PNAS
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Main Manuscript for

The temporal dynamics of sitting behaviour at work

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Classification

SOCIAL SCIENCES: Psychological and Cognitive Sciences

Keywords ***(min 3; max 6)***

Sedentary behaviour, Time-to-event analysis, Survival analysis, Fatigue, Occupational health

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Main Text
Figures 1 to 2
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Abstract

Sitting for prolonged periods of time impairs people's health. Prior research has mainly investigated sitting behaviour on an aggregate level, e.g., by analysing total sitting time per day. By contrast, taking a dynamic approach, here we conceptualise sitting behaviour as a continuous chain of sit-to-stand and stand-to-sit transitions. We use multilevel time-to-event analysis to analyse the timing of these transitions. We analyse ~30,000 objectively-measured posture transitions from 156 people during worktime. Results indicate that the temporal dynamics of sit-to-stand transitions differ from stand-to-sit transitions, that people are quicker to switch postures later on the workday, and quicker to stand up after having been more active in the recent hours. We found no evidence for associations with physical fitness. Altogether, these findings provide insights into the origins of people's stand-up and sit-down decisions, show that sitting behaviour is fundamentally different from exercise behaviour, and provide pointers for the development of interventions.

Significance Statement

Nowadays, most people spend large parts of their waking time sitting. Problematically, sitting for long, uninterrupted periods of time harms people's health. To develop effective interventions, we need a solid understanding of the aetiology of unhealthy sitting patterns. We proposed a novel approach to studying sitting behaviour, which aims to unravel the temporal dynamics of sitting patterns. Our research yielded novel insights regarding why and when people sit (e.g., mental fatigue may play a key role), and regarding how to best study sitting behaviour (e.g., we need to distinguish sitting behaviour from exercise behaviour). These findings have implications for the design of effective interventions targeting sitting behaviour. Moving forward, the science of sitting may benefit from adopting a dynamic approach.

Main Text

Introduction

In modern society, most people spend large parts of their waking time sitting, especially when they are at work (1–4). Numerous studies have demonstrated that sitting for extended periods of time contributes to mental and physical health conditions, such as depression, stress, obesity, diabetes, cardiovascular diseases, cancer, and all-cause mortality (5–7). Problematically, the detrimental health consequences of sitting appear present even in those who otherwise meet recommended levels of daily physical activity (6). Therefore, to improve society's health and well-being, it is vital to change people's sitting behaviour.

So far, research into sitting behaviour has yielded crucial insights, such as that for working adults extensive sitting time mostly accumulates during worktime (8, 9), and that sitting directly influences metabolism, bone mineral content, and vascular health (10, 11). However, prior research on sitting behaviour has typically examined sitting on an aggregate level. That is, typically, summary characteristics of sitting behaviour (e.g., total sitting time, average duration of sitting episodes) are used as primary outcomes. This traditional approach conceptualises sitting behaviour as a static property of a person—or at best, as a static property of a person on a specific day. This approach parallels the mainstream approach that is used to study physical exercise, where volume of exercise is usually expressed and investigated as total hours or minutes per week. Yet, when used on sitting behaviour, such a static approach overlooks the fact that sitting is a highly dynamic phenomenon that is characterised by a continuous chain of transitions between sitting and standing. Here, we examine sitting behaviour on a more granular level: the level of individual sit-to-stand and stand-to-sit transitions.

Relative to the traditional approach, our dynamic approach has three main advantages. First, our approach provides a sensitive method to capture the variability that is characteristic of natural sitting behaviour. On an average day, people transition between sitting and standing between ~70 and ~140 times; also, people may stay in a single posture for time periods ranging from a few seconds to several hours (12). These substantial variations are even present when people's sitting behaviour is strongly constrained by the physical and social context, such as when people are paid to work behind a desk. That is, in such constrained contexts, people usually still make short but frequent posture switches, for example stretching the legs, visiting the bathroom, or grabbing coffee. So, examining sitting behaviour on a person-level or day-level does not provide an ecologically valid representation of the time scale on which sitting behaviour occurs (see also(13)). Recent studies support the potential importance of acknowledging dynamic variation in sitting. That is, the time people spend in prolonged, uninterrupted periods of sitting (>30 minutes), rather than total sitting time, may be the main cause of sitting-related health problems (14, 15).

Our approach can be used to gain unique and detailed insight into the dynamic variations in sitting, and therefore into the specific unhealthy characteristics of sitting behaviour.

Second, our dynamic approach allows us to examine a range of candidate predictors to help explain the sitting behaviour. Examining individual sit-to-stand and stand-to-sit transitions will yield more precise insights into people's decision-making processes that drive their sit-to-stand and stand-to-sit transitions. Moreover, going beyond the traditional approach, a more granular investigation of sitting behaviour allows us to examine candidate predictors whose values vary throughout the day. In this research, we tested several candidate predictors: (a) We examined *time of the day* to examine natural circadian fluctuations in sit-to-stand and stand-to-sit transitions. Specifically, later during the workday people tend to experience higher levels of mental fatigue (16, 17); thus, examining time of the day may provide an insight into how mental fatigue affects sitting behaviour. (b) We examined people's *physical effort expenditure* in recent hours, as recent effort is known to affect other health behaviours (18, 19). For example, after expending effort during the workday, people are less motivated to exercise in the evening (20). (c) We examined *individual differences in physical fitness*, as people who are less physically fit likely perceive higher energetic costs of standing up when sitting (21). By examining these candidate predictors, our dynamic approach opens the door to a more detailed understanding of the psychological processes that drive sitting behaviour (22).

Third, our dynamic approach provides a way of analysing data from modern wearable technology (in our case, the activPAL monitor). Such technology records all individual sit-to-stand and stand-to-sit transitions that people make, with measurement precision in seconds. We capitalise on the richness of such time-series data by modelling individual posture transitions. For this purpose, we use multilevel time-to-event analysis.

Time-to-event analysis, also known as survival analysis, is used to examine the timing of *events*—or, transitions from one state to another (23, 24). Originally developed to predict the timing of death (24), time-to-event analysis has subsequently been used in other fields of study, for instance, to predict the timing of relapse into substance abuse (25) or to predict the timing of emotion expression in children (23, 26). To the best of our knowledge, time-to-event analysis has not yet been used to examine determinants of health behaviour. In time-to-event analysis, researchers estimate the *hazard* of an event, which refers to the conditional (i.e., given that the event has not happened yet) probability that an event occurs per unit of time. As we examine events that can happen more than once within each individual (i.e., sit-to-stand and stand-to-sit transitions), we use a multilevel framework to model random variability in the timing of sit-to-stand and stand-to-sit transitions between individuals (i.e., events nested within individuals; 23, 26).

Specifically, using multilevel time-to-event analysis, we were able to examine predictors of (a) the hazard of standing up when sitting, and (b) the hazard of sitting down when standing.

For working adults, overall unhealthy sitting behaviour is mostly accumulated during worktime (2). Thus, in this paper we limited our investigation to sitting behaviour during worktime. We analysed ~30,000 objectively measured posture transitions of 156 UK-based employees from various worksites, who performed mainly desk-based work. We used a split-samples cross-validation procedure (27, 28). Specifically, prior to looking at the data, we randomly split the data into two samples of equal size: A *training sample* (*n* = 79; 7,316 sit-to-stand and 7,263 stand-to-sit transitions) and a *testing* sample (*n* = 77; 7,216 sit-to-stand and 7,158 stand-to-sit transitions). We used the training sample for data exploration and fine-tuning of analyses and analytical decisions. After this, we preregistered our research questions and analysis plan for the testing sample at the Open Science Framework (URL to the preregistration). Unless otherwise specified, in this paper we report results from the preregistered analyses on the testing sample. We used this procedure because it diminishes the chance of reporting false positives through preregistration; at the same time, the training sample offered opportunity to explore the data, thus decreasing the probability of overlooking potentially relevant predictors (27, 28).

Results

Standing up versus sitting down

First, we estimated the baseline probability of standing up when sitting versus sitting down when standing, and whether these develop differently over time. To investigate whether sit-to-stand versus stand-to-sit transitions were qualitatively different, we tested whether the type of transition predicted the hazard of posture transition, and whether the hazard of standing up when sitting and the hazard of sitting down when standing developed differently over time.

Results are presented in Table 1. Figure 1 displays the baseline survival function (i.e., the proportion of events that has not happened yet as a function of time) of stand-to-sit transitions and sit-to-stand transitions separately. There was a significant effect of type of transition, which suggested that participants were 5.4 times more likely to sit down per minute of standing, than to stand up per minute of sitting. Median survival times indicated that 50% of the time participants sat down within 1.8 minutes of standing, and stood up within 5.6 minutes of sitting. In other words, people were quicker to select sitting over standing, i.e., they were quicker to choose the behavioural option that costs the least energy and yields most comfort in the context of desk-based working (29). This finding is in line with the classic ‘principle of least effort’ (30). These low median survival times suggest that participants were often rather quick to switch back and forth between standing and sitting. Although this result is in line with the previous finding that that people make ~70–140 posture transitions per day (12), these low median survival times seem counterintuitive given the societal concerns that people sit too long and too much. Interestingly, Figure 1 suggests that, consistent with previous research (4), 15% of sitting episodes lasted longer than 30 minutes. In fact, in our sample, 88% of participants had ≥ 3 long episodes of uninterrupted sitting on at least one single workday. Thus, despite the relatively large amount of short sitting and standing episodes, unhealthy sitting behaviour at the workplace is abundantly present.

Going beyond previous work, the significant Transitions x Event time interaction suggests that sit-to-stand and stand-to-sit transitions have distinct associated probabilities and a different development over time. Specifically, the hazard of sitting down when standing was relatively high in the first minutes of standing, and decreased quickly over the time course of a standing episode. In other words, most of the time when people were active, they quickly sat down again. Conversely, the hazard of standing up when sitting was relatively low in the first minutes of sitting, and decreased gradually over the time course of a sitting episode (See also Figure S1). This means that once participants remained seated beyond the first minutes, they were likely to remain seated for a long, uninterrupted amount of time. In conclusion, although stand-to-sit and sit-to-stand transitions together make up people's unhealthy sitting patterns, our results suggest that the decision-making processes that drive these transitions are qualitatively distinct. These data also highlight that examining sitting behaviour at the level of individual sit-to-stand and stand-to-sit transitions has the potential to yield relevant and novel insights.

Time of the day

We examined time of the day as a predictor of the hazard of standing up when sitting and the hazard of sitting down when standing (Table 1). Figure 2 displays the survival functions for sit-to-stand and stand-to-sit transitions at 9 am versus 5 pm. With each hour increase in time of the day, participants were 4% more likely to stand up per minute of sitting, and 3% more likely to sit down per minute of standing. Median survival times indicated that at 9 am, 50% of the time participants stood up within 7.1 minutes of sitting and sat down within 2.0 minutes of standing. At 5 pm, median survival times were 4.4 minutes and 1.6 minutes, respectively. This result suggests that later on the day, when fatigue had likely set in (16, 17), participants were quicker to switch back-and-forth between sitting and standing. This result seems counterintuitive, since people who experience more mental fatigue are expected to prefer behaviours that require less effort (such as sitting; 31). However, recent accounts of fatigue suggest that fatigue functions as a signal to stop the current task and switch to another (19). In line with this account, our results suggest that later on the day, when people feel more fatigued, they more quickly change their posture while working (e.g., continue work standing), more quickly switch to a different work task that involves a change in posture (e.g., decide to print some documents), and/or more quickly take a short break that involves a change in posture (e.g., walk to the coffee machine).

Activity in last 5 hours

We then examined recent activity as a predictor of the hazard of standing up when sitting and the hazard of sitting down when standing (Table 1). Figure 2 displays the survival functions for 45 minutes (15%; ≈ -1 SD) versus 150 minutes (50%; ≈ +1 SD) of activity in the last 5 hours. With each additional minute that participants had been physically active in the last 5 hours, they were 0.17% *more* likely to stand up per minute of sitting, and 0.21% *less* likely to sit down per minute of standing. Median survival times indicated that after being active for 45 minutes in the last 5 hours, in 50% of the time participants stood up within 6.7 minutes of sitting, whereas after 150 minutes of activity, they stood up within 4.1 minutes. In addition, after 45 minutes of activity, in 50% of the time participants sat down within 1.5 minutes of standing, whereas after 150 minutes of activity, they sat down within 2.5 minutes of standing. Intriguingly, these findings contradict the intuitive expectation, derived from research on other health behaviours (e.g., physical exercise), that people prefer behaviour that involves less physical effort after they have previously exerted physical effort (18, 19). Instead, after periods of standing (i.e., being active, exerting more physical effort), people were more likely to stand, and less likely to sit. This finding suggests that people display fairly stable sitting and standing behaviour tendencies over a timeframe of several hours, and that previous effort exertion does not prevent future effort exertion, at least not in the context of light physical activity (i.e., sitting versus standing and walking).

Individual differences in physical fitness

Finally, we explored associations between individual differences related to physical fitness and the hazard of standing up when sitting and the hazard of sitting down when standing. We assumed that people who have higher Body Mass Index (BMI), are older, and/or are less active in their leisure time, are less physically fit. We conducted a-priori sensitivity analyses (Supplementary Text) to determine the magnitude of effects we could detect with a power of $1 - \beta = .80$. Results indicated that we could detect medium to large effect sizes. However, based on exploratory analyses on the training sample, we expected only small effects, if any. Therefore, we decided to consider the analyses that follow exploratory, and to conduct these analyses on the full sample (training sample + testing sample), in order to provide the most precise effect size estimates that we can at this point, given the available data. There were some missing values on the predictor variables (See Methods).

Results (See Table 2) indicated that none of the indicators of physical fitness were related to the hazard of standing up or to the hazard of sitting down. This null finding contradicts findings of several other studies showing that people who are older, people with higher BMI, and people who engage in less physical activity in their leisure time, generally sit more and longer (2, 32). Possibly, as these prior studies focused only on summary statistics of sitting behaviour, it may be the case that our more dynamic approach to sitting (in which we examine sitting on the level of individual transitions) suggests a smaller role for individual differences in physical fitness. It is important to note, however, that these tests were exploratory and that statistical power for these tests was relatively low. Therefore, more research into the associations between physical fitness and sitting patterns is necessary before drawing firm conclusions.

Discussion

We investigated sitting behaviour as a continuous chain of sit-to-stand and stand-to-sit transitions, using multilevel time-to-event analysis. In line with previous findings, people in our study switched often and quickly between sitting and standing (within minutes), but also engaged in a considerable amount of prolonged, unhealthy sitting episodes at work. Extending previous research, we showed that sit-to-stand and stand-to-sit transitions, that together make up people's unhealthy sitting patterns, are different both in probability and timing. This underscores the relevance of zooming in on these individual transitions when investigating sitting behaviour. Adopting our dynamic approach, we found that people were quicker to switch postures later during the workday compared to earlier during the workday. Moreover, when people were more active (non-sitting) in the previous hours, they were quicker to stand up when sitting and slower to sit down when standing. Finally, we found no evidence that the timing of standing up and sitting down depends on individual differences in physical fitness.

Our findings yield several novel insights into the nature of sitting and standing behaviour during the workday. Perhaps most importantly, our findings suggest that sitting behaviour is critically different from other health behaviours. That is, when people feel fatigued at the end of the day, or when people have already engaged in previous effort, they are generally more prone to engage in unhealthy behaviours, such as unhealthy eating or skipping exercise sessions (18, 20, 33–35). By contrast, our findings suggest that people engage in *healthier* sitting patterns—characterised by quicker posture switching and shorter time to stand up when sitting—at the end of the workday and/or when they have been more active in the hours before. Thus, where prior research has aimed to understand sitting behaviour using the same psychological models that proved useful for other health behaviours, physical activity in particular (36), our findings suggest that sitting behaviour is not necessarily comparable to these other health behaviours. The fundamental differences in energy expenditure, frequency, duration, deliberate processing between physical activity and sitting behaviour (37) may contribute to these observations. This emphasizes that, to target sitting behaviour, practitioners cannot simply follow intervention strategies that have proven to successfully boost physical activity and exercise—rather, they have to consider the potentially unique nature of sitting behaviour.

More broadly, our findings highlight that our dynamic approach to sitting behaviour, along with the use of multilevel time-to-event analysis, complements and goes beyond the traditional approach that is used to understand sitting behaviour. We demonstrated that a dynamic approach is useful when attempting to outline the psychology of sitting (22), i.e., when attempting to uncover the decision-making processes that drive sit-to-stand and stand-to-sit transitions. However, we anticipate that other research fields that take an interest in the antecedents of sitting (e.g., environmental psychology, industrial design, medicine, and epidemiology) can also benefit from analysing sitting patterns on the level of sit-to-stand and stand-to-sit transitions, making use of time-to-event analysis. Moreover, our approach offers a useful tool for evaluating the effectiveness of interventions with greater precision.

To date, numerous interventions to decrease sitting time have been designed and tested, such as height-adjustable desks (38), and online tailored advice on how to reduce and break up sitting (39). Although these interventions indeed reduce sitting time on the short-term, the benefits seem to wear off over a few months (40, 41). A plausible explanation for this decline is that, even though theory-based interventions are known to be more effective (42), the majority of existing interventions that aim to change sitting behaviour lack a theoretical basis (40). As our dynamic approach can be used to unravel the decisions that drive sitting behaviour, we expect that our approach will substantially contribute to the theoretical understanding of sitting behaviour—and, thus, help provide a solid basis for designing interventions. In particular, to effectively reduce the number of prolonged, uninterrupted periods of sitting, interventions should aim to accelerate people's decisions to stand up when sitting. With time-to-event analysis, researchers can directly target the determinants of these crucial decisions, and thereby help identify targets for interventions that might otherwise be overlooked.

Besides gaining insights into potential intervention targets, exploring the temporal dynamics of sit-to-stand and stand-to-sit transitions also provides ideas on *when* interventions are most necessary. Our findings showed that later during the work day people naturally engage in healthier sitting patterns. This implies that interventions to change people's sitting behaviour are most needed at the beginning of the workday.

Our results suggest that unhealthy sitting behaviour is a general problem concerning many employees, not only less physically fit or older people. Conversely, we observed that people's sitting patterns are most unhealthy at the beginning of a new workday, when employees plausibly still feel fresh and fit. Sitting thus seems to be a ubiquitous consequence of present-day work. Building on our findings, along with the accumulating evidence on the negative consequences of sitting, one could argue that unhealthy sitting patterns should be considered a serious occupational risk for developing disease (see also 43). Regulation of other known occupational risks, such as exposure to loud noises, exposure to chemicals, or working nightshifts, has long been a formal responsibility of employers (‘duty of care’; 44). This line of reasoning raises the question who should take responsibility for changing employees sitting behaviour, in order to protect and improve our workforce’s physical health and mental wellbeing. Ultimately, gaining insights into the mechanisms that predict sit-to-stand and stand-to-sit transitions during worktime will provide practical starting points for both employers and employees to adopt and apply interventions that will help employees engage in healthier sitting patterns during work.

Materials and Methods

We used existing data collected by the Research Institute of Sport and Exercise Sciences at Liverpool John Moores University, UK. The dataset included objectively measured, continuous activity data of 167 working adults from various worksites in the United Kingdom. All data that we used for our analyses, and R code for data processing, analysis and visualization, is publicly available on the Open Science Framework (URL to the OSF repository for readers).

Participants and procedure.

The full sample (*n* = 167) was combined out of four different samples that were collected for different research projects. Data from sample A (*n* = 14) were collected from university desk workers (not academic staff or technicians), data from sample B (*n* = 70) were collected from call agents from two different contact centres, and data from sample C (*n* = 61) and sample D (*n* = 22) were collected from working adults without specific criteria for job role or sitting time. In each sample, the procedure for data collection was the same. All participants first provided demographics and other personal characteristics; anthropometric assessment was conducted by a trained researcher. Next, participants were instructed to continuously wear a thigh-mounted activPAL monitor (PAL Technologies, Glasgow, UK) for seven consecutive days. In addition, participants recorded the times they started and finished work each day in a log book. For all samples, study procedures were approved by the Liverpool John Moores University Ethics Committee. The samples did not significantly differ in the hazard of standing up when sitting (*p* = .991) and in the hazard of sitting down when standing (*p* = .999).

Data from participants for whom no worktime data were available were excluded, leaving *n* = 156 of the full sample, and *n* = 77 of the testing sample. Participants in the full sample had an average age of 33.92 (*SD* = 11.47), an BMI of 27.84 (*SD* = 6.84), and scored on average 3.52 (*SD* = 0.88; on a 5-point scale) on leisure time activity level. The sample included 95 females (61%; one participant had a missing value on gender). The number of workdays varied between one and seven, (*M* = 3.99, *SD* = 1.29). Per workday, participants on average sat for 5.31 hours (*SD* = 1.92) and were active for 2.18 hours (*SD* = 1.79) .

Measures.

Sitting behaviour is defined as "any waking behaviour characterized by an energy expenditure ≤ 1.5 metabolic equivalents (METs), while in a sitting, reclining or lying posture"(9). In this study, we distinguished between sitting behaviour and *activity*, referring to all non-sitting behaviour. Sitting behaviour and activity were assessed using an activPAL monitor, a device that is worn on the thigh that directly assesses posture using triaxial accelerometry. ActivPAL monitors are known to have a good reliability and validity to measure sitting and activity behaviour (See(45) for more information on the activPAL monitor). Placement was standardised to the anterior midline of the upper right thigh, with monitors inserted into a flexible waterproof sleeve and attached using a hypoallergenic waterproof adhesive strip (3M Tegaderm). *Time of the day*, in hours since midnight (precision in seconds), was calculated from the time variable in the activPAL data. *Activity in last 5 hours*, in minutes (precision in seconds), was calculated as the sum of all active (non-sitting) time in the 5 hours prior to the previous stand-to-sit or sit-to-stand transition, per participant, per day. *BMI* was calculated following an anthropometric assessment. Stature was measured to the nearest 0.1cm using a portable stadiometer and body mass to the nearest 0.1 kg using a calibrated mechanical flat scale. Body mass index was calculated as mass divided by stature (kg/m2). Data on BMI were available for 95 participants in the dataset (8222 sit-to-stand and 8172 stand-to-sit transitions). *Age* was assessed by self-report. Data on age were available for 150 participants in the dataset (14211 sit-to-stand and 14102 stand-to-sit transitions). *Leisure time activity level* was assessed by self-report on a scale from 1 (*physically inactive*) to 5 (*physically active*). Data on leisure time activity level were available for 58 participants in the dataset (6080 sit-to-stand and 6020 stand-to-sit transitions).

Data analysis.

Split-samples procedure. In this study we used a split-samples cross-validation procedure(27, 28). Prior to looking at the data, we randomly split the data into two equal samples: A *training sample* (n = 79) and a *testing* sample (n = 77). As the data were combined out of several projects, we stratified data-splitting on project. First, we used the training sample for data exploration and fine-tuning of analytical decisions. Then, we designed and preregistered a specific analysis plan for the testing sample. This preregistration (URL to the preregistration) described all research questions, all data-processing steps (i.e., calculation of variables; data exclusion based on worktimes and non-wear), all analyses, and handling of assumptions and convergence / singularity issues. Unless otherwise mentioned, the main text of this paper reports preregistered analyses on the testing sample.

Data on the between-subjects predictors BMI, age, and leisure time activity level were only available for part of the sample. We conducted a-priori sensitivity analyses (Supplementary Text) to determine the magnitude of the effects that we could detect with a power of .80. Results from this sensitivity analyses indicated that, given the sample sizes in our testing sample for BMI, age, and leisure time activity level, we could detect medium to large effects (Hazard Ratio [HR] ≈ 1.5 for positive associations; HR ≈ 0.7 for negative associations). However, based on our exploratory analyses on the training sample, we expected only small (or null) effects. Therefore, we decided to examine these predictors in an exploratory fashion, and to examine associations with these predictors on the full sample (training sample + testing sample), in order to provide the most precise effect size estimates, given the data that we have.

Exclusion of non-working hours. We excluded observations that fell outside of participants workings hours, using participants' self-reported work start and end times. First, we narrowed the work time window by 15 minutes on both start and end times to correct for recall bias, settling into the building, and to make sure that commuting time was not included in the dataset (see also(46)). Next, we excluded observations that fell outside of the narrowed work-time window. For observations crossing work start or end times, we only retained observations with at least 50% of the time inside the (narrowed) worktime window and excluded the rest (45; 75% of transitions in the training sample; 76% of transitions in the testing sample). After exclusion of non-worktimes, 7,316 sit-to-stand and 7,263 stand-to-sit transitions remained in the training sample, and 7,216 sit-to-stand and 7,158 stand-to-sit transitions remained in the testing sample.

Non-wear and extreme values. Sitting episodes with a duration longer than 8 hours were identified as non-wear (i.e., as a time period in which the participant did not wear the activPAL monitor) and excluded from the analyses (one observation in the training sample; no observations in the testing sample). In addition, active episodes with a duration longer than 8 hours were identified as extreme values and excluded from the analyses (one observation in the training sample; no observations in the testing sample).

Data preparation for time-to-event analysis. ActivPAL data were downloaded from the monitors using activPAL software and saved in event-based summary files. Event-based data files contain one row for each episode of lying/sitting, standing, and for each step. Each row indicates the time the episode begins (*start time*) and an activity code (*sitting/lying down; standing;* or *stepping*). For the current research, standing and stepping were taken together as *active*. In order to prepare the data for time-to-event analysis, we computed an *event* (*sit-to-stand* vs. *stand-to-sit*) variable and an *event time* (in minutes; precision in seconds) variable (23, 26). The event time variable contained the timing of the event since the previous event had ended (i.e., since the person was *at risk* for the event to happen). To illustrate, for each sit-to-stand transition, the event time variable indicated how long people had been sitting; for each stand-to-sit transition, the event time variable indicated how long people had been standing.

Model fitting. All statistical analyses were performed in R version 3.6.1, using the *survival* package (47). For each research question, we fit a separate shared frailty cox model on the event times for the transition of interest (posture transitions; sit-to-stand transition; or stand-to-sit transition), using the *coxph* function. In each model, we included the predictor of interest (time of the day, activity in last 5 hours, age, BMI, or leisure time activity level). We also included a *frailty term* for participant, which is comparable to a random intercept in linear mixed-level models. The frailty term captures the random variability in baseline hazard between individuals. We used Efron's method for handling ties (24). Where we conducted separate analyses for sit-to-stand transitions and stand-to-sit transitions, we split the data into two datasets: one including only event times for sit-to-stand transitions, and one including only event times for stand-to-sit transitions. For each model, we interpreted the statistical significance of the random effect. If this effect was statistically significant, we interpreted the *hazard ratio* (HR; antilog of the raw coefficient) of the predictor. Furthermore, to aid interpretation, we calculated *median survival times*, which is the event time at which 50% of the events have happened, for different meaningful values of the predictor. In addition, we examined plotted *survival functions* (i.e., proportion of events that has not happened yet as a function of time). In Figure 1 and Figure 2, we zoomed in on event times between 0 and 120 minutes to better visualise the differences in survival function for different levels of the predictor. As a result, in Figure 1, 0.29 % of the posture transitions were excluded; in Figure 2, 0.26 % of the sit-to-stand transitions and 0.32 % of the stand-to-sit transitions were excluded.

For each model, assumptions for multilevel time-to-event analysis were assessed following our preregistered analysis plan. Visual inspection of histograms indicated no concerns regarding the distribution of predictor variables. Examination of deviance residuals and score residuals (24) indicated no concerns regarding influential cases. For each model, the proportionality assumption was met, based on examination of Schoenfeld residuals (24).

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Figures and Tables

Table 1. Results of the shared frailty cox regression models for the baseline hazard of sit-to-stand and stand-to-sit transitions, and the predictors time of the day and activity in last 5 hours

Predictor	Estimate	df	SE	HR	95% CI of HR
Model 1: Transition and Transition x Event time predicting the hazard of changing posture					
Random effect θ	0.194***	74.34			
Transition[a]	1.69***	1	0.026	5.40	[5.128, 5.685]
Transition[a] x Event time	-0.094***	1	0.002	0.91	[0.906, 0.914]
Model 2: Time of the day predicting the hazard of standing up when sitting					
Random effect θ	-0.303***	73.74			
Time of the day	0.035***	1	0.005	1.036	[1.026, 1.046]
Model 3: Time of the day predicting the hazard of sitting down when standing					
Random effect θ	0.514***	74.62			
Time of the day	0.033***	1	0.005	1.034	[1.024, 1.044]
Model 4: Activity in last 5 hours predicting the hazard of standing up when sitting					
Random effect θ	0.153***	69.35			
Activity in last 5 hours	0.002***	1	< 0.001	1.002	[1.001, 1.002]
Model 5: Activity in last 5 hours predicting the hazard of sitting down when standing					
Random effect θ	0.228***	71.11			
Activity in last 5 hours	-0.002***	1	< 0.001	0.998	[0.997, 0.999]

*** $p < .001$

Note. df = degrees of freedom, SE = Standard Error, HR = Hazard Ratio, CI = Confidence Interval, [a] Transition was coded as 0 = sit-to-stand vs. 1 = stand-to-sit

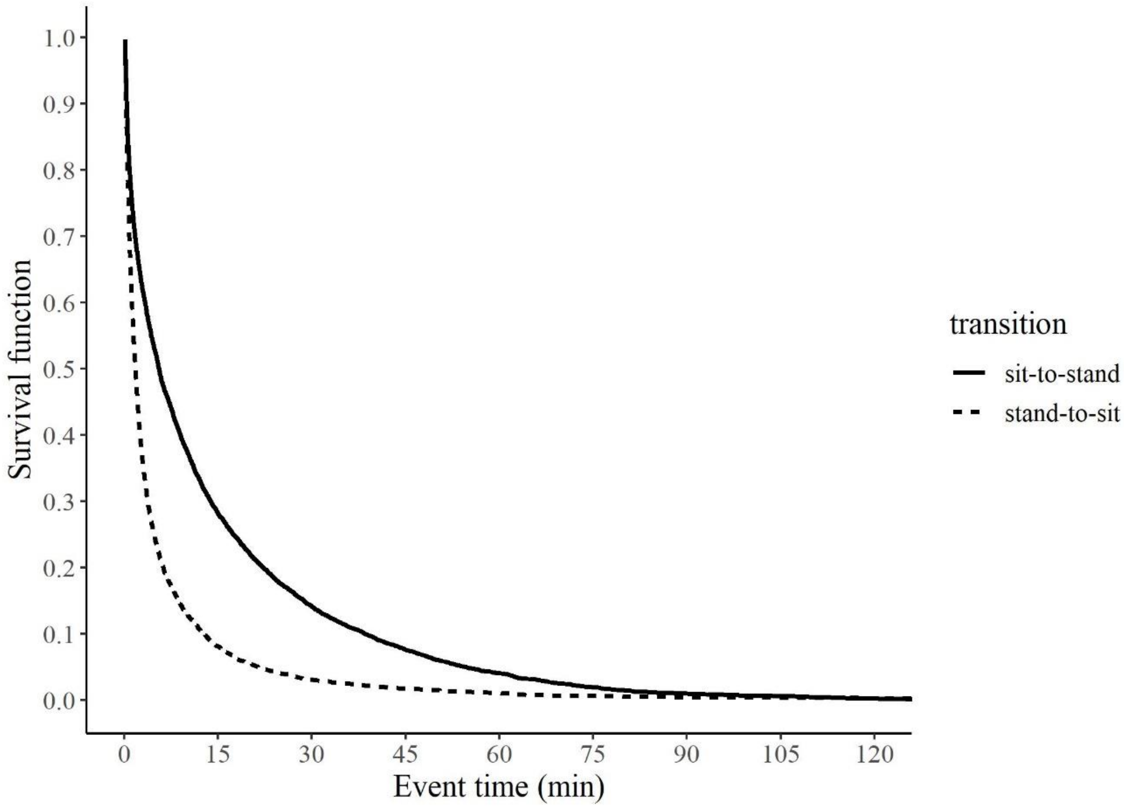

Figure 1. Baseline fitted survival functions for the hazard of standing up when sitting and the hazard of sitting down when standing separately

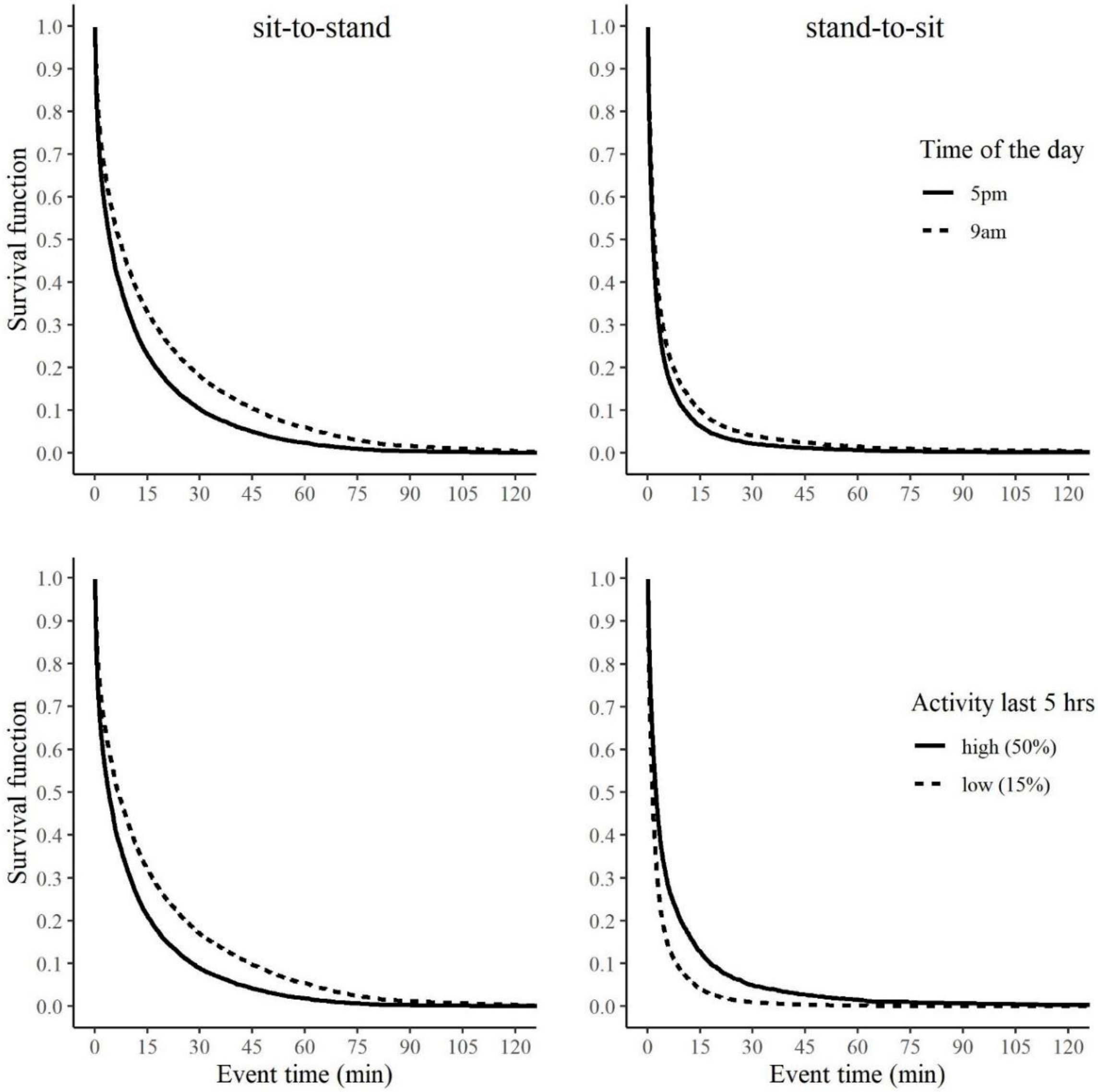

Figure 2. Baseline fitted survival functions for the hazard of standing up when sitting and the hazard of sitting down when standing separately, split out for meaningful values of time of the day and activity in last 5 hours. The values for high (50%; 150 minutes) and low (15%; 45 minutes) activity in last 5 hours roughly correspond to -1 SD and + 1 SD of the mean.

Table 2. Results of the shared frailty cox regression models for the predictors BMI, age, and leisure time activity level.

Predictor	Estimate	df	SE	HR	95% CI of HR
Model 1: BMI predicting the hazard of standing up when sitting					
Random effect θ	0.455***	90.86			
BMI	0.070	1	0.072	1.073	[0.932, 1.235]
Model 2: BMI predicting the hazard of sitting down when standing					
Random effect θ	0.477***	90.63			
BMI	0.038	1	0.102	1.039	[0.850, 1.270]
Model 3: Age predicting the hazard of standing up when sitting					
Random effect θ	0.371***	144.20			
Age	0.014	1	0.060	1.014	[0.901, 1.142]
Model 4: Age predicting the hazard of sitting down when standing					
Random effect θ	0.458***	144.70			
Age	<.001	1	0.067	1.000	[0.877, 1.141]
Model 5: Leisure time activity level predicting the hazard of standing up when sitting					
Random effect θ	0.180***	53.24			
Leisure time activity level	-0.012	1	0.066	0.988	[0.867, 1.125]
Model 6: Leisure time activity level predicting the hazard of sitting down when standing					
Random effect θ	0.381***	54.34			
Leisure time activity level	-0.026	1	0.082	0.975	[0.829, 1.146]

*** $p < .001$

Note. df = degrees of freedom, SE = Standard Error, HR = Hazard Ratio, CI = Confidence Interval

Supplementary Information

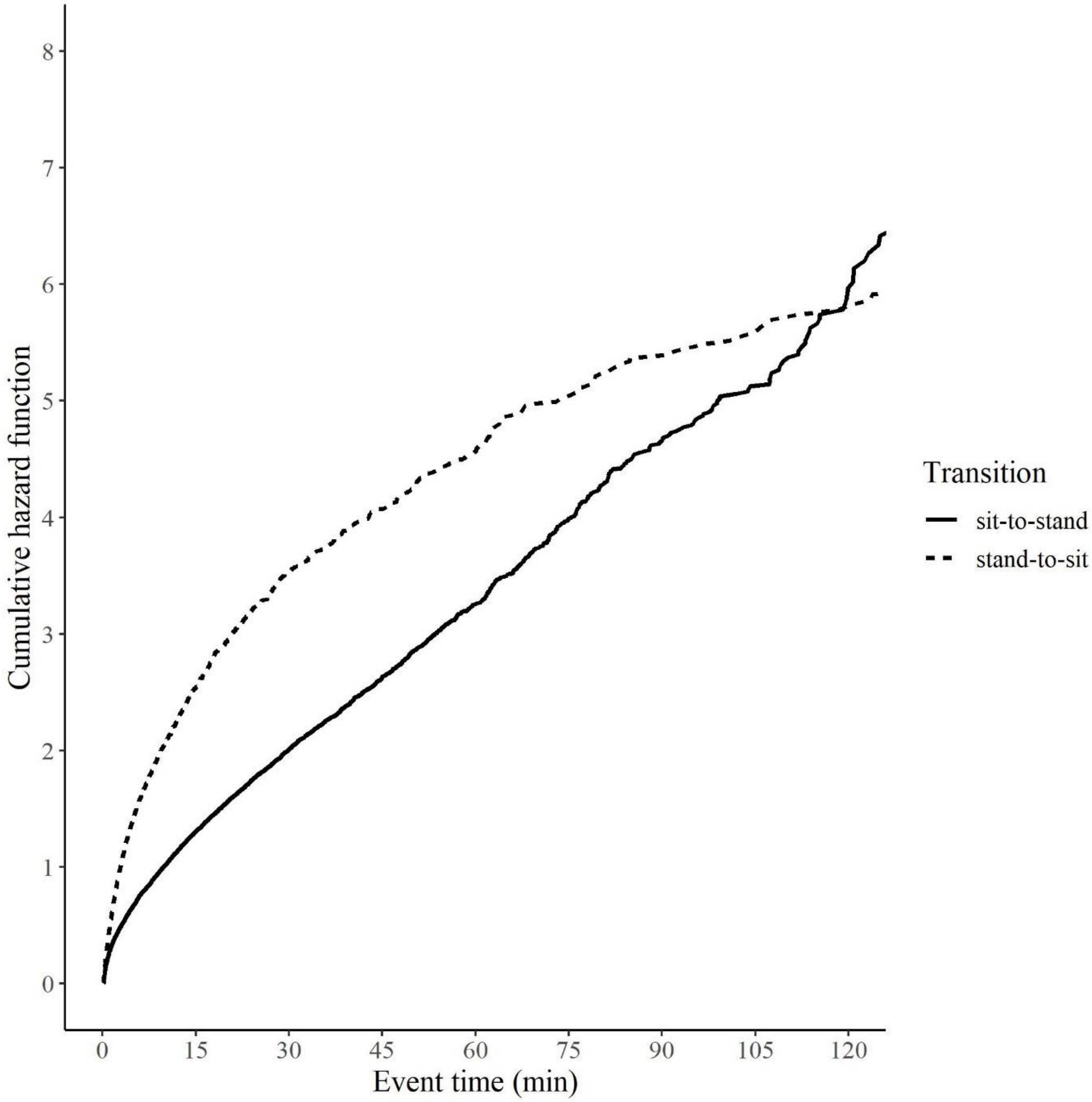

Figure S1. Baseline fitted cumulative hazard functions for the hazard of standing up when sitting and the hazard of sitting down when standing separately. The cumulative hazard at time point A refers to the total amount of accumulated hazard of event occurrence from the beginning of time until time point A.

A-priori sensitivity analysis

Because this study used existing data, sample sizes were predetermined. Given the sample size, and given that data on the between-participant predictors BMI, age, and baseline leisure activity was only available for part of the sample, we anticipated that statistical power to detect meaningful effect sizes for the associations between these between-participant predictors on the one hand, and the hazard to stand up when sitting and the hazard to sit down when standing on the other hand, may be low. So, to estimate the minimum effect sizes we could detect with adequate power ($1 - \beta = .80$) for these associations, given the available data, we conducted an a-priori sensitivity analysis.

Specifically, we ran a power simulation in R, using the *paramtest* package. For each sample size ($n = 49$ for BMI; $n = 77$ for age; $n = 30$ for leisure time activity level), we simulated a set of datasets with varying positive and negative effect sizes (Hazard Ratios; HRs). Each simulated dataset was characterized by (a) the respective number of participants, (b) a normally-distributed between-subjects predictor with a mean of 0 and a standard deviation of 1, and (c) an event time variable, such that in each dataset there was a slightly different HR for the association between the predictor and the hazard of the event. The number of events per participant was randomly drawn from a gamma distribution with scale and shape parameters that were based on the distributions of events we observed from participants in the training sample.

Next, for each of the different HRs, we ran 1000 shared frailty cox models on the event times using the *coxph* function, including the predictor and a frailty term for participant. We used Efron's method for handling ties(1). Based on these 1000 simulations, we calculated the power for detecting each HR as the proportion of tests with $p < 0.05$ for the association between the predictor and the hazard of the event. More details regarding this sensitivity analysis, and R code, are available from the corresponding author upon request. Finally, we selected the minimal HR for a positive association and the maximal HR for a negative association for which power was closest to .80. Results are indicated in table S1. Based on suggestions by Azuero and colleagues(2) that "small, medium, and large HRs for a standard deviation increase in the predictor would be 1.14, 1.47, and 1.9, respectively", these effects can be considered medium to large.

Based on data exploration on the training sample, we expected only small effects for BMI, age, and baseline leisure activity. Therefore, we decided to examine these predictors in an exploratory fashion, and to examine associations with these predictors on the full sample (training sample + testing sample), in order to provide the most precise effect size estimates, given the data that we have.

Table S1. The minimal hazard ratio's that could be detected with a power of .80 given the sample size

	HR	1/HR	power
BMI (n = 49)	1.59		0.82
	0.66	1.51	0.82
Age (n = 77)	1.53		0.82
	0.70	1.43	0.78
Leisure time activity level (n = 30)	1.67		0.83
	0.62	1.62	0.79

References

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2. A. Azuero, A note on the magnitude of hazard ratios. *Cancer* (2016) https:/doi.org/10.1002/cncr.29924 (August 30, 2019).