Temporal dynamics of sitting behavior at work

Pam ten Broeke[a,1], Merlijn Olthof[a], Debby G. J. Beckers[a], Nicola D. Hopkins[b], Lee E. F. Graves[b], Sophie E. Carter[b,c], Madeleine Cochrane[b,d], David Gavin[b], Abigail S. Morris[b,e], Anna Lichtwarck-Aschoff[a], Sabine A. E. Geurts[a], Dick H. J. Thijssen[b,f], and Erik Bijleveld[a]

[a]Behavioural Science Institute, Radboud University, 6525 HR Nijmegen, The Netherlands; [b]Research Institute for Sport and Exercise Sciences, Liverpool John Moores University, L3 3AF Liverpool, United Kingdom; [c]School of Sport, York St John University, YO31 7EX York, United Kingdom; [d]Bristol Medical School, University of Bristol, BS8 1QU Bristol, United Kingdom; [e]Health Research Department, Lancaster University, LA1 4YW Lancaster, United Kingdom; and [f]Department of Physiology, Radboud University Medical Center, 6525 GA Nijmegen, The Netherlands

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Sitting for prolonged periods of time impairs people's health. Prior research has mainly investigated sitting behavior on an aggregate level, for example, by analyzing total sitting time per day. By contrast, taking a dynamic approach, here we conceptualize sitting behavior as a continuous chain of sit-to-stand and stand-to-sit transitions. We use multilevel time-to-event analysis to analyze the timing of these transitions. We analyze ∼30,000 objectively measured posture transitions from 156 people during work time. Results indicate that the temporal dynamics of sit-to-stand transitions differ from stand-to-sit transitions, and that people are quicker to switch postures later in 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 behavior is fundamentally different from exercise behavior, and provide pointers for the development of interventions.

sedentary behavior | time-to-event analysis | survival analysis | fatigue | occupational health

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 behavior.

So far, research into sitting behavior has yielded crucial insights, such as that, for working adults, extensive sitting time mostly accumulates during work time (8, 9), and that sitting directly influences metabolism, bone mineral content, and vascular health (10, 11). However, prior research on sitting behavior has typically examined sitting on an aggregate level. That is, typically, summary characteristics of sitting behavior (e.g., total sitting time, average duration of sitting episodes) are used as primary outcomes (12). This traditional approach conceptualizes sitting behavior 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 behavior, such a static approach overlooks the fact that sitting is a highly dynamic phenomenon that is characterized by a continuous chain of transitions between sitting and standing. Here, we examine sitting behavior 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 behavior. 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 (13). These substantial variations are presumably also present when people's sitting behavior 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 still make short but frequent posture switches, for example, stretching their legs, visiting the bathroom, or grabbing coffee (14, 15). So, examining sitting behavior on a person level or day level does not provide an ecologically valid representation of the time scale on which sitting behavior occurs (see also ref. 16). 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 min), rather than total sitting time, may be the main cause of sitting-related health problems (17, 18). 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 behavior.

Second, our dynamic approach allows us to examine a range of candidate predictors to help explain sitting behavior. 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

Significance

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 etiology of unhealthy sitting patterns. We proposed an approach to studying sitting behavior that aims to unravel the temporal dynamics of sitting patterns. Our research yielded insights regarding why and when people sit (e.g., mental fatigue may play a key role), and regarding how to best study sitting behavior (e.g., we need to distinguish sitting behavior from exercise behavior). These findings have implications for the design of effective interventions targeting sitting behavior. Moving forward, the science of sitting may benefit from adopting a dynamic approach.

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Data deposition: All data that we used for our analyses, and R code for data processing, analysis, and visualization, are available in EASY at https://easy.dans.knaw.nl/ui/datasets/id/easy-dataset:161600.

[1]To whom correspondence may be addressed. Email: p.tenbroeke@psych.ru.nl.

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of sitting behavior allows us to examine candidate predictors whose values vary throughout the day. In this research, we tested several candidate predictors: 1) We examined *time of 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 (19, 20); thus, examining time of day may provide an insight into how mental fatigue affects sitting behavior. 2) We examined people's *physical effort expenditure* in recent hours, as recent effort is known to affect other health behaviors (21, 22). For example, after expending effort during the workday, people are less motivated to exercise in the evening (23). 3) We examined *individual differences in physical fitness*, as people who are less physically fit likely perceive higher energetic costs of standing up when sitting (24). By examining these candidate predictors, our dynamic approach opens the door to a more detailed understanding of the psychological processes that drive sitting behavior (25).

Third, our dynamic approach provides a way of analyzing 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 capitalize on the richness of such time series data by modeling 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 (26, 27). Originally developed to predict the timing of death (27), time-to-event analysis has subsequently been used in other fields of study, for instance, to predict the timing of relapse into substance abuse (28) or to predict the timing of emotion expression in children (26, 29). To the best of our knowledge, time-to-event analysis has not yet been used to examine determinants of health behavior. 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; refs. 26 and 29). Specifically, using multilevel time-to-event analysis, we were able to examine predictors of 1) the hazard of standing up when sitting and 2) the hazard of sitting down when standing.

For working adults, overall unhealthy sitting behavior is mostly accumulated during work time (2). Thus, in this paper, we limited our investigation to sitting behavior during work time. We analyzed ~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 (30, 31). 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 analysis plan for the testing sample on the Open Science Framework (https://osf.io/rbaqx/?view_only=da51924da62242d7a5808ede6192561a). As the present study uses timing of sit-to-stand and stand-to-sit transitions as the primary outcome, and as we could reasonably expect associations with predictors in different directions, we anticipated a range of different study outcomes. Thus, rather than specifying one-sided hypotheses, we preregistered 1) our research questions, 2) a detailed analysis plan, and 3), for all plausible outcomes, what our interpretation would be. Unless otherwise specified, in this paper, we report results from the preregistered analyses on the testing sample, along with the preregistered interpretation. We used this split-samples procedure because it diminishes the chance of reporting false positives through preregistration; at the same time, the training sample offered an opportunity to explore the data, thus decreasing the probability of overlooking potentially relevant predictors (30, 31).

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. Fig. 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 min of standing and stood up within 5.6 min of sitting. In other words, people were quicker to select sitting over standing, i.e., they were quicker to choose the behavioral option that costs the least energy (32) and yields most comfort in the context of desk-based working (33). These low median survival times suggest that participants were often rather quick to switch back and forth between standing and sitting. On the other hand, Fig. 1 suggests that, consistent with previous research (4), 15% of sitting episodes lasted longer than 30 min. In fact, in our sample, 88% of participants had three or more long episodes of uninterrupted sitting on at least one single workday. Thus, despite the relatively large number of short sitting and standing episodes, unhealthy sitting behavior at the workplace is abundantly present.

Going beyond previous work, the significant Transition × 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 (*SI Appendix*, Fig. 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.

Time of Day. We examined time of day as a predictor of the hazard of standing up when sitting and the hazard of sitting down when standing (Table 1). Fig. 2 displays estimated survival functions for sit-to-stand and stand-to-sit transitions for a typical beginning (9 AM) and end (5 PM) of a workday. With each hour increase in time of day, participants were 4% more likely to stand up per minute of sitting, and 3% more likely to sit down per minute of standing. Estimated median survival times for 9 AM indicated that, 50% of the time, participants stood up within 7.1 min of sitting and sat down within 2.0 min of standing. At 5 PM, estimated median survival times were 4.4 min and 1.6 min, respectively. This result suggests that, later in the day, when fatigue had likely set in (19, 20), participants were quicker to switch back and forth between sitting and standing.

Activity in Last 5 h. We then examined recent activity, specifically, activity in the last 5 h, as a predictor of the hazard of standing up when sitting and the hazard of sitting down when standing

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 day and activity in last 5 h

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

df = degrees of freedom, SE = Standard Error, HR = Hazard Ratio, CI = Confidence Interval. ***$P < 0.001$.
†Transition was coded as 0 = sit-to-stand vs. 1 = stand-to-sit.

(Table 1). We chose a 5-h time window, based on previous studies on muscle fatigue that show that physical discomfort tends to set in within 2 h to 5 h of activity (34, 35). Fig. 2 displays the estimated survival functions for 45 min (15%; ∼−1 SD) versus 150 min (50%; ∼+1 SD) of activity in the last 5 h. With each additional minute that participants had been physically active in the last 5 h, 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. We estimated median survival times for low activity in the last 5 h (i.e., 45 min of activity in the last 5 h), and for high activity in the last 5 h (i.e., 150 min of activity in the last 5 h). Our estimates suggest that, when participants had been relatively inactive in the last 5 h, they stood up within 6.7 min of sitting, 50% of the time. However, when participants had been relatively active, they stood up within 4.1 min of sitting, 50% of the time. Also, when participants had been relatively inactive in the past 5 h, they sat down within 1.5 min of standing, 50% of the time. However, when participants had been relatively active, they sat down within 2.5 min of standing, 50% of the time. So, after periods of more standing (i.e., being active, exerting more physical effort), people were more likely to stand, and less likely to sit.

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 (*SI Appendix*, *SI Text*) to determine the magnitude of effects we could detect with a power of $1 - \beta = 0.80$. 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 regarding individual differences 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 *Materials and Methods*).

Results (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. These results suggest that the timing of standing up while sitting and sitting down while standing does not depend on one's level of 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 behavior 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; ref. 13), but also engaged in a considerable amount of prolonged, unhealthy sitting episodes at work (4). Extending previous research, we showed that sit-to-stand and stand-to-sit transitions are different both in probability and timing. This

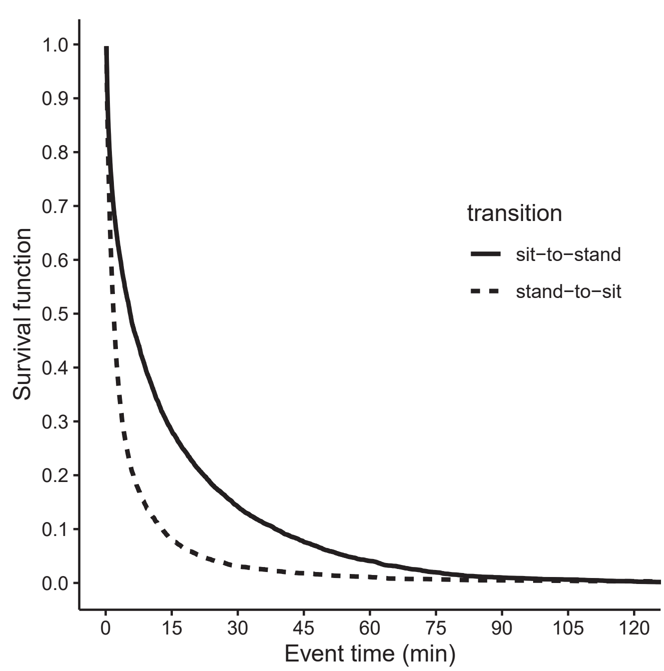

Fig. 1. Baseline survival functions for the hazard of standing up when sitting and the hazard of sitting down when standing separately.

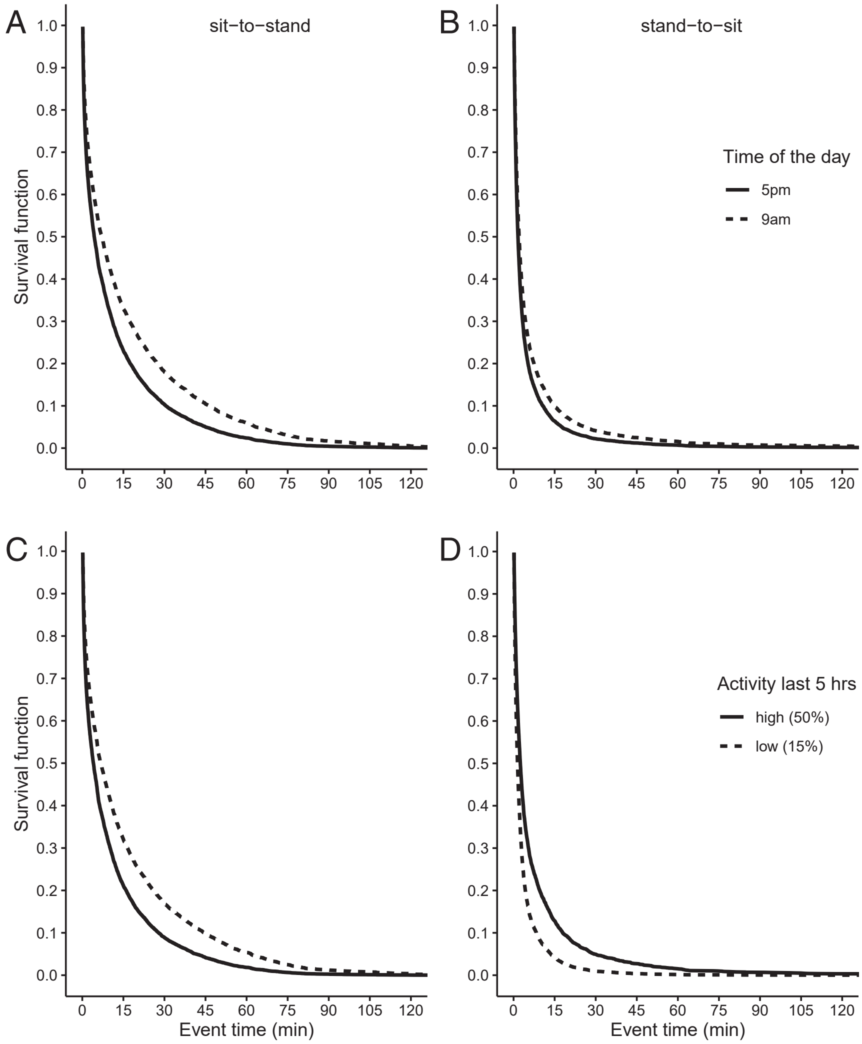

Fig. 2. Estimated survival functions based on model predictions for indicative values of time of day and activity in last 5 h. (*A*) The estimated survival function for the hazard of standing up when sitting for 9 AM vs. 5 PM time of day, (*B*) the estimated survival function for the hazard of sitting down when standing for 9 AM vs. 5 PM time of day, (*C*) the estimated survival function for the hazard of standing up when sitting for high vs. low activity in the last 5 h, and (*D*) the estimated survival function for the hazard of sitting down when standing for high vs. low activity in last 5 h. The values for high (50%; 150 min) and low (15%; 45 min) activity in last 5 h roughly correspond to −1 SD and +1 SD of the mean.

underscores the relevance of zooming in on these individual transitions when investigating sitting behavior. 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 (nonsitting) in the previous hours, they were quicker to stand up when sitting and slower to sit down when standing. Finally, whereas previous findings indicate that people who are older, have a higher BMI, or engage in less physical activity in their leisure time generally sit more and longer (2, 36), we found no evidence that the timing of standing up and sitting down depends on individual differences in physical fitness.

Our findings yield several insights into the nature of sitting and standing behavior during the workday. First, our findings suggest that sitting behavior is critically different from other health behaviors. When people feel fatigued at the end of the day, they are generally more prone to engage in unhealthy behaviors, such as unhealthy eating or skipping exercise sessions (21, 23, 37–39). By contrast, our findings regarding time of day suggest that, when people feel fatigued at the end of the day, they engage in healthier sitting patterns—characterized by quicker posture switching. Although this finding is somewhat counterintuitive, it is in line with a recent account of fatigue, which suggests that fatigue functions as a signal to stop the current task and switch to another (22, 40). Specifically, our findings are consistent with the idea that, later in the day, people feel more fatigued (and possibly more restless and less concentrated); as a result, they more quickly change posture while working (e.g., stand up while reading a document), 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).

In a similar vein, our findings on activity in the last 5 h also contradict previous findings on other health behaviors. That is, previous research suggests that people are less motivated to engage in active behavior after they have exerted effort (e.g., people are less motivated to go to the gym after an effortful workday; refs. 21–23). In contrast, our findings show that people display fairly stable sitting and standing patterns over a timeframe of several hours. Thus, our findings imply that previous effort exertion does not necessarily diminish future effort exertion, at least not in

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	<0.001	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	0.181***	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]

df = degrees of freedom, SE = Standard Error, HR = Hazard Ratio, CI = Confidence Interval. ***$P < 0.001$.

the context of light physical activity (i.e., sitting versus standing and walking).

Thus, where prior research has aimed at understanding sitting behavior using the same psychological models that proved useful for other health behaviors, physical activity in particular (41), our findings suggest that sitting behavior is not necessarily comparable to these other health behaviors. The fundamental differences in energy expenditure, frequency, duration, and deliberate processing between physical activity and sitting behavior (42) may contribute to these observations. This emphasizes that, to target sitting behavior, 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 behavior.

Second, our findings highlight that our dynamic approach to sitting behavior, along with the use of multilevel time-to-event analysis, complements and goes beyond the traditional approach that is used to understand sitting behavior. We demonstrated that a dynamic approach is useful when attempting to outline the psychology of sitting (25), that is, 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 analyzing sitting patterns on the level of sit-to-stand and stand-to-sit transitions, making use of time-to-event analysis.

To date, numerous interventions to decrease sitting time have been designed and tested, such as height-adjustable desks (43), and online tailored advice on how to reduce and break up sitting (44). Although these interventions indeed reduce sitting time in the short term, the benefits seem to wear off over a few months (45, 46). A plausible explanation for this decline is that, even though theory-based interventions are known to be more effective (47), the majority of existing interventions that aim to change sitting behavior lack a theoretical basis (45). As our dynamic approach can be used to unravel the decisions that drive sitting behavior, we expect that our approach will substantially contribute to the theoretical understanding of sitting behavior—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. 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 show that, later during the workday, people naturally engage in healthier sitting patterns. This implies that interventions to change people's sitting behavior are most needed at the beginning of the workday.

With our dynamic approach, future research can isolate the determinants of sit-to-stand and stand-to-sit decisions—and, thus, help identify targets for interventions that may otherwise be overlooked. A limitation of the current study is that we did not directly assess psychological states, such as mental fatigue, with self-report measures. Thus, in our view, it would be worthwhile for future research to combine our dynamic approach with an experience sampling procedure. This combined design would allow researchers to study how the impact of psychological states, including fatigue, varies over the course of a day (e.g., using models that include time-varying predictors; refs. 48 and 49). Such research should aid the development of interventions that target specific decision-making processes at specific moments in time (e.g., just-in-time adaptive interventions; ref. 50).

Our results suggest that unhealthy sitting behavior 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 ref. 51). 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"; ref. 52). This line of reasoning raises the question of who should take responsibility for changing employees sitting behavior, 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 work time 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, United Kingdom. The dataset included objectively measured, continuous activity data of 167 working adults from various worksites in the United Kingdom.

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 centers, 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) 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 = 0.991) and in the hazard of sitting down when standing (P = 0.999).

Data from participants for whom no work time 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 y (SD = 11.47 y), a BMI of 27.84 (SD = 6.84), and scored, on average, 3.52 (SD = 0.88, on a five-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 (mean = 3.99, SD = 1.29). Per workday, participants on average sat for 5.31 h (SD = 1.92 h) and were active for 2.18 h (SD = 1.79 h).

Measures. Sitting behavior is defined as "any waking behavior characterized by an energy expenditure of ≤1.5 metabolic equivalents (METs), while in a sitting, reclining or lying posture" (9). In this study, we distinguished between sitting behavior and *activity*, referring to all nonsitting behavior. Sitting behavior 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 behavior (see ref. 53 for more information on the activPAL monitor). Placement was standardized 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 day, in hours since midnight (precision in seconds), was calculated from the time variable in the activPAL data. Activity in last 5 h, in minutes (precision in seconds), was calculated as the sum of all active (nonsitting) time in the 5 h prior to the previous stand-to-sit or sit-to-stand transition, per participant, per day. This variable was calculated before exclusion of nonwork hours, such that we also took into account activity accumulated in the hours prior to starting the workday. BMI was calculated following an anthropometric assessment. Stature was measured to the nearest 0.1 cm using a portable stadiometer, and body mass was measured to the nearest 0.1 kg using a calibrated mechanical flat scale. BMI was calculated as mass divided by stature (kg/m^2). Data on BMI were available for 95 participants in the dataset (8,222 sit-to-stand and 8,172 stand-to-sit transitions). Age was assessed by self-report. Data on age were available for 150 participants in the dataset (14,211 sit-to-stand and 14,102 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 (6,080 sit-to-stand and 6,020 stand-to-sit transitions).

Data Analysis.

Split-samples procedure. In this study, we used a split-samples cross-validation procedure (30, 31). 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 (https://osf.io/rbaqx/?view_only=da51924da62242d7a5808ede6192561a) described all research questions, preregistered interpretations of results, all data-processing steps (i.e., calculation of variables, data exclusion based on work times and nonwear), all analyses, 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 (*SI Appendix*, *SI Text*) to determine the magnitude of the effects that we could detect with a power of 0.80. 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 nonworking hours. We excluded observations that fell outside of participants' working hours, using participants' self-reported work start and end times. First, we narrowed the work time window by 15 min on both start and end times to correct for recall bias and settling into the building, and to make sure that commuting time was not included in the dataset (see also refs. 53 and 54). 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) work time window and excluded the rest (ref. 53; 75% of transitions in the training sample; 76% of transitions in the testing sample). After exclusion of nonwork times, 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.

Nonwear and extreme values. Sitting episodes with a duration longer than 8 h were identified as nonwear (i.e., as a time period in which the participant did not wear the activPAL monitor; ref. 53) 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 h 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 and of 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 (26, 29). 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 (55). For each research question, we fit a separate shared frailty Cox model (see *SI Appendix*, *SI Text* for model equations) on the event times for the transition of interest (posture transitions; sit-to-stand transition; or stand-to-sit transition), using the coxph function. We used the Cox approach because 1) it is a well-established approach for event data measured in continuous time (27), and 2) it provides robust estimates without requiring a priori knowledge about the exact shape of the hazard function (26, 29). In each model, we included the predictor of interest (time of day, activity in last 5 h, 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 (27). 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 fixed effect. If this effect was statistically significant, we interpreted the 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, based on model predictions for different values of the predictor. In addition, we examined estimated *survival functions* (i.e., proportion of events that has not happened yet as a function of time). In Figs. 1 and 2, we zoomed in on event times between 0 min and 120 min to better visualize the differences in survival function for different levels of the predictor. As a result, in Fig. 1, 0.29% of the posture transitions were excluded; in Fig. 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 (27) indicated no concerns regarding influential cases. For each model, the proportionality assumption was met, based on examination of Schoenfeld residuals (27).

Data Availability. All data that we used for our analyses, and R code for data processing, analysis, and visualization, are available in EASY at https://easy.dans.knaw.nl/ui/datasets/id/easy-dataset:161600 (56).

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