Physical activity trajectories of hospitalized patients: a latent class analysis

Master thesis

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ABSTRACT

Background: Sedentary behavior (SB) and a lack of physical activity (PA) increase the risk of functional decline and medical complications in hospitalized patients. Longitudinal methods are necessary to study activity trends during hospitalization and to examine whether there are patients with specific activity patterns who would be at risk for low PA and functional decline.

***Aim**:* To examine patients' daily time spent on SB and PA throughout hospitalization and to identify activity subgroups and patient-related factors associated with the distinct activity trajectories.

***Methods**:* In this observational mono-center study data of 512 adults hospitalized in 14 hospital wards were longitudinally analyzed. Patients' SB and PA measured with an accelerometer were utilized for statistical subgrouping. Subgroups were identified using latent class mixed modeling, characteristics were compared through variance, proportion, mean and median testing. Factors associated with subgroup placement were identified using multinomial logistic regression.

Results: Three subgroups were identified: a low active group (n=77) with a mean daily PA of 33 minutes, a moderate active group (n=260) with a mean PA of 80 minutes, and an active group (n=175) with a mean PA of 174 minutes. Factors associated with placement into the low active group were: higher BMI [odd ratio OR 1.054 (95% CI: 1.002-1.108)] [OR 1.097 (95% CI: 1.037-1.161)], lower handgrip strength score [OR 0.968 (95% CI: 0.942-0.994)] [OR 0.957 (95% CI: 0.930-0.984)] and longer hospital length of stay (HLOS) [OR 1.050 (95% CI: 1.016-1.085)] [OR 1.065 (95% CI: 1.022-1.110)] when compared to the moderate and active group. Higher ADL-dependency [OR 0.370 (95% CI: 0.140-0.980)] was associated with placement into the low active group when compared to the active group.

Conclusion and key findings: Hospitalized patients can have different activity trajectories throughout admission in which three distinct subgroups could be identified. BMI, handgrip strength, HLOS, and ADL-dependency were all factors mildly associated with subgroup placement. Patients' activity levels might cohere with latent variables and constructs.

Impact statement

Predicting patients' activity trajectories is intricate. Physical therapists should monitor patients' activity and target interventions towards subgroups with low PA rather than generically target interventions towards predefined groups based on predefined clinical factors.

Word count: 349

Keywords: Sedentary behavior, physical activity, hospitalization, latent class analysis.

INTRODUCTION

Hospitalized patients spend approximately 87-100% of their time lying or sitting.(1,2) This sedentary behavior (SB) during hospitalization is often associated with adverse outcomes, such as increased risks for a decline in physical fitness, ADL-activities, cognitive functioning, and an increased risk for medical complications.(3–5) In contrast, mild and moderate levels of physical activity (PA) during hospitalization contribute to improved physical functioning and decreased length of stay.(6,7)

Whilst the effects of SB and PA in hospitalized patients are thoroughly explored and studied, only little is known about the day-to-day activity patterns of hospitalized patients.(6–8) Various studies have tried to estimate patients' activity behavior during hospitalization with a wide variety of cross-sectional methods.(1,3,9,10) Cross-sectional methods have a limited ability to provide insight into patients' change in activity over time.(11) Longitudinal methods are necessary to study trends in activity during hospitalization and to examine whether there are patients with specific patterns who would be at risk for low PA and functional decline.(12)

A trajectory modeling technique, such as longitudinal latent class analysis, is a suitable approach to identify subgroups with distinct activity trajectories.(13) Latent class analysis is a robust method used to identify unmeasured class membership amongst subjects utilizing observed variables.(14) Once subgroups with distinct activity trajectories are identified the characteristics of the patients in the subgroups can be examined.(13) Furthermore, the patient-related factors associated with subgroup placement can be explored.(15–17) Identification of subgroups with distinct PA trajectories and information about subgroups at risk would be valuable. These outcomes can be used to target patients, with distinct activity patterns, with interventions to increase or maintain PA during their hospital stay.(18,19)

To correctly perform latent class analysis and identify subgroups at risk, hypotheses should be formulated based on available information.(20) Based on prior conducted cross-sectional research the existence of three subgroups was hypothesized. Multiple studies about elderly patients and patients with higher illness severity were utilized to hypothesize the existence of a group with a decreasing level of PA throughout admission is.(21–23) The second hypothesized group concerns patients who have moderate to low PA levels and maintain those levels throughout the entire admission with little to no change.(3,8,24) The last hypothesized group is a physically active group, in example young patients and elective surgery patients, with higher levels of PA at onset and throughout admission.(25,26)

However, due to the lack of longitudinal studies, it is not known whether subgroups with distinct activity trajectories actually exist. In this study we therefore aim to examine patients' daily time spent on SB and PA throughout hospitalization and to identify subgroups with distinct activity trajectories. Furthermore, we aim to explore which patient-related factors are associated with the identified subgroups.

METHODS

Design

This study is an observational cohort study using latent class analysis to examine prospectively collected data from the "Deventer Hospital in motion" project. The Deventer Hospital (DH) (the Netherlands) is a regional teaching hospital with room for 380 patients. Data were collected between November 2016 and August 2018. This study was registered at the Ethics Committee of the Isala Klinieken (Zwolle, the Netherlands, number 16-06113-DZ). The reporting of this study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement.(27)

Participants

Data of Dutch adults, hospitalized in one of the fourteen different hospital wards of the DH, were collected. Hospitalized patients were approached for participation by the researchers and were included when they were ≥18 years and when they were admitted to one of the following hospital wards: neurology, cardiology, gerontology, gynecology, internal medicine, intestinal medicine, oncology, orthopedic surgery, trauma surgery, oncology, nephrology, pulmonology, urology, or vascular medicine. All participants gave written informed consent before inclusion. Patients were excluded when they were unable to give informed consent due to severe mental impairment (as confirmed in the electronic medical record) and/or when they were wheelchair-bound prior to admission and/or when their expected hospital length of stay was ≤48 hours and/or when they had insufficient ability to understand the Dutch or English language. Additionally, patients were excluded from the analytic sample when they had less than 20 hours of Active8 data, meaning less than 1 day consisting of 15 hours of consecutive Active8 data and 1 day consisting of 5 hours of Active8 data.

Outcome measures

Activity data

Patients' activity was measured using the Active8 accelerometer(30x32x10 mm, 20 grams), produced by 2M Engineering Ltd®. The Active8 can differentiate between time spent lying down, sitting, standing, walking, cycling, and running.(32) The Active8 determines a subject's posture and activity every 5 seconds. Non-surgical patients received the Active8 on the day of admission, surgical patients received the Active8 within 24 hours after surgery. The Active8 was worn by patients on the upper thigh as suggested by the producers of the accelerometer. Patients were instructed to wear the Active8 24 hours a day throughout the entire hospital stay. Only the first 8 days of patients' activity data were utilized for the analysis. Day 8 was chosen as a cut-off point based on the European average length of hospital stay.(29)

PA was operationalized as patients’ daily waking minutes spent on activities with a METs value >1.5. Standing, walking, cycling, and running were considered as activities with a METs value >1.5.(28) Activities with a METs value ≤1.5 were operationalized as SB. Lying down or sitting were considered activities with a METs value ≤1.5.(28,29) Waking hours were operationalized for each patient as the time between 7:00 and 22:00 (15 hours).

Characteristics

Baseline characteristics obtained at the day of admission included: age in years, surgery (yes/no), gender (male/female), Body Mass Index (BMI), medical ward, and patients' prior living situation. The hospital length of stay (HLOS) and the location of discharge were derived from the electronic medical record (EMR). The Short Nutritional Assessment Questionnaire score (SNAQ) was utilized to determine the risk for malnourishment at admission. The SNAQ classifies patients into three categories: well-nourished, moderately malnourished, or severely malnourished.(30) Comorbidities were derived from the EMR and transformed into a Charlson Comorbidity Index (CCI) score by the researchers. The CCI is based on several conditions that are each assigned an integer weight from 1 to 6, with a weight of six representing the most severe morbidity.(31) The handgrip strength, expressed in kilograms, was obtained using the JAMAR dynamometer within 48 hours after admission. The JAMAR dynamometer is a simple and reliable tool to assess muscle strength in hospitalized adults.(32,33) The performance of ADL activities before hospitalization was scored using the Katz-ADL questionnaire within 48 hours after admission. The Katz-ADL concerns six activities: (1) bathing, (2) dressing, (3) toileting, (4) transferring, (5) continence, and (6) feeding. The Katz-ADL provides an ordinal scale (0-6), the higher the score the more severe the functional ADL impairment.(34,35)

Data analysis

Descriptive statistics were used to summarize categorical data. Normally distributed continuous data are presented as mean and standard deviation (SD).(36) Non-normal distributed continuous data are presented with a median and interquartile range (IQR). Missing data were evaluated to determine the missing data mechanism.(37) The characteristics belonging to the patients with missing variables were tabulated and screened on patterns to determine if the data were missing due to conditions of the characteristics.(37) Within this study, the missing data were considered missing at random. The missing data were imputed using the multiple imputation techniques, imputing missing values 5 times.(37,38) SPSS version 26.0 was used for the descriptive statistics.

The statistical analysis of patients’ activity trajectories throughout hospitalization was performed in two steps. First, spaghetti plots were made to observe patients’ daily hours spent sedentary and daily minutes spent physically active throughout hospitalization using the R GGplot2 package.(39) Additionally, the mean trajectory was plotted for both SB and PA. As a second step, latent class mixed models (LCMM) were used to identify latent subgroups among PA trajectories using the R LCMM package.(40–42) The finite model with latent classes was obtained by building up from a one-group model to a five-group model and comparing each model with the previous model for fit of the data.(16,43) One group at a time was added and analysed for fit using linear and quadratic models. The best-fitting model was selected based on 4 predefined criteria: (1) The Bayesian information criterion (BIC), the lowest BIC is preferred since a lower BIC implies a better fit.(16,43) (2) The entropy statistic, the threshold for the entropy statistic was set to ≥0.5. Entropy values ≥0.5 indicate a sufficient separation of the latent classes.(44) (3) The average of the maximum posterior probability of assignments (APPA-value), the APPA threshold was set to ≥70%, in all classes.(20) (4) The subgroup sample size, the potential subgroups needed to contain at least 5% of the sample, when that criterion was not met the model with K-1 subgroups was selected.(42,45) The selected model had to meet all 4 criteria or else the existence of subgroups could not be substantiated sufficiently.

After the selection of the best fitting latent classes, the baseline characteristics of the subgroups were compared. The overall variance was tested using the one-way ANOVA test for continuous data and the (weighted) Chi-squared test for categorical and ordinal data.(46,47) Additional testing was utilized to explore which groups significantly differentiated from each other. The t-test was used for parametric data, Hodges-Lehman median tests for non-parametric data, and the Chi-squared test for categorical and ordinal data.(48) A multinomial backward logistic regression analysis was conducted to determine which characteristics were associated with subgroup placement.(49) The predefined factors were tested for multicollinearity using the variance inflation factor (VIF) test.(50) VIFs >5 warranted corrective measures.(50,51) Correction of highly correlating independent variables consisted of removing the variable with the highest VIF.(50) These analyses were conducted using SPSS version 26.0.

RESULTS

Study population

Out of 834 hospitalized patients, 512 patients met the inclusion criteria and were included in this study. Within the sample, the 14 medical wards were represented proportionally with a mean sample of 7.4%. The characteristics of the patients are presented in table 1.

Table 1. Characteristics of the study population

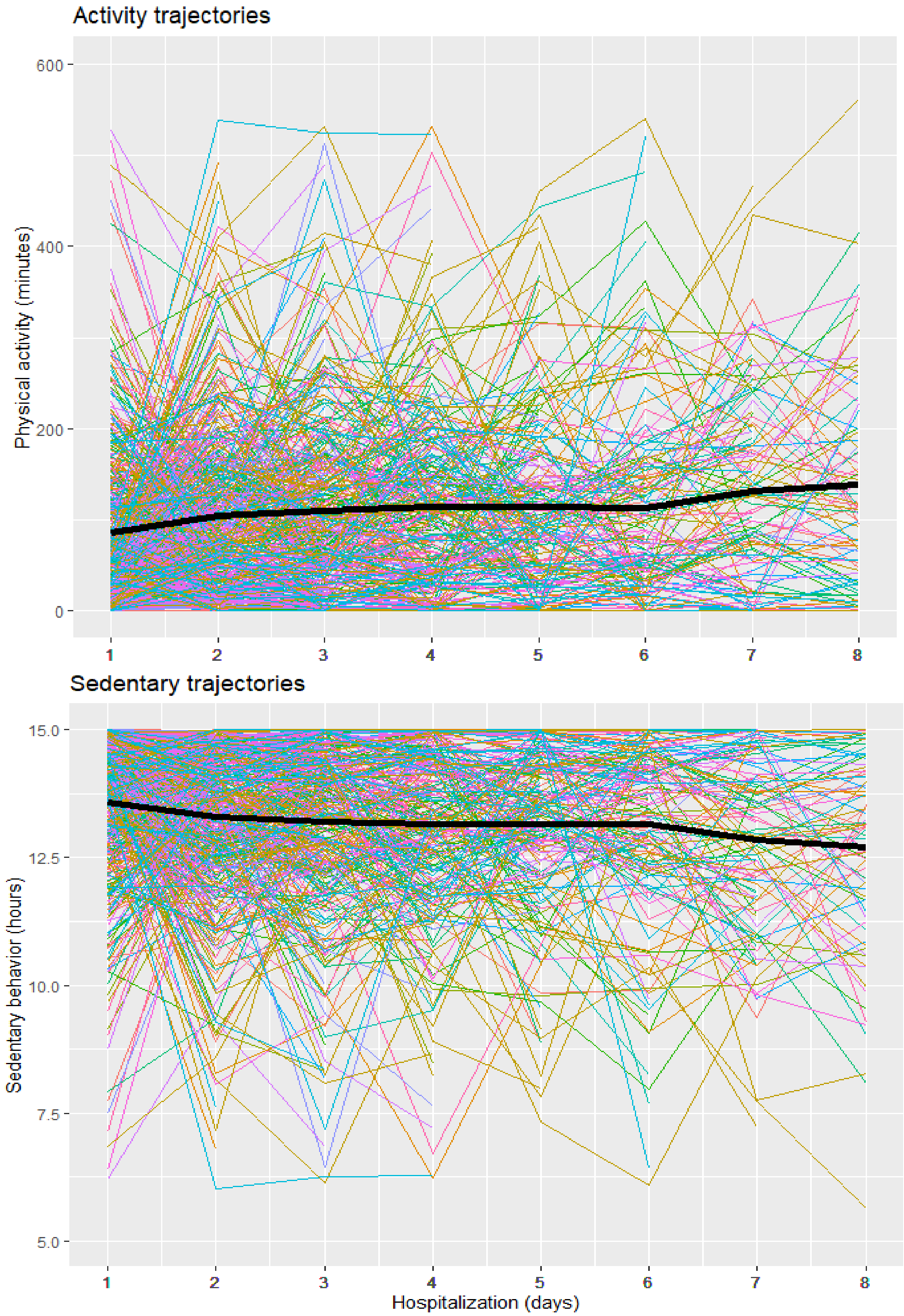
Characteristics	N=512
Age mean (SD)	70.3 (13.8)
Gender (male) % (n=)	54.3 (278)
BMI mean (SD)	26.7 (4.9)
Hospital length of stay median (IQR)	9.1 (2-16)
Surgery (yes) % (n=)	3.9 (194)
Invasive devices per patient† median (IQR)	1 (0-2)
CCI-score mean (SD)	4.5 (2.4)
Handgrip strength (KG/force) mean (SD)	27.5 (11.4)
Katz-ADL score† % (n=)	
Low dependency ADL	79,3 (406)
Moderate ADL dependency	11.5 (59)
Severe ADL dependency	9.2 (47)
SNAQ-score % (n=)	
Low risk of malnutrition	74.6 (382)
Moderate risk of malnutrition	4.1 (21)
High risk of malnutrition	21.3 (109)
Living situation before hospitalization % (n=)	
Independent at home	72.6 (372)
Home-based care	18.2 (93)
Care facility†	8.4 (43)
Rehabilitation center	0.8 (4)

BMI: body mass index. CCI-score: Charlson comorbidity index score. IQR; interquartile range. SD; standard deviation.† Invasive devices included; Oxygen line, central line, drain, peripheral lines, catheter line, telemetric line, and nutritional probe line Katz-ADL scores; 0-1 equals low dependency, 2-4 moderate dependency, and 5-6 severe dependency. SNAQ: Short Nutritional Assessment Questionnaire. †Care facilities included; nursing homes, assisted living facilities, and residential care centers.

Activity trajectories

Throughout hospitalization, patients spent an average of 13.2 (SD 1.6) out of the 15 waking hours a day on SB. The range of daily waking hours spent sedentary was 5.7-15 hours. The mean time of daily waking minutes spent on PA was 106 (SD 64) minutes. The range of daily waking minutes spent on PA was 0-561 minutes. The sample size on days 1 and 2 consisted of 512 participants. The sample size reduced to n=418 at day 3, n=317 at day 4, n=229 at day 5, n=171 at day six, n=128 at day 7, and n=82 at day 8. The trajectories and estimated mean trajectories of daily hours spent sedentary and minutes spent physically active were plotted for each patient in the sample and are presented in figure 1.

Figure 1. Patients' daily waking time spent on PA and SB during hospitalization



Note figure 1: Minutes PA and hours SB observed during patients' 15 waking hours (7:00-22:00). Colors are used for graphic visibility. The black line represents the estimated mean sample trajectory.

Activity trajectory subgroups

Based on the four predefined criteria the quadratic model with 3 classes was selected. This model had the lowest BIC-value (26668.75), the entropy threshold criterium ≥0.5 was met (0.508) and the APPA values surpassed the 70% threshold in each class. Lastly, each class of the quadratic 3 class model contained more than 5% of the sample. Table 2 shows the BIC-values, entropy statistics, APPA values, and percentages of patients within each class for the linear and quadratic models for the physical activity trajectories.

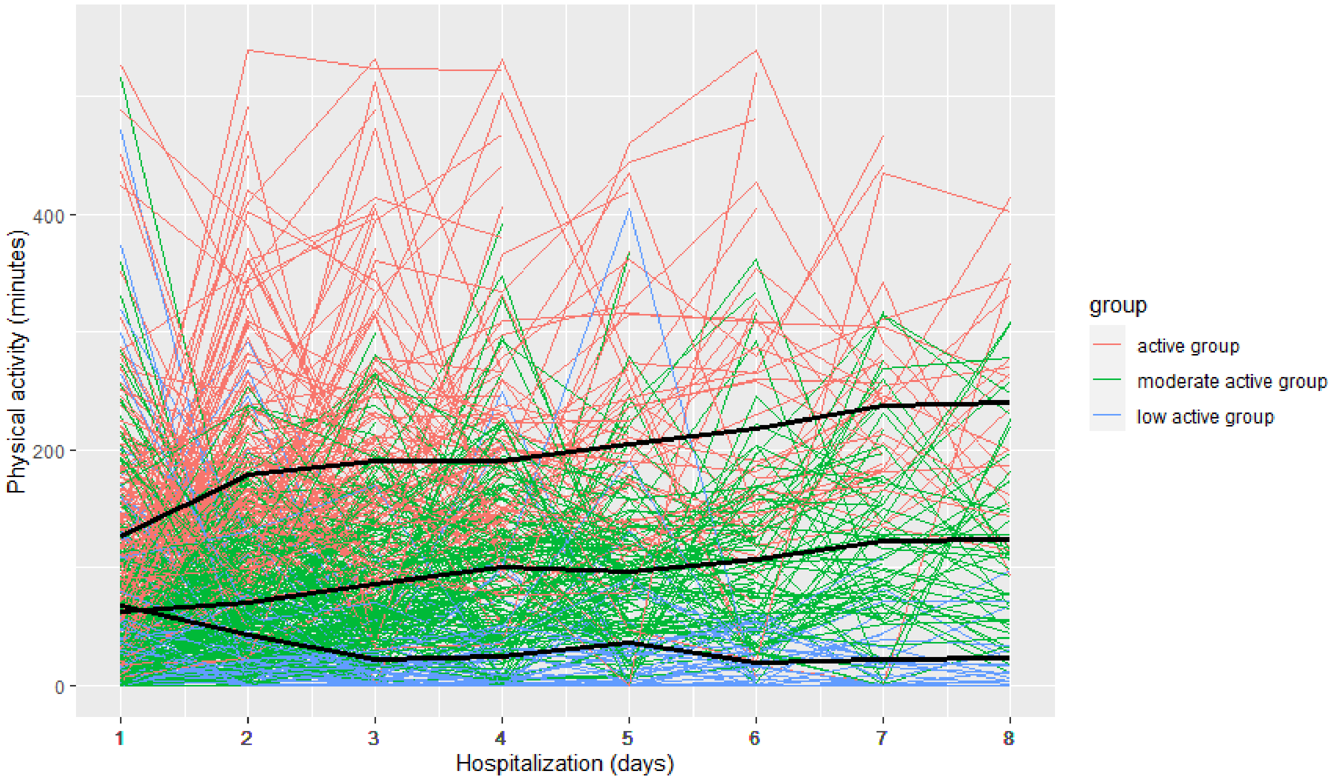
The 3 distinguished groups from the chosen model were defined as the "active group" (group 1, n= 175), the "moderately active group" (group 2, n=260), and the "low active group" (group 3, n=77). Figure 2 shows the physical activity trajectories and the estimated mean trajectories for the 3 groups.

Table 2. BIC values, entropy statistics, APPA-values, and sample % for linear and quadratic models of the activity trajectories

Class (C)	BIC	Entropy	Subgroup size% C1 (APPA value)	Subgroup size% C2 (APPA value)	Subgroup size% C3 (APPA value)	Subgroup size% C4 (APPA value)	Subgroup size% C5 (APPA value)
Quadratic slopes							
1	27058.02	1.000	100% (1.0)				
2	26716.99	0.578	63.2% (0.87)	36.7% (0.86)			
3	26668.75	0.508	34.2% (0.80)	50.8% (0.71)	15.0% (0.82)		
4	26674.06	0.429	12.9% (0.57)	38.5% (0.66)	32.6% (0.59)	16.0% (0.78)	
5	26677.86	0.469	41.9% (0.58)	2.5%** (0.74)	32.6% (0.7)	10.5% (0.71)	32.8% (0.63)
Linear slopes							
1	28417.06	1.000	100% (1.0)				
2	28081.19	0.697	18% (0.85)	82% (0.92)			
3	28019.33	0.720	2.5%** (0.92)	74.8% (0.89)	22.7% (0.78)		
4	27980.72	0.576	2.7%** (0.86)	47.1% (0.76)	39.5% (0.66)	10.7% (0.78)	
5	27975.30	0.614	0.6%** (0.75)	48.4% (0.77)	1.7%** (0.79)	39.8% (0.65)	3.3%** (0.82)

Selected model in green **Model with classes containing <5% of the sample

Figure 2. Subgroup trajectories for physical activity



Note figure 2: the black lines represent the estimated mean trajectories for the three groups as modeled by the LCMM prediction.

Subgroup comparison

On average, the patients in the low active group spent 14.4 out of the 15 daily waking hours on SB and 33 minutes on PA. Within the low active group, the PA decreases throughout admission. The estimated mean trajectory for the low active group decreases from 81 minutes on day 1 to approximately 24 minutes on day 3. After day 3 the estimated mean trajectory for the low active group oscillates around 24 minutes. The mean time spent on SB was 13.6 daily waking hours for the moderate active group, this group spent 80 daily minutes on PA on average. The estimated mean trajectory for the moderate active group increases to a mean PA of 100 minutes around day 4 and increases further towards 110 minutes after day 7. The high active group spent an average of 12.1 waking hours a day on SB and 174 minutes on PA. The estimated mean trajectory for the high active group increases from 120 minutes on day 1 to 170 minutes on day 2. After day 2 the estimated mean trajectory gradually increases towards 220 minutes on days 7 and 8.

The characteristics of the patients in the 3 subgroups were statistically compared, the overall variance comparison outcomes are presented in table 3. Additional mean, median, and proportion testing were utilized to explore which groups significantly differentiated from each other. Between the high active group and the low active group the BMI p=0.013 (t-statistic: 2.49 [95% CI: -3.0449, -0.3603]), the HLOS p=0.002 (Hodges-Lehman statistic: 10.78 [95% CI: 1.00-3.00]), the handgrip strength p= 0.0001 (t-statistic: -3.91 [95% CI: 2.878-8.7290]) and ADL-dependency p=0.008 (Chi-statistic: 9.96 [95% CI: 0.051-7.378]) significantly differentiated. Between the moderate active group and the low active group the HLOS p=0.008 (Hodges-Lehman statistic: 7.99 [95% CI: 1.00-3.00]) and handgrip strength p=0.05 (t-statistic: -2.81 [95% CI: -7.071, -1.2432]) also differentiated significantly. The proportion of patients in the different hospital wards did not significantly differentiate between the groups.

Table 3. Comparison of subgroup characteristics

Characteristics	"active group" (n= 175)	"moderate active group" (n= 260)	"low active group"(n= 77)	p-value
Age mean (SD)	69.3 (13.1)	68.2 (14.9)	70.6 (13.9)	0.382
Gender (male) % (n=)	56 (98)	55.4 (144)	46.8 (36)	0.896
BMI mean (SD)	26.2 (4.4)	27.0 (4.9)	27.9 (6.1)	0.034*
Hospital length of stay median (IQR)	7.24 (2-16)	7.87 (3-15)	11.45 (4-24)	0.0003*
Surgery (yes) % (n=)	37.1 (65)	38.8 (101)	36.5 (28)	0.898
Invasive devices† per patient median (IQR)	1 (0-2)	1 (0-2)	1 (0-2)	0.739
CCI- score mean (SD)	3.98 (2.1)	4.3 (2.5)	4.55 (2.5)	0.153
Handgrip strength (KG/force) mean (SD)	30.2 (11.5)	28.5 (12.0)	24.4 (9.1)	0.001*
Katz-ADL score % (n=)†				
Low dependency ADL	84.6 (148)	77.7 (202)	72.7 (56)	
Moderate ADL dependency	9.7 (17)	13.5 (35)	9.1 (7)	
Severe ADL dependency	5.7 (10)	8.8 (23)	18.2 (14)	0.018*
SNAQ-score % (n=)				
Low risk of malnutrition	74.3 (130)	75.8 (197)	71.4 (55)	
Moderate risk of malnutrition	5.1 (9)	3.1 (8)	5.2 (4)	
High risk of malnutrition	20.6 (36)	21.2 (55)	23.4 (18)	0.789
Living situation before hospitalization % (n=)				
Independent at home	78.3 (137)	72.3 (188)	61 (47)	
Home-based care	17.1 (30)	17.7 (46)	22.1 (17)	
Care facility †	4 (7)	9.2 (24)	15.6 (12)	
Rehabilitation center	0.6 (1)	0.8 (2)	1.3 (1)	0 .055

*BMI: body mass index. CCI-score: Charlson comorbidity index score. IQR; interquartile range. SD; standard deviation.† Invasive devices included; Oxygen line, central line, drain, peripheral lines, catheter line, telemetric line, and nutritional probe line Katz-ADL scores; 0-1 equals low dependency, 2-4 moderate dependency, and 5-6 severe dependency. SNAQ: Short Nutritional Assessment Questionnaire. †Care facilities included; nursing homes, assisted living facilities, and residential care centers. Chi-squared test with Yates correction. *The level of significance was set at p ≤0.05.*

Association between baseline characteristics and the identified trajectories

Six predefined predictors were selected for the multinomial logistic regression analysis based on the group comparison outcomes, the hypotheses, and clinical relevance. No collinearity was found. When the low active group is compared to the moderate active group BMI, handgrip strength score, and HLOS were found to be significant predictors. Patients with a higher BMI [odd ration OR 1.054 (95% CI: 1.002-1.108)], a lower handgrip score [OR 0.968

(95% CI: 0.942-0.994)] and a longer HLOS [OR 1.050 (95% CI: 1.016-1.085)] had a higher odds of placement into the low active group. Higher BMI [OR 1.097 (95% CI: 1.037-1.161)], a lower handgrip strength score [OR 0.957 (95% CI: 0.930-0.984)] and longer HLOS [OR 1.065 (95% CI: 1.022-1.110)] also increase the likelihood of placement into the low active group when compared to the high active group. A lower Katz-ADL score [OR 0.370 (95% CI: 0.140-0.980)], hence a lower ADL dependency, decreases the likelihood of placement into the low active group when compared to the active group. When the moderate active group is compared to the active group, the only factor associated with subgroup placement is the CCI-score. Higher CCI-scores are associated [OR 1.169 (95% CI: 1.032-1.326)] with placement into the moderate active group when compared to the active group. The results of the multiple multinomial logistic regression model are presented in Table 4.

Table 4. Multinomial logistic regression outcomes

		Odds ration [95% CI], p-value	
Predictor	*"low active group versus moderate active group"*	*"low active group versus high active group"*	*"moderate active group versus high active group"*
BMI	1.054 (1.002-1.108) p=0.042*	1.097 (1.037-1.161) p=0.001*	1.041 (0.988-1.087) p=0.060
Age	1.012 (0.984-1.041) p=0.401	0.980 (0.951-1.010) p=0.197	0.969 (0.948-0.989) p=0.303
Handgrip strength score	0.968 (0.942-0.994) p=0.015*	0.957 (0.930-0.984) p=0.002*	0.989 (0.970-1.007) p=0.288
Hospital length of stay	1.050 (1.016-1.085) p=0.003*	1.065 (1.022-1.110) p=0.003*	1.014 (0.977-1.053) p=0.463
CCI-score	0.958 (0.832-1.116) p=0.581	1.120 (0.944-1.330) p=0.194	1.169 (1.032-1.326) p=0.014*
KATZ-ADL ✝			
Low ADL dependency	0.702 (0.308-1.599) p=0.400	0.370 (0.140-0.980) p=0.046*	0.527 (0.230-1.207) p=0.130
Moderate ADL dependency	0.357 (0.121-1.046) p=0.060	0.274 (0.079-0.949) p=0.041*	0.767 (0.293-2.011) p=0.590
Severe ADL dependency	**ref** †	**ref** †	**ref** †

BMI: Body Mass Index. CCI-score: Charlson comorbidity index score ***significant p-value (p<0,05)** *† parameter is the reference category. ✝ Katz-ADL scores; 0-1 equals low dependency, 2-4 moderate dependency, and 5-6 severe dependency.* ******The level of significance was set at p ≤0.05.*

DISCUSSION

In this study we identified three subgroups with distinct PA trajectories: a "low active group", a "moderate active group" and an "active group". The majority of the hospitalized patients belonged to the moderate active group. Patients in the low active group had a longer hospital length of stay and a lower handgrip strength score compared to the patients in the moderate active and active group. In addition, patients in the low active group had a higher BMI and a more severe ADL-dependency when compared to the patients in the active group. We identified a higher BMI, a lower handgrip strength score, a lower Katz-ADL score, and a prolonged hospital length of stay as factors mildly associated with a higher likelihood of placement into the "low active group" when compared to the two other groups.

In line with previously published findings, our data confirm the overall lack of physical activity, while contradicting the notion that this applies to all hospitalized patients. The patients in the low active group (n=77) spent 14.4 out of the 15 daily waking hours on SB (96%) and the patients in the moderate active group (n=260) spent 13.6 waking hours on SB (91%). These outcomes align with the findings of several studies stating that hospitalized patients spent 87% to 100% on SB during the day.(5-8) The aforementioned studies state that all hospitalized patients have the same level of inactivity. The existence and activity patterns of the active group as found in our study contradict the common perception that all hospitalized patients have the same levels of inactivity. The patients in the active group (n=175) spent an average of 12.1 waking hours on SB and 174 minutes on PA. These patients spent twice as much time on PA when compared to the moderate active group and six times more when compared to the low active group. Furthermore, our study also provides new insight into factors associated with inpatient activity. Previous cross-sectional research shows that higher BMI, longer HLOS, higher ADL-dependency, and less muscle strength are risk factors for inpatient inactivity.(12-14) These findings align with our findings, but the strengths of the associations found in our study are fairly weak when compared to the cross-sectional studies.(12-14) Opposed to multiple studies, we did not find a distinct influence of age, amount of comorbidities, and presence of invasive devices on the level of physical activity throughout admission.(8,21,25) These contradicting results might be due to the difference in applied methods. The cross-sectionally found associating factors reflect an association with PA measured at one or two points in time, the strength of the associated factors might diminish when PA is measured over time. The findings of our study suggest that patients' change in PA over time is not strongly associated with the studied patient-related factors.

Strengths and limitations

The main strength of this study was the use of latent class mixed modeling. LCMM is a robust method to approach the longitudinal data and allow variation in HLOS between patients. The allowance of variation in trajectory length represents the natural variation of HLOS in hospitalized patients. The analysis is based on patients' actual trajectories and not on imputed or standardized data. Also, the fitting of the data into classes is more rigorous in LCMM due to the model-based approach which utilized several statistical tests to assess the proper fit.(43-45) The selection of classes and estimated mean trajectories are therefore better substantiated than in other clustering analysis techniques.(46) Despite the multiple robust statistical tests performed, the ability to predict subgroup placement based on the studied clinical factors remains intricate. A limitation of this study is a shortfall in the inclusion of behavioral factors. In this study we mainly included clinical characteristics and physical performance tests. Prior conducted research shows that behavior and beliefs towards physical activity might influence activity levels of hospitalized patients.(19) Another limitation is the usage of the Active8 accelerometer. The Active8 is presented as the best available tool to quantify predefined body postures and movements.(52) Nonetheless, the Active8 has some limitations, the distinction between lying and sitting is less accurate than the distinction between other body postures.(53) When a patient sits longer than 5 minutes without any counts the activity is registered as lying down.(53,54) The effect of this inaccuracy is limited in this study since both lying and sitting down were classified as "sedentary behavior". Another limitation of the Active8 is that it registers nonwear as lying down.(53) Although patients were thoroughly instructed to wear the Active8 at all times, short periods of nonwear could be registered as lying down.

Based on the findings of this exploratory study we infer that hospitalized patients have varying activity patterns throughout hospitalization. Within this study we found three subgroups with distinct PA patterns, the moderate, the active, and the low active group. Future studies should externally validate the existence of the three found subgroups. Externally validating the existence of the subgroups will broaden the generalizability, since the findings of this mono-center study solely represent the observations from one hospital. Predicting patients' subgroup placement based on clinical factors is intricate, the associations found in this study are fairly weak. This indicates that even though subgroups were found, the factors that robustly contribute to subgroup placement remain unknown. This might be due to more complex underlying latent constructs. In this study we included a broad variety of clinical factors and the 14 different hospital wards were equally represented in the sample with a mean of 7.4%. However, future research should focus on trying to uncover latent constructs and factors that might explain PA patterns. It is therefore recommended to include behavioral factors in future explanatory research. Physical therapists should not stare blindly into patients' clinical factors. Physical therapists should monitor patients' activity and target interventions towards subgroups with low PA rather than generically target interventions towards predefined groups based on predefined clinical factors.

CONCLUSION

In conclusion, within hospitalized patients, three groups with distinct PA trajectories can be distinguished: a “low active” group, a “moderate active group” and a “high active group”. Predicting in which subgroup a patient will be placed based on clinical characteristics and performance tests is intricate. Physical therapists should thoroughly monitor patients’ PA throughout admission. Patients with low PA patterns should be targeted with interventions to increase or maintain PA during their hospital stay.

WORD COUNT: (3677) Introduction-discussion with tables excluded.

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