reviewed and approved by the ethics committee of the Medical University of Innsbruck (EK Nr: 1206/2021).

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and analysed during the current study are not publicly available due to data protection reasons. The R-codes are available from the corresponding author on reasonable request.

Competing interest

The authors declare that they have no competing interest.

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Authors' contributions

CD and ML designed the study and collected the data. PU and PH carried out the statistical analysis. CD, PH, PU and HW co-wrote the paper. ML supervised the study. All authors contributed ideas, revised different manuscript versions and approved the final manuscript.

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References

1. Stuck, A.E., Siu, A.L., Wieland, G.D., Rubenstein, L., Adams, J.: Comprehensive geriatric assessment: A meta-analysis of controlled trials. The Lancet **342**(8878), 1032–1036 (1993)
2. Pepersack, T.: Minimum geriatric screening tools to detect common geriatric problems. The Journal of Nutrition Health and Aging **12**(5), 348–352 (2008)
3. Elsawy, B., Higgins, K.E.: The geriatric assessment. American Family Physician **83**(1), 48–56 (2011)
4. Williams, B.C., Fries, B.E., Foley, W.J., Schneider, D., Gavazzi, M.: Activities of daily living and costs in nursing homes. Health Care Financing Review **15**(4), 117 (1994)
5. Wojtusiak, J., Asadzadehzanjani, N., Levy, C., Alemi, F., Williams, A.E.: Computational Barthel index: An automated tool for assessing and predicting activities of daily living among nursing home patients. BMC Medical Informatics and Decision Making **21**(1), 1–15 (2021)
6. Hong, Y.-J., Kim, I.-J., Ahn, S.C., Kim, H.-G.: Activity recognition using wearable sensors for elder care. In: 2008 Second International Conference on Future Generation Communication and Networking, vol. 2, pp. 302–305 (2008). IEEE
7. Liu, J., Sohn, J., Kim, S.: Classification of daily activities for the elderly using wearable sensors. Journal of Healthcare Engineering **2017** (2017)
8. Guralnik, J.M., Ferrucci, L., Pieper, C.F., Leveille, S.G., Markides, K.S., Ostir, G.V., Studenski, S., Berkman, L.F., Wallace, R.B.: Lower extremity function and subsequent disability: Consistency across studies, predictive models, and value of gait speed alone compared with the short physical performance battery. The Journals of Gerontology Series A: Biological Sciences and Medical Sciences **55**(4), 221–231 (2000)
9. Prasitsiriphon, O., Weber, D.: Objective physical measures and their association with subjective functional limitations in a representative study population of older Thais. BMC Geriatrics **19**(1), 1–12 (2019)
10. Jonkman, N.H., Colpo, M., Klenk, J., Todd, C., Hoekstra, T., Del Panta, V., Rapp, K., Van Schoor, N.M., Bandinelli, S., Heymans, M.W., *et al.*: Development of a clinical prediction model for the onset of functional decline in people aged 65–75 years: Pooled analysis of four european cohort studies. BMC Geriatrics **19**(1), 1–12 (2019)
11. Collin, C., Wade, D., Davies, S., Horne, V.: The Barthel ADL index: A reliability study. International Disability Studies **10**(2), 61–63 (1988)
12. Gobbens, R.J., van Assen, M.A.: The prediction of ADL and IADL disability using six physical indicators of frailty: A longitudinal study in the Netherlands. Current Gerontology and Geriatrics Research **2014**, 358137 (2014)
13. Duchowny, K.A., Peterson, M.D., Clarke, P.J.: Cut points for clinical muscle weakness among older americans. American Journal of Preventive Medicine **53**(1), 63–69 (2017)
14. Sinoff, G., Ore, L.: The Barthel activities of daily living index: Self-reporting versus actual performance in the old-old ($\geq$ 75 years). Journal of the American Geriatrics Society **45**(7), 832–836 (1997)
15. Hartigan, I.: A comparative review of the Katz ADL and the Barthel index in assessing the activities of daily living of older people. International Journal of Older People Nursing **2**(3), 204–212 (2007)
16. Deppermann, K.-M., Friedrich, C., Herth, F., Huber, R.M.: Geriatrische assessments und diagnostik beim älteren patienten. Oncology Research and Treatment **31**(Suppl. 3), 6–14 (2008)
17. Tinetti, M.E.: Performance-oriented assessment of mobility problems in elderly patients. Journal of the American Geriatrics Society **34**(2), 119–126 (1986)
18. Köpke, S., Meyer, G.: The Tinetti test. Zeitschrift für Gerontologie und Geriatrie **39**(4), 288–291 (2006)
19. Podsiadlo, D., Richardson, S.: The timed "Up & Go": A test of basic functional mobility for frail elderly persons. Journal of the American Geriatrics Society **39**(2), 142–148 (1991)
20. Choquette, S., Bouchard, D., Doyon, C., Sénéchal, M., Brochu, M., Dionne, I.J.: Relative strength as a determinant of mobility in elders 67–84 years of age. A nuage study: Nutrition as a determinant of successful aging. The Journal of Nutrition, Health & Aging **14**(3), 190–195 (2010)
21. Folstein, M.F., Folstein, S.E., McHugh, P.R.: "Mini-Mental State": A practical method for grading the cognitive state of patients for the clinician. Journal of Psychiatric Research **12**(3), 189–198 (1975)
22. Watson, Y.I., Arfken, C.L., Birge, S.J.: Clock completion: An objective screening test for dementia. Journal of the American Geriatrics Society **41**(11), 1235–1240 (1993)
23. Nikolaus, T., Bach, M., Oster, P., Schlierf, G.: The timed test of money counting: A simple method of recognizing geriatric patients at risk for increased health care. Aging Clinical and Experimental Research **7**(3), 179–183 (1995)
24. Guigoz, Y., Vellas, B., Garry, P.J.: Assessing the nutritional status of the elderly: The mini nutritional assessment as part of the geriatric evaluation. Nutrition Reviews **54**(1), 59 (1996)
25. Burns, R., Nichols, L., Calkins, E., Blackwell, S., Pragay, D.: Nutritional assessment of community-living well elderly. Journal of the American Geriatrics Society **34**(11), 781–786 (1986)
26. Schutz, Y., Kyle, U., Pichard, C.: Fat-free mass index and fat mass index percentiles in Caucasians aged 18–98 y. International Journal of Obesity **26**(7), 953–960 (2002)
27. Brown, J.S., Bradley, C.S., Subak, L.L., Richter, H.E., Kraus, S.R., Brubaker, L., Lin, F., Vittinghoff, E., Grady, D.: The sensitivity and specificity of a simple test to distinguish between urge and stress urinary incontinence. Annals of Internal Medicine **144**(10), 715–723 (2006)
28. Sommeregger, U., Dovjak, P., Fasching, P., *et al.*: Österreichisches geriatrisches Basisassessment. Österreichische Gesellschaft für Geriatrie und Geronotologie **19**, 1070 (2011)
29. Carabellese, C., Appollonio, I., Rozzini, R., Bianchetti, A., Frisoni, G.B., Frattola, L., Trabucchi, M.: Sensory impairment and quality of life in a community elderly population. Journal of the American Geriatrics Society **41**(4), 401–407 (1993)
30. Chapman, C.R., Casey, K., Dubner, R., Foley, K., Gracely, R., Reading, A.: Pain measurement: An overview. Pain **22**(1), 1–31 (1985)
31. Sheikh, J.I., Yesavage, J.A.: Geriatric depression scale (GDS): Recent evidence and development of a shorter version. Clinical Gerontologist: The Journal of Aging and Mental Health **5**(1–2), 165–173 (1986)
32. Nikolaus, T., Bach, M., Oster, P., Schlierf, G.: Prospective value of self-report and performance-based tests of functional status for 18-month outcomes in elderly patients. Aging Clinical and Experimental Research **8**(4), 271–276 (1996)
33. Bahat, G., Tufan, A., Tufan, F., Kilic, C., Akpinar, T.S., Kose, M., Erten, N., Karan, M.A., Cruz-Jentoft, A.J.: Cut-off points to identify sarcopenia according to european working group on sarcopenia in older people (EWGSOP) definition. Clinical Nutrition **35**(6), 1557–1563 (2016)
34. Tibshirani, R.: The LASSO method for variable selection in the Cox model. Statistics in Medicine **16**(4), 385–395 (1997)
35. Friedman, J., Hastie, T., Tibshirani, R., Narasimhan, B.: Package 'glmnet'. CRAN R Repositary (2021)
36. Zou, K.H., Yu, C.-R., Liu, K., Carlsson, M.O., Cabrera, J.: Optimal thresholds by maximizing or minimizing various metrics via ROC-type analysis. Academic Radiology **20**(7), 807–815 (2013)
37. Unal, I.: Defining an optimal cut-point value in ROC analysis: An alternative approach. Computational and Mathematical Methods in Medicine **2017** (2017)
38. Youden, W.J.: Index for rating diagnostic tests. Cancer **3**(1), 32–35 (1950)
39. Perkins, N.J., Schisterman, E.F.: The Youden index and the optimal

cut-point corrected for measurement error. Biometrical Journal: Journal of Mathematical Methods in Biosciences **47**(4), 428–441 (2005)
40. Greiner, M., Pfeiffer, D., Smith, R.: Principles and practical application of the receiver-operating characteristic analysis for diagnostic tests. Preventive Veterinary Medicine **45**(1-2), 23–41 (2000)
41. R Core Team: R: A language and environment for statistical computing (2021). R Foundation for Statistical Computing
42. Friedman, J., Hastie, T., Tibshirani, R.: Regularization paths for generalized linear models via coordinate descent. Journal of Statistical Software **33**(1), 1–22 (2010)
43. Khan, M.R.A., Brandenburger, T.: ROCit: Performance assessment of binary classifier with visualization (2020). R Package Version 2.1.1
44. Fox, J., Weisberg, S.: An R Companion to Applied Regression, 3rd edn. Sage, Thousand Oaks CA (2019). https://socialsciences.mcmaster.ca/jfox/Books/Companion/
45. Sallinen, J., Stenholm, S., Rantanen, T., Heliövaara, M., Sainio, P., Koskinen, S.: Hand-grip strength cut points to screen older persons at risk for mobility limitation. Journal of the American Geriatrics Society **58**(9), 1721–1726 (2010)
46. Galasko, D., Klauber, M.R., Hofstetter, C.R., Salmon, D.P., Lasker, B., Thal, L.J.: The mini-mental state examination in the early diagnosis of Alzheimer's disease. Archives of Neurology **47**(1), 49–52 (1990)
47. McDowell, I., Kristjansson, B., Hill, G., Hebert, R.: Community screening for dementia: The mini mental state exam (MMSE) and modified mini-mental state exam (3MS) compared. Journal of Clinical Epidemiology **50**(4), 377–383 (1997)
48. Trzepacz, P.T., Hochstetler, H., Wang, S., Walker, B., Saykin, A.J.: Relationship between the montreal cognitive assessment and mini-mental state examination for assessment of mild cognitive impairment in older adults. BMC Geriatrics **15**(1), 1–9 (2015)
49. Perneczky, R., Wagenpfeil, S., Komossa, K., Grimmer, T., Diehl, J., Kurz, A.: Mapping scores onto stages: Mini-mental state examination and clinical dementia rating. The American Journal of Geriatric Psychiatry **14**(2), 139–144 (2006)

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