Sedentary Behavior in Daily Life: Assessment Issues, Psychological Antecedents and Consequences.

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Sedentary behavior in daily life: Assessment issues, psychological antecedents and consequences.

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Summary

Physical inactivity has been identified as the fourth leading risk factor for global mortality. Technological and social changes in domestic, environmental and occupational settings have led to an increasingly inactive lifestyle among different cultures and countries. For example, computers have replaced once physically exhausting work. Thus, many activities in today's daily life are performed without the need to be physically active. In other words, humans spend much of their time in a sitting position with low energy expenditure, i.e., sedentary behavior. According to physiological studies, more than the mere absence of physical activity, sedentary behavior is an independent behavior with its own physiological mechanisms. Thus, given the urgent need to reduce physical inactivity, it might be a promising direction to thoroughly examine the nature of sedentary behavior.

A decade later, although the number of studies on sedentary behavior has greatly increased, the research field is still in its early stages. It took a while for researchers to agree on a widely accepted definition of the concept. Sedentary behavior is characterized by dual components, i.e., a lying/reclining/sitting body posture and an intensity of ≤ 1.5 metabolic equivalents (METs). Accordingly, appropriate methods are required to accurately assess sedentary behavior. Many previous studies have used self-reported sedentary time or television time as an indicator of sedentary behavior. However, due to recall and social desirability biases, self-reported methods may lead to an inappropriate measurement of sedentary behavior. Recently, activity monitors such as accelerometers have become the preferred method thanks to their portability, affordability and to the opportunity they afford to gather large amounts of dense information. Nevertheless, assessing the two components (i.e., body posture and energy expenditure) of sedentary behavior is a challenging task. Thus, while only very few monitors can capture sedentary behavior accurately, there is an urgent need to develop further device-based methods. Although accelerometers are currently the instrument of choice to assess quantitative aspects of sedentary behavior, they are limited to informing researchers about qualitative aspects such as type of behavior or contextual information. However, assessing complete patterns of sedentary behavior (i.e., both quantitative and qualitative aspects) might be relevant to obtaining in-depth insights into antecedents and consequences, which forms the basis for developing individually tailored interventions to reduce sedentary behavior.

More recently, studies have focused primarily on the association between sedentary behavior and physiological markers such as cardiometabolic health. In particular, these studies have mostly applied experimental study designs under laboratory conditions or cross-sectional study designs yielding between-subject effects; e.g., individuals who spend more time in a sedentary position have a poorer health status. However, two issues have been less thoroughly explored. First, of course experimental and cross-sectional studies are crucial and have led to a higher awareness of sedentary behavior in public media ("Sitting is the new smoking") and in research, but their results have limited ecological validity and have not unraveled dynamic within-subject associations. Second, as mentioned above, most studies have focused on the association between sedentary behavior and physiological markers, whereas the mental component has rarely been taken into account. This is critical, since the prevalence and incidence of mental disorders have increased over the past few years. Exploring the associations between sedentary behavior and mental health outcomes would expand our knowledge of the possible health consequences of too much sitting.

Mood is a central indicator of mental well-being in healthy populations and is altered in many mental disorders (e.g., diminished mood in major depression disorder, enhanced mood in manic episodes, and high mood fluctuations in borderline personality disorder). Moreover, mood is known to be a fluctuating state that varies across time. Thus, a dynamic within-subject process between sedentary behavior and mood might be a reasonable assumption, e.g., prolonged sitting may lead to a worsened mood. Ambulatory Assessment (AA) is currently the state-of-the-art methodology for assessing within-subject associations between physical behavior and mood. This method comprises the continuous and device-based measurement of physical behavior via accelerometers and the repeated assessment of psychological states such as mood via electronic diaries on smartphones. Furthermore, AA has many advantages, namely, an assessment in everyday life and in real time, and assessing data with a high sampling frequency. Thus it bypasses laboratory distortions and minimizes the recall biases associated with more traditional approaches such as paper-pencil questionnaires. Advanced statistical approaches such as multilevel modeling enable the analysis of nested data structures (e.g., assessments nested within persons). Moreover, within-subject and between-subject effects can be estimated simultaneously in one statistical model.

The primary purposes of this thesis were i) to address the methodological aspects of the assessment of sedentary behavior and ii) to expand our knowledge of the psychological antecedents and consequences of sedentary behavior in daily life.

In our first paper, therefore, we compared the validity of different accelerometers (ActivPAL, ActiGraph, and Move). More specifically, 20 healthy adults participated in a structured protocol with a series of full- and semi-standardized sessions under laboratory conditions. Direct observation via video recording was used as a criterion measure of body positions (sitting/lying vs. nonsitting/lying). Furthermore, by combining direct observation with metabolic equivalent tables, protocol activities were also categorized as sedentary or nonsedentary. Our results indicated that the Move 4 [thigh] showed excellent ratings, the Move 4 [hip] showed moderate-to-excellent ratings, and the ActiGraph showed weak-to-good ratings for the assessment of body postures. For the sedentary behavior component, the Move 4 [thigh] revealed excellent ratings, the ActivPAL showed almost excellent ratings, the Move 4 [hip] showed good-to-excellent ratings, and the ActiGraph showed weak-to-excellent ratings. These findings suggest that thigh-worn devices, namely, the Move 4 accelerometer and the ActivPAL, achieved up to excellent validity in measuring body position and sedentary behavior and are recommended for future studies.

In our second paper, we introduced sedentary triggered Ecological Momentary Assessment (EMA) as a methodological advancement in the field of sedentary behavior research and examined the accuracy of sedentary triggered EMA in three different studies among healthy adults. Moreover, we estimated the added value of sedentary triggered EMA compared to a simulation of a random-trigger design. Sedentary triggered EMA comprises the continuous assessment of sedentary behavior via accelerometers and repeated contextual assessments via electronic diaries (i.e., an application on a smartphone). More specifically, the accelerometer analyzes and transfers data on body position (sitting/lying or upright) via Bluetooth Low Energy (BLE) to a smartphone in real time and triggers the deployment of questionnaires. Each time a participant spends a specified amount of time (e.g., 20 min) in a sedentary position, the e-diary triggers contextual assessments. To test the accuracy of this method, we calculated a percentage score for all triggered prompts in relation to the total number of bouts that could trigger a prompt. On average, the accuracy by participant was over 80%. Compared to simulations of random prompts (every 120 min), the accuracy of the sedentary triggered EMA was up to 47.9% higher. Moreover, prolonged bouts (≥ 20 min) occurred during leisure activities and when participants were not alone. Thus, study findings suggest that sedentary triggered EMA offers a real advancement, as it can be used to collect social and environmental contextual information or to unravel dynamic associations.

In our third paper, we investigated whether sedentary behaviors influence mood dimensions. In particular, we conducted an Ambulatory Assessment study of the everyday life of 92 university employees over 5 days. We continuously measured sedentary behavior via accelerometers and repeatedly assessed mood multiple times each day on smartphone diaries. To optimize our sampling strategy, we used a sophisticated sedentary triggered algorithm as introduced in our second paper. Our study showed that sedentary time (15-min intervals prior to each e-diary assessment) and sedentary bouts (30-min intervals of uninterrupted sedentary behavior) negatively influenced valence and energetic arousal. Simply put, being more sedentary in daily life led to lower levels of well-being and energy. Accordingly, preliminary evidence shows that sedentary behavior might be a general risk factor because it impacts both somatic and mental health.

In our fourth paper, we changed the direction of paper three and investigated whether mood dimensions influence subsequent sedentary behavior. Moreover, we examined whether the association between mood and sedentary behavior may depend on the methodological perspective. Therefore, we employed multiple regression analyses to analyze between-subject effects from questionnaire data and multilevel modeling to analyze within-subject effects from the Ambulatory Assessment study. Our results revealed that higher momentary ratings of valence and energetic arousal predicted lower amounts of subsequent sedentary behavior, whereas higher ratings of calmness predicted higher amounts of subsequent sedentary behavior. The context moderated the effect of energetic arousal and calmness on sedentary behavior, with increased effects in the home compared to the work context. Our results indicated that mood might regulate sedentary behavior in everyday life. Time-sensitive analyses, such as moment-to-moment analysis, revealed an association between mood and sedentary behavior (within-subject), whereas analyses between different individuals revealed no associations (between-subject). According to the results of our third paper, there is preliminary evidence of a reciprocal relationship between sedentary behavior and mood.

In our fifth paper, we focused on the potential positive effects of sedentary breaks on mood enhancement. In particular, we investigated the degree to which sedentary break patterns influence mood dimensions in everyday life. We analyzed data from the above-mentioned Ambulatory Assessment study. We defined distinct break patterns, such as variations in frequency (number of breaks), duration (length of breaks), intensity (metabolic equivalent) and context (home or work) to analyze the within-subject effects of sedentary break patterns on mood. Our results showed that break intensity was positively associated with subsequent valence, energetic arousal and calmness. Break frequency was positively associated with subsequent valence and energetic arousal, while break duration was not associated with mood. Exploratory analyses indicated that breaking up sedentary behavior was more beneficial at home than at work. These findings suggest that breaking up sedentary behavior frequently and intensively, for example by walking instead of standing, may be most beneficial to enhancing mood. Such ecologically valid findings can serve as the impetus to formulating more precise public health recommendations aiming to "minimize sedentary time in everyday life."

According to the current state of knowledge, our results above contribute to the field of sedentary behavior in several ways. First, in line with previous studies, we have shown that accelerometers are the method of choice to assess the quantitative aspects of sedentary behavior. Moreover, electronic diaries (e.g., an application on a smartphone) may prove valuable in assessing the qualitative aspects of sedentary behavior. Second, as one of the first studies to do so, we investigated the relationship between sedentary behavior and mood in everyday life and found evidence of a reciprocal relationship between both constructs and that breaking up sedentary behavior may enhance one's mood. With these key findings in mind, we discuss issues for further investigation at the end of this work. In particular, we assume that assessing and analyzing all aspects of physical behavior (i.e., sleep, sedentary behavior, and physical activity) simultaneously will become increasingly important to understanding the interrelatedness of health effects. Furthermore, we assume that the issue of causality will arise if future research work verifies the reciprocal relationship between sedentary behavior and mood. Lastly, we assume that the psychophysiological response to sedentary behavior will become an increasing focus of research.

Zusammenfassung

Körperliche Inaktivität wurde als viertgrößter Risikofaktor für die globale Sterblichkeit identifiziert. Technologische und soziale Veränderungen im häuslichen, ökologischen und beruflichen Umfeld haben zu einem zunehmend inaktiven Lebensstil in verschiedenen Kulturen und Ländern geführt. So haben beispielsweise Computer einst körperlich anstrengende Arbeit ersetzt. Als Konsequenz werden heutzutage viele Alltagsaktivitäten ohne anstrengende körperliche Aktivität ausgeführt. Mit anderen Worten, eine Vielzahl an Menschen verbringt einen Großteil ihrer Zeit in einer sitzenden Körperhaltung mit geringem Energieaufwand, d.h. im sedentären Verhalten. Ausgehend von Forschungsergebnissen über die physiologischen Auswirkungen ist sedentäres Verhalten nicht nur „körperliche Inaktivität", sondern vielmehr ein eigenständiges Verhalten mit eigenen physiologischen Mechanismen. Angesichts der dringenden Notwendigkeit körperliche Inaktivität zu reduzieren, könnte es ein vielversprechender Ansatz sein das Konstrukt des sedentären Verhaltens gründlich zu untersuchen.

Ein Jahrzehnt später, trotz der gestiegenen Anzahl der Studien über sedentäres Verhalten, befindet sich das Forschungsgebiet noch immer in einem frühen Stadium. Es dauerte eine Weile, bis sich die Forschungsgemeinschaft auf eine weithin akzeptierte Definition des Konstruktes geeinigt hat. Sedentäres Verhalten wird durch zwei Komponenten gekennzeichnet, zum einen durch eine liegende/zurücklehnende/sitzende Körperhaltung und zum anderen durch eine Bewegungsintensität von ≤ 1,5 metabolischen Äquivalenten (METs). Entsprechend anspruchsvoll sind die Anforderungen an die Methodik sedentäres Verhalten gemäß den Gütekriterien (Validität, Objektivität, Reliabilität) zu erfassen. In einigen früheren Studien wurde die selbst berichtete Sitzzeit oder die Zeit des Fernsehens als Indikator für das sedentäre Verhalten verwendet. Aufgrund von Erinnerungsverzerrungen und dem Effekt der sozialen Erwünschtheit können Selbstauskünfte bzw. subjektive Methoden zu einer ungenauen Messung des sedentären Verhaltens führen. Seit einiger Zeit haben sich objektive Geräte wie Akzelerometer dank ihrer Tragbarkeit und der Möglichkeit, große Mengen an Informationen zu sammeln, zur bevorzugten Messmethodik entwickelt. Nichtsdestotrotz bleibt die Erfassung beider Komponenten (d.h. Körperhaltung und Energieverbrauch) des sedentären Verhaltens auch für

Aktivitätssensoren eine anspruchsvolle Aufgabe. Da nur sehr wenige Aktivitätssensoren sedentäres Verhalten genau erfassen können, besteht ein dringender Bedarf an der Entwicklung weiterer gerätebasierter Methoden. Obwohl Aktivitätssensoren derzeit bevorzugt werden um quantitative Aspekte (z.B. Dauer oder Intensität) des sedentären Verhaltens zu erfassen, sind Sensoren limitiert hinsichtlich der Erfassung qualitativer Aspekte (z.B. Art des Verhaltens oder Umgebungskontext). Die Erfassung des vollständigen Musters des sedentären Verhaltens, d.h. aller qualitativer und quantitativer Aspekte, ist relevant um vertiefte Einblicke in Determinanten und Konsequenzen zu erhalten, was wiederrum die Grundlage für die Entwicklung individuell zugeschnittener Interventionen zur Verringerung des sedentären Verhaltens bilden kann.

In der Vergangenheit haben sich die Studien vor allem auf den Zusammenhang zwischen einer sedentären Lebensweise und physiologischen Markern wie der kardiometabolischen Gesundheit fokussiert. Vorrangig haben diese Studien meist experimentelle Studiendesigns unter Laborbedingungen oder Querschnittdesigns angewandt und dabei Unterschiede zwischen Probanden entdeckt, z.B. haben Personen, die mehr Zeit in einer sedentären Verhaltensweise verbringen, einen schlechteren Gesundheitszustand. Insgesamt betrachtet wurden jedoch zwei Themen nicht ausführlich beleuchtet. Zum einen liefern experimentelle und querschnittliche Studiendesigns einen bedeutenden wissenschaftlichen Beitrag und haben zu einem höheren Bewusstsein für das sedentäre Verhalten sowohl in den öffentlichen Medien („Sitzen ist das neue Rauchen“) als auch in der Forschung geführt. Dennoch besitzen diese Erkenntnisse nur eine begrenzte ökologische Validität und die dynamischen Innersubjekt-Meschanismen wurden bislang kaum betrachtet. Zum anderen haben sich – wie oben erwähnt – die meisten Studien auf den Zusammenhang zwischen sedentärem Verhalten und physiologischen Markern konzentriert, während die psychische Komponente der Gesundheit nur selten berücksichtigt wurde. Dies ist bedeutsam, da die Prävalenz und Inzidenz psychischer Störungen in den letzten Jahren anstieg. Die Erforschung der Zusammenhänge zwischen sedentärem Verhalten und psychischen Konstrukten würde die Erkenntnisse über die möglichen gesundheitlichen Folgen von „zu viel Sitzen“ erweitern.

Die Stimmung ist ein zentraler Indikator für das psychische Wohlbefinden bei gesunden Menschen und wird bei vielen psychischen Störungen als verändert wahrgenommen (z.B. verschlechterte Stimmung bei schweren Depressionen, verbesserte Stimmung bei manischen Episoden und hohe Stimmungsschwankungen bei Borderline-Persönlichkeitsstörungen). Darüber hinaus ist bekannt, dass die Stimmung ein diffuser Zustand ist, der über die Zeit variiert. Demnach könnte ein dynamischer Innersubjekt-Mechanismus zwischen sedentärem Verhalten und Stimmung eine plausible Annahme sein, z.B. könnte ununterbrochenes Sitzen zu einer Verschlechterung der Stimmung führen. Ambulantes Assessment (AA) ist derzeit die vielversprechendste Methodik zur Erfassung von Innersubjekt-Mechanismen zwischen (in)aktivem Verhalten und Stimmung. Die Forschungsmethode umfasst die kontinuierliche und gerätegestützte Messung des (in)aktiven Verhaltens mittels Akzelerometrie und die wiederholte selbstberichtete Auskunft der Stimmung mittels elektronischer Tagebücher (z.B. als Applikation auf dem Smartphone). Darüber hinaus hat AA viele Vorteile, nämlich die Erfassung im Alltag, in Echtzeit sowie die dichte und hochfrequentierte Datenerfassung. Dementsprechend können laborbedingte Verzerrungen oder Erinnerungsverzerrungen minimiert werden, die mit traditionellen Ansätzen wie einer retrospektiven schriftlichen Befragung verbunden sind. Fortgeschrittene statistische Ansätze, wie die Mehrebenen-Modellierung, ermöglichen die Analyse verschachtelter Datenstrukturen (z.B. Messzeitpunkte verschachtelt in Personen). In einem statistischen Modell können so gleichzeitig Inner- und Zwischensubjekt-Effekte geschätzt werden.

Die primären Ziele dieser Arbeit waren i) methodische Aspekte der Erfassung des sedentären Verhaltens zu betrachten und ii) die Erkenntnisse über psychobehaviorale Determinanten und Konsequenzen des sedentären Verhaltens im täglichen Leben zu erweitern.

In der ersten Arbeit wurde die Validität verschiedener Akzelerometer (ActivPAL, ActiGraph und Move) verglichen. Es nahmen 20 gesunde Erwachsene unter Laborbedingungen an einem strukturierten Studienprotokoll mit einer Reihe von voll- und halbstandardisierten Bedingungen teil. Die direkte Beobachtung mittels Videoaufzeichnung wurde als Kriterium für die Körperposition (sitzend/liegend vs. nicht sitzend/liegend) verwendet. Durch die Kombination der direkten Beobachtung mit metabolischen Äquivalenztabellen wurden die Protokollaktivitäten zudem als sedentär oder nicht sedentär kategorisiert. Die Ergebnisse offenbarten, dass der Move 4 [Oberschenkel] ausgezeichnete Bewertungen, der Move 4 [Hüfte] mäßige bis ausgezeichnete Bewertungen und der ActiGraph schwache bis gute Bewertungen für die Klassifizierung von Körperposition erhielt. Für die Komponente des sedentären Verhaltens zeigte der Move 4 [Oberschenkel] ausgezeichnete Bewertungen, der ActivPAL nahezu ausgezeichnete Bewertungen, der Move 4 [Hüfte] gute bis ausgezeichnete Bewertungen und der ActiGraph schwache bis ausgezeichnete Bewertungen. Diese Ergebnisse deuten darauf hin, dass die am Oberschenkel getragenen Geräte, nämlich der Akzelerometer Move 4 und der ActivPAL, eine ausgezeichnete Validität bei der Messung der Körperposition und des sedentären Verhaltens erreichen und für zukünftige Studien empfohlen werden.

In der zweiten Arbeit wurde das getriggerte sedentäre „Ecological Momentary Assessment (EMA)" als ein methodischer Fortschritt im Bereich der Forschung über sedentäres Verhalten vorgestellt. Zusätzlich wurde die Genauigkeit der getriggerten sedentären EMA in drei verschiedenen Studien an gesunden Erwachsenen untersucht. Darüber hinaus untersuchten wir den Mehrwert der getriggerten sedentären EMA im Vergleich zu einer Simulation eines zufälligen Abfragedesigns. Getriggertes sedentäres EMA umfasst die kontinuierliche Erfassung des sedentären Verhaltens mittels Akzelerometrie und wiederholte kontextbezogene Abfragen über elektronische Tagebücher (d.h. eine Applikation auf einem Smartphone). Genauer beschrieben überträgt der Akzelerometer Daten zur Körperposition (sitzend, liegend oder aufrecht) via Bluetooth Low Energy (BLE) in Echtzeit auf ein Smartphone und triggert zu beantwortende Fragebögen. Jedes Mal, wenn ein Proband eine bestimmte Zeit (z.B. 20 Minuten) in sitzender Körperposition verbringt, löst das elektronische Tagebuch kontextbezogene Abfragen aus. Um die Genauigkeit dieser Methode zu testen wurde die prozentuale Genauigkeit aller sedentär getriggerter Abfragen im Verhältnis zur Gesamtzahl der sedentären Phasen, die durch Akzelerometer erfasst wurden und potentiell eine Abfrage auslösen könnten, berechnet. Im Durchschnitt lag die Genauigkeit über alle Probanden hinweg bei über 80 %. Im Vergleich zu Simulationen eines zufälligen Abfragedesigns (alle 120 Minuten) war die Genauigkeit des getriggerten sedentären EMA um bis zu 47,9 % höher. Die Ergebnisse zeigten darüber hinaus, dass sedenäre Phasen (≥ 20 Minuten) vorwiegend außerhalb des Arbeitskontextes auftraten und wenn die Probanden nicht allein waren. Zusammengefasst zeigte die Studie, dass getriggertes sedentäres EMA einen methodischen Fortschritt darstellt, der zur Erfassung sozialer und umweltbezogener Kontextinformationen oder zur Auflösung dynamischer Assoziationen verwendet werden kann.

In der dritten Arbeit wurde untersucht, inwiefern sedentäres Verhalten Stimmungsdimensionen beeinflusst. Hierbei wurde eine AA–Studie im Alltag von 92 Universitätsangestellten über fünf Tage durchgeführt. Sedentäres

Verhalten wurde kontinuierlich mittels Akzelerometrie gemessen und die Stimmung mehrmals täglich in elektonischen Tagebüchern via Smartphone-Applikation erfasst. Zur Varianzmaximierung verwendeten wir einen getriggerten sedentären Algorithmus, der in der zweiten Arbeit vorgestellt wurde. Die Ergebnisse zeigten, dass sedentäres Verhalten (15-Minuten-Intervalle vor jeder Stimmungsbewertung) und sedentäre Phasen (30-Minuten-Intervalle mit ununterbrochenem sedentären Verhalten) die Stimmungsdimensionen Gute-Schlechte Stimmung und Wache-Müde negativ beeinflussten. In anderen Worten: Mehr sedentäres Verhalten im täglichen Leben führte zu einem niedrigeren Niveau des Wohlbefindens und des Energielevels. Dementsprechend verweisen erste Erkenntnisse darauf, dass sedentäres Verhalten ein allgemeiner Risikofaktor sein könnte, der sowohl die somatische als auch die psychische Gesundheit beeinflusst.

In der vierten Arbeit untersuchten wir den reziproken Einfluss der dritten Arbeit, inwiefern die aktuelle Stimmungsbewertung das nachfolgende sedentäre Verhalten beeinflusst. Darüber hinaus untersuchten wir, ob der Zusammenhang zwischen Stimmung und sedentärem Verhalten von der methodischen Perspektive abhängen könnte. Hierfür verwendeten wir multiple Regressionsanalysen zur Auswertung von Zwischensubjekt-Effekten aus Fragebogendaten und den Ansatz der Mehrebenen-Modellierung zur Analyse von Innersubjekt-Effekten aus der AA-Studie. Die Ergebnisse zeigten, dass höhere Bewertungen der Stimmungsdimensionen Gute-Schlechte Stimmung und Wach-Müde zu einer geringeren nachfolgendenen Dauer des sedentären Verhaltens prognostizierten, während höhere Bewertungen der Stimmungsdimension Ruhe-Unruhe eine längere Dauer an nachfolgendem sedentären Verhalten prognostizierten. Die Effekte der Stimmungsdimensionen Wach-Müde und Ruhe-Unruhe auf das sedentäre Verhalten wurden durch den Umgebungskontext moderiert; so fallen die Effekte im Setting „Zuhause“ stärker aus als im Setting „Arbeit“. Die Ergebnisse deuten darauf hin, dass die Stimmung das sedentäre Verhalten im Alltag regulieren könnte. Zeitsensitive Analysen, wie z.B. von Abfragezeitpunkt zu Abfragezeitpunkt, ergaben einen Zusammenhang zwischen Stimmung und sedentärem Verhalten (Innersubjekt-Analyse), während Analysen zwischen verschiedenen Personen keine Zusammenhänge ergaben (Zwischensubjekt-Analysen). Basierend auf den Erkenntnissen der zweiten und dritten Arbeit deuten die Ergebnisse auf eine reziproke Beziehung zwischen sedentärem Verhalten und Stimmung hin.

In der fünften Arbeit wurde der Einfluss verschiedener Facetten einer Unterbrechung des sedentären Verhaltens auf die Stimmungsdimensionen im Alltag untersucht. In der aus Arbeit zwei beschriebenen AA-Studie wurden verschiedene Unterbrechungsmuster wie folgt definiert: Variation in der Häufigkeit (Anzahl der Unterbrechungen), Dauer (Länge der Unterbrechungen), Intensität (metabolisches Äquivalent der Unterbrechung) und Umgebungskontext (Zuhause/Arbeitsplatz). Der Einfluss des jeweiligen Unterbrechungsmusters auf die Stimmung wurde in einem Innersubjekt-Design analysiert. Die Ergebnisse zeigten, dass die Intenstät der Unterbrechung positiv mit den nachfolgenden Stimmungsdimensionen Gute-Schlechte Stimmung, Wach-Müde und Ruhe-Unruhe assoziiert war. Die Häufigkeit der Unterbrechung war positiv mit den nachfolgenden Stimmungsdimensionen Gute-Schlechte Stimmung und Wach-Müde assoziiert, während die Dauer der Unterbrechung nicht mit der Stimmung assoziiert war. Explorative Analysen zeigten zudem, dass Unterbrechungen des sedentären Verhaltens im Setting „Zuhause“ einen größeren Effekt zeigten als im Setting „Arbeit“. Insgesamt betrachtet deuten die Ergebnisse darauf hin, dass ein häufiges und intensives Unterbrechen des sedentären Verhaltens, z.B. durch Gehen statt Stehen, am vorteilhaftesten für die Verbesserung der Stimmung sein könnte. Diese Erkenntnisse aus dem Alltag können als Beitrag für die Formulierung präziserer Gesundheitsempfehlungen dienen, die darauf abzielen, „das sedentäre Verhalten im Alltag zu minimieren“.

Nach dem derzeitigen Wissensstand tragen unsere angeführten Ergebnisse in unterschiedlicher Hinsicht zu einem Erkenntnissgewinn im Bereich des sedentären Verhaltens bei. Zum einen wurde in Übereinstimmung mit früheren Studien gezeigt, dass Akzelerometer die bevozugte Methode ist um quantitative Aspekte des sedentären Verhaltens zu messen. Darüber hinaus können sich elektronische Tagebücher (z.B. eine Applikation auf dem Smartphone) als wertvoll für die Erfassung der qualitativen Aspekte des sedentären Verhaltens erweisen. Zum anderen untersuchten wir als eine der ersten Studien die Zusammenhänge zwischen sedentärem Verhalten und Stimmung im Alltag und fanden erste Evidenz für einen reziproken Zusammenhang zwischen beiden Konstrukten sowie, dass Unterbrechungen des sedentären Verhaltens sich positiv auf die Stimmung auswirken können. Vor dem Hintergrund dieser zentralen Ergebnisse werden im letzten Kapitel dieser Thesis diverse Themen disktutiert, die in weiteren Untersuchungen betrachtet werden könnten. Wir gehen davon aus, dass die gleichzeitige

Erfassung und Analyse aller Aspekte des (in)aktivem Verhaltens (d.h. Schlaf, sedentäres Verhalten und körperliche Aktivität) für das Verständnis der Wechselbeziehung und deren gesundheitlichen Auswirkungen immer wichtiger werden. Weiterhin gehen wir davon aus, dass sich die Frage der Kausalität stellen wird, wenn zukünftige Forschungsarbeiten den reziproken Zusammenhang zwischen sedentärem Verhalten und Stimmung bestätigen. Letztlich erwarten wir, dass die psychophysiologische Reaktion des sedentären Verhaltens zunehmend in den Mittelpunkt der Forschung rücken wird.

Preface

Parts of this work have been published or have been submitted for publication. Thus, the following chapters can be read independently from each other:

Chapter II: Giurgiu, M., Bussmann, J. B. J, Hill, H., Anedda, B., Kronenwett, M., Koch, E. D., … & Reichert, M. (submitted). Validating accelerometers for the assessment of body position and sedentary behaviour. *Journal for the Measurement of Physical Behaviour*.

Chapter III: Giurgiu, M., Niermann, C., Ebner-Priemer, U. W., & Kanning, M. (submitted). Sedentary triggered EMA: A methodological advancement for the assessment of contextual information on sedentary behavior in daily life. *JMIR mHealth and uHealth. doi:10.2196/17852*

Chapter IV: Giurgiu, M., Koch, E. D., Ottenbacher, J., Plotnikoff, R. C., Ebner-Priemer, U. W., & Reichert, M. (2019). Sedentary behavior in everyday life relates negatively to mood: An ambulatory assessment study. *Scandinavian journal of medicine & science in sports,* 29 (9), 1340-1351. doi: 10.1111/sms.13448.

Chapter V: Giurgiu, M., Plotnikoff, R. C., Nigg, C. R., Koch, E. D., Ebner-Priemer, U. W., & Reichert, M. (submitted). Momentary mood predicts upcoming real-life sedentary behaviour. *Scandinavian journal of medicine & science in sports.*

Chapter VI: Giurgiu, M., Koch, E. D., Plotnikoff, R. C., Ebner-Priemer, U. W., & Reichert, M. (2020). Breaking Up Sedentary Behavior Optimally to Enhance Mood. *Medicine and science in sports and exercise,* 52(2), 457-465. doi: 10.1249/mss.0000000000002132

Chapter I

I

General Introduction

Physical inactivity has been identified as the fourth leading risk factor for global mortality (World Health Organization, 2010). Thus, the World Health Organization (WHO) has set a global target to reduce physical inactivity by 10% by 2025 (World Health Organization, 2013). A pooled analysis of 1.9 million participants revealed that the WHO target is “not on track” (Guthold, Stevens, Riley & Bull 2018; Kruger, 2019). In line with this outlook, researchers have reported that approximately 80% of US adults and adolescents are insufficiently active, which means that they do not meet current physical activity recommendations, for example being moderately physically active for 150 minutes throughout the week (Piercy et al., 2018; Tremblay et al., 2017). Technological and social changes in domestic, environmental and occupational settings have led to an increasingly inactive lifestyle among different cultures and countries (Church et al., 2011). In this context, the construct of sedentariness has received significant attention within the scientific community. Based on the Latin word sedere, meaning “to sit,” several definitions of sedentary behavior have evolved over the past decade. According to the Sedentary Behavior Research Network (SBRN), sedentary behavior is defined as “any waking behavior characterized by an energy expenditure ≤ 1.5 MET´s, while in a sitting, reclining or lying posture.” (Tremblay et al., 2017).

Although sedentary behavior is indeed a form of physical inactivity, physiological studies have identified the unique mechanisms and characteristics of sedentary behavior, and thus suggest sedentary behavior be considered an independent behavior with its own characteristics, not only an absence of physical activity (Hamilton, Hamilton & Zderic, 2007). Thus, given the urgent target to reduce physical inactivity, it may be a promising direction to thoroughly examine the nature of sedentary behavior. Using the established Medical Subject Headings (MeSH) for sedentary behavior, Figure 1 illustrates the rising interest in sedentary behavior research in the scientific community (Lynch, Matthews & Wijndaele, 2019).

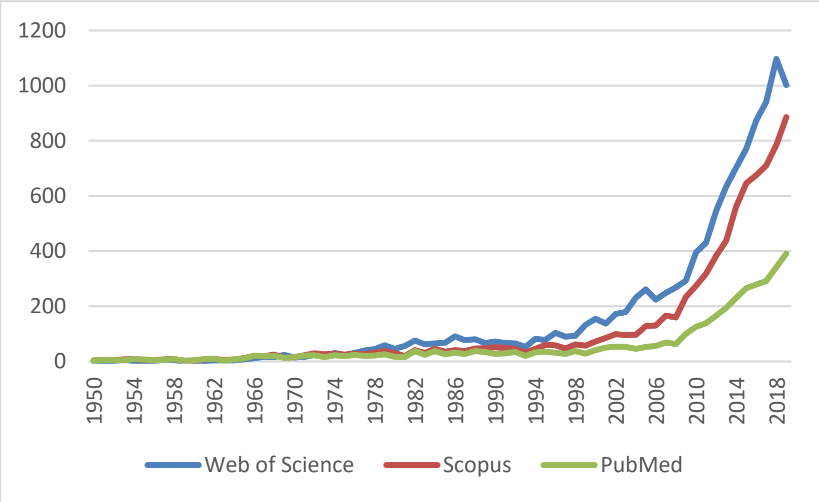

Figure 1. The number of entries in the databases Scopus, Web of Science, and PubMed over the past 69 years (1950-2019) screened by the title that includes the keywords: *"sedentary behavior"*, *"sitting"*, or *"screen time"*.

As shown in Figure 1, the number of publications on the topic has increased sharply, especially over the past decade. However, although researchers have intensified efforts to gain a better understanding of the construct of sedentariness, this research field is still at an early stage. This becomes apparent when we ask such questions as: "How should we assess sedentary behavior?" or "Can sufficient physical activity counter the adverse health effects of sedentary behavior?" Before answering such complex questions as the last one, researchers must clarify the fundamental prerequisites for high-quality research, such as the use of appropriate research methods. In the field of physical behavior (i.e., physical activity, sedentary behavior, and sleep), traditional approaches such as self-reported questionnaires are widely used. However, subjective measures are prone to recall and social desirability biases, which may result in an inappropriate measurement of physical behavior (Chastin, Culhane & Dall, 2014; Lagersted-Olsen et al., 2014; Prince et al., 2008). Thus, currently activity monitors such as pedometers or accelerometers have become the preferred method thanks to their portability and affordability, and the opportunity they afford to gather large amounts of dense information (Bassett, 2012; Strath et al., 2013). Furthermore, technological advancements have led to the increased accessibility of activity monitors. However, most currently available activity monitors do not accurately assess both components of sedentary behavior (i.e., body posture and energy expenditure) (Kang & Rowe, 2015). In one of the latest overviews of sedentary behavior and health, Katzmarzyk and colleagues (2019) summarized the situation as follows: "There is a pressing need to develop objective field methods to simultaneously assess these two components of the definition that can be applied in both surveillance and research settings to properly quantify time spent in sedentary behaviour."

To examine the validity of different accelerometers, i.e., ActivPAL, ActiGraph, and Move, we conducted a validation study (Giurgiu et al., submitted) under laboratory conditions among healthy university students and employees. In particular, participants performed a series of full- and semi-standardized sessions using direct observation via video recording as a criterion measure.

Topic I: Validation of different accelerometers for the assessment of body position and sedentary behavior

In this first work (Giurgiu et al., submitted), we found that thigh-worn accelerometers, namely, the ActivPAL and Move, achieved up to excellent validity in measuring sedentary behavior. Our finding is in line with previous studies showing that thigh-worn accelerometers are currently the method of choice used to capture the quantitative aspects of sedentary behavior such as time spent being sedentary or the frequency of sedentary bouts, i.e., uninterrupted intervals of sedentary time. However, sedentary behavior is a multifaceted behavior influenced by the complex interaction of individual, sociocultural, and environmental factors (Owen et al., 2011). Thus, there is significant interest in capturing all the information of an individual's sedentary behavior, not only its quantitative aspects such as frequency and duration but also its qualitative aspects such as type and context. Here, accelerometers are limited to informing researchers about the type of behavior or contextual information, which is crucial to understanding behavioral aspects. Thus, subjective information can be a valuable addition to the use of accelerometers.

Ecological Momentary Assessment (EMA) is a methodological approach that enables researchers to assess the qualitative aspects of behavior via electronic diaries (e.g., an application on a smartphone). Several advantages, such as assessments in everyday life, in real time and repeated measurements with a high sampling frequency, have led to the use of EMA in a wide range of research areas. Moreover, it bypasses laboratory distortions and minimizes the recall biases associated with more traditional approaches such as paper-pencil questionnaires (Bussmann, Ebner-Priemer & Fahrenberg, 2009; Fahrenberg, Myrtek, Pawlik & Perrez, 2007). Combining device-based measurements via accelerometers and self-reported assessments via e-diaries, known as Ambulatory Assessments (AA), provides a more complete picture of sedentary patterns, i.e., frequency, volume, intensity, type, and context. AA methodology has been previously used to unravel the associations between physical activity and psychological outcomes in daily life (Koch et al., 2018; Reichert et al., 2017).

Since the sampling scheme, i.e., when and how often participants should be asked via an e-diary, has a significant impact on data collection, Ebner-Priemer and colleagues (2013) developed and applied triggered e-diaries. These triggered e-diaries, a technical advance in AA methodology, maximize the within-subject variance of the parameter of interest and minimize participants' burden. An advance over nontriggered time- and event-based designs, triggered e-diaries are connected to external devices such as accelerometers or geolocation tracking systems and trigger EMA-prompts to the participants in situations of interest. Ebner-Priemer and colleagues (2013) developed a sophisticated activity triggered algorithm that focused primarily on physically active episodes in everyday life. Based on similar technical requirements, we have now developed a sedentary triggered algorithm. In simple terms, accelerometers monitor and analyze sedentary behavior continuously in real time and e-diary questions are triggered during phases of low or high sedentary behavior.

In our second work (Giurgiu, Niermann, Ebner-Priemer & Kanning, submitted), we introduce sedentary triggered EMA as a methodological advancement in the field of sedentary behavior research and point out the feasibility of sedentary triggered EMA in three different studies among healthy adults.

Topic II: Sedentary triggered EMA – a methodological advancement

Thus far, we have shown that accelerometers are a valid measure of assessing the quantitative aspects of sedentary behavior and that EMA proves a valuable addition to assessing the qualitative aspects. Moreover, we introduced sedentary triggered EMA as an accurate sampling strategy to capture "just in time" information about sedentary behavior. To sum up, a valid and reliable assessment of sedentary behavior forms the essential basis from which to examine the health effects of sedentariness in a discernable manner.

"Sitting is the new smoking" or "Why a sedentary lifestyle is killing you": these and similar headlines have received significant media attention in recent years. These headlines, based on study results, show that sedentary behavior has deleterious effects on cardiometabolic health, e.g., on levels of insulin resistance or inflammatory markers such as the C-reactive protein. This finding is especially true for uninterrupted sedentary bouts that exceed 30 minutes (Dunstan, Thorp & Healy, 2011; Hamilton, Healy, Dunstan, Zderic & Owen, 2008). Many previous studies have investigated the relationship between sedentary behavior and physical health. However, as physical health comprises only one aspect of the complete health status (World Health Organization, 1948), if we are interested in the effects of sedentary behavior on health, the associations between sedentary behavior and mental health outcomes should not be disregarded. The following model, modified from Bouchard and colleagues (2012), serves as a theoretical framework to describe the associations between sedentary behavior and health (see Figure 2).

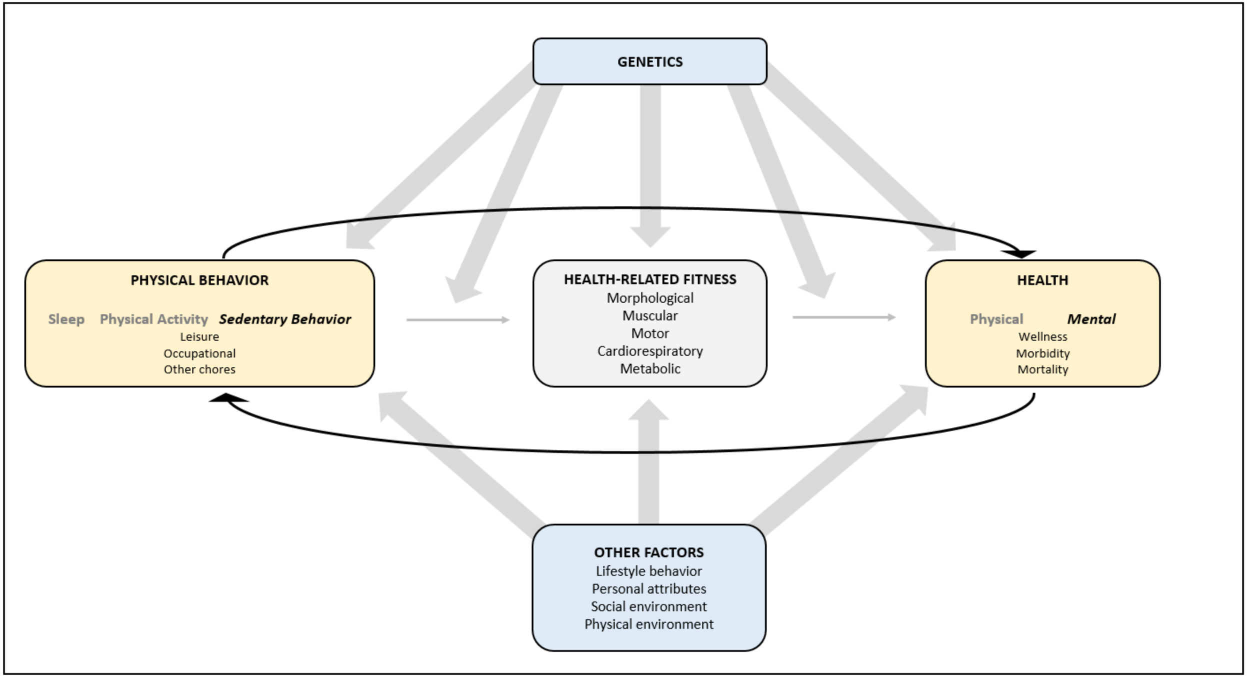

Figure 2. Associations between physical behavior, health-related outcomes, and health status (modified version of Bouchard and colleagues model, 2012, p. 18).

The original model of Bouchard and colleagues (2012) describes the complex relationship among levels of physical activity, health-related fitness (e.g., parameters such as blood pressure, power, agility, insulin sensitivity, body composition), and health status. In short, the original model illustrates reciprocal dependencies among physical activity, health-related fitness, and health status, which are influenced by genetic characteristics and other factors such as personal attributes or physical and social environmental conditions. The interdependence of these three central areas can take different directions; for example, on average regular physical activity increases health-related fitness such as cardiorespiratory endurance, which in turn has a favorable effect on health status. However, a beneficial effect of physical activity on health is possible without an additional gain in fitness (Bouchard, Blair & Haskell, 2012). Moreover, there is evidence of a reciprocal structure, since the paths are not causal. For instance, with increasing fitness, people tend to become more active and the fittest becomes the most active

We modified the original model while extending two components. First, since there is growing evidence that sedentary behavior, as well as sleep, influences health outcomes (Cappuccio, Cooper, D'Elia, Strazzullo & Miller, 2011; Katzmarzyk et al., 2019; Watson et al., 2015), we extended the physical activity component to include physical behavior, (i.e., physical activity, sedentary behavior and sleep). Second, in line with the definition of health by the WHO, we extended the health component to include both physical and mental health. In the following sections, the present work focuses on the associations between sedentary behavior and mental health (black arrows in Figure 2). As mentioned above, most previous studies have focused on the associations between sedentary behavior and physical health, whereas the association between sedentary behavior and mental health has rarely been investigated. Nevertheless, Faulkner and Biddle (2013) summarized the present state of research as follows: “While this field is still in its infancy, findings from these studies demonstrate emerging evidence of at least an association between sedentary behaviour and mental health.” Some cross-sectional studies have shown that prolonged sedentary behavior is associated with increased risk of mental disorders such as depression (Vancampfort et al., 2018) and other mental health outcomes such as psychological distress (Kilpatrick, Sanderson, Blizzard, Teale & Venn, 2013) or well-being (Hamer, Stamatakis & Mishra, 2010).

Since mood is a central indicator of both mental well-being in healthy populations and is altered in many mental disorders (e.g., diminished mood in major depression disorder, enhanced mood in manic episodes, high mood fluctuations in borderline personality disorder), we focused on the associations between sedentary behavior and mood. In our third work (Giurgiu et al., 2019), we conducted an Ambulatory Assessment (AA) study of the everyday life of 92 university employees over five days. We continuously measured sedentary behavior via accelerometers and repeatedly assessed mood (i.e., valence, energetic arousal, calmness) ten times each day on smartphone diaries.

Topic III: Mood-changes as a consequence of sedentary behavior

We found that sedentary time (15-min intervals prior to each e-diary assessment) and sedentary bouts (30-min intervals of uninterrupted sedentary behavior) negatively influenced valence and energetic arousal. In particular, the more participants were sedentary in their everyday life, the less they felt well and energized (Giurgiu et al., 2019). This finding is in line with an experimental finding showing that experimentally induced sedentariness led to mood disturbances (Endrighi, Steptoe & Hamer, 2016); a finding from an EMA-study showing that momentary sedentary behavior in real life leads to decreased positive affect; and findings from cross-sectional studies (Ellingson et al., 2018; Ellingson, Kuffel, Vack & Cook, 2014) showing that being less sedentary was associated with lower levels of fatigue. Thus, there is growing evidence that sedentary behavior impacts mood in daily life. However, according to the modified model of Bouchard and colleagues (2012) and to an empirical finding from a longitudinal study (DeMello et al., 2018), there might be a reciprocal relationship between sedentary behavior and mood. In other words, is sedentary behavior also a consequence of worsened or brightened mood? The timely chronological order in our AA study among university employees allows us in our fourth work (Giurgiu et al., 2020) to examine whether mood is an antecedent of sedentary behavior. Moreover, we considered the methodological issue of whether the relationship between mood and sedentary behavior may vary as a function of the methodological approach (between-subject analyses vs. within-subject analyses).

Topic IV: Is mood an antecedent of sedentary behavior?

We found that higher ratings of momentary valence and energetic arousal were associated with subsequently lower amounts of sedentary behavior, whereas higher ratings of momentary calmness were associated with subsequently higher amounts of sedentary behavior. This finding accounts for the within-subject analyses but not for the between-subject analyses. More specifically, we found no association at a between-subject level in either the self-reported data (paper-pencil questionnaires) or in the aggregated between-level data from the AA study. In general, the evidence for the assumption that mood is an antecedent of sedentary behavior is inconclusive. Schwerdtfeger and colleagues (2010) and DeMello and colleagues (2018) found such a relationship, whereas Maher et al. (2019) and Kim et al. (2019) found no associations. Thus, the reciprocal relationship between momentary mood and sedentary behavior is still not well understood. However, we would argue that in general there is more evidence that mood is a consequence of sedentary behavior and less evidence that mood is an antecedent of sedentary behavior.

Our finding that a worsened mood is a consequence of sedentary behavior is only one example of many. Previous studies have found different negative health consequences of sedentary behavior, such as an increased risk for cardiovascular diseases, type 2 diabetes, or depression (Katzmarzyk et al., 2019; Vancampfort, Stubbs, Firth, van Damme & Koyanagi, 2018). Accordingly, sedentary behavior can be considered a general risk factor for human health because it impacts both physical and mental health. Given the high prevalence of sedentary behavior globally, a rising need exists to address this challenge. Breaking up sedentary behavior appears to be a promising strategy to prevent its negative effects on human health. Therefore, official public health guidelines for adults recommend both reducing sedentary time and breaking up sedentary behaviors by physical activity whenever possible (Ministry of Health, 2018; Stamatakis et al., 2018). However, in contrast to physical activity guidelines for adults (World Health Organization, 2010), for example 30 minutes of moderate-intensity activity five times per week, the recommendations for breaking up sedentary behaviors are highly unspecific;

for instance, “break up long periods of sitting” (Ministry of Health, 2018). Moreover, to make recommendations more specific, it is crucial to add information on beneficial break patterns related to frequency, intensity, type, volume and context. Since we know very little about the potential effectiveness of sedentary breaks on mental health outcomes such as mood, we investigated to what degree sedentary break patterns influence mood dimensions in everyday life.

Topic V: Optimal break pattern to enhance mood.

In our fifth work (Giurgiu, Koch, Plotnikoff, Ebner-Priemer & Reichert, 2020), we found that break intensity was associated with an enhancement in all three mood dimensions, and break frequency was related to enhancement in two of three mood dimensions (valence and energetic arousal); however, break duration was not significantly associated with mood at all. Our findings also indicate that breaking up sedentary behavior to enhance feelings of energy is more beneficial in the home than in the workplace context. These insights can serve as starting points in building an evidence base regarding the mood outcomes of breaking up sedentary behavior in order to elicit more specific public health recommendations. Thus, we suggest as preliminary recommendations that individuals break up their sedentary behavior as frequently as possible within an hour with at least moderate-intensity activities, such as slow walking; ideally, this practice would take place in any context.

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Chapter I

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Chapter II

Validating accelerometers for the assessment of sedentary behavior.

Paper 1: Validating accelerometers for the assessment of body position and sedentary behavior.

Slightly modified version of the submitted manuscript

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Abstract

There is growing evidence that sedentary behaviour is a risk factor for somatic and mental health. However, there is still a lack of objective field methods, which can assess in combination the two components of sedentary behaviour: the postural part (sitting/lying) and the movement intensity/energy expenditure part. The purpose of the study was to compare the validity of different accelerometers (ActivPAL, ActiGraph, and Move). 20 adults (10 females; age 25.68 ± 4.55 years) participated in a structured protocol with a series of full- and semi-standardized sessions under laboratory conditions. Direct observation via video recording was used as a criterion measure of body positions (sitting/lying vs. non-sitting/lying). By combining direct observation with metabolic equivalent tables, protocol activities were also categorized as sedentary or non-sedentary. Sensitivity, specificity, accuracy, informedness, markedness, and phi-coefficient were calculated to compare accelerometer and video recordings. Across all conditions, for the measurement of body position, the Move 4 [thigh] showed excellent ratings (96-99%), the Move 4 [hip] showed moderate to excellent ratings (76-97%), and the ActiGraph showed weak to good ratings (67-88%). For the sedentary behaviour part, the Move 4 [thigh] revealed excellent ratings (94-98%), the ActivPAL showed almost excellent ratings (90-97%), the Move 4 [hip] showed good to excellent ratings (81-97%), and the ActiGraph showed weak to excellent ratings (67-97%) overall conditions. Especially the thigh worn devices, namely the Move 4 accelerometer and the ActivPAL, achieved up to excellent validity in measuring body position and sedentary behaviour and are recommended for future studies.

Introduction

There is growing evidence that sedentary behaviour is negatively associated with several somatic and mental health outcomes, such as cardiometabolic health or depression (Katzmarzyk et al., 2019; Vancampfort et al., 2018). Importantly, research has shown that adults spent the majority of the wake time, i.e., about 8-11 hours per day in a sedentary position (Diaz et al., 2016; Donaldson, Montoye, Tuttle & Kaminsky, 2016). Thus, given the high prevalence of sedentary behaviour and the societal relevance of this topic, high-quality studies are needed to gain a better understanding and to draw conclusions about the health consequences of sedentary behaviour. One aspect of high quality is a valid and reliable assessment of the construct of interest, such as sedentary behaviour (Atkin et al., 2012).

Based on the Latin term “sedere”, meaning “to sit”, several definitions of sedentary behaviour evolved over the past decade. Trembley and colleagues (Tremblay et al., 2017) identified more than ten different definitions of sedentary behaviour, which leads to a lack of consistency and a high degree of confusion. For example, in sport and exercise research, the term sedentary is frequently used to describe the absence of some thresholds of light physical activity (LPA) or as a synonym of physical inactivity (Paffenbarger Jr, Hyde, Wing & Hsieh, 1986). However, the predominant opinion is that sedentary behaviour is an independent behaviour with unique physiological mechanisms (Owen, Healy, Matthews & Dunstan, 2010). The widely accepted definition of the sedentary behaviour research network (SBRN) covers two components, namely energy expenditure and body posture: “Sedentary behaviour is any waking behaviour characterized by an energy expenditure ≤ 1.5 metabolic equivalents (METs), while in a sitting, reclining or lying posture.” (Tremblay et al., 2017). Moreover, different operationalization’s of sedentary behaviour (e.g., based only on the postural component vs. based only on the energy component vs. based on the dual-components) may lead to different outcomes of sedentary behaviour (Fanchamps et al., 2018).

Since the interest in sedentary behaviour research increased, the measurement methods continued to develop. A variety of subjective measures (e.g., questionnaire, interview, and activity-recall instruments) are currently available and provide useful information about the type and context of behaviour. However, subjective measures are prone to recall and social desirability biases, which may result in an inappropriate measurement of sedentary behaviour (Chastin, Culhane & Dall, 2014; Kang & Rowe, 2015;

Lagersted-Olsen et al., 2014). Nowadays, activity monitors such as accelerometers have become the preferred method, due to their portability, affordability, and opportunity to obtain large amounts of dense information (Bassett, 2012; Strath et al., 2013). Initially, accelerometers were built to measure physical activity through changes in acceleration. Thus, even though they can indicate the absence of movement, this means not automatically that they can distinguish between body postures such as sitting and standing, which may increase the intangible risk of an over- or underestimation of sedentary behaviour (Dowd, Harrington, Bourke, Nelson & Donnelly, 2012; Kang & Rowe, 2015). For instance, standing still and sitting still at the bus stop can not be distinguished, while by definition sitting still is a sedentary behaviour and standing still is a non-sedentary behaviour. Moreover, there is initial evidence that sitting and standing may have different health effects (Buckley, Mellor, Morris & Joseph, 2014; Hamilton, Hamilton & Zderic, 2007; Thorp, Kingwell, Owen & Dunstan, 2014). To overcome this gap, an inclinometer-function had been developed or incorporated into accelerometers to detect body postures accurately (Janssen & Cliff, 2015; Peterson, Sirard, Kulbok, DeBoer & Erickson, 2015).

Technological advancements led to increased accessibility of activity monitors. However, most current available activity monitors do not accurately assess both components of sedentary behaviour (i.e., body posture and energy expenditure) (Kang & Rowe, 2015). In the latest overview about sedentary behaviour and health, Katzmarzyk and colleagues (Katzmarzyk et al., 2019) summarized it as follows: “There is a pressing need to develop objective field methods to simultaneously assess these two components of the definition that can be applied in both surveillance and research settings to properly quantify time spent in sedentary behaviour”. According to previous validation studies, only a few activity monitors such as the thigh-worn ActivPAL (PAL Technologies Ltd, Glasgow, UK) have proven to be an accurate sensor for device-based measuring sedentary behaviour (Grant, Ryan, Tigbe & Granat, 2006; Kim, Barry & Kang, 2015; Kozey-Keadle, Libertine, Lyden, Staudenmayer & Freedson, 2011), although the ActivPAL as a 3D-accelerometer was initially developed to measure body postures and therefore missed to directly implement an energy expenditure threshold of ≤ 1.5 MET, which might lead to a misclassification of sitting or lying activities with higher energy expenditure (> 1.5 MET) (Kang & Rowe, 2015).

The Move 4 (movisens GmbH, Karlsruhe, Germany) is a single unit activity monitor based on a three-axial accelerometer (movisens GmbH, 2018). Based on calculations of movement acceleration intensity and body postures, this sensor potentially fulfills the requirements to measure the two components of sedentary behaviour, i.e., a) identification of sedentary postures (sitting/lying; the “postural part”) as well as b) movement intensity (the “energy expenditure(EE)” part). In a previous study (Anastasopoulou et al., 2014), the EE of the Move sensor has been validated while there is currently no data available on the validity of the Move 4 monitor for recording body position (i.e., sitting/lying or non-sitting/lying). However, the latter postural part is an essential prerequisite to measure sedentary behaviour according to the accepted definition (Tremblay et al., 2017).

The purpose of this study was to evaluate the validity of different accelerometers (i.e., Move 4 thigh/hip, ActivPAL and ActiGraph) as a device-based measure of body position and sedentary behaviour. In particular, we compared (i) the body-posture measurements of the accelerometers and (ii) the sedentary behaviour measurements of the accelerometers by conducting a structured study protocol under laboratory conditions with a video-recorded observational analysis as the criterion comparison.

Method

Participants

A convenience sample of 20 adults was recruited from employees and students at the Karlsruhe Institute of Technology (KIT). Only healthy participants capable of performing the study protocol were included, i.e., those without physical diseases or injuries. All twenty participants (ten females) aged 25.68 ± 4.55 years (range from 18 to 32) with a Body Mass Index (BMI) of 22.9 ± 3.43 kg/m2 (range from 18.28 to 30.93) completed the study. The Ethics Committee of the Karlsruhe Institute of Technology (KIT) approved this study. All eligible participants received written and oral information regarding the study procedures before written informed consent was obtained. Participants were free to withdraw from the study at any time.

Procedures

Participants followed a structured study protocol while performing a series of 32 consecutive conditions. The protocol was divided into two sections: a full-standardized section (conditions 2-6, 8-11, 13) and a semi-standardized section (conditions 1, 7, 12, 14-32). The full-standardized section was performed under a fixed order of instructions, whereas the semi-standardized section was performed in a natural way and order. All conditions occurred in a laboratory setting, i.e., gym and outdoor area (400 meters tartan track) at the Karlsruhe Institute of Technology (see Figure 1; see also Supplementary file 1, which provides a comprehensive overview including description and location of each condition).

Before testing, we initialized all activity monitors on the same computer, allowing the output parameters from the activity monitors to be time-synchronized. Furthermore, to prove the synchronization, participants performed three vertical jumps at the beginning and the end of the measurement. Participant’s body weight and height were measured without shoes using an electronic column scale (Seca Ltd. & co. kg, Hamburg, Germany). Before testing, participants were fitted with the activity monitors.

Figure 1. A) Study protocol with 32 conditions separated in semi-standardized, full-standardized, and daily life sessions. B) Laboratory setting of conditions 1 to 26. C) Outdoor setting of condition 27 to 32.

Criterion measure

All performed activities were recorded on a digital video camera (Canon legria HF R46, Canon Germany Gmbh, Krefeld, Germany). The observation of the videos was used as the criterion measure. All video recordings were analyzed independently from the activity monitors by the same pair of raters with a time resolution of 1-sec. Video analysis focused on the classification of both body position and sedentary behaviour. Body positions were classified as lying, sitting, standing or unknown position. The classification of sedentary behaviours (sedentary, non-sedentary, unknown) was based on the body position analysis (sitting, lying) and MET values (< 1.5 MET for sedentary behaviours) from the Compendium of Physical Activities (Ainsworth et al., 2011). Based on this, activities in the protocol could be clearly classified as sedentary (conditions: 1-11; 16; 18; 22) or non-sedentary behaviour (conditions: 12-15; 17; 19-21; 23-32) (see Figure 1). Thus, based on the study protocol, we expected that 35.2% of all seconds will classified as sedentary behaviour, and 40.7% as sitting/lying.

Prior to the video analysis, the raters were trained to assess body positions and sedentary behaviours. All raters followed the definitions from the Terminology Consensus Project of the Sedentary Behaviour Research Network (SBRN) (Tremblay et al., 2017). To determine the interrater reliability, a pair of raters watched the video records separately (Windows Media Player) and entered their results in an Excel-template. Finally, if both raters had classified differently, the video recordings were reviewed again, until a final decision was found.

Activity monitors

ActiGraph GT3X+ (ActiGraph LLC, Pensacola, FL) is one of the worldwide most used triaxial activity monitor with a size of 33 x 46 x 15 mm and a mass of 19 g (ActiGraph LLC). The sensor records acceleration at a range of ± 6 g and a sampling rate of 30-100 Hz. The ActiGraph GT3X+ was attached at the right waist over the hip (perfectly vertical) using an elastic belt. The manufacturer's software ActiLife (v6.13.3) was used to initialize the monitor and to download time-stamped data with a 1-sec resolution. To validate the body position, we took the classification from the inclinometer and recoded them into a dichotomous parameter (i.e., sitting/lying vs. non-sitting/lying). To validate sedentary behaviour, we used the threshold of ≤ 100 counts per minute (cpm), which has been widely used with three-axis vector magnitude data from the ActiGraph (Matthews et al., 2008; Migueles et al., 2017).

Additionally, we analyzed the data by using the ≤ 150 cpm threshold and an own algorithm based on a combination of the inclinometer-function and the ≤ 100 cpm threshold (i.e., sedentary behaviour, if ≤ 100 cpm and body position: sitting/lying).

ActivPAL3 micro (PAL Technologies Ltd, Glasgow, UK), known as the gold-standard for measuring sedentary behaviour, is a triaxial activity monitor with a size of 23.5 x 43 x 5 mm and a mass of 10 g. The monitor records data at a range of ± 2 g and a sampling rate of 20 Hz. The activPAL3 micro was attached according to the manufacturer´s guidelines, i.e., to the mid-anterior position of the right thigh by using TegadermTM skin tape. We used the software's PALconnect (v8.10.5.55) and PALbatch (v8.10.6.33) to initialize the monitor and to download data. The "event" file provided the observed time with seconds when sedentary to non-sedentary behaviour occurred. For later analyses, we expanded the "event" file to a second-by-second data file by using Matlab R2015b (The MathWork Inc., Natick, Massachusetts). We used monitor-derived information from the parameter "activity code" (sedentary vs. standing vs. stepping) for the analyses. Because this parameter provided no sole information about the body position, we did not embed the ActivPAL monitor within our body position analyses. To validate sedentary behaviour, we recoded the parameter "activity code" to a dichotomous variable by combining the categories standing and stepping to a single category, namely non-sedentary behaviour.

Move 4 (movisens GmbH, Karlsruhe, Germany) is a triaxial activity monitor with a size of 62 x 39 x 11 mm and a mass of 25 g (movisens GmbH, 2018). The sensor records acceleration at a range of ± 16 g and a sampling rate of 64 Hz. The Move 4 accelerometers were attached laterally on the top of the anterior superior iliac spine on the right hip using an elastic belt, and at the lateral aspect of the right thigh by using TegadermTM skin tape. We used the manufacturer´s software SensorManager (v1.11.19) to initialize and download the data and the software DataAnalyzer (v.1.13.5) to calculate time-stamped data with a 1-sec resolution. We used monitor-derived information of the body position from the thigh (sitting/lying, upright) and hip (lying back, lying prone, lying left, lying right, sitting, standing) for the analyses. To validate the body position, we recoded the body position variable from the hip monitor to a dichotomous variable by combining the categories lying back, lying prone, lying left, lying right and sitting to a single category named sitting/lying. To validate sedentary behaviour, we used the dichotomous variable (sedentary vs. non-sedentary) from the DataAnalyzer, which is based on a sedentary algorithm including information of the body position and movement acceleration/intensity.

Statistical Analyses

First, we timely synchronized the Excel files of the video observation and the activity monitors by merging all files to a final data set via SPSS version 25.0 (IBM). From the entire duration of each performed activity, we omitted the first and last 5-sec epoch for statistical analyses, due to possible biases such as delayed body positions while starting the activity or early termination of the activity. Moreover, we excluded all unknown classifications from the video observations (e.g., a participant runs outside of the recording area).

To determine the validity of the activity monitors (Move 4 [hip], Move 4 [thigh], ActiGraph GT3X+, and ActivPAL3 micro), we compared the video reference to the records of each activity monitor on a second-by-second basis. In particular, we calculated percentage (i) sensitivity, i.e., degree to which the true positive rate was detected correctly by the activity monitor, (ii) specificity, i.e., degree to which the true negative rate was detected correctly by the activity monitor, (iii) accuracy, i.e., agreement between all samples of observation and activity monitor, (iv) informedness, i.e., how informed a predictor is for the specified condition, and specifies the probability that a prediction is informed in relation to the condition (versus chance), (v) markedness, i.e., how marked a condition is for the specified predictor, and specifies the probability that a condition is marked by the predictor (versus chance), and (vi) phi coefficients were obtained as an index of association with the criterion measure (Guilford, 1941; Powers, 2011; Toon et al., 2016). Figure 1 presents the equation of each parameter. According to previous procedures (Nooijen, Groot, Stam, van den Berg-Emons, & Bussmann, 2015), we used following categories to rank the outcomes: 0-70% weak, 71-80% moderate, 81-90% good and 91-100% excellent. Based on the observational video analysis, the interobserver agreement was calculated using kappa-statistics. A kappa value of < 0 is indicative of poor strength of agreement, between 0 and 0.2 of slight agreement, between 0.21 and 0.4 of fair agreement, between 0.41 and 0.6 of moderate agreement, between 0.61 and 0.8 of substantial agreement, and between 0.81 and 1.0 of almost perfect agreement (Landis, & Koch, 1977). We calculated kappa statistics across all conditions and separately for the full-standardized and semi-standardized conditions. All statistical analyses were conducted using SPSS (version 25, IBM).

		Activity monitor	
		Sedentary	*Non-Sedentary*
Criterion measure	*Sedentary*	True Sedentary (TS)	False Sedentary (FS)
	Non-Sedentary	False Non-Sedentary (FNS)	True Non-Sedentary (TNS)

$$\textbf{Sensitivity} = \frac{\mathrm{TS}}{\mathrm{TS} + \mathrm{FNS}}$$

$$\textbf{Specifictiy} = \frac{\mathrm{TNS}}{\mathrm{TNS} + \mathrm{FS}}$$

$$\textbf{Accuracy} = \frac{\mathrm{TS} + \mathrm{TNS}}{\mathrm{TS} + \mathrm{TNS} + \mathrm{FS} + \mathrm{FNS}}$$

$$\textbf{Informedness} = \left(\frac{\mathrm{TS}}{\mathrm{TS+FNS}} + \frac{\mathrm{TNS}}{\mathrm{TNS+FS}}\right) - 1$$

$$\textbf{Markedness} = \left(\frac{\mathrm{TS}}{\mathrm{TS+FS}} + \frac{\mathrm{TNS}}{\mathrm{TNS+FNS}}\right) - 1$$

$$\textbf{Phi Coefficient} = \frac{(\mathrm{TS} * \mathrm{TNS}) - (\mathrm{FS} * \mathrm{FNS})}{\sqrt{(\mathrm{TS} + \mathrm{FS}) * (\mathrm{FNS} + \mathrm{TNS}) * (\mathrm{TS} + \mathrm{FNS}) * (\mathrm{FS} + \mathrm{TNS})}}$$

Figure 2. Equation of statistical parameters.

Results

Body Position

The interobserver agreement (Landis, & Koch, 1977) was 0.94, 1.00, and 0.91 for the observation of activities performed overall conditions, full-standardized conditions, and semi-standardized conditions, respectively. 57.2% of the video observations were classified as non-sitting/lying and 37.3% as sitting/lying, which is close to our expectations based on the study design (i.e., 40.7% sitting/lying). Moreover, 5.5% were classified by the raters as unknown and thus, excluded from the analyses. Table 1 provides an overview of the results for the analyses of body positions.

The ActiGraph showed weak to good validity across all conditions and weak to excellent validity for full- and semi-standardized conditions (see Table 1).

Considering the individual conditions, a higher number of misclassifications were found for several conditions such as lying right, sitting leaned forward, set the table or cycling (see also Supplementary file 2). Additionally, we calculated the accuracy for each participant, revealing a range from 69.4-94.8% across all conditions, 77.9-100% for the full-standardized conditions, and 66.3-97.1% for the semi-standardized conditions.

The Move 4 accelerometer attached at the thigh revealed excellent validity overall conditions and excellent validity while separating the conditions by full- and semi-standardized sessions. Taking into account the individual conditions, a higher number of misclassifications were found for cycling. Additionally, we calculated the accuracy for each participant, revealing a range from 95.3-99.9% across all conditions, 99.2-100% for the full-standardized conditions, and 94-99.9% for the semi-standardized conditions.

The Move 4 accelerometer attached at the hip showed good to excellent validity overall conditions and weak to excellent validity for full- and semi-standardized conditions. Taking into account the individual conditions, a higher number of misclassifications were found for leaned forward conditions such as sitting leaned forward, working at PC, reading newspaper or cycling. Additionally, we calculated the accuracy for each participant, revealing a range from 82.6-97.3% across all conditions, 89.3-100% for the full-standardized conditions, and 80.6-98.6% for the semi-standardized conditions. A comprehensive overview, including confusion matrices per condition for each monitor, is provided in the appendix (see Supplementary file 2). Findings are summarized in Figure 3 showing all validity parameters.

Table 1. Results of statistical parameters for body positions separated across all, full-standardized, and semi-standardized conditions.

		ActiGraph GT3X+ [sec]		Move 4 hip [sec]		Move 4 thigh [sec]	
All Conditions							
		Sitting/lying	Non-sitting/lying	Sitting/lying	Non-sitting/lying	Sitting/lying	Non-sitting/lying
Criterion measure	Sitting/lying	31953	7432	30269	9116	38175	1210
	Non-sitting/lying	8396	52080	815	59661	365	60111
Sensitivity:		79%		97%		99%	
Specificity:		88%		87%		98%	
Accuracy:		84%		90%		98%	
Informedness:		67%		84%		97%	
Markedness:		67%		76%		96%	
Phi coefficient:		0.67		0.80		0.97	
Full-Standardized Conditions							
		ActiGraph GT3X+ [sec]		Move 4 hip [sec]		Move 4 thigh [sec]	
		Sitting/lying	Non-sitting/lying	Sitting/lying	Non-sitting/lying	Sitting/lying	Non-sitting/lying
Criterion measure	Sitting/lying	17556	2629	18508	1677	20165	20
	Non-sitting/lying	611	1654	0	2265	0	2265
Sensitivity:		97%		100%		100%	
Specificity:		39%		57%		99%	
Accuracy:		86%		93%		100%	
Informedness:		35%		57%		99%	
Markedness:		60%		92%		100%	
Phi coefficient:		0.46		0.73		1.00	
Semi-Standardized Conditions							
		ActiGraph GT3X+ [sec]		Move 4 hip [sec]		Move 4 thigh [sec]	
		Sitting/lying	Non-sitting/lying	Sitting/lying	Non-sitting/lying	Sitting/lying	Non-sitting/lying
Criterion measure	Sitting/lying	14397	4803	11761	7439	18010	1190
	Non-sitting/lying	7785	50426	815	57396	365	57846
Sensitivity:		65%		94%		98%	
Specificity:		91%		89%		98%	
Accuracy:		84%		89%		98%	
Informedness:		56%		82%		96%	
Markedness:		62%		60%		93%	
Phi coefficient:		0.59		0.70		0.95	

Table 2. Results of statistical parameters for sedentary behaviour separated across all, full-standardized, and semi-standardized conditions.

		ActivPAL3 micro [sec]		ActiGraph GT3X+ [sec]		Move 4 hip [sec]		Move 4 thigh [sec]	
All Conditions									
		SB[1]	*N-SB[2]*	*SB*	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*
Criterion measure	*SB[1]*	32590	2376	33441	1525	28836	6130	33031	1935
Criterion measure	*N-SB[2]*	2287	67456	14234	55947	971	69179	554	69596
Sensitivity:		93%		70%		97%		98%	
Specificity:		97%		97%		92%		97%	
Accuracy:		96%		85%		93%		98%	
Informedness:		90%		67%		89%		96%	
Markedness:		90%		75%		81%		94%	
Phi coefficient:		0.90		0.71		0.85		0.95	
Full-Standardized Conditions									
		ActivPAL3 micro [sec]		ActiGraph GT3X+ [sec]		Move 4 hip [sec]		Move 4 thigh [sec]	
		SB	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*
Criterion measure	*SB*	18895	1290	20051	134	18500	1685	19981	204
Criterion measure	*N-SB*	0	2265	2253	12	4	2261	0	2265
Sensitivity:		100%		90%		100%		100%	
Specificity:		64%		8%		57%		92%	
Accuracy:		94%		99%		92%		99%	
Informedness:		64%		0%		57%		92%	
Markedness:		94%		0%		91%		99%	
Phi coefficient:		0.77		0.00		0.72		0.95	
Semi-Standardized Conditions									
		ActivPAL3 micro [sec]		ActiGraph GT3X+ [sec]		Move 4 hip [sec]		Move 4 thigh [sec]	
		SB	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*
Criterion measure	*SB*	13695	1086	13390	1391	10336	4445	13050	1731
Criterion measure	*N-SB*	2287	65629	11981	55935	967	66918	554	67331
Sensitivity:		86%		53%		91%		96%	
Specificity:		98%		98%		94%		97%	
Accuracy:		96%		84%		93%		97%	
Informedness:		84%		50%		85%		93%	
Markedness:		89%		73%		69%		87%	
Phi coefficient:		0.87		0.61		0.76		0.90	

[1] SB: Sedentary behaviour; [2] N-SB: Non-Sedentary behaviour

Sedentary Behaviour

The interobserver agreement was 0.96, 0.97, and 0.92 for the observation of activities performed overall conditions, full-standardized conditions, and semi-standardized conditions, respectively. Data from the video observation revealed that 66.4% were classified as non-sedentary behaviour and 33.1% as sedentary behaviour, which fits very well to our expectations based on the study design (i.e., 35.2% sedentary behaviour). Moreover, 0.5% were classified as unknown by the raters and thus, excluded from the analyses. Table 2 presents an overview of the statistical parameters for the sedentary behaviour analyses.

The ActivPAL showed almost excellent validity across all conditions. According to the full-standardized conditions, the ActivPAL revealed weak to excellent validity and good to excellent validity across all semi-standardized conditions (see Table 2). Taking into account the individual conditions, a higher number of misclassifications were found for reclining, and tidy up (see also Supplementary file 3). Additionally, we calculated the accuracy for each participant, revealing a range from 80.8-99.3% across all conditions, 90-100% for the full-standardized conditions, and 76.7-99.9% for the semi-standardized conditions.

According to the overall results, the ActiGraph showed weak to excellent validity. Separated by full- and semi-standardized conditions, the ActiGraph showed weak to excellent validity for the full-standardized conditions and good to excellent validity for the semi-standardized conditions. Considering the individual conditions, a higher number of misclassifications were found for conditions with no acceleration such as natural standing, standing still, set the table, or get dressed. Besides the 100 cpm threshold, we also analyzed the data using the 150 cpm threshold and a combined algorithm of the 100 cpm threshold and the inclinometer function. Across all conditions, data revealed no more than +/-1% differences between 100 cpm and 150 cpm threshold, while a combined algorithm increased sensitivity (83%), accuracy (89%), informedness (75%), and decreased specificity (92%). Separated by full- and semi-standardized conditions, again data revealed no more than +/-1% differences between 100 cpm and 150 cpm threshold, whereas a combined algorithm increased sensitivity (full: 97%; semi: 69%), specificity (full: 38%), accuracy (semi: 90%), informedness (full: 35%; semi: 64%), markedness (full: 60%) and decreased accuracy (full: 85%), specificity (semi: 95%) ,and markedness (semi: 71%). Additionally, we calculated the accuracy for each participant, revealing a range from 76.7-88.4% across all conditions, 88.6-90.1% for the full-standardized conditions, and 73.5-87.9% for the semi-standardized conditions.

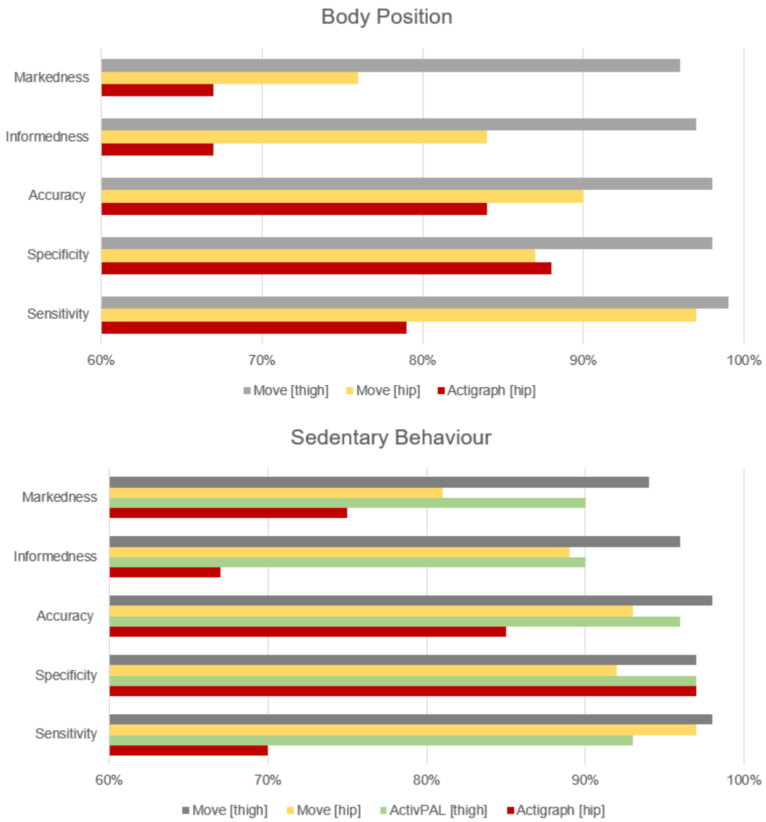

Figure 3. Summary of all validity parameters across all conditions.

The Move 4 accelerometer attached at the thigh showed excellent validity across all conditions and for the full-standardized conditions. Moreover, the Move 4 [thigh] showed good to excellent validity for the semi-standardized conditions. Taking into account the individual conditions, a higher number of misclassifications were found for tidy up and cycling. Additionally, we calculated the accuracy for each participant, revealing a range from 91.6-

99.6% across all conditions, 95.6-100% for the full-standardized conditions, and 90.6-99.7% for the semi-standardized conditions.

The Move 4 accelerometer attached at the hip showed good to excellent results across all conditions and weak to excellent validity for full- and semi-standardized conditions, respectively. Considering the individual conditions, a higher number of misclassifications were found for leaned forward conditions such as sitting leaned forward, working at PC or reading newspaper. Additionally, we calculated the accuracy for each participant, revealing a range from 85.9-99.6% across all conditions, 89.2-100% for the full-standardized conditions, and 85.1-99.8% for the semi-standardized conditions. A comprehensive overview, including confusion matrices per condition for each activity monitor, is provided in the appendix (see Supplementary file 3). Findings are summarized in Figure 3 showing all validity parameters.

Discussion

The purpose of the study was to determine the validity of different accelerometers to measure body position and sedentary behaviour in healthy adults while performing a structured study protocol with a series of full- and semi-standardized activities. In line with previous studies (Grant et al., 2006; Kim et al., 2015; Kozey-Keadle et al., 2011), the ActivPAL showed almost excellent validity for measuring sedentary behaviour. The ActiGraph showed weak to good validity for the measurement of body position and weak to excellent validity for the measurement of sedentary behaviour. The results of the thigh-worn Move 4 showed excellent validity for measuring body position and sedentary behaviour. The Move 4 attached at the hip revealed moderate to excellent validity for measuring body position and good to excellent validity for measuring sedentary behaviour.

The accelerometer devices in our study show to differ in validity results. A primary reason this is the sensor position (hip vs. thigh) (Cleland et al., 2013). Since accelerometers became the method of choice for the assessment of physical behaviours (i.e., sleep, physical activity, and sedentary behaviour), hip or wrist-worn accelerometers were recommended for population-based physical behaviour research (Sievanen & Kujala, 2017). Aiming to provide a comprehensive range of activities, especially the hip position, is prone to be the best single location (Cleland et al., 2013). However, growing interest over the past decade in sedentary behaviour research clarified that the hip position increases the risk of misclassification between a sitting and a standing body position (Dowd et al., 2012; Kang & Rowe, 2015). The results of our study support this point of view since both hip-worn accelerometers revealed not consistently excellent results. For example, sitting with a forward leaned upper body was highly misclassified as a non-sitting/lying body position and thus as non-sedentary behaviour. Another misclassification-risk concern the used algorithm, since there is evidence that using only an intensity thresholds such as 100 or 150 cpm and not a combination of intensity and postural components lead to the risk of an overestimation of sedentary behaviour (Gibbs, Hergenroeder, Katzmarzyk, Lee & Jakicic, 2015; Janssen & Cliff, 2015; Rosenberger, 2012). Additional analyses of the ActiGraph revealed that a combined algorithm (i.e., ≤ 100 cpm and inclinometer-function: sitting/lying) showed better results than just an intensity threshold of 100/150 cpm, as used by ActiGraph. However, the posture classification of the ActiGraph GT3X+ should be carefully interpreted, since we found in line with other studies a potentially large risk of misclassifications (Hänggi, Phillips & Rowlands, 2013; McMahon, Brychta & Chen, 2010). To sum up, to measure sedentary behaviour validly, it is inevitable to consider both parts of the sedentary behaviour definition (i.e., postural part and movement intensity/EE part) (Fanchamps et al., 2018).

Both, the ActivPAL and the Move 4 attached at the thigh showed almost excellent ratings for the assessment of sedentary behaviour. Thus, in line with the results of our study and as a possible implication for future studies. The Physical Activity, Sitting, and Sleep consortium (ProPASS) emphasizes to use thigh-worn activity monitors as they provide information on multiple dimensions of movement behaviour, including movement intensity (e.g., light, moderate and vigorous PA) and posture (e.g., sitting/lying, standing) (Stamatakis et al., 2019). Given the technological advancements, thigh-worn accelerometers provide greater ability to distinguish between different body postures robustly and, thus establishes the basis for a valid recording of sedentary behaviour (Byrom, Stratton, Mc Carthy & Muehlhausen, 2016). Therefore, if sedentary behaviour is of primary interest, we recommend using thigh-worn accelerometers such as the ActivPAL or the Move 4, which enables researchers to perform more precise recording of sedentary behaviour compared to the usage of other sensor positions such as hip-worn accelerometers.

Since research about physical activity, sedentary behaviour, and sleep has become widely differentiated, a bunch of knowledge has been generated.

However, although those behaviours belong in principle to the same construct, i.e., physical behaviour, the relationship between each (in)activity is quite unexplored (Rosenberger et al., 2019). This leads to crucial unanswered questions such as whether the adverse health effects of sedentary behaviour are independent of physical activity or not. Therefore, according to the 24-h Activity Cycle (24-HAC) (Rosenberger et al., 2019) as a new paradigm of exploring interrelationships between physical behaviours, future studies may be interested in assessing all activities of the 24-h cycle validly. Based on our results and previous studies, we currently recommend a multi-sensor system of at least two sensor positions if the differentiation of both physical activity and sedentary behaviour is of central interest. In particular, thigh-worn accelerometers such as the ActivPAL or Move 4 are preferred to assess physical activity, and sedentary behaviour (Montoye, Pivarnik, Mudd, Biswas & Pfeiffer, 2016; Holtermann et al., 2017) and according to the literature (Quante et al., 2015) an accelerometer attached at the wrist is the position of the choice to assess sleep.

Some limitations of this study merit further discussion. First, according to the definition of sedentary behaviour, both the postural and the energy components are required to operationalize sedentary behaviour (Tremblay et al., 2017). To validate the energy component of the accelerometer, a reference measure of energy expenditure, e.g., using a portable indirect calorimeter might be beneficial for future research (Ainslie, Reilly & Westerterp, 2003). However, according to the compendium of physical activities (Ainsworth et al., 2011), we selected only conditions which could be clearly classified as sedentary behaviour or non-sedentary behaviour. For example, lying or sitting with very little movements such as lying on the back or reading newspaper are classified with an intensity of about 1.3 MET, whereas activities of daily life such as vacuuming or tidy up are classified between 2.5 and 3.3 MET. Moreover, (i) this does not influence the significance of the result that the Move 4 is a valid activity monitor for assessing body positions and (ii) the Move accelerometer had been validated for human energy expenditure already (Anastasopoulou et al., 2014). Second, we recruited a convenience sample of healthy adults, and thus, the validity of the Move 4 accelerometer should be substantiated in different samples such as in children or older adults. Third, the ecological validity is limited, since we did not assess a 24-h phase in daily life with a criterion measure such as video recording. Although some previous studies used ActivPAL monitors solely as the criterion measure, we call for further studies to use wearable camera systems to validate the Move 4 during free-living activities (Harms et al., 2019; Loveday, Sherar, Sanders, Sanderson & Esliger, 2015). Moreover, to validate accelerometers during a 24-h cycle in daily life, would clearify unanswered questions such as wheather the accelerometers are able to classify car driving as a sedentary behaviour and particularly to clearify wheather accelerometers are able to distinguish between sleep and lying/sitting still and wheather a multisensor system (e.g., wrist and thigh) is necessary.

Conclusion

Using video recordings as a criterion measure, our laboratory study revealed that thigh-worn devices, i.e., the ActivPAL and Move 4 achieved up to excellent validity for the assessment of sedentary behaviour in comparison to hip-worn devices (Move 4 [hip] and ActiGraph). Moreover, the Move 4 attached at the thigh showed excellent validity for measuring body position. Since there are is a pressing need to develop objective field methods to assess sedentary behaviour, the Move 4 accelerometer can be seen as a valid device. From a public health perspective, it is an urgent issue to garner deeper understanding about the construct of sedentariness with its adverse effects on human health and to find answers on questions such as whether the effects of sedentary behaviour are independent of physical activity or not. Researchers can answer these societal relevant issues only based on a valid assessment of sedentary behaviour.

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Supplementary files

Supplementary file 1: Study protocol.

Nr.	Condition	Instruction	Location	Duration [min]
1	Natural lying	Lying in habitual way	Gym	2
2	Lying horizontal	Lying on back with straight legs	Gym	2
3	Lying left	Lying on left side with bended legs	Gym	2
4	Lying right	Lying on right side with bended legs	Gym	2
5	Lying prone	Lying on bellies with straight legs	Gym	2
6	Reclining	Lounging with stretched legs on a chair	Gym	2
7	Natural sitting	Sitting in habitual way	Gym	2
8	Sitting leaned forward	Sitting with leaned forward upper body on a chair	Gym	2
9	Sitting leaned backward	Sitting with leaned backward upper body on a chair	Gym	2
10	Sitting crossed leg right	Sitting with a crossed right leg on a chair	Gym	2
11	Sitting crossed leg left	Sitting with a crossed left leg on a chair	Gym	2
12	Natural standing	Standing in their habitual way	Gym	2
13	Standing still	Standing with no contribution from the upper body	Gym	2
14	Standing still with upper body movement	Standing with some contribution from the upper body that causes an increase in energy expenditure (i.e., dribbling a ball)	Gym	2
15	Light activity	Take a slow walk in habitual way	Gym	3
16	Working at PC	Working at PC in habitual way	Gym	3
17	Set the table	Set the table in habitual way	Gym	3
18	Reading newspaper	Reading newspaper in habitual way	Gym	3
19	Tidy up	Tidy up in habitual way	Gym	3
20	Get dressed	Get dressed in habitual way	Gym	3
21	Put sheet on the bed	Put sheet on the bed in habitual way	Gym	3
22	Smartphone usage	Smartphone usage in habitual way	Gym	3
23	Hang out the laundry	Hang out the laundry in habitual way	Gym	3
24	Vacuuming	Vacuuming in habitual way	Gym	3
25	Window cleaning	Window cleaning in habitual way	Gym	3
26	Slope up – slope down	Climbing stairs	Gym	3
27	Walking 2,8 km/h	Walking with 2,8 km/h by following a bicycle with a speedometer	Tartan track	5
28	Walking 3,2 km/h	Walking with 3,2 km/h by following a bicycle with a speedometer	Tartan track	5
29	Walking 5,4 km/h	Walking with 5,4 km/h by following a bicycle with a speedometer	Tartan track	5
30	Jogging 7,6 km/h	Jogging with 7,6 km/h by following a bicycle with a speedometer	Tartan track	5
31	Jogging 12,0 km/h	Jogging with 12,0 km/h by following a bicycle with a speedometer	Tartan track	3
32	Cycling	Riding a bike in habitual way	Tartan track	5
33	Daily life	Individuals perform their normal daily routines	Tartan track	24 h

II

Supplementary file 2 Confusion matrices of body position for each condition.

CONDITIONS		ActiGraph GT3X+		Move 4 hip		Move 4 thigh	
		Sitting/ lying	*Non sitting /lying*	*Sitting/ lying*	*Non sitting /lying*	*Sitting/ lying*	*Non sitting /lying*
Natural Lying	*Sitting/lying*	2015	212	2227	0	2227	0
	Non sitting/lying	0	0	0	0	0	0
Lying horizontal	*Sitting/lying*	2121	109	2230	0	2230	0
	Non sitting/lying	0	0	0	0	0	0
Lying left	*Sitting/lying*	2239	1	2240	0	2240	0
	Non sitting/lying	0	0	0	0	0	0
Lying right	*Sitting/lying*	1561	664	2225	0	2225	0
	Non sitting/lying	0	0	0	0	0	0
Lying prone	*Sitting/lying*	1996	269	2237	28	2245	20
	Non sitting/lying	0	0	0	0	0	0
Reclining	*Sitting/lying*	2220	5	2225	0	2225	0
	Non sitting/lying	0	0	0	0	0	0
Natural Sitting	*Sitting/lying*	2166	54	2035	185	2220	0
	Non sitting/lying	0	0	0	0	0	0
Sitting leaned forward	*Sitting/lying*	985	1260	596	1649	2245	0
	Non sitting/lying	0	0	0	0	0	0
Sitting leaned backward	*Sitting/lying*	1939	316	2255	0	2255	0
	Non sitting/lying	0	0	0	0	0	0
Sitting crossed leg right	*Sitting/lying*	2260	0	2260	0	2260	0
	Non sitting/lying	0	0	0	0	0	0
Sitting crossed leg left	*Sitting/lying*	2235	5	2240	0	2240	0
	Non sitting/lying	0	0	0	0	0	0
Natural standing	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	729	1501	36	2194	0	2230
Standing still	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	611	1654	0	2265	0	2265
Standing still with upper body movement	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	695	1514	0	2209	0	2209
Light activity	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	276	3149	0	3425	4	3421
Working at PC	*Sitting/lying*	2787	653	2294	1146	3440	0
	Non sitting/lying	0	0	0	0	0	0
Set the table	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	1146	2146	9	3283	16	3276
Reading newspaper	*Sitting/lying*	2789	646	2214	1221	3435	0
	Non sitting/lying	0	3	3	0	3	0
Tidy up	*Sitting/lying*	806	374	491	689	1174	6
	Non sitting/lying	17	175	37	155	42	150
Get dressed	*Sitting/lying*	32	9	27	14	41	0
	Non sitting/lying	757	1848	136	2469	89	2516
Put sheet on the bed	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	944	2418	14	3348	4	3358

CONDITIONS		ActiGraph GT3X+		Move 4 hip		Move 4 thigh	
		Sitting/ lying	*Non sitting/ lying*	*Sitting/ lying*	*Non sitting/ lying*	*Sitting/ lying*	*Non sitting/lying*
Smartphone usage	*Sitting/lying*	2064	526	1985	605	2572	18
	Non sitting/lying	189	635	38	786	21	803
Hang out the laundry	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	799	2314	87	3026	2	3111
Vacuuming	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	869	2501	120	3250	7	3363
Window Cleaning	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	1109	2310	16	3403	3	3416
Slope up / slope down	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	35	3244	177	3102	0	3279
Walking 2.8 km/h	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	119	5856	12	5963	0	5975
Walking 3.2 km/h	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	84	5792	130	5746	0	5876
Walking 5.4 km/h	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	4	5836	0	5840	0	5840
Jogging 7.6 km/h	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	0	5880	0	5880	0	5880
Jogging 12 km/h	*Sitting/lying*	0	0	0	0	0	0
	Non sitting/lying	0	3266	0	3266	167	3099
Cycling	*Sitting/lying*	1738	2329	488	3579	2901	1166
	Non sitting/lying	13	38	0	51	7	44

II

Supplementary file 3. Confusion matrices of sedentary behavior for each condition.

CONDITIONS		activPAL micro		ActiGraph GT3X+		Move 4 hip		Move 4 thigh	
		SB	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*
Natural Lying	*SB*	2119	0	2060	59	2007	112	2007	112
	N-SB	111	0	104	7	111	0	111	0
Lying horizontal	*SB*	2230	0	2230	0	2230	0	2230	0
	N-SB	0	0	0	0	0	0	0	0
Lying left	*SB*	2240	0	2236	4	2240	0	2240	0
	N-SB	0	0	0	0	0	0	0	0
Lying right	*SB*	2225	0	2224	1	2225	0	2225	0
	N-SB	0	0	0	0	0	0	0	0
Lying prone	*SB*	2261	4	2222	43	2126	139	2130	135
	N-SB	0	0	0	0	0	0	0	0
Reclining	*SB*	939	1286	2209	16	2214	11	2214	11
	N-SB	0	0	0	0	0	0	0	0
Natural Sitting	*SB*	2107	113	2157	63	1923	297	2109	112
	N-SB	0	0	0	0	0	0	0	0
Sitting leaned forward	*SB*	2245	0	2196	49	595	1650	2184	61
	N-SB	0	0	0	0	0	0	0	0
Sitting leaned backward	*SB*	2255	0	2246	9	2232	23	2232	23
	N-SB	0	0	0	0	0	0	0	0
Sitting crossed leg right	*SB*	2260	0	2259	1	2245	15	2245	15
	N-SB	0	0	0	0	0	0	0	0
Sitting crossed leg left	*SB*	2240	0	2229	11	2196	44	2196	44
	N-SB	0	0	0	0	0	0	0	0
Natural standing	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	2235	2000	235	36	2199	0	2235
Standing still	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	2265	2253	12	0	2265	0	2265
Standing still with upper body movement	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	2230	691	1539	0	2230	0	2230
Light activity	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	3425	1	3424	0	3425	0	3425
Working at PC	*SB*	3098	171	3112	157	2041	1228	3066	203
	N-SB	171	0	171	0	150	21	150	21
Set the table	*SB*	0	0	0	0	0	0	0	0
	N-SB	182	3205	1462	1977	12	3427	0	3439
Reading newspaper	*SB*	3117	318	3181	254	2056	1379	3145	290
	N-SB	4	0	4	0	0	4	0	4
Tidy up	*SB*	830	106	569	367	225	711	824	112
	N-SB	1382	1120	1087	1415	545	1957	1081	1421
Get dressed	*SB*	36	4	18	22	8	32	8	32
	N-SB	45	3347	1204	2188	148	3244	205	3187
Put sheet on the bed	*SB*	0	0	0	0	0	0	0	0
	N-SB	171	3261	1086	2346	12	3420	4	3428
Smartphone usage	*SB*	2388	203	2289	302	1357	1234	1777	814
	N-SB	50	792	194	648	6	836	9	833
Hang out the laundry	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	3414	1101	2313	56	3358	4	3410

CONDITIONS		activPAL micro		ActiGraph GT3X+		Move 4 hip		Move 4 thigh	
		SB	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*	*SB*	*N-SB*
Vacuuming	*SB*	0	171	4	167	0	171	0	171
	N-SB	0	3256	223	3033	102	3154	0	3256
Window Cleaning	*SB*	0	0	0	0	0	0	0	0
	N-SB	171	3270	1056	2385	8	3433	8	3433
Slope up / slope down	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	3296	4	3292	0	3296	0	3296
Walking 2.8 km/h	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	5975	0	5975	0	5975	0	5975
Walking 3.2 km/h	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	5876	167	5709	0	5876	0	5876
Walking 5.4 km/h	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	5845	0	5845	0	5845	0	5845
Running 7.6 km/h	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	5880	0	5880	0	5880	0	5880
Running 12 km/h	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	3276	0	3276	0	3276	0	3276
Cycling	*SB*	0	0	0	0	0	0	0	0
	N-SB	0	5874	1426	4448	338	5536	2913	2961

Chapter III

Sedentary triggered EMA

Paper 2: Sedentary triggered EMA: A methodological advancement for the assessment of contextual information on sedentary behavior in daily life

Slightly modified version of the submitted manuscript

Giurgiu, M., Niermann, C., Ebner-Priemer, U. W., & Kanning, M. (submitted). Sedentary triggered EMA: A methodological advancement for the assessment of contextual information on sedentary behavior in daily life.

JMIR mHealth and uHealth. doi:10.2196/17852

III

Abstract

Sedentary behavior has received much attention in the scientific community over the past decade. There is growing evidence that sedentary behavior is negatively associated with physical and mental health. However, an in-depth understanding of the social and environmental context of sedentary behavior is missing. Information such as how everyday sedentary behavior occurs throughout the day (e.g., number and length of sedentary bouts), where, when, and with whom it takes place, and what people are doing while being sedentary is useful to inform the development of interventions aimed at reducing sedentary time. However, examining everyday sedentary behavior requires specific methods. The purpose of this paper was (i) to introduce sedentary triggered Ecological Momentary Assessment (EMA) as a methodological advancement in the field of sedentary behavior research and (ii) to examine the accuracy of sedentary triggered EMA in three different studies in healthy adults. Moreover, we estimated the added value of sedentary triggered EMA compared to a simulation of a random-trigger design. Sedentary triggered EMA comprises continuous assessment of sedentary behavior via accelerometers and repeated contextual assessments via electronic diaries (i.e., an application on a smartphone). More specifically, the accelerometer analyzes and transfers data regarding body position (sitting/lying or upright) via Bluetooth Low Energy (BLE) to a smartphone in real-time and triggers the deployment of questionnaires. Each time a participant spends a specified time (e.g., 20 min) in a sedentary position, the e-diary triggers contextual assessments. To test the accuracy of this method, we calculated a percentage score for all triggered prompts in relation to the total number of bouts that could trigger a prompt. Based on the accelerometer recordings, 29.3% of all sedentary bouts were classified as moderate-to-long (20-40 min) and long bouts (≥ 41 min). On average, the accuracy by participant was 82.77% (SD: ± 21.01%), ranging from 71 to 88.22% on the study level. Compared to simulations of random prompts (every 120 min), the accuracy of the sedentary triggered EMA was up to 47.9% higher. Nearly 40% of all prolonged sedentary bouts (≥ 20 min) occurred during work, and in 57% of all bouts, the participants were not alone. Conclusion: Sedentary triggered EMA is an accurate method for collecting contextual information on sedentary behavior in daily life. Given the growing interest in sedentary behavior research, this sophisticated approach offers a real advancement as it can be used to collect social and environmental contextual information or to unravel dynamic associations. Furthermore, it can be modified to develop sedentary triggered mHealth interventions.

Introduction

“Sitting is the new smoking” or “Why a sedentary lifestyle is killing you” - these and similar headlines reached a high level of media attention in recent years. There is growing evidence that sedentary behavior is a behavioral risk factor for human health (Katzmarzyk et al., 2019). In particular, researchers identified that “too much sitting” is a major risk factor for physical and mental health (Faulkner & Biddle, 2013; Owen, Healy, Matthews & Dunstan, 2010). For example, studies indicated that sedentary behavior is associated with cardiometabolic diseases, diabetes mellitus type 2, and mood (Bailey, Hewson, Champion & Sayegh, 2019; Giurgiu et al., 2019; Guo et al., 2019). Since the amount of evidence has been increasing, countries have started to publish public health guidelines for adults to reduce sedentary time (2018 Physical Activity Guidelines Advisory Committee, 2018; Ministry of Health, 2018). However, currently, there are still uncertainties and divergent views on this behavior (Stamatakis et al., 2018; van der Ploeg & Hillsdon, 2017), mainly related to inconsistencies in the definition of sedentary behavior and inaccuracies in the measurement of sedentary behaviors. This paper gives a short overview of sedentary behavior definitions and measurement methods, pointing out the currently recommended ones, and introduces sedentary triggered Ecolgical Momentary Assessment (EMA) as an innovative measurement approach for measuring contextual information.

Defining sedentary behavior

Several different definitions have evolved over the past decade (Tremblay et al., 2017). From a historical perspective, researchers began by classifying sedentary behavior as physical inactivity. Although sedentary behavior is indeed a shape of physical inactivity, the results from physiological studies identified unique mechanisms and characteristics of sedentary behavior and thus suggest that sedentary behavior is an independent behavior with its own facets and not only the absence of physical activity (Hamilton, Healy, Dunstan, Zderic & Owen, 2008). Some definitions focused on postural aspects, whereas others focused on energy expenditure without considering postural aspects (standing vs. sitting) (Magnon, Dutheil & Auxiette, 2018; Tremblay et al., 2017), which is questionable since standing may have distinct effects on health outcomes (Amaro-Gahete et al., 2019; Henson et al., 2016; Thorp, Kingwell, Owen & Dunstan, 2014). To overcome this present confusing state, the Sedentary Behavior Research Network (SBRN) (Tremblay et al., 2017) defined sedentary behavior as "any waking behavior characterized by an energy expenditure ≤ 1.5 metabolic equivalent (METs), while in a sitting, reclining or lying posture." Although this definition is now widely accepted, there are still debates about the definition (Magnon et al., 2018). Notably, the threshold of ≤ 1.5 METs is worth discussing because, on an individual level, the amount of energy expended during sitting might exceed the 1.5-MET threshold (van der Ploeg & Hillsdon, 2017). Nevertheless, currently, the definition of the SBRN seems to be widely accepted and useful for sedentary research.

Measuring sedentary behavior

Most previous studies in the field of sedentary behavior research used self-reported methods such as questionnaires, which have limited validity and are prone to recall biases and social desirability (Gibbs, Hergenroeder, Katzmarzyk, Lee & Jakicic, 2015; Stamatakis et al., 2019). Furthermore, many studies have used TV time as a marker of sedentary behavior to examine adverse health effects (Grontved & Hu, 2011). However, TV time does not reflect all facets of sedentary behavior, and it is confounded by other factors that are relevant for health outcomes such as dietary intake and socioeconomic status (Stamatakis et al., 2018). Therefore, based on the advancements in device-based measurements, new paradigms suggest using activity monitors (Rosenberger et al., 2019). Currently, an increasing number of studies have used device-based measurements of sedentary behavior

(Stamatakis et al., 2019). However, the choice of monitor placement is highly important for measuring a sitting/lying vs. standing posture accurately and, therefore, for meeting the definition mentioned above. Since hip-worn accelerometers are limited to distinguishing between sitting and standing, thigh-worn accelerometers are recommended as the "gold standard" (Janssen & Cliff, 2015; Kang & Rowe, 2015; Stamatakis et al., 2019). Some studies have already used thigh-worn accelerometers: The Maastricht Study, which focused on the etiology of type 2 diabetes (T2DM), its common complications, and its emerging comorbidities, assessed sedentary behavior data from approximately 9000 participants via thigh-worn ActivPALs (Schram et al., 2014). The Prospective Physical Activity, Sitting, and Sleep consortium (ProPASS) provides a detailed overview of existing studies that have used thigh-worn accelerometers (Stamatakis et al., 2019). Although the technical possibilities provide constant progress, this research field is still in its infancy. According to the most recent overview of sedentary behavior and health, there is a pressing need to develop further objective field methods for simultaneously assessing both components of the sedentary behavior definition, i.e., the postural part (sitting/lying) and the movement intensity/energy expenditure part (Katzmarzyk et al., 2019).

What do we (not) know about sedentary behavior?

The latest findings from Stamatakis and colleagues (2019) suggest that sedentariness is associated with all-cause and cardiovascular-disease mortality among the least physically active adults. Similar results were found in other epidemiological studies (Diaz et al., 2017; Katzmarzyk, Church, Craig & Bouchard, 2009). In particular, longer sedentary bouts, i.e., a period of uninterrupted sedentary time such as ≥ 30 min, may lead to detrimental health effects (Dempsey et al., 2018; Dunstan, Thorp & Healy, 2011). However, other studies reported that high levels of moderate intensity physical activity seem to eliminate the mortality risk associated with high sitting (Ekelund et al., 2016), which leads to an inconclusive base of evidence. Although several studies have identified sedentary behavior as a risk factor for health (Faulkner & Biddle, 2013; Katzmarzyk et al., 2019), the evidence regarding whether a physically active lifestyle may negate these adverse risks is inconclusive from an epidemiological perspective.

Furthermore, the evidence regarding the adverse effects of sedentary behavior on health should be interpreted in terms of the problems mentioned above, as different definitions and different measurements naturally lead to different results. While it is indisputable that “too much sitting” is related to risk factors for health, it remains unclear what “too much” is and what the optimal and practical sedentary break patterns are (i.e., type, volume, frequency, intensity, and context) that can buffer negative effects. Therefore, further studies with valid device-based measurements are needed (Rosenberger et al., 2019; Stamatakis et al., 2019).

Currently, thigh-worn accelerometers are the method of choice for measuring sedentary behavior accurately (Stamatakis et al., 2019). However, accelerometers are unable to provide information about the type of or the social and environmental context of sedentary bouts. According to the ecological model (Owen et al., 2011), sedentary behavior is omnipresent in daily life, and it is multifaceted; for example, it can occur during work, leisure-time, household work, or transport. Moreover, in contrast to physical activity, sedentary behavior is invisible, which means that sedentary behavior is merely a procedural subcomponent of purposeful actions such as working, talking, driving, or reading (Gardner et al., 2019). To understand everyday sedentary behavior and its antecedents and consequences, it is crucial to collect information about social and environmental contexts. Up to now, we have known little about what everyday sedentary behavior looks like, where, when, and with whom it takes place, and what people are doing while being sedentary. Moreover, to develop effective intervention strategies, it is valuable to know more about socioecological mechanisms within different contexts. Thus, with the aim of changing sedentary behavior patterns, subjective information regarding social and environmental contextual information as well as social-cognitive determinants is a valuable extension for the use of activity monitors (Gibbs et al., 2015; Kang & Rowe, 2015; van der Ploeg & Hillsdon, 2017).

To the best of our knowledge, there is a lack of studies addressing the social and environmental contexts of sedentary behavior. Fortunately, with EMA, there exists an established approach to assess social and environmental context information in daily life (Ebner-Priemer & Trull, 2009b). For example, Romanzini and colleagues' study with young adults (Romanzini et al., 2019) used an EMA design to examine sedentary behavior contexts and showed that the context with the highest occurrence of sedentary behavior was the home context, the main activity while being sedentary was “watching TV/movies”, and the main social context was “having alone time”. Such pieces of information may enable researchers to tailor context-specific intervention strategies. However, to assess social and environmental contextual information during sedentary episodes or, moreover, to know, when a meaningful moment to intervene occurs, it is crucial to assess variables or to intervene during predefined sedentary episodes (e.g., > 20 min) and not during other everyday life episodes, in which the person is physically active, for instance. The umbrella term “just-in-time adaptive interventions” (JITAIs) describes interventions that provide behavioral support that corresponds to a need in real-time when the individual is at risk of engaging in an adverse health behavior such as prolonged sedentariness. In particular, this approach comprises a system that offers “just-in-time”, automatic behavioral support without individuals' direct participation (Hardeman, Houghton, Lane, Jones & Naughton, 2019). A technical solution for a system that detects, triggers, and collects information about prolonged sedentary behavior is to combine accelerometers and EMA (e.g., via applications on smartphones) (Bussmann, Ebner-Priemer & Fahrenberg, 2009; Ebner-Priemer, Koudela, Mutz & Kanning, 2013). The sedentary triggered EMA approach enables researchers to incorporate information from subjective (e.g., questionnaire) and device-based measures (e.g., accelerometers) precisely in those situations where the event (e.g., prolonged sedentary behavior) occurs.

Objectives

The purpose of this paper is (i) to introduce sedentary triggered EMA as a methodological advancement in the field of sedentary behavior research and (ii) to examine the accuracy of sedentary triggered EMA in three different studies among healthy adults. Moreover, we estimated the added value of sedentary-triggered EMA compared to a simulation of random-trigger designs.

Methods

EMA, sometimes called the Experience Sampling Method (ESM), is currently the state-of-the-art methodology for examining within-subject associations in behavioral relationships (Ebner-Priemer & Trull, 2009a; Kanning, Ebner-Priemer & Schlicht, 2013). Several advantages, such as the ability to assess in everyday life, in real-time and repeated measurements with a high sampling frequency, have led to the use of EMA in a wide range of research areas (Bolger & Laurenceau, 2013). Currently, technological progress enables researchers to collect data in ways that were inconceivable two or three decades ago. For instance, the combination of EMA and external monitors (e.g., accelerometers) provides a wide range of new possibilities, such as triggered EMA - a technical evolution within the EMA methodology. This sampling strategy enables researchers to capture (i) specific behavioral episodes, such as prolonged sedentary behavior, and (ii) to ask participants "just in time" about momentary physical and social contexts or psychological parameters such as mood or stress.

The idea of triggered EMA (or e-diaries) is not entirely new, as Ebner-Priemer and colleagues (Ebner-Priemer, Koudela, Mutz & Kanning, 2013) developed a sophisticated activity-triggered algorithm that focused primarily on physically active episodes in everyday life. Based on similar technical requirements, we developed a sedentary-triggered algorithm for which the following equipment is necessary: a thigh-worn accelerometer (e.g., Move accelerometer; movisens.com), an electronic diary (e.g., an application on a smartphone), and a technical interface between the e-diary and accelerometer (e.g., Bluetooth Low Energy (BLE)) for feedback in real-time. In the presented studies, we used the Move 3 accelerometer, which is a single-unit accelerometer that captures movement acceleration and body positions with a range of ±16 g at a sampling frequency of 64 Hz (movisens GmbH). Raw acceleration was stored on an internal memory card. The Move accelerometer has been shown to be a valid device for recording body positions and energy expenditure (Anastasopoulou et al., 2014; Giurgiu et al., submitted). The sedentary triggered EMA algorithm works as follows: the thigh-worn sensor analyzes data on body position (sitting/lying or upright) and transfers the momentary value of the body position in real-time to the smartphone. Each time a specific (e.g., 20 or 30 min) uninterrupted amount of sitting/lying posture is recorded; an e-diary starts (triggered) to assess real time context information (see Figure 1).

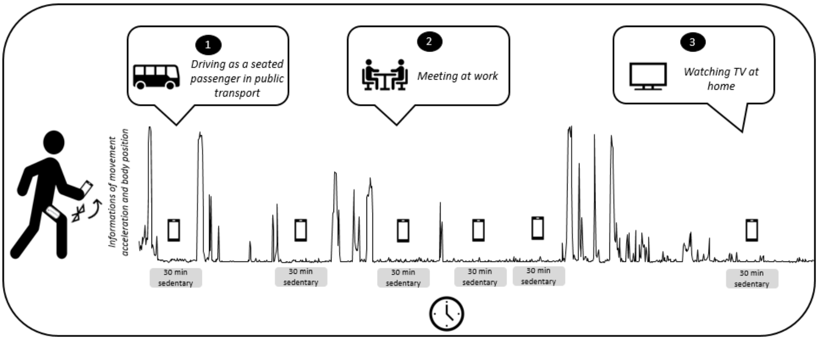

Figure 1: Examples of sedentary triggered EMA in everyday life.

Participant recruitment & Study designs

We used the sedentary triggered EMA system in three different studies, aiming to examine the accuracy of this approach. Table 1 provides an overview of the different study characteristics.

Study 1: We recruited 57 university employees from the Karlsruhe Institute of Technology (KIT, Germany) between May and August 2017. Participants carried a smartphone (Motorola Moto G) and three Move 3 accelerometers for five consecutive days. The thigh-worn monitor and the smartphone were connected via BLE. Sedentary triggered EMA was used within a mixed sampling scheme. In particular, during the time period from 7:30 am to 9:30 pm, participants received sedentary triggered prompts (i.e., after at least 30 min were spent in a sitting/lying position) and randomly triggered prompts at various time points. Additionally, time-out triggers were implemented, occurring not more often than every 40 min and at least every 100 min (see also Table 1). At each EMA prompt, participants were asked about their social (alone vs. not alone) and environmental (home vs. work vs. leisure activities) contexts. Detailed information on the study was described elsewhere (Giurgiu et al., 2019). The study was approved by the institutional review board of the Karlsruhe Institute of Technology (KIT). All eligible participants received written and oral information regarding the study procedures before written informed consent was obtained.

Study 2: We recruited 97 individuals from the University of Konstanz (Germany) between May and July 2019. Sedentary behavior was assessed for four consecutive days (Thursday to Saturday) using Move 3 accelerometers, which were coupled with smartphones (Motorola Moto G) via BLE. During the time period between 6:00 am and 10:00 pm, short questions were asked via the smartphone whenever the person sat for 20 min. We implemented a time-out trigger of 20 min (see also Table 1). The questionnaire included three questions regarding the context: 1) Where are you currently? (response options: workplace, canteen, at home, restaurant, bus/train, car, other); 2) What are you currently doing? (response options: working, resting, eating, leisure, household work, transport, childcare, other); and 3) With whom? (response options: alone, with colleagues, with friends, with family, with strangers, with others). The participants completed a short paper-pencil questionnaire before the EMA phase that included demographic variables, age, sex, educational level, height, and weight.

Study 3: We recruited 72 individuals from the University of Konstanz (Germany) between January and March 2019. For four consecutive days (Monday to Thursday), participants wore a Move 3 accelerometer on their right thigh from the time they got up in the morning to the time they went to bed in the evening. The accelerometer was connected to a smartphone (Motorola Moto G) via BLE. Prior to the assessment, participants received an extensive briefing on the use of the smartphone and accelerometers and completed a paper-pencil questionnaire that included demographic variables (age, gender, and educational level). During the time period between 6:00 am and 10:00 pm, short questionnaires were asked via the smartphone whenever the person sat for 20 min (sedentary trigger). We implemented a time-out trigger of 20 min (see also Table 1). The questionnaire included three questions regarding context: 1) To which domain would you assign your current sedentary activity? (response options: work, leisure, household work, transport); 2) What are you currently doing? (response options depended on the answer to question 1, e.g., work: meeting, leisure: watching TV, household: childcare, transport: reading); and 3) With whom? (response options: alone, with colleagues, with friends, with family, with strangers, with others).

Data were collected anonymously, and the study fully conformed to the Declaration of Helsinki and the ethics guidelines of the German Psychological Society. Participants received detailed information regarding voluntary participation, the handling of the questionnaires and the processing of their data, and they gave written informed consent according to the ethics guidelines of the German Psychological Society (Deutschen Gesellschaft für Psychologie e. V., 2016). According to the guidelines of the ethics committee of the University of Konstanz, the German Research Foundation (Deutsche Forschungsgesellschaft, 2019) and the National Science Foundation (National Science Foundation), studies 2 and 3 were exempt from the institutional Ethics Committee review. The reason was that these two surveys were purely observational (noninvasive, noninteractive) and did not induce any type of psychological stress or anxiety. The participants were not members of a vulnerable group.

Table 1. Study characteristics.

	Study 1	Study 2	Study 3
Duration [days]	5	4	4
Days	Wednesday-Sunday	Thursday-Sunday	Monday-Thursday
Participants	57	97	72
Valid participants[1] (female)	46 (27)	73 (37)	59 (28)
Sedentary trigger	30 min	20 min	20 min
Time out trigger	Minimum: 40 min Maximum: 100 min	20 min	20 min

[1] ≥ two days with ≥ 10h wear time

Study preparation and data preprocessing

The same technological system (i.e., the Move accelerometer and smartphone with Android operating system) was used in all three studies. Thus, from study preparation to data preprocessing, the study procedures were similar (see Figure 2) and included the following nine steps:

First, the sampling scheme and forms (e.g., questions about social and environmental context) were created by using the online platform movisensXS. This step included all set-up such as the selection of study duration, specification of the trigger option (e.g., triggering after 20 min or 30 min of sitting/lying), and implementation of the time-out triggers. Second, immediately before data collection, the study smartphone was connected to the online platform movisensXS by using the movisensXS-App to download the sampling scheme and forms via an individual participant code. Third, the chosen trigger option (e.g., triggering after 20 min of sitting) was calibrated to the selected body position (i.e., lateral aspect of the right thigh) and connected to the smartphone via BLE by using the movisensXS-App. Fourth, after data collection, the recorded raw acceleration data were processed in 1-min intervals by using the manufacturers' software DataAnalyzer (v.1.13.5). This resulted in an Excel sheet with a self-selected choice of parameters such as body position, movement acceleration, or activity class. Fifth, while the raw acceleration data were processed using the DataAnalyzer, a bandpass filter

(0.25 to 11 Hz) automatically eliminated gravitational components or artifacts (e.g., vibrations when cycling on a rough road surface or sensor shocks). Sixth, the smartphone entries from the participants were downloaded from the online-platform movisensXS. Seventh, all accelerometer and EMA files from different participants were synchronized and combined into a single data file by using DataMerger (v.1.8.0). Eight, prior to the analyses, we parametrized sedentary-specific variables such as sedentary bouts while calculating the cumulated sum of the dichotomous variable body position (1= sitting/lying; 0= upright). Ninth, we excluded participants from the data set if they did not fulfill the wear-time criteria of at least 2 valid days, i.e., 10 hours of wear time per day (Troiano et al., 2008), which resulted in final samples for 46 participants in study 1, 73 participants in study 2 and 59 participants in study 3. More details about the technical system used (accelerometer and online platform) are described elsewhere (Giurgiu et al., 2019; von Haaren et al., 2016).

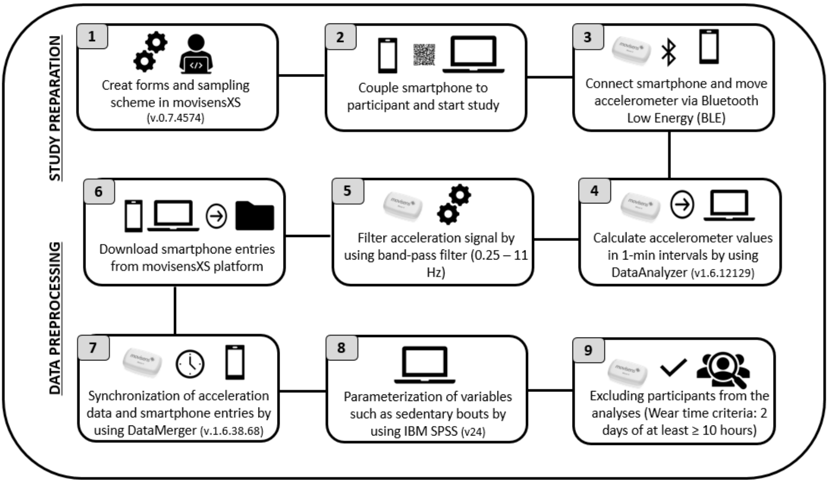

Figure 2: Process of study preparation and data preprocessing.

Statistical analyzes

To test the accuracy of sedentary triggered EMA, we calculated an accuracy score, i.e., the percentage of all triggered prompts in relation to the total number of all "possible" triggered prompts. In particular, we first calculated sedentary bouts based on the cumulative sum of the dichotomous variable body position (1= sitting/lying; 0= upright), which was recorded by the accelerometer, and categorized them into the following categories: short bouts [≤ 5 min], short-to-moderate bouts [5 – 19 min], moderate-to-long bouts [20 – 40 min], and long bouts [≥ 41 min]. Second, we included only moderate-to-long and long bouts in our analyses if the mean acceleration intensity of the bout was < 100 milli-g. Otherwise, sedentary bouts were categorized without considering acceleration or energy expenditure, for instance, a 20 min bout of cycling in a sitting posture would be incorrectly classified as a sedentary bout. Accordingly, we excluded 9.49% (total of 152 bouts) of all moderate-to-long and long bouts in study 1, 4.37% (total of 91 bouts) in study 2, and 1.94% (total of 32 bouts) in study 3. Third, we calculated the accuracy while checking whether, during accelerometer-recorded moderate-to-long and long sedentary bouts, an EMA prompt was triggered. Additionally, we analyzed the added value of sedentary triggered EMA while comparing its accuracy with that of a purely random trigger of i) every 90 min and ii) every 120 min. To add information about the social and environmental context, we used a categorization scheme that fit all studies, i.e., for social interaction: alone vs. not alone and for environmental context: work vs. not work.Results

Descriptive statistics

Table 2 presents the descriptive statistics for each study. Across all studies, we analyzed data from 178 participants (51.4% female) with an average age of 29.25 ± 10.51 years (range: 19-66) and an average Body Mass-Index (BMI) of 23.23 ± 3.1 kg/m2 (range: 17.1-32.4).

Across all studies, participants received 10,771 EMA prompts, i.e., 60.5 ± 26.5 per participant. On average, participants answered 54.63 ± 26.32% (range: 4.6 – 100) of the EMA prompts. According to the accelerometer recordings, participants wore the accelerometer 13.96 ± 1.41 hours per day (range: 10.2 – 18.6). Of that wear time, participants spent on average 9.5 ± 1.74 hours per day (range: 5.49 – 16.57) in a sitting/lying position. Our data revealed that 29.3% of all 17,278 sedentary bouts were classified as moderate-to-long (14.4%) and long bouts (14.9%), i.e., there were 7.67 ± 1.91 sedentary bouts [≥20 min] (range: 1-13) per participant per day on average.

Table 2. Participant's characteristics.

Variable	Study 1 (n = 46) Mean ± SD (Min-Max)	Study 2 (n=73) Mean ± SD (Min-Max)	Study 3 (n =59) Mean ± SD (Min-Max)
Age [yrs.]	34.0 ± 9.6 (25-62)	28.6 ± 11.6 (19-66)	26.3 ± 8.5 (21-60)
Sex [female %]	58.7%	50.7%	47.5%
BMI [kg/m^2]	22.8 ± 3.3 (17.7-32.1)	23.5 ± 3.0 (17.1-32.4)	not assessed
Total smartphone prompts [a]	12.31 ± 1.86 (8-18)	20.72 ± 7.85 (3-45)	14.83 ± 5.32 (2-29)
Total triggered prompts [a]	7.3 ± 2.99 (2-17)	20.72 ± 7.85 (3-45)	14.83 ± 5.32 (2-29)
Compliance [%] [b]	79.3 ± 17.3 (22.2-100)	43.41 ± 22.5 (4.6-100)	47.49 ± 23.7 (6.8-93.1)
Wear Time accelerometer [h/day] [a]	13.6 ± 1.1 (10.8-16.1)	14.39 ± 1.6 (10.2-18.6)	13.7 ± 1.3 (10.7-16.5)
Physical Activity of complete measurement period [milli-g] [a]	86.87 ± 22.14 (46-148)	81.18 ± 24.78 (32-141)	79.64 ± 20.26 (44-155)
Body position sitting/lying [h/day] [a]	10.2 ± 1.6 (7.4-13.7)	9.3 ± 1.9 (5.7-16.6)	9.16 ± 1.42 (5.5-12.5)
Total number of short sedentary bouts (≤ 5 min) [a]	11.1 ± 6.6 (0-29)	10 ± 6.6 (0-48)	11.9 ± 6.12 (4-39)
Total number of short-to-moderate bouts (6- ≤ 19 min) [a]	6.3 ± 2.6 (0-12)	7.1 ± 2.6 (1-13)	8.6 ± 3.2 (3-18)
Total number of moderate-to-long bouts (20- ≤ 40 min) [a]	3.5 ± 1.5 (0-7)	4 ± 1.8 (0-12)	3.8 ± 1.2 (2-7)
Total number of long sedentary bouts (≥ 41 min) [a]	4.0 ± 1.4 (1-7)	4 ± 1.4 (1-8)	3.6 ± 1.2 (1-6)

[a] aggregated within study day per participant.
[b] percentage of answered EMA prompts across each study sample.

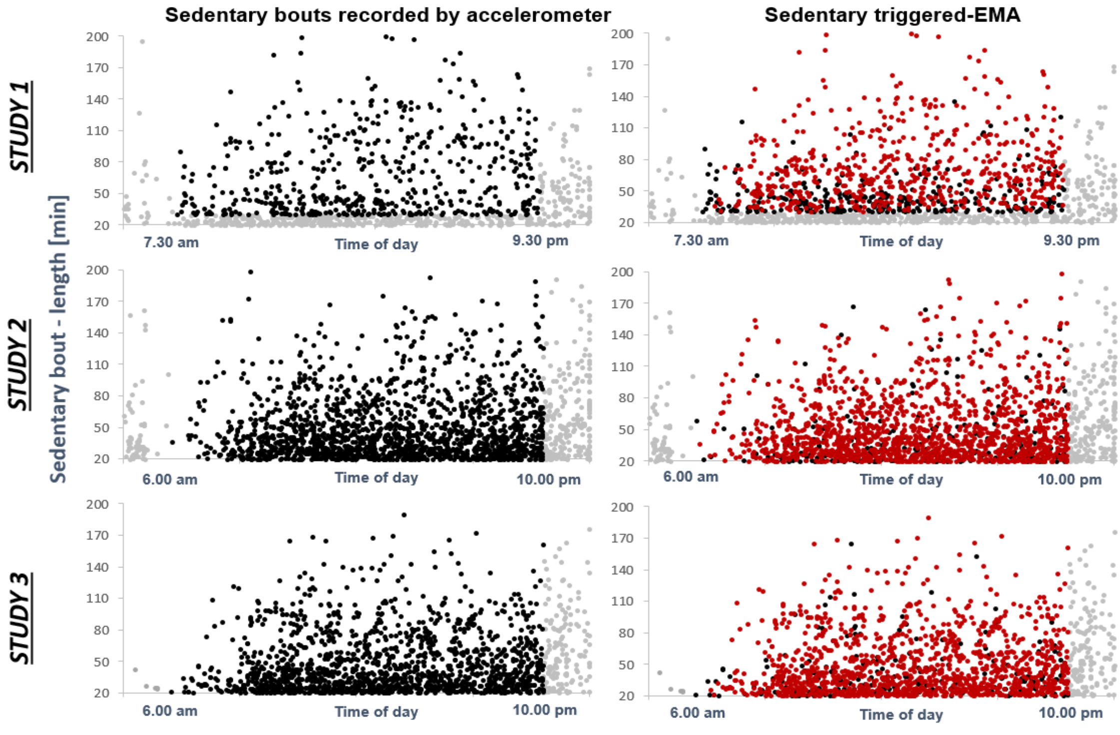

Figure 3: Accuracy of sedentary triggered EMA. Left side: Amount of accelerometer-recorded sedentary bouts per study (black dots: sedentary bouts within the study period; grey dots: sedentary bouts outside of the study period). Right side: Amount of triggered EMA diaries (red dots: triggered sedentary bouts; black dots: not-triggered sedentary bouts.

Accuracy

Figure 3 provides a comprehensive overview of the number of accelerometer-recorded sedentary bouts (left side; black dots) as well as a comprehensive overview of the number of bouts that triggered sedentary triggered EMA (right side; red dots). As a result of a 40-min time-out trigger in study 1 compared to a 20-min time-out trigger in studies 2 and 3, there were fewer triggered bouts (red dots) in study 1 than in studies 2 and 3. Moreover, Figure 3 illustrates that the occurrence of sedentary bouts (≥ 20 min) is widespread over the day, from morning to evening, in all three studies. Overall, 5,063 moderate-to-long and long sedentary bouts [≥ 20 min] were recorded via accelerometer (see also Table 3). A total of 559 bouts were excluded from the analyses because they occurred prior to or after the study period (i.e., 7.30 am – 9:30 pm (Study 1) and 6 am – 10 pm (Study 2 and 3)). Furthermore, since we implemented a sedentary trigger of ≥ 30 min in study 1, we excluded 408 bouts with a length between 20 and 29 min. This resulted in a final number of 4,034 sedentary bouts, which could potentially trigger sedentary triggered EMA. The accuracy calculation revealed that 82.77% of all possible prompts were triggered. Table 3 summarizes the accuracy on a study level.

Our additional analyses revealed that the sedentary triggered EMA in the mixed-sampling design of study 1 was 8.97% and 20.83% higher than that of a simulation of a random-trigger design with prompts every 90 min and 120 min, respectively. In study 2, the accuracy of the purely sedentary triggered EMA design was 34.42% and 43.46% higher than that of a simulation of a random triggered design with prompts each 90 min and 120 min, respectively. In study 3, the accuracy of the purely sedentary triggered EMA design was 34.25% and 47.88% higher than that of a simulation of a random-trigger design with prompts every 90 min and 120 min, respectively. These results indicated that the longer the interval between the prompts, the greater the added value of the sedentary triggered EMA system.

Table 3. Accuracy per study.

	STUDY 1	STUDY 2	STUDY 3
Number of all moderate-to-long sedentary bouts [≥20 min] recorded via accelerometer	1450	1993	1614
Sedentary bouts prior to 6 am/7:30 am	19	70	7
Sedentary bouts after 9.30/10 pm	98	218	147
Sedentary bouts: > 20 < 30 min	464	-	-
Total number of bouts, which could be triggered	869	1705	1460
Triggered sedentary bouts	617	1434	1288
Accuracy of used study design	71.00%	84.11%	88.22%
Accuracy of 90 min random triggered simulation	62.03%	49.69%	53.97%
Accuracy of 120 min random triggered simulation	50.17%	40.65%	40.34%

Each time the participants were prompted, they were asked where they were and with whom. Across all studies, in 42.8% of all answered prompts, the participants were not alone, and in 38.5%, the bouts occurred during work. Specifically, data from study 1 revealed that 50.8% of all moderate-to-long and long bouts occurred during work and 47.2% of participants were alone. Data from study 3 revealed similar results: 55.2% of all moderate-to-long and long bouts occurred during work, and 45% of participants reported that they were alone. In contrast, in study 2, 18.7% of all moderate-to-long and long bouts occurred during work, and 39% of participants were alone.

Discussion

This paper introduced sedentary triggered EMA as an innovative methodological advancement in the field of sedentary behavior research and assessed the accuracy of sedentary triggered EMA in three different studies of healthy adults. The results indicated that sedentary triggered EMA captured 82.77% of all possible sedentary bouts from the different studies. Compared to a simulation of random prompts every 120 min, our data revealed that sedentary triggered EMA had an added value of up to 47.9%. Overall, the results indicate that sedentary triggered EMA is an accurate method and allows to capture social and environmental context information of sedentary behavior bouts.

Enhancing understanding of daily sedentary behavior

Sedentary behavior has received much attention in the scientific community over the past decade. However, in-depth knowledge about this “invisible” behavior is still missing (Gardner et al., 2019; Stamatakis et al., 2018). Since there is a growing number of studies that have found negative health effects due to sedentary behavior (Katzmarzyk et al., 2019), there is now an urgent need to understand more about circumstances surrounding sedentary behavior such as where it occurs, when it occurs, with whom it occurs and what people are doing while being sedentary. Thus, high-quality assessment methods, such as device-based measurements and methods that collect information on domains (e.g., work, leisure, etc.), types (e.g., watching TV while sitting) and contexts (e.g., being alone or in company) of behavior are recommended by researchers (Kang & Rowe, 2015; van der Ploeg & Hillsdon, 2017). Only a few studies differentiated among context-specific sedentary times, such as Dempsey and colleagues (Dempsey et al., 2018), which have shown that higher sitting time was associated with higher levels of individual biomarkers during TV viewing / computer use and lower levels during occupational sitting. In summary, those few studies mainly differentiated between working and nonworking hours (Clemes, O'Connell & Edwardson, 2014; Thorp et al., 2012), whereas the social context remained unconsidered. The social context might be relevant, as, for example, the social withdrawal hypothesis (Kraut et al., 1998) reported that greater use of the internet (which is mostly related to a sedentary position) was associated with declines in individuals´ social interaction and an increase in depression and loneliness. To verify such a hypothesis, sedentary triggered EMA may be a useful approach for examining both social interaction and mood in real time during sedentary bouts (e.g., internet use).

In general, EMA is an established procedure for the assessment of intrapersonal and social and environmental contextual information, and it has been widely used in previous studies, for example, in the field of physical activity research (Koch et al., 2018; Liao, Intille & Dunton, 2015; Niermann, Herrmann, von Haaren, van Kann & Woll, 2016; Reichert et al., 2017). To the best of our knowledge, there are very few studies that have applied an EMA design in the context of sedentary behavior research (Elavsky, Kishida & Mogle, 2016; Kim, Conroy & Smyth, 2019; Maher, Rebar & Dunton, 2018; Romanzini et al., 2019). However, these studies used a time-based and not a trigger-based design. Using only a random time-based design may lead to many prompts being issued during situations other than sedentary bouts. At an extreme, not using triggered EMA may impede researchers from unraveling existing associations between sedentary bouts and intrapersonal, interpersonal and environmental variables (e.g., mood, social interaction, context) if, by chance, these variables were assessed only during short sedentary bouts or episodes of physical activity but not during prolonged sedentary bouts.

These are the first studies that used a sedentary triggered EMA and that assessed social (being alone vs. being with others) and environmental contextual factors (sedentariness during work hours vs. sedentariness during nonwork hours) during prolonged sedentary bouts. Sedentary triggered EMA enables researchers to gather relevant information related to the behavior in real-time. Moreover, sedentary triggered EMA can also be used to unravel dynamic associations. In particular, future researchers may be interested in discovering dynamic associations between sedentary behavior and possible antecedents and consequences. For example, the association between sedentary behavior and time-varying constructs such as mood, stress or working memory. In such a study, it may be reasonable to combine triggered and random prompts to maximize the outcome variance. Furthermore, sedentary triggered EMA can be modified as a methodological system in a just-in-time adaptive intervention (JITAI) (Hardeman et al., 2019). For example, each time an individual exceeds a specific threshold of time spent in sedentary behavior (e.g., ≥ 30 min), mobile apps may deliver behavioral support or encouragement to break-up sedentariness, such as encouraging an individual to stand-up and walk for a few minutes. Finally, a triggered EMA study design minimizes not only retrospective bias but also the burden of participants. In particular, participants would be assessed only in situations in which a behavior of interest occurred (e.g., prolonged sedentary behavior).

Challenges while using sedentary triggered EMA

There are also some challenges when using sedentary triggered EMA. The accuracy depends on both technical stability and user compliance when participating. In particular, technical issues, such as the accelerometer stopping data recording or the accelerometer and the smartphone losing their BLE connection or not reconnecting with each other, may hinder a functional system. Furthermore, the compliance and reliability of the participant with regards to carrying the smartphone throughout the study period is a critical aspect. For example, if the participant leaves the smartphone at home while he is going to work, the BLE connection would not be available, and the trigger system would not work. This may explain why the accuracy for some participants was very low in our studies. Another issue is that if the participant does not wear the accelerometer and puts the sensor on its side, i.e., in a sitting/lying position, this may lead to the incorrect detection of a prolonged sitting bout. A similar problem could occur if the participant did not wear the accelerometer according to the manufacturer's instructions. However, this could be corrected with valid nonwear time algorithms during offline calculations. Finally, the study design highly influences the accuracy. Using a longer time-out trigger, such as in study 1 (40 min), led to a reduced accuracy compared to a shorter time-out trigger, such as in studies 2 and 3 (20 min). In contrast, the compliance with answering EMA prompts was notably higher in study 1 than in studies 2 and 3. Thus, in summary, it is a fine line between collecting as much data as possible and not burdening a participant to the point of decreasing compliance (Stone et al., 2003). This is especially true when the outcome of interest is highly prevalent, as is prolonged sedentary behavior (Hagstromer, Troiano, Sjostrom, & Berrigan, 2010). Therefore, depending on the research question, it could be reasonable to incorporate longer time-out triggers. Alternatively, to achieve a high level of adherence, researchers may tailor the sampling scheme by reducing the number of items or the number of study days (Trull & Ebner-Priemer, 2020).

Conclusions

The results of three independent studies revealed that sedentary triggered EMA is an accurate method for collecting contextual information in daily life. The accuracy of this approach can vary as a function of the study design (e.g., time-out triggers), technical stability (e.g., connection between the smartphone and accelerometer), and compliance of the participants (e.g., following study instructions). Given the growing interest in sedentary behavior research and the lack of knowledge about social and environmental circumstances surrounding sedentary behavior, this sophisticated approach can offer real advancement. Sedentary triggered EMA can be used to collect social and environmental contextual information or to unravel dynamic associations. Furthermore, it can be modified to develop sedentary triggered mHealth interventions.

Conflicts of Interest

Ebner-Priemer receives consultance fees from Boehringer-Ingelheim.

Martina Kanning, Christina Niermann and Marco Giurgiu have no conflicts of interest (non declared).

Abbreviations

EMA: Ecological Momentary Assessment

BLE: Bluetooth low-energy

METs: Metabolic equivalent

SBRN: Sedentary Behavior Research Network

JITAI: Just-in-time adaptive intervention

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III

Chapter IV

Mood-changes as a consequence of sedentary behavior

Paper 3: Sedentary behavior in everyday life relates negatively to mood: An Ambulatory Assessment study.

Slightly modified version of the published paper

Giurgiu, M., Koch, E. D., Ottenbacher, J., Plotnikoff, R. C., Ebner-Priemer, U. W., & Reichert, M. (2019). Sedentary behavior in everyday life relates negatively to mood: An ambulatory assessment study.

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Abstract

Empirical evidence shows that physical behavior positively impacts human health. Recently, researchers have started to differentiate between physical activity and sedentary behavior showing independent effects on somatic health. However, whether this differentiation is also relevant for mood dimensions is largely unknown. For investigating the dynamic relationships between sedentary behavior and mood dimensions in daily life, Ambulatory Assessment (AA) has become the state-of-the-art methodology. To investigate whether sedentary behaviors influence mood dimensions, we conducted an AA study in the everyday life of 92 university employees over 5 days. We continuously measured sedentary behavior via accelerometers and assessed mood repeatedly 10 times each day on smartphone diaries. To optimize our sampling strategy, we used a sophisticated sedentary-triggered algorithm. We employed multilevel modeling to analyze the within-subject effects of sedentary behavior on mood. Sedentary time (15-min intervals prior to each e-diary assessment) and sedentary bouts (30-min intervals of uninterrupted sedentary behavior) negatively influenced valence and energetic arousal (all $Ps < 0.015$). In particular, the more participants were sedentary in their everyday life, the less they felt well and energized. Exploratory analyses of the temporal course of these effects supported our findings. Sedentary behavior can be seen as a general risk factor because it impacts both somatic and mental health. Most importantly, physical activity and sedentary behavior showed independent effects on mood dimensions. Accordingly, future studies should consider the two sides of the physical behavior coin: *How should physical activity be promoted? and How can sedentary behavior be reduced?*

Introduction

Growing evidence shows that physical behavior positively impacts both somatic and mental health conditions among humans (Biddle, 2016; Scheers, Philippaerts & Lefevre, 2012). For example, severe illnesses such as cancer and depression are associated with diminished physical behavior. Past research on physical behavior has been limited to the sole amount of activity. In simple terms, engaging in physical behavior such as exercise and using the stairs in daily life resulted in a dimensional score, for example intensity measured by accelerometry. More recently, researchers have started to divide physical behavior into physical activity and sedentary behavior. According to the Sedentary Behavior Research Network (SBRN) (Sedentary Behavior Research Network, 2017), the latter concept is characterized by a low energy expenditure (≤ 1.5 MET) and a sitting, reclining or lying posture in waking hours. Most importantly, physical activity and sedentary behavior have independent effects on somatic health (Owen, Healy, Matthews & Dunstan, 2010). For example, sedentary behavior has deleterious effects on cardiometabolic health, e.g., levels of insulin resistance and inflammatory markers such as C-reactive protein. This finding is especially true for uninterrupted sedentary bouts that exceed 30 minutes. To which degree such deleterious effects can be compensated by physical activity is an ongoing issue (Ekelund et al., 2016; Stamatakis et al., 2018).

Whereas most studies investigated effects of sedentary behavior on somatic health, by comparison, effects on mental health outcomes are rarely explored (Faulkner & Biddle, 2013). However, evidence for negative impacts of sedentary behavior on mental health outcomes is growing, for example cross-sectional research associated sedentary behavior (e.g., prolonged screen time) with increased risk for mental disorders such as depression (Vancampfort, Stubbs, Firth, van Damme & Koyanagi, 2018) and other mental health outcomes such as psychological distress (Kilpatrick, Sanderson, Blizzard, Teale & Venn, 2013) and well-being (Hamer, Stamatakis, & Mishra, 2010). Moreover, findings from experimental studies added evidence, for instance induced sedentariness showed deleterious effects on anxiety (Edwards & Loprinzi, 2016), or led to mood disturbances (Endrighi, Steptoe & Hamer, 2016).

Mood is a central indicator for both mental well-being in healthy populations and is altered in many mental disorders (e.g., diminished mood in major depression disorder, enhanced mood in manic episodes, high mood fluctuations in borderline personality disorder). Hence, the issue of whether sedentary behavior impacts mood dimensions in everyday life is of major importance and has been subjected to recent investigations. In particular, Ellingson and colleagues (2014) investigated the influence of active and sedentary behaviors on the feelings of energy and fatigue among women (N= 73; age range 20-55 yrs) and showed that being less sedentary was associated with lower levels of fatigue. Another study by Ellingson and researchers (2018) addressed the influence of sedentary behaviors on mood, stress and sleep among healthy adults (N=271). Their longitudinal data suggest that decreasing daily sedentary time may attenuate the negative effects on mood. Using a similar study design, DeMello and colleagues (DeMello et al., 2018) examined the reciprocal relationship between sedentary behavior and mood among young adults (N= 430; age range 21-35 yrs). Based on two measurement points per participant, the researchers discovered the reciprocal relationship that less sedentary behavior was associated with improved mood, and improved mood was associated with less sedentary behavior.

Aggio et al. (2017) investigated the associations between device-based assessment of physical activity and postures (i.e., sitting, standing, and the sit-to-stand transition) and daily affect using a sample of 51 participants (age range 19-41 yrs). However, no significant between- or within-person associations were found between sitting and affect. Elavsky and colleagues (2016) examined the concurrent and lagged relationships between sedentary behavior and momentary affect in the everyday life of middle-aged woman (N= 121; age range 40-60 yrs). Positive and negative affect were assessed four times per day using a personal digital assistant, and sedentary behavior was measured using a hip-worn accelerometer. The study found that sedentary behavior was associated with negative affective consequences (Elavsky, Kishida & Mogle, 2016).

Summarizing the extant literature, studies have rarely investigated the relationship between sedentary behavior and mood, even though this relationship has been discussed as a major issue (Liao, Shonkoff, & Dunton, 2015). Moreover, although previous studies (Ellingson, Kuffel, Vack & Cook, 2014; Ellingson et al., 2018) addressed the negative health consequences of sedentary bouts (≥ 30 min), the within-subject associations between sedentary bouts and mood are rarely investigated. This issue is crucial as sedentary bouts (≥ 30 min) have been identified as a hazard behavior for somatic health outcomes (Hamilton, Healy, Dunstan, Zderic & Owen, 2008).

However, these above mentioned studies have limitations, which limit their conclusiveness on real-life associations between sedentary behavior and mood within individuals. First, although sedentary behavior is measured continuously with thousands of data points, mood is measured rarely (e.g., two or three times per participant). These lack of data preclude dynamic within-subject analyses. Second, sedentary behavior is often only operationalized as energy expenditure or body position (Kang & Rowe, 2015). This limitation affects past conclusions, especially because the use of a single hip-worn accelerometer bears the risks of misclassifying sitting and standing (Kozey-Keadle, Libertine, Lyden, Staudenmayer & Freedson, 2011). For example, different body postures (sitting vs. standing) lead to differences in physiological processes (e.g., isometric contraction or glucose tolerance) that might also impact mental health outcomes (Hamilton et al., 2008; Owen et al., 2010). Most importantly, existing studies do not define sedentary behavior as either a low energy expenditure (≤ 1.5 metabolic equivalents (MET´s)) or as a sitting, reclining or lying posture, but as a combination of both components (sedentarybehaviour.org).

To overcome these limitations and to investigate whether more or less sedentary behavior in everyday life increases or decreases mood dimensions, we conducted an Ambulatory Assessment (AA) study. AA or Ecological Momentary Assessment (EMA) is currently the state-of-the-art methodology for examining the within-subject associations between physical behavior and mood (Ebner-Priemer, Koudela, Mutz & Kanning, 2013; Kanning, Ebner-Priemer & Schlicht, 2013). AA has several advantages; namely, the assessment in everyday life, in real-time, with device-based methods and repeated measurements with a high sampling frequency, which enables researchers to track dynamic relationships. Therefore, it bypasses laboratory distortions and minimizes recall biases associated with traditional approaches such as paper-pencil questionnaires (Bussmann, Ebner-Priemer & Fahrenberg, 2009; Fahrenberg, Myrtek, Pawlik & Perrez, 2007). In our study, we used three accelerometers as a multisensor-system to assess both components of sedentary behavior, i.e. posture and energy expenditure (Sedentary Behavior Research Network, 2017). In addition, we assessed mood repeatedly (approximately 50 times) to enable dynamic within-subject analyses.

Triggered e-diaries are a technical evolution within AA methodology that maximize the within-subject variance of the parameter of interest. Empirical evidence supports the superiority of triggered e-diaries compared with random assessments (Ebner-Priemer et al., 2013; Törnros et al., 2016). We developed sedentary triggered e-diaries to increase the within-subject variance of the variables of interest. In simple terms, accelerometers monitor and analyze sedentary behavior continuously in real time and e-diary questions are triggered during phases of low or high sedentary behavior. To put it to the extreme: Not using triggered e-diaries may impede researchers from unraveling existing associations between sedentary behavior and mood, because, by chance, mood had been only assessed in situations where only sedentary behavior and no activity occurred.

Based on previous studies as well as theoretical and empirical models (DeMello et al., 2018; Elavsky et al., 2016; Ellingson et al., 2014; Endrighi et al., 2016; Koch et al., 2018; Reichert et al., 2017; Tremblay et al., 2017), we hypothesized that sedentary time [1a] and sedentary bouts (≥ 30-min) [1b] would negatively influence the mood-dimension valence (hypothesis 1). Furthermore, we expected sedentary time [2a] and sedentary bouts [2b] to negatively influence the mood-dimension energetic arousal (hypothesis 2), and sedentary time [3a] and sedentary bouts [3b] would negatively influence the mood-dimension calmness (hypothesis 3). Moreover, we conducted explorative analyses on the time course of the effects.ious studies as well as theoretical and empirical models (DeMello et al., 2018; Elavsky et al., 2016; Ellingson et al., 2014; Endrighi et al., 2016; Koch et al., 2018; Reichert et al., 2017; Tremblay et al., 2017), we hypothesized that sedentary time [1a] and sedentary bouts (≥ 30-min) [1b] would negatively influence the mood-dimension valence (hypothesis 1). Furthermore, we expected sedentary time [2a] and sedentary bouts [2b] to negatively influence the mood-dimension energetic arousal (hypothesis 2), and sedentary time [3a] and sedentary bouts [3b] would negatively influence the mood-dimension calmness (hypothesis 3). Moreover, we conducted explorative analyses on the time course of the effects.

Material and Methods

Participants

University employees from two locations were selected. First, employees were recruited from the University of Newcastle (UoN; *n* = 35), Australia between October 2016 and January 2017. Second, employees were recruited from the Karlsruhe Institute of Technology (KIT; *n* = 57), Germany between May 2017 and August 2017. Only participants without restrictions in performing their daily activities (i.e., those without disease or injury) were included, resulting in a total sample of *n* = 92 participants. Six participants were excluded from this sample for compliance reasons (<30% responses to e-diary prompts). Thus, the final sample consisted of 86 participants (62.8% female, 62.8% KIT), with a mean age of 33.7 yrs and a mean body mass Index (BMI) of 23.5 kg/m^2 (for details see Table 1). The Human Research Ethics Committee of the University of Newcastle (H-2016-0347) and the Ethics Committee of the Karlsruhe Institute of Technology (KIT) approved this study. All eligible participants received written and oral information regarding the study procedures before written informed consent was obtained. Participants were free to withdraw from the study at any time.

Study procedures

Over five days (three weekdays and two weekend days), participants carried a smartphone (Motorola Moto G, Motorola Mobility LLC, Libertyville, IL, motorla.com) and three accelerometers (two move-3 and one ECG-move-3, movisens GmbH, Karlsruhe, Germany, movisens.com) during their everyday life. The 3-dimensional accelerometers were attached to the participants at three distinct positions: the hip (move-3), chest (ECG-move3) and thigh (move-3). Prior to assessment, participants received an extensive briefing on the use of the smartphone and accelerometers and completed a survey including basic demographic measures.

E-Diary sampling strategy

The smartphone prompted the participants via an acoustic, visual, and vibration signal every 40 to 100-min within the 7:30 to 21:30 period, which resulted in a range of eight to 21 triggers per day. To optimize the assessment of the associations between sedentary behavior and mood (as stated above), we developed a sedentary trigger algorithm. In particular, the thigh sensor analyzed and transferred data on body position (sitting/lying or upright) via

Bluetooth Low Energy (BLE) to the smartphone in real time. Each time a participant spent 30 min in a sedentary position, the e-diary triggered mood ratings. In addition, fixed and random triggers were implemented, occurring no more than every 40 min and at least every 100 min. The participants had the opportunity to postpone an e-diary prompt for a maximum of 15 min. To answer a single e-diary prompt it took participants approximately 90 seconds. This mixed-sampling strategy was implemented using the software movisensXS, version 0.7.4574 (xs.movisens.com).

Mood

We used a six-item short scale developed and validated by Wilhelm and Schoebi (2007) to assess fluctuations of mood over time using e-diaries capturing three basic mood dimensions: valence (V), energetic arousal (EA), and calmness (C), with sound psychometric properties (within-subject reliability coefficients ranging between 0.72 and 0.79) in our sample. Following Wilhelm and Schoebi (2007), the KIT participants were presented with the following German translations:

Valence:

a) unwell to well (unwohl-wohl)

b) discontent to content (unzufrieden-zufrieden)

Energetic arousal:

c) without energy to full energy (energielos-energiegeladen)

d) tired to awake (müde-wach)

Calmness:

e) tense to relaxed (angespannt-entspannt)

f) agitated to calm (unruhig-ruhig)

We implemented these bipolar items on visual analogue scales (0-100) in reversed polarity and mixed order.

Physical Behavior

Participants wore accelerometers (see also Study procedures) during the entire measurement period but not during sleep. The triaxial acceleration sensors captured movements and body positions with a range of ± 16 g and a sampling frequency of 64 Hz. Raw acceleration was stored on an internal memory card. The move accelerometer was validated using indirect calorimetry as the gold standard (Anastasopoulou et al., 2014).

Sedentary Behavior and Physical Activity. According to the SBRN terminology consensus project (Sedentary Behavior Research Network, 2017; Tremblay et al., 2017), we defined sedentary behavior as any waking behavior characterized by an energy expenditure ≤ 1.5 METs while in a sitting, reclining or lying posture. In addition, we defined sedentary time as the time spent for any duration (e.g., minutes) or in any context (e.g., work) engaged in sedentary behaviors. Furthermore, we defined a sedentary bout as a ≥ 30-min period of uninterrupted sedentary time. We operationalized physical activity as the movement acceleration intensity (MAI).

Data preprocessing

First, we calculated MAI and METs using the hip accelerometer and body position data (i.e., upright, sitting/lying or unknown) on the thigh accelerometer in 1-min intervals using DataAnalyzer, version 1.6.12129 (movisens.com). The intensity parameter (MAI) represented the vector magnitude of acceleration (milli-g; i.e., g*1000) assessed with the three sensor axes. To eliminate gravitational components from the acceleration signal, we applied a high-pass filter (0.25 Hz). To exclude artifacts (e.g., vibrations when cycling on a rough road surface or sensor shocks) we filtered the acceleration data using a low-pass filter (11 Hz; for details on data processing, see von Haaren et al. (2016)). The body position parameters were created based on angle calculations. In detail, the accelerometer was attached on the right side of the right thigh. Based on the ratio from the vertical thigh to the ventral longitudinal axis of the body, the accelerometer detected either an upright body position (<20°) or a sitting/lying body position (>20°). Second, we merged the minute-by-minute values of the accelerometers (movement acceleration and body position) and the e-diary entries using DataMerger, version 1.6.38.68 (movisens.com). Third, we calculated the variables sedentary time and sedentary bouts. One minute was determined as a sedentary minute when the participant was in a lying/sitting position with an intensity of ≤ 1.5 MET. We parameterized sedentary bouts as a dichotomous variable. That is, uninterrupted sedentary time over a 30-min interval prior to an e-diary assessment was coded as “0”, whereas intervals with at least one break were coded as “1”. Fourth, we aggregated MAI and sedentary time values within the time frames of 5, 10, 15, 20, 25, 30, 35, 40, 50, 60, 70, 80, 90, and 100 minutes before each e-diary entry using SPSS, version 24 (IBM).

Statistical analyses

We focused our main analyses on the 15-min time interval prior to each e-diary assessment based on the results of Schwerdtfeger and researchers (2010) who showed that 15-min intervals of physical behavior are highly associated with momentary ratings of mood (Reichert et al., 2017). To analyze whether sedentary behavior influences mood dimensions, we conducted multilevel analyses (SPSS, version 24, IBM) as the state-of-the-art procedure in analyzing intensive longitudinal data (Bolger & Laurenceau, 2013). We calculated two-level models for each mood-dimension (valence, energetic arousal, and calmness), whereby repeated measurements (on level 1) were nested within participants (level 2). Sedentary time was included as dimensional variable representing the total minutes spent sedentary within the 15-min intervals prior to each e-diary assessment (i.e., 0-15min). Moreover, the physical activity was included as dimensional variable into our main models representing mean MAI within the 15-min intervals prior to each e-diary assessment [milli-g].

First, intraclass correlations (ICCs) were estimated using unconditional models including valence, energetic arousal, and calmness as outcomes. Second, we added the predictors time [hours], time-squared [hours2], sedentary time [min], physical activity [milli-g], age [yrs], sex [male vs. female], country [KIT, Germany vs. UoN, Australia], day [weekend day vs. weekday] and BMI [kg/m2] to our models. To standardize time and time-squared, we subtracted the start time of the study for each day (7:30). Lastly, we included significant ($P < 0.05$) random effects for each predictor. Nonsignificant random effects were deleted, resulting in different models for the three mood dimensions of valence, energetic arousal, and calmness. The final models are presented in the equations below [1-3]. In addition, these models were used for exploratory analyses of the time courses of the effects of sedentary time and physical activity on mood. For this purpose, we entered varying predictors of different cumulative time frames/aggregation levels for sedentary time and physical activity (5, 10, 20, 25, 30, 35, 40, 50, 60, 70, 80, 90, and 100 mins) prior to each e-diary entry.

Valence [hypothesis 1a]

$$Y(\boldsymbol{valence})_{ij} = \gamma_{00} + \gamma_{01} * country_j + \gamma_{02} * age_j + \gamma_{03} * BMI_j + \gamma_{04} * sex_j + \gamma_{10} * \boldsymbol{sedentary\ time}_{ij} + \gamma_{20} * physical\ activity_{ij} + \gamma_{30} * time\ of\ day_{ij} + \gamma_{40} * time\ of\ day_{ij}^2 + \gamma_{50} * weekday_{ij} + u_{0j} + u_{1j} * sedentary\ time_{ij} + u_{3j} * time\ of\ day_{ij} + u_{5j} * weekday_{ij} + r_{ij} \quad [1]$$

Energetic arousal [hypothesis 2a]

$$Y(\boldsymbol{energetic\ arousal})_{ij} = \gamma_{00} + \gamma_{01} * country_j + \gamma_{02} * age_j + \gamma_{03} * BMI_j + \gamma_{04} * sex_j + \gamma_{10} * \boldsymbol{sedentary\ time}_{ij} + \gamma_{20} * physical\ activity_{ij} + \gamma_{30} * time\ of\ day_{ij} + \gamma_{40} * time\ of\ day_{ij}^2 + \gamma_{50} * weekday_{ij} + u_{0j} + u_{1j} * sedentary\ time_{ij} + u_{3j} * time\ of\ day_{ij} + u_{5j} * weekday_{ij} + r_{ij} \quad [2]$$

Calmness [hypothesis 3a]

$$Y(\boldsymbol{calmness})_{ij} = \gamma_{00} + \gamma_{01} * country_j + \gamma_{02} * age_j + \gamma_{03} * BMI_j + \gamma_{04} * sex_j + \gamma_{10} * \boldsymbol{sedentary\ time}_{ij} + \gamma_{20} * physical\ activity_{ij} + \gamma_{30} * time\ of\ day_{ij} + \gamma_{40} * time\ of\ day_{ij}^2 + \gamma_{50} * weekday_{ij} + u_{0j} + u_{2j} * physical\ activity_{ij} + u_{3j} * time\ of\ day_{ij} + u_{5j} * weekday_{ij} + r_{ij} \quad [3]$$

On level 1, within-subject effects were estimated using participants´ (subscript $_j$) e-diary entries at any time of measurement (subscript $_i$). Y_{ij} represents the level of valence, energetic arousal and calmness, respectively, in person *j* at time *i*. Beta coefficients represent the intercept (β_{0j}) and the effects of time, time-squared, sedentary time, physical activity and day ($\beta_{1j} - \beta_{5j}$) at level 1, and r_{ij} represents the residuals at level 1. We centered sedentary time and physical activity on the participant mean to differentiate within-person from between-person effects. On level 2, between-subject effects were estimated. We included random effects (i.e., individual variation on the sample mean effect γ) for each mood dimension represented as μ_{ij}. Random slope parameters ($\mu_{1j} - \mu_{5j}$) were included only if significant variation was observed across participants. To compare the effects of sedentary behavior with other predictors, we calculated standardized beta coefficients (standardized BC) following established procedures (Hox & Roberts, 2014). Finally, we computed additional robustness analyses to test whether the exclusion criteria for participants may influence the results. In particular, we recalculate the main models with stricter compliance rates of at least ≤ 40% and ≤ 65% answered e-diary prompts. Moreover, we tested whether the results are robust against accelerometer wear-time (i.e., including only participants with at least three valid days of ≥ 10 h wear time).

Results

Descriptive statistics

The 86 participants included in our analyses were prompted 5352 times across 5 days (i.e., 9.91 prompts/participant/day on average; Range = 3.5-18.1; SD= 2.4). Approximately 51.7% of all prompts occurred at random time points, and 48.3% occurred when the participants remained ≥ 30-min in a sitting/lying position triggered by our real-time *sedentary trigger algorithm* (see above). On average, participants answered 75.5% of all prompts (SD = 17.2%). Participants reported average mood scores of 75 (valence), 63 (energetic arousal) and 68 (calmness), indicating a well-tempered sample (for details see Table 1). The ICCs revealed that 57% (ρ_I = 0.425; valence), 68% (ρ_I = 0.318; energetic arousal) and 59% (ρ_I = 0.407; calmness) of the variance in the mood ratings was due to within-subject fluctuations. On average, accelerometers were worn for 13.39 h/participant/day (Range = 5-22; SD = 3.8). Participants spent 7.2 h/participant/day sedentary (i.e., sitting/lying/reclining with an energy expenditure ≤ 1.5 METs; Table 1). Following the sedentary bout classification of Straker et al. (2014), 59.8% of all bouts were short bouts (≤ 5-min), 29.9% were moderate bouts (> 5 and ≤ 30-min) and 10.4% were long bouts (≥ 30-min). Our participants showed a frequency of 4.8 sedentary bouts of at least ≥ 30 minutes per day on average (see Table 1).

Table 1. Participants characteristics

	N	Sex (female)	Age (yrs.) (SD; Range)	BMI (kg/m^2) (SD; Range)	Sedentary Time[a] (hs/day)	Sedentary Bouts (≥ 30-min)[b] (N/day)	Physical Activity[c] (milli-g min^{-1})	V[d]	EA[e]	C[f]
UoN	32 (37%)	25 (78%)	32.6 (9.2) 22-59	24.38 (3.3) 19.38-32.49	6.8 (1.8) 2.9-12.3	4.8 (2.6) 1.1-6.2	63.2 (13.0) 43.8-92.0	78.1 (15.1) 30.6-96.4	63.4 (15.7) 26.8-87.9	71.8 (15.8) 30.1-95.9
KIT	54 (63%)	29 (54%)	34.4 (9.4) 25-62	22.9 (3.1) 17.67-32.14	7.3 (2.9) 1.4-16.1	4.8 (2.7) 0.7-7.8	66.1 (16.5) 31.7-95.5	73.3 (9.4) 50.4-89.5	63.1 (11.4) 35.6-92.6	65.7 (12.1) 26.5-87.6
Sum	86	54 (63%)	33.7 (9.3) 22-62	23.5 (3.2) 17.67-32.49	7.2 (2.5) 1.4-16.1	4.8 (2.7) 0.7-7.8	65.03 (15.3) 31.7-95.5	75.1 (12) 30.6-96.4	63.2 (13.1) 26.8-92.6	68 (13.8) 26.5-95.5

[a]Sedentary time: Hours per day and per participant spent sedentary
[b]Sedentary bout: Frequency of sedentary bouts ≥ 30 min per day and per participant
[c]Physical activity: Movement acceleration intensity (MAI) per day and per participant
[d]Valence: Mood dimension unwell up to well (0-100; assessed via e-diary, aggregated within participants per day)
[e]Energetic arousal: Mood dimension ranging from tired to awake (0-100; assessed via e-diary, aggregated within participants per day)
[f]Calmness: Mood dimension ranging from tense to relaxed (0-100; assessed via e-diary, aggregated within participants per day)

Effects of Sedentary Behavior on Mood

Valence. As hypothesized (hypothesis 1a), sedentary time negatively predicted valence (standardized BC = -0.082; P = < 0.001), i.e., spending more time sedentary was associated with lower prospective moods. In particular, being sedentary for 15 min instead of 5 min resulted in a decreased valence by 3 units on average (scale 0-100). Furthermore, time and time-squared significantly influenced valence (P < 0.001) in both negative (time: standardized BC = -0.212) and positive (time-squared: standardized BC = 0.261) directions. In practice, valence decreased during the day until approximately 2 pm, followed by a subsequent increase until the end of the day. However, physical activity (P = 0.074) and the between-subject predictors (day, BMI, age, sex, and country) did not influenced valence (Table 2). We found significant random effects for time (P = < 0.001), sedentary time (P = 0.005) and day (P = < 0.001), indicating variability between participants in their individual association between time and valence, sedentary time and valence, and day and valence. Detailed results are shown in Table 2.

To analyze whether sedentary bouts of ≥ 30 min predicted valence compared with interrupted bouts (i.e., standing) with at least one break (hypothesis 1b), we calculated the same model presented above (equation 1) but replaced sedentary time (continuous variable) with sedentary bout (dichotomous variable). Table 3 shows the fixed and random effects of these models. As hypothesized, sedentary bouts (≥ 30 min) negatively influenced valence (standardized BC = -0.035; P = < 0.015) compared with interrupted bouts; i.e., being sedentary for 30 minutes without interruption was associated with lower prospective moods.

Energetic arousal. Sedentary time negatively predicted energetic arousal (P < 0.001; standardized BC= -0.119), thereby verifying hypothesis 2a, i.e., more sedentary time was associated with lower prospective energetic arousal (see Table 2). In particular, being sedentary for 15 min instead of 5 min decreased energetic arousal by 7.6 units (scale 0-100). Moreover, time-squared was positively related to energetic arousal (P = 0.006; standardized BC = 0.208). In practice, energetic arousal decreased during the day; the level was stable between 8 am and approximately 2 pm, it decreased remarkably from 2 to 11 pm. Furthermore, neither physical activity (P = 0.122) nor between-subject predictors (day, BMI, age, sex, and country) predicted energetic arousal (see Table 2). We found significant random effects for time (P < 0.001), sedentary time (P = 0.007) and day (P < 0.001) revealing the individual slopes varied between participants. Sedentary bouts (≥ 30 min) also negatively predicted energetic arousal (standardized BC= -0.055; $P < 0.001$; Table 3), thereby confirming hypothesis 2b. Being sedentary for 30 minutes without any interruption was associated with lower prospective energetic arousal.

Calmness. Sedentary time during 15 minutes prior to the e-diary prompt did not significantly predict calmness ($P = 0.053$). However, other time frames did (see the next section). Neither sedentary bouts ($P = 0.853$) nor physical activity ($P = 0.27$) predicted calmness. Thus, hypothesis 3a and 3b were not verified. Time and time-squared were significantly related to calmness ($P < 0.001$ and $P < 0.001$) with opposing effect directions (standardized BC time = -0.258; standardized BC time-squared = 0.221). In particular, calmness decreased during the day until approximately 1 pm and increased thereafter. Furthermore, day of the week was significantly associated with calmness ($P = 0.005$); specifically, on weekends, participants felt more relaxed than on weekdays (standardized BC = 0.081). None of the between-subject predictors (BMI, age, sex, and country) influenced calmness. Time, physical activity, and day showed significant random effects ($P < 0.001$; $P = 0.003$; and $P < 0.001$), thereby indicating between-subject variation. Additional robustness analyses reveal that the associations between sedentary behavior and mood dimensions did not vary as a function of different exclusion criteria (compliance rate and accelerometer wear time).

Table 2. Multilevel model analyses predicting mood: Fixed and random effects of time [h], time-squared [h^2], sedentary time [min], physical activity [mg], day, BMI [kg/m^2], sex, age [yrs], and country

Outcome		Fixed effects					Random effects			
	Predictor	beta-coefficient	Standardized β-coefficient	Standard Error	t-value (df)	P-value	Variance Estimate	SD	Wald-Z	P-value
Model 1: Valence	Intercept	62.62		10.20	6.14	<0.001	158.59	4.19	37.83	<0.001
	Time	-0.997	-0.212	0.282	-3.53	<0.001	0.269	22.60	4.84	<0.001
	Time^2	0.079	0.261	0.018	4.48	<0.001				
	Sedentary time	-0.301	-0.082	0.082	-3.67	<0.001	0.149	0.053	2.81	0.005
	Physical activity	-0.008	-0.037	0.004	-1.79	0.074				
	Day (weekend)[a]	2.035	0.054	1.063	1.92	0.059	31.623	6.84	4.63	<0.001
	Age	0.077		0.151	0.51	0.611				
	BMI	0.494		0.449	1.10	0.274				
	Sex (female)[b]	-2.154		2.808	-0.77	0.445				
	Country (Australia)[c]	4.433		2.910	1.52	0.132				
Model 2: Energetic arousal	Intercept	52.47		12.05	4.36	<0.001	145.10	31.47	4.61	<0.001
	Time	0.032	0.005	0.386	0.08	0.935	0.929	0.233	3.98	<0.001
	Time^2	-0.065	0.208	0.024	-2.74	0.006				
	Sedentary time	-0.547	-0.119	0.108	-5.05	<0.001	0.243	0.09	2.7	0.007
	Physical activity	0.009	0.034	0.006	1.55	0.122				
	Day (weekend)[a]	-0.599	-0.013	1.12	-0.5	0.618	34.53	8.74	3.95	<0.001
	Age	0.165		0.178	0.93	0.357				
	BMI	0.455		0.538	0.86	0.391				
	Sex (female)[b]	-2.29		3.31	-0.69	0.492				
	Country (Australia)[c]	3.83		3.44	1.11	0.269				
Model 3: Calmness	Intercept	61.31		12.10	5.07	<0.001	151.41	32.10	4.72	<0.001
	Time	-1.429	-0.258	0.341	-4.19	<0.001	0.54	0.162	3.32	0.001
	Time^2	0.119	0.221	0.021	5.64	<0.001				
	Sedentary time	0.178	0.041	0.092	1.94	0.053				
	Physical activity	-0.010	-0.039	0.009	-1.11	0.27	0.001	0.001	2.97	0.003
	Day (weekend)[a]	3.621	0.081	1.24	2.92	0.005	42.4	9.74	4.35	<0.001
	Age	-0.231		0.179	-1.29	0.2				
	BMI	0.642		0.531	1.21	0.23				
	Sex (female)[b]	-1.92		3.34	-0.58	0.567				
	Country (Australia)[c]	4.943		3.45	1.43	0.156				

[a]compared with weekday; [b]compared with males; [c]compared with Germany

Table 3. Multilevel model analysis predicting mood: Fixed and random effects of time [h], time-squared [h^2], sedentary bouts ≥ 30 min], physical activity [mg], day, BMI [kg/m^2], sex, age [yrs], and country

Outcome		Fixed effects					Random effects			
	Predictor	beta-coefficient	Standardized β-coefficient	Standard Error	t-value (df)	P-value	Variance Estimate	SD	Wald-Z	P-value
Model 1: Valence	Intercept	62.78		10.16	6.18	<0.001	117.33	23.07	5.09	<0.001
	Time	-1.076	-0.229	0.284	-3.79	<0.001	0.307	0.09	3.35	0.001
	Time^2	0.087	0.286	0.018	4.92	<0.001				
	Sedentary bouts[a]	-1.375	-0.035	0.566	-2.43	0.015				
	Physical activity	0.011	0.054	0.006	1.92	0.06	0.001	0.00	2.69	0.007
	Day (weekend)[b]	2.156	0.057	1.005	2.15	0.035	29.65	6.29	4.72	<0.001
	Age	0.064		0.149	0.43	0.668				
	BMI	0.541		0.453	1.19	0.236				
	Sex (female)[c]	-0.953		2.837	-0.37	0.738				
	Country (Australia)[d]	2.79		2.91	0.96	0.34				
Model 2: Energetic arousal	Intercept	54.88		12.06	4.55	<0.001	157.44	32.44	4.85	<0.001
	Time	-0.15	-0.026	0.386	-0.39	0.697	0.865	0.220	3.94	<0.001
	Time^2	-0.051	-0.135	0.024	-2.17	0.03				
	Sedentary bouts[a]	-2.70	-0.055	0.758	-3.56	<0.001				
	Physical activity	0.044	0.166	0.008	5.54	<0.001	0.002	0.001	2.72	0.007
	Day (weekend)[b]	-0.502	-0.011	1.166	-0.43	0.668	34.92	8.430	4.14	<0.001
	Age	0.13		0.177	0.74	0.464				
	BMI	0.484		0.537	0.90	0.37				
	Sex (female)[c]	-1.809		3.360	-0.54	0.592				
	Country (Australia)[d]	2.717		3.450	0.79	0.433				
Model 3: Calmness	Intercept	60.75		12.00	5.06	<0.001	158.79	32.50	4.89	<0.001
	Time	-1.52	-0.274	0.347	-4.36	<0.001	0.701	0.187	3.75	<0.001
	Time^2	0.13	0.353	0.021	5.93	<0.001				
	Sedentary bouts[a]	-0.127	-0.003	0.682	-0.19	0.853				
	Physical activity	-0.012	-0.052	0.007	-1.80	0.076	0.002	0.001	2.83	0.005
	Day (weekend)[b]	2.979	0.067	1.191	2.5	0.014	41.18	9.136	4.51	<0.001
	Age	-0.22		0.176	-1.25	0.214				
	BMI	0.712		0.535	1.33	0.186				
	Sex (female)[c]	-1.043		3.35	-0,31	0.756				
	Country (Australia)[d]	2.59		3.433	0.75	0.453				

[a]compared with interrupted bouts; [b]compared with weekday; [c]compared with males; [d]compared with Germany

Effects of Sedentary Time over Time

To test our main hypotheses [1-3], we used 15-min segments of physical activity and sedentary time prior to each e-diary prompt. Although this time frame has been shown to be superior compared with longer time frames with respect to physical activity and mood (Koch et al., 2018; Reichert et al., 2017; Schwerdtfeger, Eberhardt, Chmitorz, & Schaller, 2010), empirical evidence regarding sedentary time is lacking. In simple terms, it might be the case that 15 minutes of sedentary time does not influence mood, whereas 16, 20 or 30 minutes do. The opposite case would also benefit from examining more time windows. Having a significant finding for the 15-minute time frame but no effects for the 10- and 20-minute time frames would question the reliability of the findings. Therefore, we computed a series of additional multilevel models across the smaller (5- and 10-min) and graded (20- to 100-min) time frames. For these additional analyses, we omitted random effects to keep the analyses stable across the additional time frames. Figure 1 depicts the results. The x-axis represents the temporal aggregation level of physical activity and sedentary time in minutes prior to each e-diary prompt.

Valence. Sedentary time predicting valence (solid green line) was stable across distinct time frames. The standardized BCs were negative and significant, ranging from -0.054 (time-frame: 5-min) to -0.091 (time-frame: 80-min). By contrast, physical activity predicting valence (broken green line) did not show significance in any of the models.

Energetic arousal. Sedentary time predicting energetic arousal (solid red line) was stable across distinct time frames. The standardized BCs were negative and significant, ranging from -0.105 (time frame: 5 min) to -0.146 (time frame: 70 min). Moreover, physical activity predicting valence (broken red line) was significant only in the 5-, 10-, and 15-min time-frame models, all with positive beta coefficients.

Calmness. Sedentary time predicting calmness (solid blue line) showed significance only for the 5- and 10-minute time frames. The standardized BCs were positive and ranged from 0.051 (time frame: 5 min) to 0.043 (time frame: 10 min). As mentioned in the hypothesis section of the results, the 15-minute time frame approached significance (P =.053). Physical activity predicting calmness (broken blue line) showed significance only for the 5- and 10-minute time frames, with a negative beta coefficient (ranging from -0.047 to -0.046).

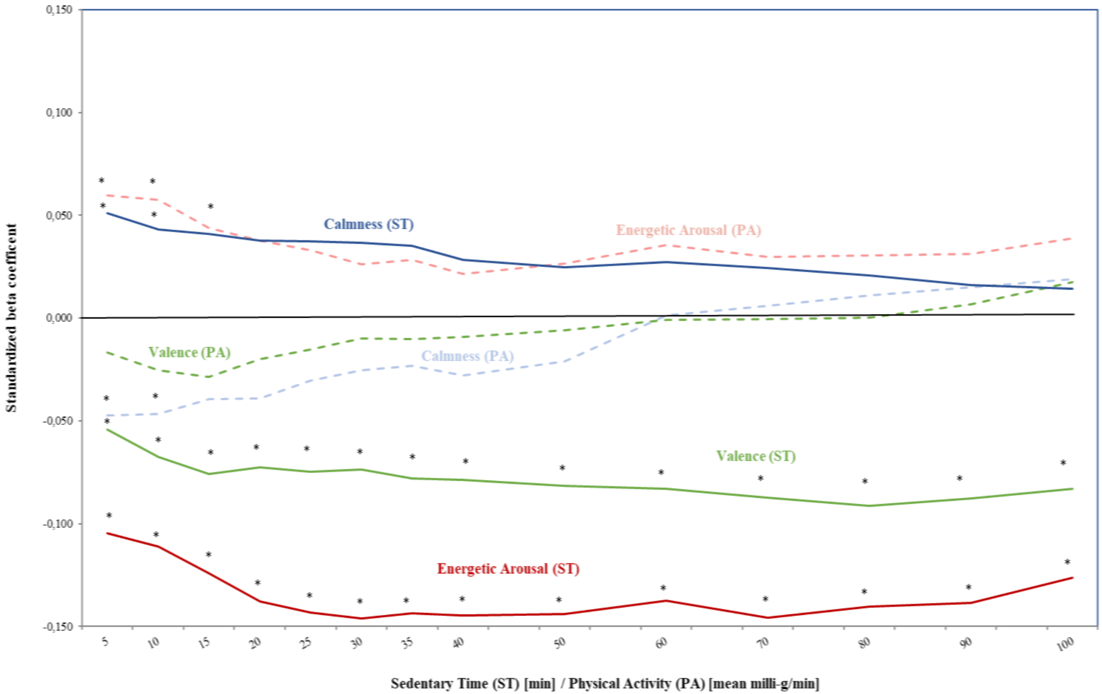

Figure 1. Effects of sedentary time and physical activity on mood averaged within different time frames. The x-axis depicts the temporal aggregation level of sedentary time and physical activity in minutes prior to each e-diary prompt. Accordingly, the value "30" represents the average sedentary time and the average acceleration aggregated within the 30 min prior to each e-diary prompt. The y-axis depicts the standardized BCs from the multilevel models for sedentary time and physical activity to predict valence, energetic arousal and calmness. Significant effects are indicated with * ($P \leq 0.05$).

Discussion

This study investigated the influence of device-based assessment of sedentary behavior on mood dimensions. As hypothesized, we found negative effects of momentary sedentary time on valence and energetic arousal. Moreover, sedentary bouts of ≥ 30 min negatively influenced both valence and energetic arousal compared with interrupted bouts with at least one break (hypotheses 1 and 2). Our analyses did not consistently verify an association between sedentary behavior and the mood-dimension calmness (hypothesis 3).

Momentary sedentary time and bouts (≥ 30-min) showed a significant negative effect on valence: the more time participants spent in sedentary behavior prior to a particular e-diary prompt, the less well they felt. Our additional, exploratory analyses that compared various time frames revealed a stable effect on valence over time, supporting the robustness of our findings. This finding is in line with Elavsky and researchers (2016), who showed that momentary sedentary behavior in real life leads to decreased positive affect and Endrighi et al. (2016), whose experimental finding revealed mood disturbances after two weeks of induced sedentariness and along with longitudinal studies (DeMello et al., 2018; Ellingson et al., 2018). By contrast, Aggio and colleagues (2017) did not find an association between sitting and mood. In principle multiple theories may account for this finding, ranging from evolutionary perspectives (Dual-Mode Model; DMM) (Ekkekakis, 2003) across cognition centered porcesses (rumination about negative health consequences of sedentary behavior) (Owen et al., 2011) to social withdrawal hypothesis for example suggesting that displacement of physical activity or social activities with passive sedentary behavior might encourage social isolation (Kraut et al., 1998).

Sedentary behavior significantly and negatively influenced energetic arousal: the more time participants spent in sedentary behavior prior to a particular e-diary prompt, the less energized they felt. Again, we investigated the robustness of our findings using various time frames which was stable across all investigated time frames. This result is consistent with Ellingson and colleagues (2014), who showed that higher amounts of sedentary bouts are related to higher levels of fatigue. Here, the DMM (Ekkekakis, 2003) may provide one possible evolutionary theory potentially underlying this observation. In very simple terms, it proposes that humans do feel more energized in phases of non-sedentary behavior to prevent the organism from becoming exhausted thus describing a protective evoloutionary mechanism. Whereas functional neuroimaging research has shown that the central nervous system is generally involved in humans energy perception (DeLuca, Genova, Capili, & Wylie, 2009), the exact neurobiological underpinnings accounting for real-life associations between sedentary behavior and mood remain elusive and warrant further investigations.

Sedentary behavior was not significantly or negatively associated with calmness in our main models. However, investigations of different time frames of sedentary behavior prior to the mood ratings revealed that sedentary behavior within brief time frames (5- and 10-mins) positively predicted calmness but not at other aggregation levels. This finding suggests that only brief sedentary bouts calmed participants. While this result is thus inconclusive, experimental evidence showing that sedentary behavior resulted in robust increases in psychological distress which was in turn related to InterLeukine-6 pro-inflammatory stress circuits (Endrighi et al., 2016).

Our study expands knowledge on differential effects of physical behavior (i.e., sedentary behavior, physical activity) on mood. First, in line with previous experimental (Endrighi et al., 2016) and longitudinal studies (DeMello et al., 2018; Ellingson et al., 2018), sedentary behavior was negatively related to two of three mood dimensions. Second, our results support findings from previous studies that physical activity is postively related to energetic arousal, but not consistent to valence and calmness (Koch et al., 2018; Liao et al., 2015; Reichert et al., 2017). Third, the effects of sedentary behavior in our sample were independent, inverse and approximately twice the size as those of physical activity on mood. Moreover, it is noteworthy the current study appears to be the first to have: i) classified sedentary behavior according to international accepted definition (Sedentary Behavior Research Network, 2017; Tremblay et al., 2017) by combining energy expenditure and the measure of sitting, reclining or lying posture; ii) included approximately 50 data points per participant to estimate valid within-subject associations; and iii) used a triggered e-diary to maximize covariance.

Our findings show that sedentary bouts (≥ 30 min) led to a more unwell and fatigue state while sedentary breaks enhanced mood. This finding is critical, given that humans spent predominant parts of their everyday life in sedentary behaviors, but only 6-7h with a high percentage of light and a low percentage of moderate to vigorous physical activities (Matthews et al., 2008). Therefore breaking up sedentary behavior and shifting time from sedentary behavior to physical activity should be a major health priority. Capitalizing on the tremendous progress in mobile technology, may help to integrate physical activity interventions into everyday life, such as Ambulatory Assessment interventions on smartphones. Ambulatory intervention studies may shed light on thus far unanswered issues such as the optimal characteristics (i.e., variation in intensity, duration, type, and context) of sedentary breaks. To integrate all facets of the concept of physical behavior, sleep variables such as quality, duration, and latency may be important confounders of the within-subject associations between sedentary behavior and mood (Konjarski, Murray, Lee & Jackson, 2018). Therefore, we call for future studies to integrate a 24 h assessment of physical behavior (Rosenberger et al., 2019), and thus to examine interactive relations between all facets of physical behavior and mental health outcomes such as mood.

Several limitations of our work merit further discussion. First, the study devices (smartphone and accelerometers) were not water- or shockproof and therefore could not be worn during all types of physical behaviors (e.g., swimming). Thus, our assessments may not have captured certain physical activities. However, our analyses were focused on within-subject processes of sedentary behavior and mood dimensions, and not on the total amount of physical behavior, making this limitation a minor issue. Second, we included university employees as this population is at high risk for sedentary behavior. Although this decision might have maximized the effects of interest, we cannot generalize our findings to other populations; thus, additional investigations are warranted. Third, Powell and colleagues (2018) questioned the validity of detecting sedentariness by single sensor systems. Thus, we applied a custom-developed multi-sensor system with accelerometers at hip, chest, and thigh to enable precise detection of body posture. This system enabled us to both quantify sedentary behavior according to its international definition (sedentarybehaviour.org) and to apply triggered e-diaries that are necessary to adequately capture within-subject variance (Ebner-Priemer et al., 2013). Fourth, we cannot exclude residual confounds (e.g., those due to other everyday life factors that influence mood such as social or nutritional behaviors, partnership quality, employment status, quantity and quality of sleep, and drug consumption such as alcohol and caffeine). However, our findings were stable across a sample of 86 individuals. Fifth, because we were interested in the influence of sedentary behavior on mood, we investigated sedentary behavior in 15-min segments prior to each e-diary prompt. Accordingly, our data show a clear chronological order, with sedentary behavior preceding mood ratings. However, chronology constitutes only one aspect of causality (Susser, 1991). Chronology suggests but does not prove causality because hidden third variables might show similar time-related characteristics. To substantiate a causal hypothesis, additional studies are needed. One approach might be to use ecological momentary interventions to experimentally induce sedentary behavior in everyday life (Myin-Germeys, Klippel, Steinhart & Reininghaus, 2016).

Perspective

Our study demonstrated a significant and coherent effect of sedentary behaviors on mood dimensions. In particular, the more participants were sedentary in everyday life the less well and energized they felt. Accordingly, sedentary behavior can be considered as a general risk factor for human health because it impacts on both somatic and mental health. Given the high prevalence of sedentary behavior globally, a rising need exists to address this challenge with sustainable interventions. Breaking up sedentary behavior appears to be a promising strategy to prevent the negative effects on human health. Importantly, physical activity and sedentary behavior showed independent effects on mood. This finding is in accordance with empirical somatic health evidence (Healy et al., 2008; Owen et al., 2010), which emphasizes the need to differentiate between physical activity and sedentary behavior in research and intervention strategies. Accordingly, future studies should consider the two sides of the physical behavior coin: How should physical activity be promoted? and How can sedentary behavior be reduced?

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Supporting Information

To test whether the likelihood (missing vs. answered AA survey) varied as a function of time-invariant (demographic) factors (i.e., group, sex, age, BMI) and time-varying temporal variables (i.e., weekday, time of the day, mood, physical behavior level), we conducted additional multilevel logistic regression analysis (Maher, Rebar & Dunton, 2018; Dunton, Liao, Kwabata & Intille, 2012). In the following, we provide odds ratios (OR), which quantify the estimated likelihood of a missing versus an answered AA survey.

Table 4. Multilevel logistic regression analyses to test the likelihood of answered vs. missing AA-surveys

Binary outcome: AA-survey [answered vs. missing]

		b (SE)[1]	OR[2]	95% CI[3]
Fixed effects	Intercept	-2.42 (0.81)**	0.089	0.018 – 0.439
	Group[a]	0.25 (0.23)	1.284	0.71 – 1.2
	Age	-0.002 (0.01)	0.998	0.98 – 1.02
	BMI	0.01 (0.04)	1.010	0.94 – 1.08
	Sex[b]	0.21 (0.22)	1.230	0.80 – 1.90
	Valence[c]	0.01 (0.01)	1.005	0.99 – 1.02
	Energetic Arousal[c]	-0.001 (0.003)	0.999	0.99 – 1.01
	Calmness[c]	-0.01 (0.004)	0.992	0.98 – 1.00
	Physical activity[d]	0.003 (0.001)**	1.003	1.001 – 1.005
	Sedentary behavior[d]	-0.01 (0.01)	0.991	0.98 – 1.01
	Time of day	0.001 (0.02)	1.001	0.97 – 1.04
	Weekday[e]	-0.08 (0.13)	0.921	0.71 – 1.20

Note[1]*:* Unstandardized estimates and standard errors; [2] Odds Ratio; [3] 95%-Confidence-Interval of OR; [a]compared to KIT; [b]compared to males; [c]lagged mood dimension (preceding survey); [d]lagged physical behavior (30 min-prior to the AA-survey); [e]compared to weekday
* P < .05; ** P < .01

Overall, the relative risk that participants answered an AA survey was approximately 2.3 times higher compared to not answering an AA survey. We found no significant associations of the lagged predictors sedentary behavior, mood (valence, energetic arousal, calmness), time of the day, weekday, group, sex, age, and BMI on missingness. Only the momentary physical activity level showed a significant relationship with the missingness: The likelihood for a missing (vs. an answered AA survey) increased significantly if physical activity level [milli-g] was increased across 30 min prior to the AA survey ($B = 0.003$; $p < .01$; $OR = 1.003$). This result is in line with a previous study from Dunton and colleagues (2012).

Supporting References

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Chapter V

Mood as an antecedent of sedentary behavior

Paper 4: Momentary mood predicts upcoming real-life sedentary behaviour.

Slightly modified version of the submitted manuscript

Giurgiu, M., Plotnikoff, R. C., Nigg, C. R., Koch, E. D., Ebner-Priemer, U. W., & Reichert, M. (submitted). Momentary mood predicts upcoming real-life sedentary behaviour.

Scandinavian journal of medicine & science in sports.

Abstract

Humans in the industrialized world spend a large amount of daily time in sedentary behaviour. Since sedentariness negatively impacts a variety of psycho-physiological outcomes the identification of antecedents that lead to sedentary behaviour is an important public health issue. In this context, mood, a central indicator for both psychological well-being and mental health, is severely understudied.

To investigate whether mood dimensions influence subsequent sedentary behaviour, we assessed both constructs at baseline via questionnaires and via Ambulatory Assessment (AA) over 5 days in 92 university employees. We continuously measured sedentary behaviour using accelerometers and assessed mood repeatedly 10 times each day on smartphone diaries. We employed multiple regression analyses to analyze between-subject effects and multilevel modeling to analyze within-subject effects.

Higher momentary ratings of valence ($p < 0.05$) and energetic arousal ($p < 0.01$) predicted lower amounts of subsequent sedentary behaviour, whereas higher ratings of calmness ($p < 0.01$) predicted higher amounts of subsequent sedentary behaviour. The context moderated the effect of energetic arousal and calmness on sedentary behaviour with increased effects in the home compared to the work context. Mood significantly predicted sedentary behaviour on a within-subject but not on a between-subject level.

Preliminary evidence suggests that mood regulates sedentary behaviour in everyday life. Time-sensitive analyses, such as from moment to moment revealed an association between mood and sedentary behaviour (within-subject), whereas analyses between different individuals revealed no associations (between-subject). These preliminary findings may inform

multicomponent intervention strategies that target mood, to reduce sedentary behaviour in daily life.

Introduction

Sedentary behaviour negatively impacts a variety of psycho-physiological health outcomes, such as cardiometabolic diseases and depression (Faulkner & Biddle, 2013; Katzmarzyk et al., 2019). Technological and social changes in home, environmental and occupational settings have led to an increasingly sedentary lifestyle among different cultures and countries (Church et al., 2011). On average, humans in the industrialized world spend around 9-11 hours/day in sedentary behaviour, i.e., any waking behaviour characterized by an energy expenditure ≤1.5 metabolic equivalents (METs), while in a sitting, reclining or lying posture (Tremblay et al., 2017). Thus, from a public health perspective, reducing sedentary behaviour has become a major issue. An important step to address this challenge is to identify antecedents of sedentary behaviour, as they could help tailor effective intervention strategies.

According to the ecological model of sedentary behaviour (Owen et al., 2011), a wide variety of factors, such as demographic variables, psychological attitudes, social norms, and the environment may influence the choice of behaviour. In a systematic review, Rhodes and colleagues (Rhodes, Mark, & Temmel, 2012) concluded that research on antecedents of sedentary behaviours is still in its infancy. Most of the studies focused on static demographic variables such as age, Body Mass Index (BMI) or ethnicity, whereas in contrast the influence of timely antecedents such as psychological variables like mood has been less explored. Mood is a central indicator for both mental well-being in healthy populations and is altered in many mental disorders (e.g., diminished mood in major depressive disorder or high mood fluctuations in borderline personality disorder) (World Health Organization, 2010). According to Wilhelm and Schoebi (2007), mood can be defined as diffuse affective states that subtly affect our experience, cognition, and behaviour. There is an ongoing discussion about the conceptualization of mood. Some authors tend to argue for a two-dimensional structure with negative and positive affect (Watson & Tellegen, 1985), whereas other authors tend to argue for a three-dimensional model, including basic mood-dimensions such as valence, energetic arousal and calmness. In this context, Wilhelm and Schoebi (2007) demonstrated that a two-dimensional model fit their data when taking a between-subjective perspective, whereas a three-dimensional model was superior when taking a within-subject perspective.

Previous studies have started to explore whether mood is associated with sedentary behaviour. In particular, DeMello and colleagues (2018) examined the reciprocal relationship between mood states (e.g., vigor, tension, fatigue) and sedentary behaviour in a 1-year longitudinal study. Their results indicated that worsened mood leads to higher levels of sedentary behaviour. Schwerdtfeger and colleagues (2010) examined the relationship between affective states and physical behaviour in daily life, with the result that affect is inversely associated with sedentary periods, suggesting that both positive and negative affective states are associated with a decrease in sedentary activities. Moreover, Maher and researchers (2019) investigated the extent to which within-subject variability in positive affect and feelings of energy predicted sedentary time. This study did not reveal any association between within-subject variability in affect or energy and sedentary time. In summary, the evidence for the association between mood and sedentary behaviour is inconclusive.

To the best of our knowledge, only two studies, i.e., Schwerdtfeger and colleagues (2010) and Maher and colleagues (2019) focused on a dynamical within-subject association between mood and sedentary behaviour, whereas DeMello and researchers´ study (2018) focused on a longitudinal approach over 1 year. Methodological discrepancies and limitations may be one reason which may explain the divergent findings. In all studies, the operationalization of sedentary behaviour includes only information of participant's motion but not about body postures which is incongruent with the international definition of sedentary behaviour. Thus, there is an intangible risk of misclassifying sitting and standing postures, which may result in an over- or underestimation of sedentary behaviour (Kozey-Keadle, Libertine, Lyden, Staudenmayer & Freedson, 2011). Another reason might be the conceptual approach of data collection and data analysis. In particular, DeMello et al. (2018) considered and analyzed data over one year with two mood-assessments per participant, while Schwerdtfeger et al. (2010) and Maher et al. (2019) considered possible dynamical within-subject associations, i.e., several mood-assessments per participant per day. Although the DeMello and colleagues´ (2018) study design included the lowest number of a within-subject analysis structure, i.e., two assessments per participant, it did not consider possible dynamical relations. Thus, their study focused primarily on differences between participants, e.g., participants with a poor mood spent more time in sedentary behaviour (DeMello et al., 2018). In principle, such an approach can be misleading and may contribute to the ongoing problem of the “ecological fallacy” – the perspective that the relationship between variables at one level (between person) can be presumed to exist at another (within-person) level (Robinson, 2009). A well-known example of the difference between the between-subject and within-subject approach is the relationship between blood pressure and physical activity. During physical activity, blood pressure is elevated (i.e., a positive association between physical activity and blood pressure from a within-person perspective); however, individuals with chronic high blood pressure engage in less physical activity (i.e., a negative association from a between-subject perspective) (Kamarck, Schwartz, Janicki, Shiffman & Raynor, 2003). Since mood varies over time (Ebner-Priemer & Trull, 2009), the within-subject approach is indeed sensitive to unravel possible temporal variations such may occur between mood and sedentary behaviour. In general, only within-subject approaches can reveal antecedents.

Taking all this into account, there is a lack of evidence, whether mood is an antecedent of sedentary behaviour among healthy adults. Furthermore, if mood is an antecedent of sedentary behaviour, it is unclear, which methodological approach (between-subject and/or within-subject) may unravel this association. To overcome this limitation and to analyze, whether mood is associated with sedentary behaviour on a between-subject and/or within-subject level, we conducted a study among healthy adults using Ambulatory Assessment (AA). AA is the state-of-the-art methodology for assessing psychological variables such as mood via smartphone-based electronic diaries and objectively captured sedentary behaviour by accelerometers in real-time during participants' everyday life (Bussmann, Ebner-Priemer & Fahrenberg, 2009; Kanning, Ebner-Priemer & Schlicht, 2013). Moreover, prior to the AA assessment, we assessed mood and self-reported sedentary time via paper-pencil questionnaires. We recruited university employees, a population shown to be at high risk for sedentary behaviour (Clemes et al., 2016), thereby aiming to maximize the effects of interest.

While there are only few empirical studies on the association between mood and sedentary behaviour, several theories and conceptual models, e.g., based on psychological hedonism or on a dual-processing perspective allow to derive assumptions on how mood dimensions may influence behaviour (Williams, Rhodes & Conner, 2019). For example, the Dual-Mode Model

(DMM) (Ekkekakis, 2003) is widely used to explain the relationship between physical behaviour and mood, suggesting that momentary effects of mood on physical behaviour may depend on cognitive processes. Put simply, knowledge on the negative health consequences of sedentary behaviour (e.g., cardiometabolic risk) may lead to decreased mood when being sedentary. Further, the social withdrawal hypothesis (Kraut et al., 1998) allows to derive the assumption that if individuals replace social interactions through time spent in digital media usage, this might result in decreased mood and subsequently increased sedentary behaviour (Vallance et al., 2011).

Based on previous studies (DeMello et al., 2018; Schwerdtfeger et al., 2010) and theoretical considerations (Ekkekakis, 2003; Kraut et al., 1998; Vallance et al., 2011; Williams et al., 2019) , we hypothesized that on a between-subject level lower mood ratings of valence, calmness, and energetic arousal would relate to higher amounts of device-based assessment of sedentary behaviour (hypothesis 1a). Additionally, we hypothesized that lower questionnaire-based mood ratings would predict higher amounts of self-reported sedentary time (hypothesis 1b). Moreover, we expected on the within-subject level lower ratings of the mood dimensions valence, calmness, and energetic arousal would lead to higher levels of device-based assessment of sedentary behaviour (hypothesis 2). Furthermore, we conducted exploratory analyses to test whether the association of mood dimensions (valence, energetic arousal, and calmness) and sedentary behaviour varied as a function of the environmental context (at home vs. work).

Materials and Methods

Participants

University employees (n=92) were recruited at two locations. First, between October 2016 and January 2017 at the University of Newcastle, Australia (UoN; n=35), second from May 2017 to August 2017 at the Karlsruhe Institute of Technology, Germany (KIT; n=57). Only participants without restrictions in performing their daily activities (i.e., those without injury or disease) were included in the study. Twelve participants were excluded from this sample for compliance reasons, i.e., <30% responses to e-diary prompts (Delespaul, 1995) and/or $<$ 3 valid days of minimum $\geq$ 10h per day accelerometer wear-time (Migueles et al., 2017). This resulted in a final sample of 80 participants.

The Human Research Ethics Committee of the University of Newcastle (H-2016-0347) and the Ethics Committee of the Karlsruhe Institute of Technology (KIT) approved this study. All eligible participants received written and oral information regarding the study procedures before written informed consent was obtained. Participants were free to withdraw from the study at any time.

Study design and procedures

We conducted an AA study over five consecutive days (three weekdays and two weekend days). During this time frame, participants carried three accelerometers (two move-3 and one ECG-move-3, movisens GmbH, Karlsruhe, Germany, movisens.com) and a smartphone (Motorola Moto G, Motorola Mobility LLC, Libertyville, IL, motorla.com) in daily life. Prior to the AA-study, participants received an extensive briefing on the use of the devices and completed a basic survey (including the WHO-five Well-Being Index (WHO5), the Global Physical Activity Questionnaire (GPAQ), and basic demographic measures).

Participants wore the triaxial accelerometers attached at three distinct positions: hip (move-3), thigh (move-3), and chest (ECG-move3). The participants were instructed to wear the accelerometers continuously during the entire measurement period except during sleep, showering or swimming. The sensors captured movement and body position with a range of ±16 g and a sampling frequency of 64 Hz. Raw acceleration was stored on an internal memory card. Both high-pass filter (0.25 Hz) and low-pass filter (11 Hz) were used to eliminate gravitational components and to exclude artefacts from the acceleration data. Anastasopoulou and colleagues (Anastasopoulou et al., 2014) showed that move accelerometers used in this study are appropriate for assessing humans' energy expenditure.

The smartphone prompted the participants via an acoustic, visual, and vibration signal every 40 to 100 minutes within the 7:30 am to 9:30 pm period. In other words, if a participant would spent zero minutes in a sedentary position between 7:30 am and 9:30 pm, the smartphone would trigger eight prompts per day. In contrast, if a participant spent each minute in a sedentary position between 7:30 am and 9:30 pm, the smartphone would trigger a maximum of 21 prompts per day. The participants had the opportunity to postpone an e-diary prompt for a maximum of 15 minutes. To optimize the assessment of the association between mood and sedentary behaviour, we implemented a mixed-sampling strategy using the software movisensXS (version 0.7.47574; xs.movisens.com). In particular, we developed a sedentary trigger algorithm, i.e., the thigh sensor analyzed and transferred data on body position (sitting/lying or upright) via Bluetooth Low Energy (BLE) to the smartphone in real-time. Each time a participant spent 30 minutes in a sitting/lying position, the e-diary triggered mood ratings. To minimize participant's burden, we implemented time out triggers, occurring no more than every 40 minutes and at least every 100 minutes. Additionally, to maximize variance, i.e., both sedentary and active phases, we used random triggers at various time points throughout a day.

Measures

Sedentary Behaviour. We parameterized sedentary behaviour according to its international accepted definition (Tremblay et al., 2017). In particular, one minute was defined as a sedentary minute if the participant was in a lying/sitting position with an intensity of ≤ 1.5 metabolic equivalents (MET´s). In contrast, a non-sedentary minute was defined as the participant being in a lying/sitting/upright position with an intensity of ≥ 1.51 MET. We calculated the parameters body position and MET in 1-minute intervals using the software DataAnalyzer (version 1.6.12129; movisens.com). Following established procedures, MET was defined as the metabolic rate of a human relative to the basal metabolic rate in relation to his body weight (Ainsworth et al., 1993). Body position was defined as the ratio from the vertical thigh to the ventral longitudinal axis of the body. The accelerometer detected either an upright body position (<20°) or a sitting/lying body position (>20°) (movisens.com).

To analyze within-subject effects of mood dimensions on sedentary behaviour, we aggregated sedentary minutes within the time frame of 30 minutes after each e-diary prompt using SPSS (version 25, IBM). To analyze between-subject effects of mood dimensions on sedentary behaviour, we calculated i) the mean sedentary time for each participant (hypothesis 1a), and ii) the self-reported sedentary time from the GPAQ (hypothesis 1b).

Mood. To assess within-subject fluctuations of mood across time, we used a short version of the Multidimensional Mood Questionnaire (MDMQ) presented on electronic smartphone diaries on visual analog scales (0-100) in reversed polarity and mixed order. This six-item short-scale (Wilhelm & Schoebi, 2007) captured three basic mood dimensions: valence, energetic arousal, and calmness, with acceptable psychometric properties (reliability coefficients ranging between 0.65 and 0.76) in our sample. The following items were presented:

Valence was determined by items i) unwell to well, ii) content to discontent; energetic arousal was determined by items i) full energy to without energy, ii) tired to awake; and calmness was determined by items i) relaxed to tense, ii) agitated to calm. The KIT participants were presented the German translation (Wilhelm & Schoebi, 2007). In addition, the German subsample was asked to report on their current location, e.g., home or work. To analyze between-subject effects of mood, we used the participant's average value of all e-diary mood assessments (hypothesis 1a) and the WHO5-Index score of each participant (hypothesis 1b), respectively. The WHO5 questionnaire includes five items, of which three of them are congruent with the basic mood-dimensions from the MDMQ (for details see (Topp, Østergaard, Søndergaard & Bech, 2015)). In particular, item two of the WHO5-questionnaire, i.e. "I have felt calm and relaxed", and the two items of the MDMQ, i.e., agitated/calm and relaxed/tense, both target the mood-dimension calmness. Item three of the WHO5 "I have felt active and vigorous", and the items tired/awake and full of energy/without energy of the MDMQ, both target the mood-dimension energetic arousal. Finally, item one of the WHO5 "I have felt cheerful and in good spirits", and the items content/discontent and unwell/well of the MDMQ, both target the mood-dimension valence.

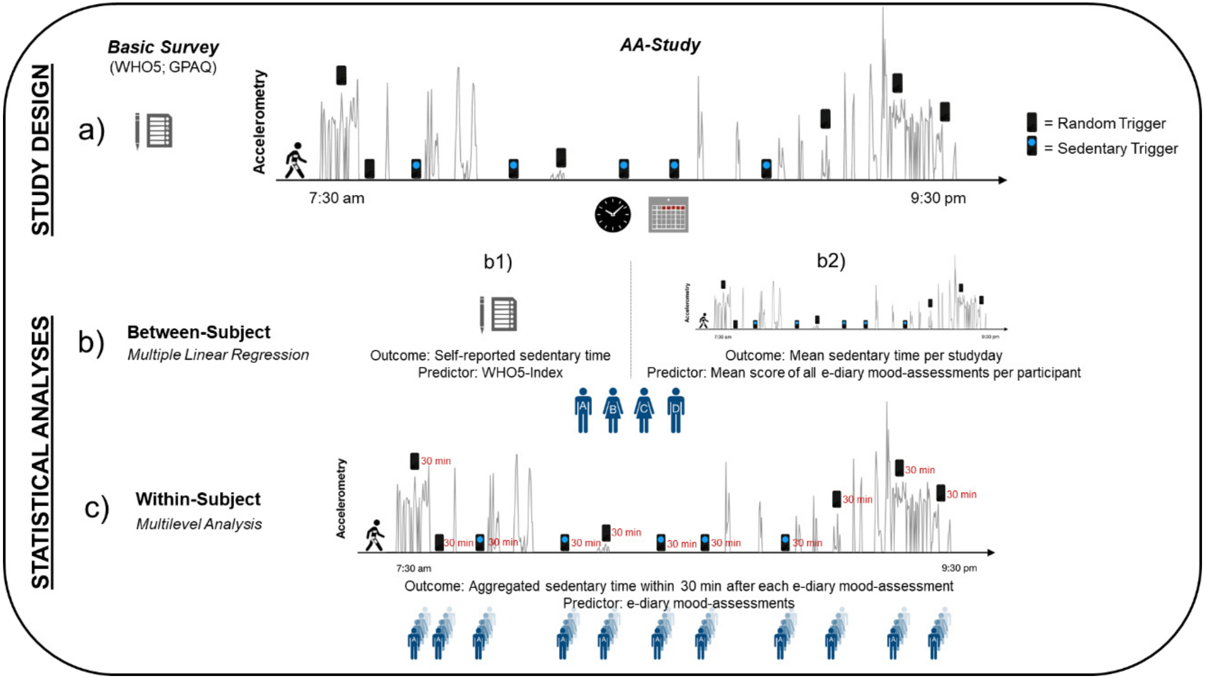

Figure 1. a) Study design: Basic survey (WHO5; GPAQ) and AA-Study period (Accelerometry; MDMQ) over 5 days. Statistical Analyses: b) Between-subject analyses based on b1) questionnaire data and b2) average values of the AA-study. c) Within-subject analyses with the dynamical relationship between mood and sedentary behaviour.

Statistical analyses

We merged the physical behaviour data with the mood ratings by using DataMerger (version 1.6.38.68; movisens.com). To test hypotheses 1a and 1b, i.e., between-subject effect of mood on sedentary behaviour, we conducted two multiple linear regression models. In the first model (hypothesis 1a), participants´ mean of the device-based assessment of sedentary time was our outcome, and we added participants average value of all e-diary mood assessments for the dimensions valence [0-100], energetic arousal [0-100], and calmness [0-100] and the predictors age [years], BMI [kg/m^2], sex, group [KIT vs. UoN]. In the second model (hypothesis 1b), self-reported sedentary behaviour (GPAQ) was our outcome, and we added participants` score of the WHO5-Index [0-100] and further predictors such as age [years], BMI [kg/m^2], sex, group [KIT vs. UoN]. In addition to hypothesis 1a and 1b, we conducted further analyses, whether the WHO5-Index may predict participant´s average of device-based assessments of sedentary time. To test for model assumptions, we checked for linearity, multicollinearity, outliers, and distribution of the residuals, prior to the analyses of our main models

To test hypothesis 2, i.e., within-subject effects of mood on sedentary behaviour, we conducted multilevel analyses (Bolger & Laurenceau, 2013). Multilevel analysis has several advantages, such as (i) the analysis of hierarchically structured data (i.e., multiple mood assessments nested within participants), (ii) separate within- and between-subject effects, and (iii) robustness concerning missing data points. We set up two-level-models and nested repeated measurements (level 1) within participants (level 2). First, intraclass correlation coefficients (ICCs) were estimated. ICCs indicate the amount of variance on the within- vs. between-subject level and they are estimated using unconditional (null-) models. We computed this ICCs for sedentary time segments of 30 minutes after each mood assessment, to estimate the amount of variance on the between vs. within-subject level in our outcome variable sedentary time. Second, we added the predictors time [hours], time-squared [hours^2], valence [0-100], energetic arousal [0-100], calmness [0-100], age [years], sex [male vs. female], group [KIT vs. UoN], day [weekend day vs. weekday] and BMI [kg/m^2] to our models.

To analyze exploratory analyses, we added the context variable [work vs. home] as a further covariate into our model in the German subsample. Moreover, to standardize time and time of the day squared, we subtracted the start time of the study for each day (7:30 am). The predictor time of day (squared) was included in the main model to control for potential nonlinear (quadratic) time-effects. The final model of the within-subject analyses is presented in the equations [1-9] below.

Within-subject analyses [hypothesis 3]:

$$\text{level}-1:\ \mathrm{Y(sedentary\ time)_{ij}} = \beta_{0j} + \beta_{1j}\,(\mathrm{valence_{ij}}) + \beta_{2j}\,(\mathrm{energetic\ arousal_{ij}}) + \beta_{3j}\,(\mathrm{calmness_{ij}}) + \beta_{4j}\,(\mathrm{time\ of\ day_{ij}}) + \beta_{5j}\,(\mathrm{time\ of\ day\ squared_{ij}}) + \beta_{6j}\,(\mathrm{weekday_{ij}}) + \beta_{7j}\,(\mathrm{context_{ij}}) + \mathrm{r_{ij}} \quad [1]$$

$$\text{level}-2:\ \beta_{0j} = \gamma_{00} + \gamma_{01}(\mathrm{group}) + \gamma_{02}(\mathrm{age}) + \gamma_{03}(\mathrm{BMI}) + \gamma_{04}(\mathrm{sex}) + \mu_{0j} \quad [2]$$

$$\text{level}-2:\ \beta_{1j} = \gamma_{10} \quad [3]$$

$$\text{level}-2:\ \beta_{2j} = \gamma_{20} + \mu_{2j} \quad [4]$$

$$\text{level}-2:\ \beta_{3j} = \gamma_{30} + \mu_{3j} \quad [5]$$

$$\text{level}-2:\ \beta_{4j} = \gamma_{40} \quad [6]$$

$$\text{level}-2:\ \beta_{5j} = \gamma_{50} \quad [7]$$

$$\text{level}-2:\ \beta_{6j} = \gamma_{60} + \mu_{6j} \quad [8]$$

$$\text{level}-2:\ \beta_{7j} = \gamma_{70} + \mu_{7j} \quad [9]$$

On level 1, within-subject effects were estimated for participants´ (subscript $_j$) sedentary time after each e-diary entry at any time of measurement (subscript $_i$). Y_{ij} represents the amount of aggregated sedentary time [range from 0-30 minutes], respectively, in person *j* at time *i*. Beta coefficients represent the intercept (β_{00}) and the effects of valence, energetic arousal, calmness, time, time-squared, and day ($\beta_{1j} - \beta_{7j}$) at level 1, and $\mathrm{r_{ij}}$ represents the residuals at level 1 [1]. We centered valence, energetic arousal, and calmness on the participant mean. On level 2, between-subject effects were estimated. We included random effects (i.e., individual variation on the sample mean effect γ) for each predictor represented as μ_{ij}. Random slope parameters ($\mu_{1j} - \mu_{7j}$) were kept in the model only if significant (*p* <

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.05) variation was observed across participants [2-9]. To compare the effects of each mood dimension, we calculated standardized beta coefficients (stand. BC) following established procedures (Hox & Roberts, 2014). Finally, we conducted additional analyses. First, we added participants´ mean ratings of valence, energetic arousal, and calmness across the AA-study period as between-subject predictors into our main model to test whether they predict momentary sedentary time. Second, we conducted a multilevel random-intercept model to test, whether the type of trigger (random vs. triggered) may influence subsequent sedentary behaviour.

Results

In Table 1, the sample characteristics are detailed. Over 5 days, participants were prompted 4,556 times. 77% of all prompts were answered. On a participant level, missing e-diary prompts ranged from 2-60 prompts across the study period. On average, participants answered 44.03 ± 13.15 prompts across the study period (ranging from 10-79 prompts). The amount of sedentary triggered prompts ranged from 0 to 82 across the study period, with an average of 31.7 ± 21 prompts. Because of technical issues, seven participants received only random prompts. Participants reported on a scale ranging from 0 to 100, average mood scores of 63.22 (energetic arousal), 75.88 (valence), and 68.48 (calmness) via e-diary. The WHO-5- Index ranged between 20 and 96 with a mean index-score of 64.65 ± 14.29 points, indicating a well-tempered sample (Topp, Østergaard, Søndergaard & Bech, 2015). Context assessments were only available from the German subsample. In particular, 25.7% of 2323 total assessments in the German subsample occurred during work. On average, accelerometers were worn for 15.47 ± 3.47 h/participant/day. Participants spent 8.03 ± 2.71 h/day sedentary. Participants reported via GPAQ a mean sedentary time of 8.14 ± 2.52 h/participant/day. Device-based and self-reported sedentary time correlated significantly on a weak to moderate level (r = .277; p = .013). 93% (ρI = 0.07) of the variance in the aggregated sedentary time [ranging from 0-30 minutes] after the mood prompt was due to within-subject fluctuations.

Table 1. Participants characteristics (n =80).

Variable	Mean ± SD[1]	Minimum	Maximum
Female	n= 52; 65 %	---	---
Age [years]	33.88 ± 9.53	22	62
Group (UoN[2])	n= 31; 39 %	---	---
BMI[3] [kg/m^2]	23.55 ± 3.28	17.67	32.49
Answered Mood Assessments [per day][a]	8.33 ± 2.38	2.5	15.8
Valence [0-100][a]	75.88 ± 11.57	35.95	96.35
Calmness [0-100][a]	68.48 ± 13.85	26.49	95.93
Energetic Arousal [0-100][a]	63.22 ± 13.11	30.81	92.55
WHO5-Index [0-100]	64.65 ± 14.29	20	96
Self-reported Sedentary Time [h/day]	8.14 ± 2.52	3	15
Wear Time Accelerometer [h/day][b]	15.47 ± 3.47	8.87	22.84
Sedentary Time Accelerometer [h/day][b]	8.03 ± 2.71	1.55	16.09
Number of prompts per day [c]	10.29 ± 4.07	1	21
Number of random prompts per day [c]	5.05 ± 2.45	0	9
Number of sedentary triggered prompts per day [c]	5.24 ± 4.88	0	21
Context of assessment – Work [%] [d]	39.2 ± 12.47	4.8	69.7

[1] Standard deviation; [2] University of Newcastle; [3] Body-Mass-Index
[a] assessed via e-diary, aggregated within participants
[b] aggregated within participants
[c] aggregated within participants per day
[d] aggregated within participants (context was only assessed in the KIT Group)

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Hypothesis 1: Between-subject analyses

In both models, mood did not significantly predict sedentary time (see Table 2). In particular, neither aggregated mood-ratings via e-diary, i.e., valence, energetic arousal, and calmness predicted device-based assessment of sedentary time, nor the WHO5-Index predicted self-reported sedentary time. Moreover, none of the predictor's group, age, BMI, and sex were significantly associated with device-based and self-reported sedentary time in both models. For the first model [hypothesis 1a], the goodness of fit was 0.9% with a lower than small effect size ($R^2 = 0.009$; $f^2 = 0.095$), and for the second model [hypothesis 1b] 5.3% with a medium effect size ($R^2 = 0.053$; $f^2 = 0.237$). Moreover, additional analyses revealed that the WHO5-Index did not significantly predict (stand. $\beta = -0.156$; $p = 0.164$) participant´s average of device-based measurements of sedentary time.

Hypothesis 2: Within-subject analyses

Valence and energetic arousal negatively predicted sedentary time (see Table 3). Contrary, calmness positively predicted sedentary time. In particular, higher ratings (e.g., 90) compared to lower ratings (e.g., 20) of valence were associated with lower amounts of sedentary time of about 2.77 minutes (scale: 0-30 minutes). Higher ratings (e.g., 90) of energetic arousal compared to lower ratings (e.g., 20) were associated with lower amounts of sedentary time of about 4.45 minutes. Put simply, higher values of valence and energetic arousal were associated with lower subsqeuent sedentary time. Contrary, higher ratings of calmness (e.g., 90) compared to lower ratings (e.g., 20) were associated with higher amounts of sedentary time of about 5.54 minutes. Furthermore, age and weekday were significantly related to sedentary time. On average participants aged ≥ 50 years spent 2.37 minutes less in sedentary behaviour compared to participants aged ≤ 30 years. Moreover, on average, participants spent 2.26 minutes less in sedentary behaviour on weekend days compared to workdays. None of the other predictors' group, BMI, sex, time of day and time of day squared were significantly associated with sedentary time. Furthermore, we found significant random effects for energetic arousal, calmness, time of the day, and weekday revealing that effects of these predictors on sedentary time varied between participants. According to Arend and Schäfer´s (2019) rules of thumb for minimum detectable effect sizes (MDES), our data allows the detection of small effects for within-subject associations and medium to large effects for between-subject associations. Additional analyses revealed that participants´ average valence (β = -0.05; *p* =.433), energetic arousal (β = -0.03; *p* = .502), and calmness (β = 0.05; *p* = .268) (aggregated mean ratings across the AA-study period) were not associated with subsequent momentary sedentary time (i.e., sedentary behaviour immediately after the e-diary prompt). Thus, this indicates that momentary mood ratings are a better predictors of subsequent sedentary time for individuals than their average mood. Finally, a robust analyses revealed the type of trigger (random vs. triggered) was associated with subsequent sedentary behaviour. The triggered prompts predicted higher subsequent sedentary behaviour compared to random prompts (β = 4.85; $p \leq .001$). This finding is in line with our expectations that random prompts increases the variance of participants´ physical behaviour and indicated that participants´ did not systematically change their subsequent behaviour through a triggered e-diary assessment. To explore whether the within-subject association between basic mood dimensions and subsequent sedentary behaviour were stable over time, we conducted a series of further analyses (see supporting information).

Table 2. Multiple regression analyses to predict device-based and self-reported sedentary time.

		b (SE)[1]	Stand. BC	t-value	p-value
	***Outcome:* Device-based sedentary time [h/day]**				
Hypothesis 1a	Intercept	520.54 (175)	---	2.97	.004
	Group[a]	34.79 (41.4)	0.105	0.84	.073
	Age	-2 (2.14)	-0.117	-0.93	.353
	BMI	0.94 (6.38)	0.019	0.15	.884
	Sex[b]	73.85 (40.64)	0.218	1.82	.073
	Valence	2.31 (3.64)	0.164	0.64	.528
	Energetic Arousal	0.06 (2.19)	0.005	0.03	.977
	Calmness	-3.2 (2.75)	-0.272	---	.249
	***Outcome:* Self-reported sedentary time [h/day]**				
		b (SE)[1]	**Stand. BC**	**t-value**	**p-value**
Hypothesis 1b	Intercept	269 (144)	---	1.87	.065
	Group[a]	36.26 (36.58)	0.117	0.99	.325
	Age	-0.68 (1.17)	-0.043	-0.36	.717
	BMI	10.7 (5.66)	0.232	1.89	.062
	Sex[b]	62.7 (36.2)	0.199	1.73	.087
	WHO5-Index	-0.83 (1.17)	-0.079	-0.71	.480

[1] Unstandardized estimates and standard errors
[a]compared to KIT; [b]compared to males

Table 3. Multilevel model analyses to predict sedentary time: Fixed and random effects.

		b (SE)[1]	Stand. BC[2]	t-value (df)[3]	95% CI[4]	p-value
	Outcome: Sedentary Time [0-30 min]					
Fixed effects	Intercept, $\boldsymbol{\beta_{00}}$	21.34 (2.51)	---	8.52 (77)	16.35, 26.33	< .001
	Group[a], $\boldsymbol{\beta_{01}}$	0.57 (0.70)	0.03	0.8 (73.1)	-0.83, 1.97	.420
	Age, $\boldsymbol{\beta_{02}}$	-0.12 (0.04)	-0.13	-3.3 (70.8)	-0.19, -0.05	.002
	BMI, $\boldsymbol{\beta_{03}}$	0.2 (0.11)	0.07	1.9 (68.4)	-0.01, 0.41	.065
	Sex[b], $\boldsymbol{\beta_{04}}$	-0.84 (0.68)	-0.05	-1.2 (68)	-2.2, 0.52	.222
	Valence, $\boldsymbol{\beta_{10}}$	-0.03 (0.02)	-0.04	-2 (2428)	-0.07, -0.0004	.047
	Energetic Arousal, $\boldsymbol{\beta_{20}}$	-0.06 (0.01)	-0.08	-4.4 (80)	-0.08, -0.03	< .001
	Calmness, $\boldsymbol{\beta_{30}}$	0.07 (0.02)	0.11	4.4 (107)	0.04, 0.1	< .001
	Time of day, $\boldsymbol{\beta_{40}}$	0.09 (0.18)	0.04	0.5 (2791)	-0.26, 0.44	.608
	Time of day squared, $\boldsymbol{\beta_{50}}$	-0.01 (0.01)	-0.07	-0.9 (2898)	-0.03, 0.01	.388
	Weekday[c], $\boldsymbol{\beta_{60}}$	-2.26 (0.52)	-0.12	-4.4 (72)	-3.29, -1,23	<.001
		b (SE)[1]		**Wald Z**	**95% CI[4]**	**p-value**
Random effects	Intercept, $\boldsymbol{\mu_0}$	1.25 (1.48)		0.85	0.12, 12.6	.396
	Energetic Arousal, $\boldsymbol{\mu_2}$	0.003 (0.002)		2.19	0.001, 0.008	.028
	Calmness, $\boldsymbol{\mu_3}$	0.01 (0.002)		2.45	0.003, 0.01	.014
	Time of day, $\boldsymbol{\mu_4}$	0.03 (0.02)		1.97	0.01, 0.09	.049
	Weekday[c], $\boldsymbol{\mu_6}$	5.36 (1.63)		3.28	2.95, 9.73	.001
	Residual, $\mathbf{r}$	64.95 (1.78)		36.52	61.58, 68.53	<.001

[1] Unstandardized estimates and standard errors; [2] standardized β-coefficient; [3] t-values and degrees of freedom; [4] 95%-Confidence-Interval
[a]compared to KIT; [b]compared to males; [c]compared to weekday

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Hypothesis 2: Within-subject analyses

Valence and energetic arousal negatively predicted sedentary time (see Table 3). Contrary, calmness positively predicted sedentary time. In particular, higher ratings (e.g., 90) compared to lower ratings (e.g., 20) of valence were associated with lower amounts of sedentary time of about 2.77 minutes (scale: 0-30 minutes). Higher ratings (e.g., 90) of energetic arousal compared to lower ratings (e.g., 20) were associated with lower amounts of sedentary time of about 4.45 minutes. Put simply, higher values of valence and energetic arousal were associated with lower subsequent sedentary time. Contrary, higher ratings of calmness (e.g., 90) compared to lower ratings (e.g., 20) were associated with higher amounts of sedentary time of about 5.54 minutes. Furthermore, age and weekday were significantly related to sedentary time. On average participants aged ≥ 50 years spent 2.37 minutes less in sedentary behaviour compared to participants aged ≤ 30 years. Moreover, on average, participants spent 2.26 minutes less in sedentary behaviour on weekend days compared to workdays. None of the other predictors' group, BMI, sex, time of day and time of day squared were significantly associated with sedentary time. Furthermore, we found significant random effects for energetic arousal, calmness, time of the day, and weekday revealing that effects of these predictors on sedentary time varied between participants. According to Arend and Schäfer´s (2019) rules of thumb for minimum detectable effect sizes (MDES), our data allows the detection of small effects for within-subject associations and medium to large effects for between-subject associations. Additional analyses revealed that participants´ average valence (β = -0.05; p =.433), energetic arousal (β = -0.03; p = .502), and calmness (β = 0.05; p = .268) (aggregated mean ratings across the AA-study period) were not associated with subsequent momentary sedentary time (i.e., sedentary behaviour immediately after the e-diary prompt). Thus, this indicates that momentary mood ratings are a better predictors of subsequent sedentary time for individuals than their average mood. Finally, a robust analyses revealed the type of trigger (random vs. triggered) was associated with subsequent sedentary behaviour. The triggered prompts predicted higher subsequent sedentary behaviour compared to random prompts (β = 4.85; $p \leq .001$). This finding is in line with our expectations that random prompts increases the variance of participants´ physical behaviour and indicated that participants´ did not systematically change their subsequent behaviour through a triggered e-diary assessment. To explore whether the within-subject association between basic mood dimensions and subsequent sedentary behaviour were stable over time, we conducted a series of further analyses (see supporting information).

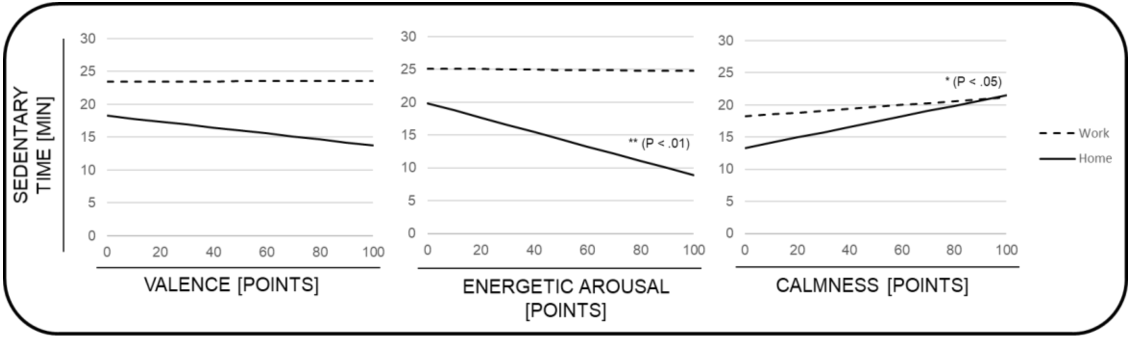

Figure 2. Multilevel interaction analyses: context moderates associations between mood dimensions and sedentary time. For each of the three models, the y-axis depicts the amount of sedentary time [ranging from 0-30 min]. The x-axis depicts the mood scores [scale: 0-100].

Exploratory context analyses

Figure 2 shows interaction effects. In particular, context moderated the associations between energetic arousal and sedentary time, and between calmness and sedentary time. Translated to practice, higher ratings (e.g., 90) compared to lower ratings (e.g., 20) of energetic arousal were associated with subsequent lower amounts of sedentary time of about 7.69 minutes (scale: 0-30 minutes) in the home context, and of about 0.27 minutes in the work context. Furthermore, higher ratings (e.g., 90) compared to lower ratings (e.g., 20) of calmness were associated with subsequent higher amounts of sedentary time of about 5.75 minutes in the home context, and of about 2.05 minutes in the work context.

Discussion

The study aimed to investigate, whether mood is (i) associated with sedentary behaviour and (ii) whether the association depends on the conceptual approach, i.e., between-subject vs. within-subject level. We found mood was not to be associated with sedentary behaviour on a between-subject level, but was so on a within-subject level. In particular, we found neither in the self-reported data (paper-pencil questionnaires) nor in the between-level aggregated data from the AA-study, an association on a between-subject level. Interestingly within-subject AA data revealed that context (at home vs. work) moderated the effect of mood on sedentary behaviour.

We found that higher ratings of momentary valence and energetic arousal were associated with subsequently lower amounts of sedentary behaviour, whereas higher ratings of momentary calmness were associated with subsequently higher amounts of sedentary behaviour. In line with the present results, a previous finding from Schwerdtfeger et al. (2010) shows that increased affect ratings were associated with lower amounts of sedentary behaviour. Contrary to our results, Maher et al. (2019) did not find a within-subject association between positive affect and feelings of energy. There might be several possible explanations for this inconclusive state of research. For example, the usage of different assessments of mood and sedentary behaviour, different samples or study designs may influence the results.

Also contrary to our expectations, our study did not find a significant association between mood and sedentary behaviour on a between-subject level, whereas DeMello and colleagues (2018) have reported a reciprocal relationship between mood states (e.g., vigor, tense, fatigue) and sedentary behaviour. Further studies are needed to clarify the issue, whether mood is associated with sedentary behaviour on a between-subject level. In a previous work (Giurgiu et al., 2019), we reported that sedentary behaviour negatively predicted two mood-dimensions (i.e., valence and energetic arousal). Thus, the issue of a reciprocal relationship is a crucial question for future research endeavors, which may be of interest to address the question of causality. Even though our data show a chronological order with mood ratings predicting subsequent sedentary behaviour, this chronology constitutes only one aspect of causality (Susser, 1991). The chronology suggests but does not prove causality because hidden third variables might show similar time-related characteristics. To substantiate a reciprocal causal hypothesis, additional studies with different methods are needed. For example, Dunton (2017) suggests to apply computational strategies such as Dynamical Systems Modeling (DSM) for time-varying relations such as between mood and physcial behaviour. Another promising approach may be to use ecological momentary interventions (EMI) or just-in-time adaptive interventions (JITAI´s) to experimentally induce mood in everyday life (Hardeman, Houghton, Lane, Jones & Naughton, 2019). For instance, mobile apps to regulate individual’s emotions may lead to higher mood-states, and thus may minimize individual’s subsequent sedentary behaviour. Moreover, EMI or JITAI can address different contexts of individuals, which might be relevant since our data revealed that in two of three models the effects were moderated through the context. For example, higher ratings of energetic arousal in the home context compared to the work context were associated to subsequently lower amounts of sedentary behaviour.

To the best of our knowledge, regarding the relation between mood and sedentary behaviour, no study has compared whether the results of the conceptual approach (within-level vs. between-level) differs within the same data set. While there is evidence that the conceptual approach may lead to different results (Kamarck et al., 2003; Robinson, 2009), all previous studies (DeMello et al., 2018; Maher et al., 2019; Schwerdtfeger et al., 2010) used different approaches. However, research from different areas has shown that the conceptual approach differed widely. For instance, Maher and colleagues (Maher, Doerksen, Elavsky & Conroy, 2014) found that physical behaviour (i.e., physical activity and sedentary behaviour) was associated with satisfaction with life on a within-subject level, but not on a between-subject level. Similar results were found by Zawadzki et al. (2017) showing that self-reported anger and objective blood pressure were associated on a within-subject level, but not on a between-subject level. In the same manner, our study adds first evidence that mood is associated with sedentary behaviour on a within-subject level but not on a between-subject level. Social/psychological theories such as the social withdrawal hypothesis might explain the association between mood and sedentary behaviour. Kraut and colleagues (1998) reported that greater use of Internet was associated with declines in individuals´ social interaction and increase in depression and loneliness. Thus individuals may remove themselves from social interactions and increase time in computer use, television watching or smartphone usage (mostly in a sedentary position), which may increase the risk for worsened mood and, thus for longer sedentary time (Vallance et al., 2011). However, because this research field is still at an early stage, we call for further studies to confirm this preliminary finding and to add evidence to the current inconclusive state of research.

Since studies have shown that sedentary behaviour has adverse effects on somatic and mental health (Faulkner & Biddle, 2013; Katzmarzyk et al., 2019), researchers are interested in tailoring effective intervention strategies to reduce sedentary behaviour in daily life. One popular example is the implementation of sit-to-stand workstations within the work context. However, because sedentary behaviour is a multifaceted behaviour, which is influenced by a complex interaction of individual, socio-cultural and environmental factors (Owen et al., 2011), it may be necessary to intervene on different levels (e.g., on the behavioral and the social environmental). A recent review and meta-analysis by Compernolle and colleagues (2019), revealed that self-monitoring (i.e., keeping records of specified behaviour for example via diary) as a behaviour change technique (BCT) (Michie et al., 2011) has the potential to effectively reduce sedentary behaviour. Since the process of self-monitoring takes place on an individual level it seems reasonable that studies which focus on a within-subject level provide more in-depth insights than between-subject approaches for the development of tailored intervention strategies. Furthermore, complex interaction of individual, socio-cultural and environmental factors may vary from person to person and within a person from moment to moment. Thus, knowledge about the within-subject fluctuations of individual´s behaviour could be a promising target to change sedentary habits.

So far, studies have shown that environmental changes such as the implementation of sit-to-stand workstations (Dutta, Walton & Pereira, 2019) as well as behavioural support such as self-monitoring (Compernolle et al.,

2019) can effectively reduce sedentary behaviour. Therefore, multicomponent interventions on both individual and environmental levels may be the most effective strategies. In this context, our preliminary finding that momentary mood predicted subsequent sedentary behaviour, may serve as a starting point that regulation of mood could be beneficial as an additional intervention strategy. According to Williams and colleagues integrative framework (Williams et al., 2019), following three routes may crucial for health behaviour change. First, direct modification of specific affect constructs, e.g., to reduce dread about possible adverse health consequences of “too much sitting”. Second, intervention upon moderators of the affect-behaviour link, e.g., to address habits of sitting through daily work. Third, direct modification of other sources of behavioural influence, e.g. focuses on anticipated affective reactions such as “proud to avoid prolonged sedentary behaviour (≥ 30 min). However, since the implementation of effective interventions is at an early stage, we call for future research to evolve possibilities of interventions, using e.g. EMI or JITAI´s, to implement strategies for enhancing mood and decreasing sedentary behaviour.

Several aspects of this study need to be acknowledged. First, the accelerometers were not water- or shockproof and therefore could not be worn during all types of physical behaviour (e.g., swimming). Thus, our assessments may not have captured certain physical activities. However, our analyses were focused on the association between mood dimensions and sedentary behaviour, and not on the total amount of physical behaviour, minimizing this limitation. Second, we cannot exclude residual confounders (e.g., everyday life factors that influence sedentary behaviour such as social or environmental conditions or quantity and quality of sleep) (Owen et al., 2011). However, our findings were stable within a sample of 80 individuals. Third, our study sample comprises University employees, some of which may be familiar with exercise psychology or particularly interested in the associations of sedentary behaviour and mood. This might have influenced the findings. However, since the participants were employees from various fields and sectors of the university staff, we assume this to be a minor issue. A noteable strength of our study is the custom-developed multi-sensor system with accelerometers at hip, chest, and thigh to enable more precise detection of sedentary behaviour. This system enabled us to quantify sedentary behaviour according to its international definition (Tremblay et al., 2017).

Perspective

Our study is one of the first studies that investigated whether mood is an antecedent of sedentary behaviour in daily life and whether different conceptual approaches (between-subject level vs. within-subject level) may lead to different results. Our findings revealed that mood is associated with sedentary behaviour on a within-subject level, but not on a between-subject level, thus indicating a time-varying relationship between mood and sedentary behaviour. Translated into practice, there is preliminary evidence that mood may have an essential function in the regulation of sedentary behaviour. Therefore, regulation of mood may be a promising addition in multicomponent intervention strategies to reduce sedentary behaviour in daily life.

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Supporting Information

To explore whether the within-subject association between basic mood dimensions and subsequent sedentary behaviour were stable over time, we conducted a series of further analyses. For this purpose, we analysed the short- and long-term effects of mood on subsequent sedentary behaviour by calculating 30 multilevel models using different outcome variables, i.e., subsqeuent sedentary behaviour within the time frames [1–10], [1–20], [1–30], ... up to [1–300] min following each e-diary prompt. We applied the model of hypothesis 2; however, we simplified the random part by only allowing for variation in the participants' individual intercepts. On the y-axis of Figure 3, the standardized beta coefficients are depicted, i.e., each mood dimension (valence, energetic arousal, and calmness) predicting subsequent sedentary behaviour aggregated across the increasing time frames after the e-diary prompt (i.e., 1–10min; 1–20min, [...], 1–300min; refer to the x-axis).

For all three mood dimensions, Figure 3 shows the effects over time. In particular, the effects of all mood dimensions are mostly stable over time, even if the effect diminishes over longer periods of time. In detail, calmness showed, except for three models, a significant effect on subsequent sedentary behaviour, whereas valence and energetic arousal showed a negative effect. While the effect of energetic arousal on subsequent sedentary behaviour was significant across all time frames, the effect of valence on sedentary behaviour was significant for the models until the 50 minute time frame and in the models between until 90 to 110 minutes. These analyses supporting the findings from the main model showing that higher ratings of calmness were associated with higher amounts of subsequent sedentary behaviour, whereas higher ratings of valence and energetic arousal were associated with lower amounts of subsequent sedentary behaviour.

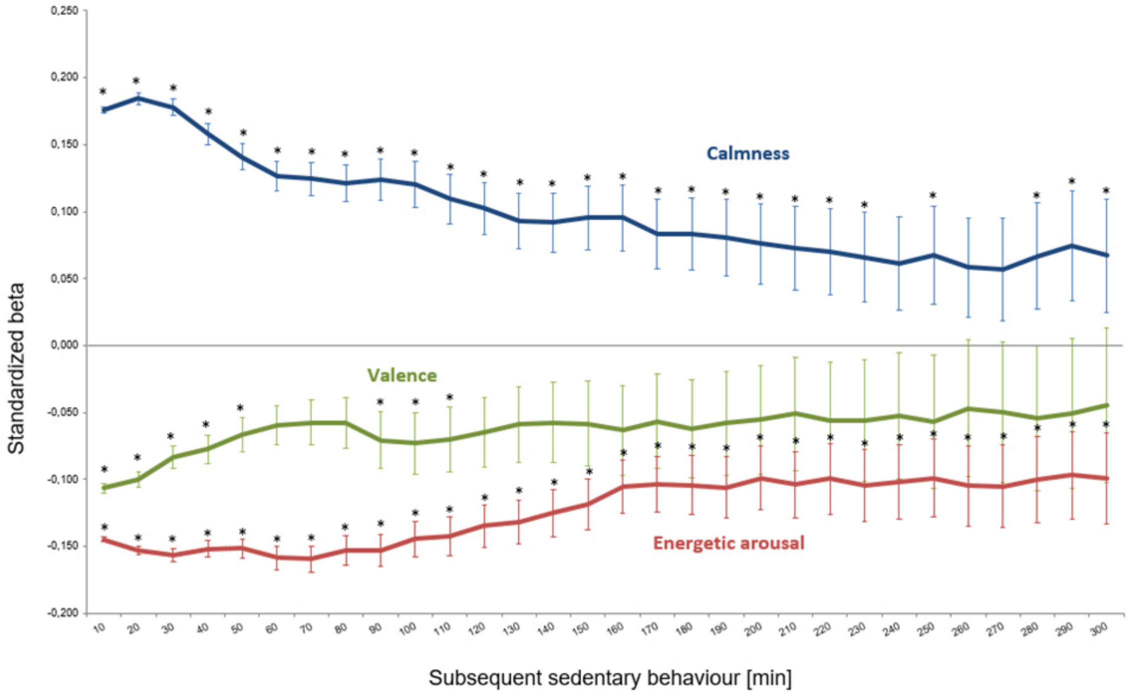

Figure 3. Effects of mood on subsequent sedentary behaviour aggregated across increasing time intervals after the e-diary prompt. The standardized beta coefficients for valence, energetic arousal and calmness predicting sedentary behaviour are presented at the y-axis. The x-axis shows the increasing time intervals of sedentary behaviour, e.g., the sum of sedentary time from min 1 up to min 40 after an e-diary prompt is represented by the axis label [40]. Significant effects of valence, energetic arousal and calmness predicting subsequent sedentary behaviour are indicated with * ($p \leq 0.05$).

Chapter VI

Breaking up sedentary behavior to enhance mood

Paper 5: Breaking-up sedentary behavior optimally to enhance mood

Slightly modified version of the published paper

Giurgiu, M., Koch, E. D., Plotnikoff, R. C., Ebner-Priemer, U. W., & Reichert, M. (2019). Breaking Up Sedentary Behavior Optimally to Enhance Mood.

Medicine and science in sports and exercise, 52(2):457-465. doi: 10.1249/mss.0000000000002132

Abstract

Experimental evidence shows that breaking-up sedentary behavior is positively associated with positive mental health outcomes. However, whether sedentary breaks influence mood in everyday life is largely unknown. Moreover, it is unclear which break patterns are most beneficial to enhance mood. To investigate the degree to which sedentary break patterns influence mood dimensions in everyday life, we conducted an Ecological Momentary Assessment (EMA) study in 92 university employees over 5 days. We continuously measured physical behavior (physical activity and sedentary behavior) objectively via accelerometers and assessed mood 10 times a day on smartphone diaries. We defined distinct break patterns, such as variations in frequency (number of breaks), duration (length of breaks), intensity (metabolic equivalent) and context (home or work), and used multilevel modeling to analyze the within-subject effects of sedentary break patterns on mood. Break intensity was positively associated with subsequent valence ($P< 0.01$), energetic arousal ($P< 0.01$) and calmness ($P< 0.05$). Break frequency was positively associated with subsequent valence and energetic arousal (all $Ps < 0.01$), but break duration was not associated with mood. Exploratory analyses indicated that breaking-up sedentary behavior was more beneficial at home than at work. These ecologically valid findings suggest breaking-up sedentary behavior as a promising strategy to enhance mood in everyday life. In particular, breaking-up sedentary behavior frequently and intensively, for example by walking instead of standing, may be most beneficial. We call for future studies to substantiate these accounts and to identify both practical and optimal break patterns among different samples. This evidence informs

official public health recommendations aiming to “minimize sedentary time in everyday life”.

Introduction

Official public health guidelines for adults recommend both reducing sedentary time and breaking-up sedentary behaviors by physical activity whenever possible (Ministry of Health, 2018; Stamatakis et al., 2018). Furthermore, public health campaigns such as “move more, sit less” (Bluearth, 2019) emphasize the importance of regular sedentary breaks throughout the day. However, in contrast to physical activity guidelines for adults, for example 30 minutes of moderate-intensity activity 5 times per week (World Health Organization, 2010), the recommendations for breaking-up sedentary behaviors are highly unspecific, for instance “break up long periods of sitting” (Ministry of Health, 2018). Moreover, different break patterns may lead to different health outcomes (Janssen & Cliff, 2015), e.g., to break up sedentary behavior three times per hour with a duration of five minutes at high intensity may be more beneficial than taking a break one time per hour for 15 minutes at low intensity. Thus, to specify recommendations, it is crucial to add information on beneficial break patterns related to frequency, intensity, type, duration and context.

As one of the first studies on this topic, Healy and colleagues (2008) introduced the concept of breaks in sedentary time in 2008. The authors showed that more breaks in sedentary time are associated with reduced metabolic risk. Thereafter, epidemiological studies added evidence that breaking-up sedentary behavior has a beneficial effect on various physiological health outcomes, such as postprandial glucose or insulin responses (Dunstan et al., 2012). However, in contrast to the literature about the positive effects of sedentary breaks on physiological health outcomes, only a few studies have investigated the impact of sedentary breaks on mental health outcomes (Bergouignan et al., 2016; Dempsey et al., 2018; De Jong et al., 2018; Sperlich, Clerck, Zinner, Holmberg & Wallmann-Sperlich, 2018; Thorp, Kingwell, Owen & Dunstan, 2014).

Given the rising prevalence of mental disorders and the growing evidence that sedentary behavior is a risk factor for mental health, a deeper understanding of the potential effectiveness of sedentary breaks on mental health outcomes such as mood is highly relevant (Faulkner & Biddle, 2013). Mood is a central indicator for mental well-being in healthy populations and is altered in many mental disorders (e.g., depression, manic episodes, and personality disorder) (American Psychiatric Association, 2013). According to Wilhelm and Schoebi (2007), mood can be defined as a rather diffuse affective state that subtly affects our experience, cognitions, and behavior.

Summarizing the extant literature, only a small number of studies have shown that sedentary breaks are associated with enhanced feelings of vigor and reduced levels of fatigue (Bergouignan et al., 2016; Dempsey et al., 2018; De Jong et al., 2018; Sperlich et al., 2018; Thorp et al., 2014). These results were found mostly under experimental conditions in occupational settings (Bergouignan et al., 2016; Thorp et al., 2014). In particular, frequently breaking-up sedentary behavior with a short duration (3-5 minutes) appears to be more beneficial than breaking-up sedentary behavior only once with a longer duration (≥ 30 minutes). Moreover, studies have revealed that different forms of intensity, for instance standing (Thorp et al., 2014), moderate walking (Bergouignan et al., 2016; De Jong et al., 2018) or high-intensity exercise (Sperlich et al., 2018), have a positive impact on mood dimensions. However, it remains unknown whether these findings can be translated to the everyday life of adult humans.

Ecological Momentary Assessment (EMA) or Ambulatory Assessment (AA) is currently the ‘state-of-the-art’ methodology for assessing psychological and behavioral variables in daily life, such as mood via smartphone-based electronic diaries and objectively captured physical behaviors (i.e., physical activity, sedentary behavior, sleep) by accelerometers (Liao, Shonkoff & Dunton, 2015). This assessment strategy enables researchers to track and examine within-subject associations between sedentary breaks and mood in real time during participants’ everyday life (Ebner-Priemer, Koudela, Mutz & Kanning, 2013). Moreover, an EMA study with several mood assessments per day bypasses the limitations of a retrospective assessment of mood (e.g., one assessment point at the end of the day, potential biases of systematic distortions such as the affective valence effect, the mood-congruent memory effect, and the duration neglect effect) (Ebner-Priemer & Trull, 2009).

To the best of our knowledge, no EMA study has compared different break patterns (i.e., variations in frequency, intensity, type, duration and context) on mood (Rosenberger, 2012). Most of the experimental studies to date have compared only two possible break patterns, i.e., short frequent breaks (1-5 minutes) with light to vigorous intensity vs. a single long break (≥ 30 minutes) with light to moderate intensity in an occupational setting. However, given the large variety of possible break patterns, it is still unclear which break patterns may be most beneficial to enhancing mood dimensions and whether these break patterns are independent of the context. To investigate the associations between sedentary break patterns (i.e., variations in frequency, duration, intensity, and context) and basic mood dimensions (i.e., valence, calmness, energetic arousal), we conducted an EMA study using mobile methodology in daily life. We recruited healthy university employees, a population shown to be at high risk for sedentary behavior (Clemes et al., 2016), thereby aiming to maximize the effects of interest.

Based on previous studies (Bergouignan et al., 2016; Dempsey et al., 2018; Jong et al., 2018; Sperlich et al., 2018; Thorp et al., 2014), we hypothesized that break frequency (1a), break duration (1b), and break intensity (1c) positively influence the mood dimension valence (hypotheses 1a-1c). Furthermore, we expected break frequency, break duration, and break intensity to positively influence the mood dimensions energetic arousal (hypotheses 2a-2c) and calmness (hypotheses 3a-3c). Moreover, we conducted exploratory analyses to test whether the associations between break patterns (i.e., variations in frequency, duration, and intensity) and mood dimensions (valence, energetic arousal, and calmness) vary as a function of the environmental context (at home vs. work).

Methods

Participants

Between October 2016 and August 2017, university employees were recruited from two locations. First, employees were recruited from the University of Newcastle (UoN; n = 35), Australia. Second, employees were recruited from the Karlsruhe Institute of Technology (KIT; n = 57), Germany. Only participants without restrictions on performing activities of daily life (i.e., those without injury or disease) were included. The Human Research Ethics Committee of the University of Newcastle (H-2016-0347) and the Ethics Committee of the Karlsruhe Institute of Technology (KIT) approved this study. All included participants received oral and written information regarding the study procedures before they provided written informed consent. Participants were informed about the main research question but not about the specific hypothesis of the study. Participants were free to withdraw from the study at any time.

Study design and sampling strategy

Over the course of five days (three working and two weekend days), participants carried three accelerometers (two move-3 and one ECG-move-3, movisens, Karlsruhe, Germany, movisens.com) and a smartphone (Motorola Moto G, Motorola Mobility LLC, Libertyville, IL, motorla.com) during their daily lives. The triaxial accelerometers were attached to different positions: the chest (ECG-move3), hip (move-3) and thigh (move-3). Prior to the start of the study, participants received an extensive briefing on the use of the devices and completed a basic survey, including demographic measures such as sex, age and BMI.

The smartphone prompted the participants via an acoustic, visual, and vibration signal every 40 to 100 minutes within the 7:30 am to 9:30 pm period (see Figure 1). We applied a mixed-sampling strategy. To optimize the assessment of the associations between sedentary behavior and mood, we developed a sedentary triggered algorithm. In particular, the thigh sensor analyzed and transferred data on body position (sitting/lying or upright) via Bluetooth Low Energy (BLE) to the smartphone in real time. Each time a participant spent more than 30 minutes in a sitting/lying position, the e-diary triggered mood ratings. In addition, random triggers at various times were implemented. To minimize participants' burden, triggers occurred no more often than every 40 minutes but at least every 100 minutes. The participants had the opportunity to postpone an e-diary prompt for a maximum of 15 minutes. On average, participants answered a single mood prompt within 35 seconds (standard deviation ± 29 seconds). This mixed-sampling strategy was implemented using the software movisensXS (version 0.7.4574; xs.movisens.com).

Measures

Mood. We used a six-item scale developed and validated by Wilhelm and Schoebi (2007) to assess within-subject fluctuations of mood over time using e-diaries. This scale captures three basic mood dimensions: valence (V), energetic arousal (EA), and calmness (C), with sound psychometric properties (within-subject reliability coefficients ranging between 0.72 and 0.79) in our sample. We implemented the bipolar items on visual analogue scales (0-100) in reversed polarity and mixed order. The KIT participants were presented with German translations (in parentheses): valence: a) unwell to well (unwohl-wohl), b) discontent to content (unzufrieden-zufrieden); energetic arousal: a) without energy to full energy (energielos-energiegeladen), b) tired to awake (müde-wach); and calmness: a) tense to relaxed (angespannt-entspannt), and b) agitated to calm (unruhig-ruhig)

Sedentary Breaks. Following the most common definition (Tremblay et al., 2017), we defined a sedentary break as "a non-sedentary bout in between two sedentary bouts". In particular, a sedentary bout is defined as "a period of uninterrupted sedentary time". Sedentary time is defined as "the time spent for any duration (e.g., minutes per day) or in any context (e.g., at school or work) in sedentary behaviors", and sedentary behavior is defined as "any waking behavior characterized by an energy expenditure ≤ 1.5 metabolic equivalent (MET) while in a sitting, reclining or lying posture" (Tremblay et al., 2017). Furthermore, we differentiated distinct break patterns, i.e., frequency, duration, intensity, and context.

Participants wore accelerometers during the entire measurement period but not during sleep. The triaxial accelerometers captured movements and body positions with a range of ± 16 g and a sampling frequency of 64 Hz. The move accelerometer has been shown to be appropriate for assessing human energy expenditure (Anastasopoulou et al., 2014). Raw acceleration was stored on an internal memory card. To eliminate gravitational components and artifacts from the acceleration signal, a bandpass filter (0.25 - 11 Hz) was used (for details on data processing, see von Haaren et al. (2016)). We calculated the parameters MET and body position at 1-minute intervals using DataAnalyzer, (version 1.6.12129; movisens.com). Here, MET represents the metabolic rate of a human relative to the basal metabolic rate in relation to his body weight. Body position was defined as the ratio from the vertical thigh to the ventral longitudinal axis of the body, resulting in either an upright or a sitting/lying body position (movisens GmbH, 2019). Based on the MET values from the hip sensor and the body position values from the thigh sensor, we calculated the dichotomous variable sedentary time. Accordingly, one minute was defined as a sedentary minute when the participant was in a sitting/lying position with an intensity of ≤ 1.5 METs. In contrast, one minute was defined as a non-sedentary minute when the participant was in a lying/sitting/upright position with an intensity of > 1.5 METs.

To avoid overlapping time frames, we focused our main analyses on the 80-minute time frame prior to each e-diary assessment because the average period between two e-diary prompts was 80.55 ± 56.82 minutes. Importantly, we distinguished among the various break patterns. In the first pattern, break frequency represented the sum of all (at least one-minute) intervals of non-sedentary time during the 80-minute time frames. Second, break duration represented the mean length of all (at least one-minute) intervals of non-sedentary time during the 80-minute time frames. Third, break intensity was parameterized as MET values from the hip accelerometer within the non-sedentary minutes. Fourth, the break context was represented as the current location (at home vs. work) of the participants while they answered the mood prompt.

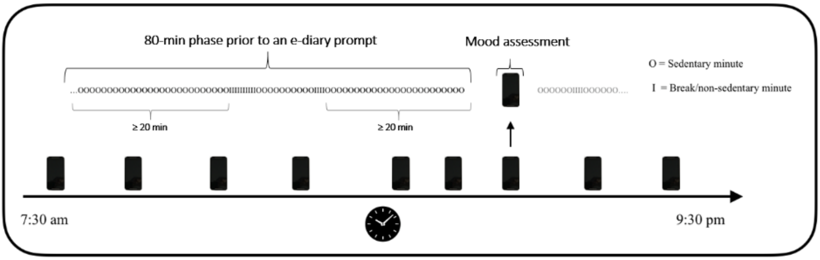

Figure 1. Example of a study day with 9-10 mood assessments from 7:30 am to 9:30 pm.

Data preprocessing and statistical analyses

The minute-by-minute file of the accelerometers and the e-diary entries were merged using the software DataMerger (version 1.6.38.68; movisens.com). According to the definition of a sedentary break, we only included time frames in which sedentariness was evident and in which the length of the time frame was interrupted by a break. Therefore, we included 80-minute phases in our analyses if they comprised (i) a minimum of two sedentary bouts with at least 20 minutes of uninterrupted sedentary time and (ii) 48 minutes (60%) of sedentary time overall. As an exception, we kept pure 80-minute phases of sedentary time in our statistical analyses. In total, 1089 phases were analyzed, i.e., 12.2 ± 7.7 phases per participant on average.

To analyze whether different break patterns influence mood dimensions in different ways, we conducted multilevel analyses (SPSS, version 25, IBM), the ‘state-of-the-art’ procedure in analyzing intensive longitudinal data. Multilevel analysis has several advantages, such as (i) the analysis of hierarchically structured data (i.e., multiple mood assessments nested within participants), (ii) the analysis of within- and between-subject effects simultaneously in one statistical model, and (iii) robustness with regard to missing data points (Bolger & Laurenceau, 2013). We set the α-level to 0.05 for all analyses. We calculated two-level models for each mood dimension (valence, energetic arousal, and calmness) and nested e-diary ratings (on level 1) within participants (level 2). Intraclass correlations (ICCs) were estimated using unconditional models including valence, energetic arousal, and calmness as outcomes. Here, we first entered the predictors time [hours], time-squared [hours2], break frequency [absolute frequency]/ break duration [minutes]/ break intensity [MET], age [years], sex [male vs. female], country [KIT, Germany vs. UoN, Australia], day [weekend day vs. weekday], BMI [kg/m2] and break context [at home vs. work] into our models. To standardize time and time-squared, we subtracted the start time of the study for each day (7:30). The following equation shows the exemplified model for hypothesis 2a.

Hypothesis 2a:

$$\begin{aligned} \boldsymbol{Y(energetic\ arousal)_{ij}} &= \boldsymbol{\beta_{00} + \beta_{01} * country_j + \beta_{02} * age_j + \beta_{03} * BMI_j} \\ &\quad \boldsymbol{+ \beta_{04} * sex_j + \beta_{10} * break\ frequency_{ij} + \beta_{20}} \\ &\quad \boldsymbol{* time\ of\ day_{ij} + \beta_{30} * time\ of\ day_{ij}^2 + \beta_{40}} \\ &\quad \boldsymbol{* weekday_{ij} + u_{0j} + u_{2j} * time\ of\ day_{ij} + r_{ij}} \end{aligned}$$

On level 1, within-subject effects were estimated using participants´ (subscript j) e-diary entries at any time of measurement (subscript i). $\boldsymbol{Y_{ij}}$ represents the level of valence, energetic arousal and calmness in person j at time i. Beta coefficients represent the intercept $\boldsymbol{\beta_{00}}$ and the effects of time, time-squared, break frequency/duration/intensity and day ($\boldsymbol{\beta_{10} - \beta_{40}}$) at level 1, and $\boldsymbol{r_{ij}}$ represents the residuals at level 1. We centered break frequency/duration/intensity on the participant mean. On level 2, between-subject effects were estimated. We included random effects (i.e., individual variation on the sample mean effect γ) for each mood dimension represented as $\boldsymbol{u_{ij}}$. Random slope parameters ($\boldsymbol{u_{1j} - u_{4j}}$) were included only if significant (P < 0.05) variation between participants was observed. To compare the effects of break frequency, break duration, and break intensity, we calculated standardized beta coefficients (standardized BCs) following established procedures (Hox & Roberts, 2014). Finally, we conducted control analyses to test whether momentary sedentary time (i.e., sedentary behavior within 5, 10, 15 or 20 minutes prior to the mood assessment) or total daily sedentary time (i.e., hours per day spent in sedentary behavior) may have influenced the associations between sedentary breaks and mood, adding momentary sedentary time and total daily sedentary time as predictors of no interest.

Results

The sample characteristics are detailed in Table 1a. Overall, participants were prompted 5352 times across 5 days. 70.55% of all prompts were answered, i.e., on average 8.26 ± 2.51 per participant per day. Participants reported average mood scores of 63.67 (energetic arousal), 75.4 (valence), and 68.31 (calmness), indicating a well-tempered sample. The ICCs revealed that 67% (β= 0.33; energetic arousal), 57% (β = 0.43; valence), and 59% (β = 0.41; calmness) of the variance in the mood ratings was due to within-subject fluctuations.

On average, accelerometers were worn for 12.97 ± 5.14 h/participant/day. Participants spent 7.6 ± 2.88 h/participant/day sedentary, indicating a sample that engaged in moderate to high levels of sedentary behaviors in daily life. We included 1089, 80-minute phases in our analyses, i.e., 12.2 ± 7.7 per participant. 11.3% of these phases were pure sedentary phases, i.e., 80-minutes uninterrupted sedentary time. Table 1b shows sedentary break patterns revealing a mean break frequency of 2.8 per 80-minute phase, a mean duration of 3.67 minutes and a mean intensity of 2.08 MET per break. Additionally, Table 2 presents the classification of breaking up sedentary behavior with distinct activity classes as detected by the hip and thigh accelerometer (Anastasopoulou, Tansella, Stumpp, Shammas & Hey, 2012), showing that most break minutes can be attributed to standing. Context assessments were only available from the German subsample. In particular, 66.5% of 612 phases occurred during work.

Table 3. Participants characteristics (n = 92) and sedentary break patterns.

	Variable	Mean ± SD	Minimum	Maximum
A) PARTICIPANTS CHARACTERISTICS	Female (%)	n= 60; 65%	---	---
	Age [yrs.]	33.73 ± 9.58	22	62
	Australian sample (UoN) (%)	n= 35; 38%	---	---
	BMI [kg/m^2]	23.44 ± 3.19	17.67	32.49
	Answered mood assessments [per day][a]	8.26 ± 2.51	2.4	15.8
	Valence [0-100][a]	75.4 ± 12.19	33.76	98.14
	Calmness [0-100][a]	68.31 ± 13.83	24.33	95.72
	Energetic arousal [0-100][a]	63.67 ± 13.4	29.86	94.27
	Wear time accelerometer [h/day][b]	12.97 ± 5.14	0	22.84
	Sedentary time [h/day][b]	7.6 ± 2.88	0	16.09
	Context of assessment – work [%]	66.5%	---	---
	Variable	**Mean ± SD; Percentile (25%- 50% - 75%)**	**Minimum**	**Maximum**
B) BREAK PATTERNS	Break frequency [absolute frequency][c]	2.79 ± 1.94 (1 – 3 – 4)	0	11
	Break frequency [work[d]]	2.64 ± 1.86 (1 – 2 – 4)	0	9
	Break frequency [home[d]]	3.03 ± 2.19 (2 – 3 – 4)	0	11
	Break duration [minutes][e]	3.67 ± 3.91 (1 – 2 – 4)	1	30
	Break duration [work[d]]	3.91 ± 4.03 (1 – 2 – 5)	1	27
	Break duration [home[d]]	3.12 ± 3.34 (1 – 2 – 4)	1	21
	Break intensity [MET][e]	2.07 ± 0.67 (1.62 – 1.93 – 2.36)	1	7.19
	Break intensity[work[d]]	2.13 ± 0.72 (1.64 – 1.96 – 2.45)	1	7.19
	Break intensity[home[d]]	2.01 ± 0.54 (1.68 – 1.91 – 2.23)	1	4.95

[a] assessed via e-diary, depicted are person mean values aggregated across the whole sample
[b] assessed via accelerometry, depicted are person mean values aggregated across the whole sample
[c] mean frequency per 80 minute phase
[d] mean frequency/duration/intensity of breaks patterns separated by contexts within the German subsample
[e] mean duration/intensity per sedentary break

Table 2. Descriptive statistics of activity classes derived from the hip and thigh accelerometer during sedentary breaks.

Activity Class	Break minutes [%][1]	Mean ± SD[2] [MET]	Min-Max[3] [MET]	Percentile (25%- 50%- 75%) [MET]	Compen-dium[4] [MET]
"active" Lying[a]	2.4	1.89 ± 0.35	1.5 - 3.27	1.64 – 1.81 – 2.04	1.3 – 2.8
"active" Lying[a] [Work[b]]	0.7	1.89 ± 0.34	1.51 – 2.71	1.66 – 1.79 – 2.05	
"active" Lying[a] [Home[b]]	6.3	1.88 ± 0.32	1.5 – 3.26	1.65 – 1.82 – 2.08	
"active" Sitting[a]	25.3	2.01 ± 0.56	1.5 – 8.42	1.66 – 1.86 – 2.17	1.3 – 3.8
"active" Sitting[a] [Work[b]]	22.3	2.04 ± 0.55	1.5 – 5.43	1.66– 1.88 – 2.22	
"active" Sitting[a] [Home[b]]	34.3	1.94 ± 0.42	1.5 – 5.06	1.66 – 1.85 – 2.07	
Standing	45.6	1.62 ± 0.55	1.13 – 7.1	1.25 – 1.25 – 1.85	1.3 – 4.5
Standing [Work[b]]	51.8	1.64 ± 0.61	1.18 – 5.26	1.25 – 1.25 – 1.87	
Standing [Home[b]]	34.2	1.68 ± 0.54	1.15 – 4.59	1.25 – 1.54 – 1.97	
Walking	22.1	3.46 ± 0.97	1.51 – 7.13	2.69 – 3.27 – 4.2	2 – 9.5
Walking [Work[b]]	19.6	3.6 ± 0.88	2.01 – 6.26	2.9 – 3.42 – 4.25	
Walking [Home[b]]	18.5	3.33 ± 0.93	1.96 – 6.25	2.63 – 3.03 – 4.01	
Slope down	1.4	3.32 ± 0.73	1.97 – 5.9	2.84 – 3.2 – 3.59	3.3 – 3.5
Slope down [Work[b]]	2.0	3.26 ± 0.67	2.21 – 5.9	2.84 – 3.2 – 3.48	
Slope down [Home[b]]	1.1	4.05 ± 0.85	2.44 – 5.52	3.59 – 3.95 – 4.69	
Slope up	1.8	5.8 ± 1.23	3.53 – 10.09	4.93 – 5.66 – 6.60	4 – 9.8
Slope up [Work[b]]	2.6	5.81 ± 1.03	3.74 – 8.3	5.01 – 5.81 – 6.47	
Slope up [Home[b]]	1.8	5.97 ± 1.46	3.87 – 10.09	4.94 – 5.7 – 6.81	
Jogging/Running	0.1	7.13 ± 1.66	5.8 – 10.79	6.05 – 6.58 – 7.59	6 – 23
Jogging/Running [Work[b]]	0.1	6.48 ± 0.74	5.96 – 7	5.96 – 6.48 – 7	
Jogging/Running [Home[b]]	---	---	---	---	
Unknown	1.2	1.17 ± 0.38	1 – 3.5	1 – 1 – 1.12	---
Unknown [Work[b]]	0.4	1.24 ± 0.46	1 – 2.81	1 – 1 – 1.43	
Unknown [Home[b]]	3.7	1.09 ± 0.21	1.00 – 2.13	1 – 1 – 1.02	

[1] Percentage of all break minutes assigned to the respective activity class within our sample; [2] Mean and standard deviation; [3] Range of MET/min; [4] For reasons of comparison, we depicted a range of MET values from the compendium of physical activities (25)

[a] Please note that "active" sitting/lying values refers to an energy expenditure ≥ 1.5 MET. Following the definition of sedentary behavior (21), we defined a sedentary break as either being in a non-sitting/non-lying position or having an energy expenditure ≥ 1.5 MET; [b] Descriptive statistics of activity classes separated by contexts within the German subsample

Effects of Break Patterns on Valence

Table 3 shows that break frequency (stand. BC = 0.07; $P < 0.01$) and break intensity (stand. BC = 0.07; $P < 0.01$) were positively associated with valence, verifying hypotheses 1a and 1c. However, break duration (stand. BC = 0.003; $P = 0.83$) did not positively predict valence. In particular, breaking-up sedentary behavior once during 80 minutes enhanced valence by 0.6 points, whereas three breaks enhanced valence by 1.83 points. Breaking-up sedentary behavior with an intensity of approximately 1.6 MET, such as by standing (Ainsworth et al., 2011), enhanced valence by 8.29 points (scale 0-100), whereas higher intensities, such as moderate walking (i.e., approximately 3.5 MET) (Ainsworth et al., 2011), enhanced valence by 18.13 points on average. Additional exploratory analyses did not reveal any significant interactions between break patterns. Moreover, the day of the week was significantly associated with valence ($P = 0.031$); specifically, on weekends, participants felt better than on weekdays. None of the predictors (time, time-squared, age, BMI, sex, or country) were significantly associated with valence. Furthermore, no random effects were found, indicating a homogenous sample.

Effects of Break Patterns on Energetic Arousal

Break frequency (stand. BC = 0.12; $P < 0.01$) and break intensity (stand. BC. = 0.08; $P < 0.01$) positively predicted energetic arousal, verifying hypotheses 2a and 2c. In contrast, break duration (stand. BC = 0.01; $P = 0.46$) did not positively predict energetic arousal. Translated to practice, breaking-up sedentary behavior more frequently and more intensively was associated with higher prospective energetic feelings (see Table 3). More specifically, on average, breaking-up sedentary behavior once during 80 minutes enhanced energetic arousal by 1.4 points (scale 0-100), whereas three breaks enhanced energetic arousal by 2.8 points. Breaking-up sedentary behavior with an intensity of approximately 1.6 MET, such as by standing, enhanced energetic arousal by 11.69 points, whereas higher intensities, such as moderate walking (i.e., approximately 3.5 MET), enhanced energetic arousal by 25.58 points on average. Further exploratory analyses revealed a significant ($P < 0.01$) interaction between break frequency and break intensity, indicating that within 80-minute phases, single breaks with higher intensities were more beneficial than any other variation. Furthermore, time and time-squared were significantly related to energetic arousal ($P = 0.027$ and $P < 0.001$) with opposing directions of effects. Translated to practice, energetic arousal decreased during the day, with an accelerated decrease from 14:00 to 23:00. None of the predictors (day, BMI, age, sex, or country) were significantly associated with energetic arousal. Furthermore, we found a significant random effect for the time of day ($P < 0.01$), revealing that effects varied among participants.

Effects of Break Patterns on Calmness

As hypothesized (hypothesis 3c), break intensity positively predicted calmness (stand. BC = 0.058; $P = 0.014$). In particular, breaking-up sedentary behavior with an intensity of approximately 1.6 MET (e.g., standing) was associated with an increase in calmness by 7.65 points (scale 0-100) on average. Higher intensities such as moderate walking (i.e., approximately 3.5 MET) were related to enhanced calmness by 16.74 points. However, contrary to hypotheses 3a and 3b break duration (stand. BC = -0.002; $P = 0.874$) and break frequency (stand. BC = 0.03; $P = 0.193$) did not significantly predict calmness. We did not find any interaction effects between break patterns in our exploratory analyses. Furthermore, the day of the week was significantly associated with calmness ($P = 0.004$); in particular, participants felt more calm on weekends than on weekdays. Again, time-squared was significantly related to calmness ($P = 0.012$), i.e., calmness decreased during the day until approximately 13:00 and increased thereafter. None of the predictors (age, BMI, sex, and country), were significantly associated with calmness, and we found no random effects, which indicates a homogenous sample.

Context Effects of Break Patterns on Mood

In Figure 2, a total of two significant interaction effects for context (at home vs. work) moderating the association between break patterns and mood are depicted. Specifically, context moderated the associations between break frequency and energetic arousal and between break intensity and energetic arousal. Translated to practice, while breaking-up sedentary behavior, for example, three times over 80 minutes enhanced energetic arousal in the home context by 11.29 points (scale: 0-100), breaking-up sedentary behavior in the work context enhanced energetic arousal by 3.43 points. Furthermore, breaking-up sedentary behavior with an intensity of 1.6 (e.g., standing or moderate walking) enhanced energetic arousal in the home context by 35.59 points but in the work context by 3.46 points. Additional analyses revealed the associations between break patterns and mood dimensions were neither influenced by momentary sedentary time (i.e., sedentary behavior immediately prior to the e-diary prompt) nor mean daily sedentary time.

Discussion

The purpose of our study was to investigate to what degree sedentary break patterns (i.e., variations in frequency, duration, intensity and context) influence basic mood dimensions (valence, energetic arousal and calmness). Our results provide the first evidence that sedentary breaks were associated with mood among healthy adults in daily life. In particular, break intensity was associated with enhancement in all three mood dimensions, and break frequency was related to enhancement in two of three mood dimensions (valence and energetic arousal); however, break duration was not significantly associated with mood at all. Exploratory analyses revealed that the effects of break frequency on energetic arousal, as well as the effect of break intensity on energetic arousal, were significantly higher in the home than in the workplace context.

We found that frequently breaking-up sedentary behavior is beneficial to enhance mood. In simple terms, a higher number of transitions from sedentary behavior to physically active behavior enhanced mood. This finding is in line with studies which have shown that hourly breaks of moderate-intensity were associated with higher self-perceived feelings of vigor and lower levels of fatigue under laboratory and everyday life conditions (Bergouignan et al., 2016; De Jong et al., 2018). Moreover, this finding is consistent with an experimental study that examined the transitioned from a sitting to a standing work posture, which led to a significant reduction in fatigue (Thorp et al., 2014). Our finding that breaking-up sedentary behavior more frequently is more beneficial to human mood than breaking-up sedentary behavior less frequent should be substantiated by experimental studies in everyday life to enable causal conclusions. Here, one approach might be to use ecological momentary interventions (Myin-Germeys, Klippel, Steinhart & Reininghaus, 2016), e.g., mobile apps to encourage participants to break up sedentary behavior after a specific time period of sedentariness (e.g., ≥ 30 minutes).

Table 3. Multilevel model analyses to predict mood dimensions: Fixed and random effects

	Outcome: VALENCE			*Outcome:* ENERGETIC AROUSAL			*Outcome:* CALMNESS		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
	b (SE)[1]	**b (SE)**	**b (SE)**	**b (SE)**	**b (SE)**	**b (SE)**	**b (SE)**	**b (SE)**	**b (SE)**
Fixed effects									
Intercept, $\boldsymbol{\beta_{00}}$	53.00 (11.72)**	52.22 (11.72)**	56.79 (11.6)**	45.76 (13.84)**	44.08 (13.91)**	50.5 (13.93)**	42.37 (12.35)**	41.86 (12.29)**	46.1 (12.37)**
Country[a], $\boldsymbol{\beta_{01}}$	5.24 (3.24)	5.21 (3.24)	4.91 (3.18)	5.52 (3.85)	5.63 (3.88)	5.22 (3.85)	6.08 (3.40)	6.03 (3.39)	5.79 (3.38)
Age, $\boldsymbol{\beta_{02}}$	0.15 (0.17)	0.15 (0.17)	0.17 (0.17)	0.19 (0.21)	0.19 (0.21)	0.22 (0.21)	0.11 (0.18)	0.11 (0.18)	0.13 (0.18)
BMI, $\boldsymbol{\beta_{03}}$	0.68 (0.50)	0.70 (0.50)	0.57 (0.49)	0.39 (0.59)	0.43 (0.59)	0.23 (0.59)	0.94 (0.52)	0.95 (0.52)	0.84 (0.52)
Sex[b], $\boldsymbol{\beta_{04}}$	-2.14 (3.15)	-2.14 (3.15)	-1.98 (3.09)	-0.71 (3.73)	-0.65 (3.75)	-0.37 (3.72)	-2.13 (3.30)	-2.12 (3.28)	-1.97 (3.27)
Break frequency, $\boldsymbol{\beta_{10}}$	0.61 (0.23)**	---	---	1.42 (0.29)**	---	---	0.35 (0.27)	---	---
Break duration, $\boldsymbol{\beta_{10}}$	---	0.02 (0.08)	---	---	0.05 (0.10)	---	---	-0.01 (0.09)	---
Break intensity, $\boldsymbol{\beta_{10}}$	---	----	5.18 (1.65)**	---	---	7.31 (2.12)**	---	---	4.78 (1.93)*
Time of day, $\boldsymbol{\beta_{20}}$	-0,40 (0.61)	-0.47 (0.61)	-0.51 (0.61)	1.76 (0.79)*	1.60 (0.8)*	1.54 (0.8)	-1.10 (0.71)	-1.15 (0.71)	-1.19 (0.71)
Time of day squared, $\boldsymbol{\beta_{30}}$	0.03 (0.04)	0.04 (0.04)	0.04 (0.04)	-0.19 (0.05)**	-0.18 (0.05)**	-0.17 (0.05)**	0.10 (0.04)*	0.11 (0.04)*	0.11 (0.04)*
Weekend day[c], $\boldsymbol{\beta_{40}}$	2.25 (1.04)*	2.15 (1.05)*	2.44 (1.05)*	-1.94 (1.34)	-2.21 (1.36)	-1.80 (1.35)	3.40 (1.23)**	3.33 (1.23)**	3.62 (1.23)**
Random effects									
Intercept, $\boldsymbol{u_0}$	160.09 (28.80)**	159.86 (29.23)**	153.42 (27.77)**	179.96 (39.80)**	181.23 (40.31)**	177.69 (39.5)**	169.95 (31.24)**	168.05 (31.14)**	167.23 (30.71)**
Time of day, $\boldsymbol{u_2}$	---	---	---	1.06 (0.38)**	1.06 (0.38)*	1.07 (0.38)**	---	---	---
Residual	172.20 (7.74)**	173.41 (7.80)**	172.25 (7.74)**	277.11 (12.95)**	283.47 (13.25)**	280.4 (13.11)**	239.70 (10.76)**	240.28 (10.79)**	238.92 (10.72)**

Note[1]: Unstandardized estimates and standard errors
[a]compared to Germany; [b]compared to males; [c]compared to weekday
* P < .05; ** P < .01

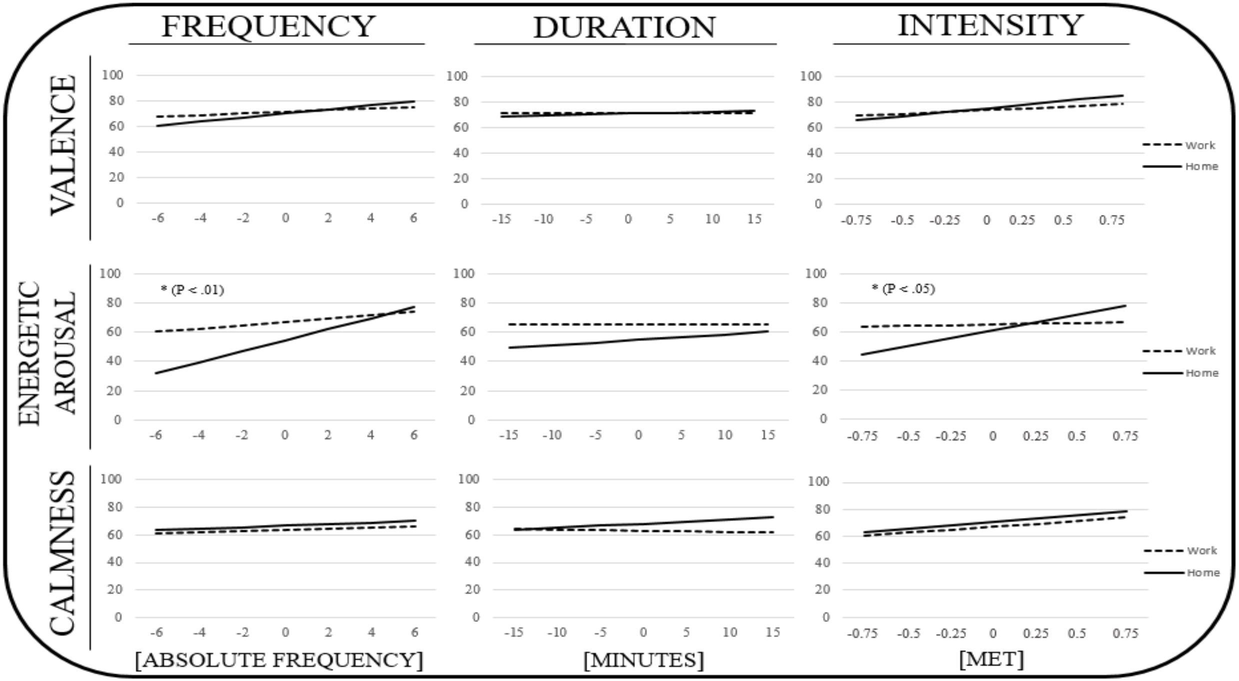

Figure 2. Multilevel interaction analyses testing whether context moderates' associations of break patterns with mood. For each of the nine models, the y-axis depicts the mood ratings [scale: 0-100]. The x-axis depicts the absolute frequency, the mean duration in minutes and the intensity as MET. Please note that break pattern values to the left of the x-axis refer to below-average values within a person while break pattern values to the right depict above-average values within a person in everyday life (for details, see methods section).

Several studies showed that both shorter and longer bouts of physical activity are positively associated with mood, for example exercises such as 30 minutes of jogging or non-exercise activities such as 15 minutes biking for transport (Liao et al., 2015; Penedo & Dahn, 2005; Reichert et al., 2017). However, contrary to expectations, our study did not find any significant association between sedentary break durations and mood. Based on our study design with multiple mood assessments per day, we chose the average time frame between two e-diary prompts, i.e., 80.55 minutes, to avoid overlapping time frames. One possible explanation for our null finding might be the restricted variance of the bout duration within our data (approximately 75% of all breaks lasted less than 5 minutes). Thus, further experimental studies with varying break durations in everyday life are needed to clarify this issue.

A large and growing body of literature has investigated the effects of exercise and non-exercise activities on mood dimensions across several subpopulations (Liao et al., 2015; Penedo & Dahn, 2005; Puetz, Flowers & O'Connor, 2008). In particular, positive effects of physical activity on mood were found on the entire intensity continuum, across both exercise and non-exercise activities. While effects of sedentary break intensities are less investigated. For example, Thorp et al. (2014) showed that sit-to-stand transitions every 30 minutes enhanced feelings of energy, and Sperlich et al. (2018) showed that a 6-minute session of high-intensity interval exercise led to enhanced feelings of vigor. However, most previous studies focused solely on the effectiveness of a single break pattern on mood but did not directly compare the effects of different break intensities on mood. While we did not systematically vary beak intensities but conducted a naturalistic study observing the break intensities as they naturally occurred in participants everyday life, we found that breaking-up sedentary behavior with higher intensity such as walking with moderate pace has a stronger impact on mood dimensions than breaking up with light intensity such as standing up. This finding may have practical implications suggesting that humans should stand up and move rather than only standing up if they are interested in enhancing mood. However, it is critical to choose the right intensity since studies have shown that more intense forms of exercise may lead to displeasure, although such feelings can subside with time after exercise (Ekkekakis, 2003).

Another important result was that breaking-up sedentary behavior to enhance feelings of energy was more beneficial in the home than in the workplace context. This finding may have important practical implications, since most previous studies have investigated the effects of sedentary breaks on mood solely in the occupational context, and interventions are focused solely on work settings, for instance developing sit-stand workstations (Dutta, Koepp, Stovitz, Levine & Pereira, 2014). In contrast, our findings suggest that the intervention strategy to break up sedentary behavior may be more beneficial for human mood within other contexts, such as at home. While there is a strong influence of the environment and social norms on human behavior (e.g., sitting in meetings) (Owen et al., 2011), it is reasonable to assume that humans have more opportunities to vary their break patterns at home, which may impact the effects of sedentary breaks on mood. Many other factors may also impact the effects of sedentary breaks on mood such as the purpose of a break (e.g., run to fetch some papers from the printer or watering flowers while gardening), social interactions (e.g., being alone or in company) or setting specific conditions (e.g., stressful work or relaxed cooking in the kitchen), which may vary as a function within a context and between different contexts. Here, context assessments such as geo-location tracking or the use of wearable camera systems can help to determine the influence of context on the association between sedentary break patterns and mood in more depth (Loveday, Sherar, Sanders, Sanderson & Esliger, 2015; Törnros et al., 2016). Moreover, since studies showed that aerobic exercise has the potential to buffer stress (Smith, 2013), a stress buffering effect of sedentary breaks are in principle conceivable. Here, especially stressful work contexts can be a valuable setting for research endeavors on this issue.

Suggestions for future research and limitations of our work merit further discussion. First, we cannot exclude residual confounds (e.g., those due to other daily life factors that may influence mood, such as social or nutritional behaviors, partnership quality, employment status, quantity and quality of sleep, and drug consumption [such as alcohol and caffeine]). For example, since exercise can decrease anxiety elevated due to caffeine intake (Youngstedt, O'Connor, Crabbe & Dishman, 1998) and caffeine intake may be increased in working contexts, the interaction of sedentary breaks, mood and caffeine intake would be a reasonable proposal for future investigations. Second, the study devices (smartphone and accelerometers) were not water- or shockproof and therefore could not be worn during all types of physical behaviors (e.g., swimming). However, our analyses were focused on within-subject processes of sedentary breaks and mood and not on the total amount of physical behavior, making this limitation a minor issue. Third, even though our data show a clear chronological time order, this is only one aspect of causality (Susser, 1991). Chronology suggests but does not prove causality because hidden third variables might show similar time-related characteristics. Therefore, to substantiate a causal hypothesis, additional studies are needed. One approach might be to use ecological momentary interventions (Myin-Germeys et al., 2016). Fourth, our data were limited in revealing information on the setting or environment in which participants engaged in sedentary breaks, which could have influenced the degree of the psychological benefit. For example, walking in the train station may lead to different effects on mood as hiking in a mountain landscape. Therefore, we call for future real life studies, for example using geo-location data (Törnros et al., 2016) or wearable camera systems (Loveday et al., 2015) to increase knowledge on contextual effects (e.g., environmental locations such as indoor vs. outdoor) on the association between sedentary breaks and mood. Fifth, there is evidence that exercises at very high intensities may first lead to an initial negative shift in mood, which subsides after exercise and is followed by positive changes (Ekkekakis, 2003). Thus, since we used a high sampling frequency of mood assessments, it might be possible that participants performed a sedentary break with high intensity and thereafter the participants were immediately prompted to rate their mood. However, sedentary breaks of high intensities are very rare in our sample.

Conclusions

We conducted one of the first studies investigating associations between sedentary break patterns and basic mood dimensions in daily life. Our ecologically valid findings are in line with those of studies showing that frequently breaking-up sedentary behavior is beneficial to human mood. Our findings significantly extend those in the literature, revealing that breaking-up sedentary behavior with light or moderate-intensity walking has a stronger impact on mood than merely standing up. Our findings also indicate that breaking-up sedentary behavior to enhance feelings of energy is more beneficial in the home than in the workplace context. These insights can serve as starting points to build an evidence-base on mood outcomes of breaking-up sedentary behavior for more specific public health recommendations. Thus, we suggest as preliminary recommendations that individuals should break up their sedentary behavior as frequently as possible within an hour with at least moderate-intensity activities, such as slow walking; ideally, this practice would take place in any context. Given the high prevalence of sedentary behavior around the globe and the concurrent increase in the incidence of mental disorders, we call for more studies identifying optimal and practical break patterns in daily life in different samples.

Conflicts of Interest and Source of Funding

All other authors declare no conflicts of interest. The results of the present study do not constitute endorsement by the American College of Sports Medicine. Furthermore, the results of the present study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation.

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Chapter VII

General discussion

In our work, the construct of sedentary behavior became our research focus. We considered both the methodological aspects of sedentary behavior and the relationship between sedentary behavior and mood in daily life. In particular, we showed that

(a) thigh-worn accelerometers such as the ActivPAL or Move 4 achieved up to excellent validity in measuring sedentary behavior;

(b) sedentary triggered EMA is an accurate sampling strategy to collect “just in time” social and environmental context information in daily life;

(c) sedentary behavior is negatively associated with valence and energetic arousal;

(d) the association between mood and sedentary behavior formed a reciprocal relationship, while higher ratings of valence and energetic arousal were associated with subsequently lower amounts of sedentary behavior;

(e) intense and frequent sedentary breaks were most beneficial in enhancing mood.

Over the past decade, the scientific community has increased its efforts to gain a better understanding of the associations between sedentary behavior and health outcomes. A recently published summary of the 2018 physical activity guidelines concluded that there is further evidence of an association between sedentary behavior and all-cause mortality, while the need remains to develop field methods to accurately assess sedentary behavior (Katzmarzyk et al., 2019). Therefore, since the research field of sedentary behavior is still in its infancy, our work contributes to a better understanding of (i) measuring sedentary behavior and (ii) unraveling the antecedents and consequences of sedentary behavior in daily life, especially regarding the dynamic relationship between sedentary behavior and mood. Most previous studies have used the Ambulatory Assessment approach to focus on the association between physical activity and mood dimensions (Dunton, 2017; Koch et al., 2018; Liao, Shonkoff & Dunton, 2015; Reichert et al., 2017; Reichert, Tost, Reinhard, Zipf, Salize, Meyer-Lindenberg & Ebner-Priemer, 2016). In contrast, very few studies investigate the associations between sedentary behavior and mood (Elavsky, Kishida & Mogle, 2016; Kim, Conroy, & Smyth, 2019; Maher et al., 2019; Maher, Rebar & Dunton, 2018). Our findings are a further step toward a better understanding of the assessment of sedentary behavior and the association with mood in daily life. However, as mentioned above, the research field is in its very early stage and thus we assume that future research will shed more light on this important issue. In the following section, we discuss three issues that might be interesting for future research endeavors. First, The 24-hour cycle – a new paradigm in physical behavior research? Second, The ladder of causality – how to examine it in daily life? Third, The psychophysiological response to sedentary behavior – how to integrate it into daily life?

Issue 1: The 24-hour cycle – a new paradigm in physical behavior research?

Today, humans spend a large portion of their daily time in a sedentary position. For example, a typical day may include the following routines: driving by car to work, working at a computer in a seated position, driving back home and, finally, reclining on the couch while watching TV. Previous studies have reported that adults in different cultures and countries spend a large amount of time in a sedentary position (Matthews et al., 2008; Smith et al., 2015; Yang et al., 2019). However, sedentary behavior is only one aspect of humans' daily physical behavior. Physical behavior, i.e., physical activity, sedentary behavior and sleep, can be conceptualized as a 24-hour cycle of movement and nonmovement behavior (see Figure 1). Although our work focused primarily on sedentary behavior, it is promising and, at the same time, a necessary approach for future research to assess and analyze data over the full spectrum of the 24-hour cycle. Following the example of an ongoing discussion serves as a showcase for the necessity of assessing and analyzing more than only a single aspect of physical behavior. Since researchers have shown that sedentary behavior may increase all-cause mortality, an important question has arisen: Can sufficient physical activity counter the adverse health effects of sedentary behavior? More recently, studies have emerged offering contradictory findings regarding this issue. For example, Ekelund and colleagues (2016) concluded that high levels of moderate-intensity physical activity seem to eliminate the increased mortality associated with high sitting time.

In contrast, Biswas and colleagues (2015) concluded that prolonged sedentary time was independently associated with deleterious health outcomes regardless of physical activity. This inconclusive evidence is reflected in several other studies reporting divergent findings (Chau et al., 2013; Edwards & Loprinzi, 2016; Ekelund et al., 2019; Katzmarzyk, Church, Craig & Bouchard, 2009; Koster et al., 2012; Stamatakis et al., 2019). In short, the dependency between sedentary behavior and physical activity is an important issue, one that can only be resolved if both behaviors are measured simultaneously and can be separated during data analysis. In our third work, we addressed the interrelationship between sedentary behavior and physical activity while showing that the negative influence of sedentary behavior on valence and energetic arousal was independent of physical activity (Giurgiu et al., 2019). To verify our preliminary finding, further studies are needed to measure and analyze both aspects of physical behavior.

Sleep, completing the 24-hour cycle, is well-known as a health-related behavior (Watson et al., 2015). According to the Consensus Statement of The American Academy of Sleep Medicine and the Sleep Research Society (Watson et al., 2015), sleep is related to several aspects of human health. For instance, sleep is critically involved in systematic physiology such as metabolism (Magee & Hale, 2012), cardiovascular systems (Wang, Xi, Liu, Zhang & Fu, 2012), mood regulation (Minkel et al., 2012), brain functions, including neurobehavioral, cognitive and safety-related performance (Van Dongen, Maislin, Mullington & Dinges, 2003), and many other health-related outcomes (Watson et al., 2015). However, researchers have only recently begun to integrate all aspects of physical behavior by focusing on the interrelatedness of sleep, physical activity, and sedentary behavior, thereby aiming to answer questions such as: Does sleep possibly increase time spent in moderate-to-vigorous physical activity (MVPA)? or Is there a threshold of MVPA minutes per day that counters the adverse health effects of sedentary behavior? To answer those questions, Rosenberger et al. (2019) introduced the 24-h Activity Cycle (24-HAC) model as a paradigm to explore the interrelatedness of health effects among all aspects of physical behavior. In short, the 24-HAC may provide the basis on which to create public health guidelines, to define health risks, to discover synergies and to refine interventions.

Thus far, we have highlighted and discussed some reasons why future research endeavors may be interested in focusing on all aspects of physical behavior instead of solely targeting one aspect. We would now like to address the selection of methods to accurately capture all aspects of physical behavior. In particular, we would like to expand on current recommendations and future directions regarding the operationalization of physical behavior. Based on illustrations by Tremblay and colleagues (2017) and Rosenberger and colleagues (2019), we present the 24-hour cycle of physical behavior as follows:

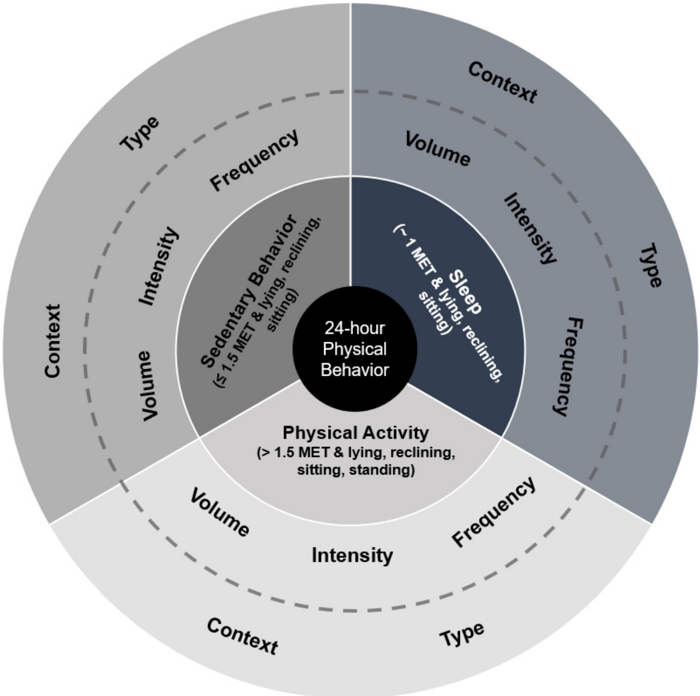

Figure 1. The 24-hour cycle of physical behavior.

Figure 1 illustrates physical behavior conceptualized as a 24-hour component. The inner ring comprises a differentiation among all aspects of physical behavior, i.e., sleep, sedentary behavior and physical activity. Importantly, according to the definition of sleep as "A naturally recurring and easily reversible state that is characterized by reduced or absent consciousness, perceptual disengagement, immobility, and the adoption of a characteristic sleeping posture" (Rosenberger et al., 2019; Watson et al., 2015), of sedentary behavior as "Any waking behavior characterized by an energy expenditure ≤ metabolic equivalents (METs), while in a sitting, reclining, or lying posture" (Tremblay et al., 2017), and of physical activity as "Any voluntary movement produced by skeletal muscles that results in energy expenditure" (Caspersen, Powell & Christenson, 1985), there are some unique characteristics that separate each behavior from the others.

First, sleep and sedentary behavior are characterized by lying, reclining or sitting body postures. Thus, for example, differentiating between a standing and a sitting posture is crucial (Buckley, Mellor, Morris & Joseph, 2014; Thorp, Kingwell, Owen & Dunstan, 2014). Second, by definition there is a threshold value of energy expenditure or movement intensity during sleep (~ 1 MET) and sedentary behavior (≤ 1.5 METs). Therefore, an intensity marker is required to differentiate each behavior accurately. For example, cycling, mainly performed in a seated position, should be classified as a physical activity. Third, sleep is a state of reduced or absent consciousness. Thus, sleep-wake detection is critical to differentiating, for example, between reclining while awake and napping in front of the television. Those three issues are fundamental prerequisites for accurately differentiating among sleep, sedentary behavior and physical activity.

Before we discuss the selection of accurate methods, we would like to introduce the outer ring of Figure 1, which is separated into quantitative and qualitative aspects by a dashed line. In simple terms, each physical behavior can be operationalized by various qualitative and quantitative parameters, which together form a complete pattern of behavior. To fully understand the associations between physical behavior and health-related outcomes, it may be necessary to capture the complete behavior pattern. For example, the physical activity pattern may comprise the following characteristics: Frequency (e.g., how many times a day was physical activity performed?); Volume (e.g., what is the cumulative sum of physical activity during a day?); Intensity (e.g., was the intensity of physical activity light, moderate or vigorous?); Type (e.g., was the purpose of physical activity transportation or exercise?); Context (e.g., did physical activity occur indoors or outdoors?). To sum up, each physical behavior has a pattern, which forms the basis of dense information.

A variety of subjective measures (e.g., questionnaire, interview, activity-recall instruments) are currently available and provide useful information about the type and context of behavior. However, subjective measures are prone to recall and social desirability biases, which may result in an inappropriate measurement of physical behavior patterns (Chastin, Culhane & Dall, 2014; Kang & Rowe, 2015; Lagersted-Olsen et al., 2014; Prince et al., 2008). Currently, activity monitors such as accelerometers have become the preferred method, thanks to their portability, affordability, and opportunity to gather large amounts of information (Bassett, 2012; Strath et al., 2013). In line with previous studies (Byrom, Stratton Mc Carthy, & Muehlhausen, 2016; Montoye, Pivarnik, Mudd, Biswas & Pfeiffer, 2016), our first work (Giurgiu et al., submitted) has shown that thigh-worn accelerometers achieved up to excellent validity in measuring body position and sedentary behavior. Therefore, aiming to differentiate body postures and energy expenditure (i.e., a prerequisite to differentiating among physical behaviors – see also the inner ring of Figure 1), thigh-worn accelerometers are preferred (Holtermann et al., 2017; Stamatakis et al., 2019). In contrast, sleep assessment is slightly more sophisticated. In particular, the most accepted measure of sleep is polysomnography (Keenan, 2007), which is typically expensive and burdensome and not practical for use in daily life studies. Thus, small wearables such as accelerometers are often used to estimate sleep and wake time using movement detection (Ancoli-Israel et al., 2015). Compared with polysomnography as a gold standard, wrist-worn activity monitors achieved high accuracy (Marino et al., 2013). Interestingly, the position of choice for sleep assessment is the nondominant wrist because it optimizes the recording of small movements that occur at the distal extremities when the individual is supine (Ancoli-Israel et al., 2015; Quante et al., 2015). Additionally, sophisticated features of wrist-worn accelerometers, such as a light sensor or a photometer, enable researchers to record light exposure of individuals' environments, which may provide a further important data source to differentiate between sleep and wake time.

Based on current recommendations and findings from our first work (Ancoli-Israel et al., 2015; Giurgiu et al., submitted; Stamatakis et al., 2019), a multisensor system comprising a wrist and thigh-worn accelerometer is necessary to capture all quantitative aspects of physical behavior and to accurately differentiate among sleep, sedentary behavior, and physical activity. However, accelerometers are limited to informing researchers about qualitative aspects such as the type of behavior or contextual information (e.g., indoor vs. outdoor), which are crucial to understanding a behavior's antecedents and consequences. Fortunately, evolving technology has led to the possibility of collecting data more easily during one's daily life. For example, methods such as electronic diaries via a smartphone application has become an established approach to assessing social and environmental context information in real time (Ebner-Priemer & Trull, 2009). Notably, since the number of smartphone users worldwide has now reached 3.5 billion (Statista, 2018), material facilities are almost available. In combination with accelerometers, the Ambulatory Assessment (AA) approach has several advantages, namely, the assessment in daily life and in real time, with device-based methods and repeated measurements with a high sampling frequency, enabling researchers to track dynamic relationships. Therefore, it bypasses laboratory distortions and minimizes recall biases associated with traditional approaches such as paper-pencil questionnaires (Bussmann, Ebner-Priemer & Fahrenberg, 2009; Fahrenberg, Myrtek, Pawlik & Perrez, 2007). Moreover, as shown in our second work (Giurgiu, Niermann, Ebner-Priemer & Kanning, submitted), triggered e-diaries as a technical advance is an accurate method of capturing qualitative aspects "just in time" (Kanning, Ebner-Priemer & Schlicht, 2015). Thus, the AA approach is a promising method used to capture full patterns of physical behaviors and thus to obtain in-depth insights into everyday physical behaviors. Given the current relevance of assessing and analyzing all aspects of physical behavior simultaneously, we expect that technological development would allow researchers to capture more and more aspects of physical behavior. For instance, the next generation of accelerometers might have an integrated Global Positioning System (GPS) or Magnetometer for geolocation tracking, or the smartphone's internal sensor might be used, or new algorithms for voice recognition or further applications such as previous-day recalls via smartphones might be developed (Matthews et al., 2019).

Lastly, to explore the interrelatedness of health effects among all aspects of physical behavior, new statistical methods are required. Traditional regression techniques are inadequate because the components of the 24-HAC add up to a finite amount of 24 hours. In particular, an increase in one behavior ultimately leads to a decrease in at least one of the other behaviors and thus the components are entirely interdependent. Therefore, several research groups have worked on various strategies to acknowledge the codependency between behaviors and to apply rather sophisticated statistical approaches. Based on models for the substitution of food components, Mekary and colleagues (2013) applied an approach to physical behavior data. The aim of the Isotemporal Substitution Model (ISM) is to estimate the effect of replacing one specific behavior with another behavior for the same amount of time. A second analytic method is compositional data analysis (CoDA). Initially used in geology and to create drugs, Chastin and colleagues (2015) applied this approach to physical behavior data. In contrast to ISM, the assumption of the relationship between covariates and outcomes varies in the CoDA approach. In simple terms, ISM assumes linear relationships, whereas CoDA assumes nonlinear relationships and transforms the covariates into the composite variables of a whole (Rosenberger et al., 2019). Since both approaches are relatively new, we expect that further methods will emerge within the next few years. Moreover, it might be interesting to transfer compositional analyses into a nested data structure and to develop analyses for within-subject associations.

Issue 2: The ladder of causality – how to climb it in daily life?

As one of the first to study this issue, we investigated the bidirectional association between sedentary behavior and mood. The main finding from our third work (Giurgiu et al., 2019) revealed that the more participants were sedentary in their everyday life, the less they felt well and energized. Moreover, sedentary bouts (30-min intervals of uninterrupted sedentary behavior) negatively influenced valence and energetic arousal. In our fourth work (Giurgiu et al., submitted), we found that higher ratings of valence and energetic arousal predicted lower amounts of subsequent sedentary behavior, whereas higher ratings of calmness predicted higher amounts of subsequent sedentary behavior. In summary, our AA study indicated a reciprocal relationship between sedentary behavior and mood among healthy university employees. This finding is in line with results by DeMello and colleagues (2019) and Kim and colleagues (2019) indicating a reciprocal relationship between sedentary behavior and mood. Thus, although time-sensitive analyses between sedentary behavior and mood are in their early stages, there is preliminary evidence of a reciprocal relationship. This association fits well with the theoretical framework presented in chapter I. Figure 2 shows a simplified version of the theoretical framework, highlighting the reciprocal relationship between physical behavior and health status.

Along with a reciprocal relationship between two constructs, the question of causality rises. Which construct may influence the other first? Is mood an antecedent or a consequence of sedentary behavior? In other words, do individuals feel worse because they have been sedentary or are they sedentary because they felt worse? Experimental research under laboratory conditions may unravel such questions because the laboratory setting reveals a high internal validity. However, transfer into daily life is limited and restricts ecological validity. In contrast, observational studies in daily life under real-world conditions reveal a high ecological validity but cannot establish causality. For example, unmeasured or hidden third variables may confound the findings. This leads to the question: how to examine causality in daily life?

According to Susser (1991), causality is defined as the way constructs influence one another across time and space. More specifically, the following four aspects of causality should be considered. First, a causal factor (X) must occur together with the effect (Y). Based on statistical analyses, an association between both constructs should be apparent in empirical data. In line with previous studies (DeMello et al., 2018; Kim et al., 2019), our third and fourth works (Giurgiu et al., 2019; Giurgiu et al., submitted) have shown that sedentary behavior is associated with mood. Second, a suspect causal factor (X) must precede effect (Y). In particular, the chronological “time order” of cause and effect should be present. Accordingly, our high-resolution data with continuous measurements of sedentary behavior and repeated assessments of mood (Giurgiu et al., 2019; Giurgiu et al., submitted) show a clear chronological order. However, chronology suggests but does not prove causality, as hidden third variables might exhibit similar time-related characteristics. This brings us to the third point, namely, that any other plausible explanation for the association between the two constructs must be eliminated. As mentioned above, unmeasured variables may confound the findings. Since sedentary behavior is merely a procedural subcomponent of purposeful actions such as working, talking, driving, or reading (Gardner et al., 2019), it might be reasonable to expect that the consequence of a worsened mood might not stem from being sedentary but perhaps from performing tasks while being sedentary, such as strenuous work at the computer, fewer social interactions, or rush hour traffic. Given these examples, we cannot exclude that third variables may account for mood changes rather than sedentary behavior itself. Fourth, the direction between cause and effect should be clarified. In other words, e.g., one must show that a change in sedentary behavior leads to a change in mood or vice versa. Susser (1991) concluded: “Direction is the crux of the difficulties in making a valid causal inference.” At this point, an observational study as presented in our third, fourth and fifth works is limited to making a valid causal inference. Therefore, to substantiate a causal hypothesis, additional studies with appropriate designs are required.

Thus far, we have described some elementary characteristics of causal inference. Before we discuss some promising study designs for future research endeavors, we would like to briefly introduce the ladder of causation. In a recently published book, Pearl and Mackenzie (2018) introduced readers to the three levels of causation. The first level is called association and is based on passive observations. At this rung of the ladder, researchers can answer the questions “What if I see…?” or “How are the variables related?” However, even though we can use appropriate statistics with good predictions, we still require good explanations. The second level is called intervention and at this point researchers begin to change the environment. This rung of the ladder is characterized by questions such as “What if I do…?”, “How?” or “What would Y be if I do X?” Although intervening is an important step on the causal ladder, it still may not answer all questions of interest. Simply put, the individual’s mood decreased, but why? Was sedentary behavior the reason or was it a negative conversation with a colleague? This leads to the third level, which is called counterfactuals and is characterized by questions such as “What if I had done…?”, “Why?”, “Was it X that caused Y?” or “What if X had not occurred?” Transferring the current state of knowledge about the relationship between sedentary behavior and mood to the ladder of causality, we have only reached the first rung of the ladder and future research may enable a move to the second rung.

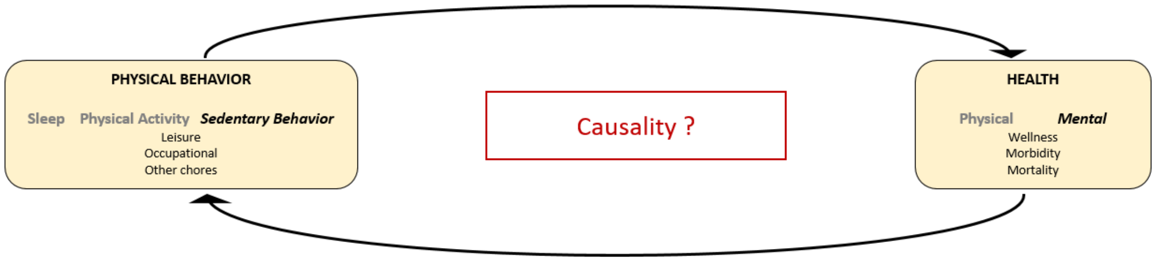

Figure 2. Reciprocal relation between physical behavior and health status.

One approach might be to integrate interventions in daily life. Based on technological development, eHealth interventions such as web-based interventions or serious gaming has become a sophisticated approach to behavior research (Mohr, Burns, Schueller, Clarke & Klinkman, 2013). One example of eHealth interventions is the use of mobile health (mHealth) interventions. So-called Ecological Momentary Interventions (EMI) have been used in a variety of different research areas (Free et al., 2013). In combination with continuous device-based measurements of physical behavior (see also issue 1), the EMI approach can be used as an Ambulatory Assessment Intervention (AAI) approach, for instance by prompting participants multiple times across the day and instructing them to change their physical behavior pattern. Notably, the induced intervention on the physical behavior pattern is most likely independent of the exposure to third unmeasured variables. In other words, a prompt with a precise specification of being sedentary (e.g., without a specific task) is unlikely to coincide with being sedentary while driving a car or working strenuously at a computer. Moreover, according to Myin-Germeys and colleagues (2016), two advantages could be adopted in the field of physical behavior research. First, as smartphones are now widespread (Statista, 2018), a large number of individuals could be reached using the EMI approach. Second, integrating assessment in real life enables one to individually tailor interventions, e.g., by providing interventions at moments when they are needed, primarily because sedentary patterns may vary among individuals or among days, underpinning the need for an individualized person-tailored approach. In our second work (Giurgiu et al., submitted), we introduced sedentary triggered EMA as an accurate method to trigger prompts following a self-selected amount of sedentary behavior, e.g., after a sedentary bout of ≥ 30 min. The sedentary triggered EMA approach can be modified to develop sedentary triggered mHealth interventions.

We assume that if researchers gain a more profound understanding of how to examine everyday causal inference, this could solve many unanswered questions in physical behavior research. Moreover, it will serve to develop evidence-based recommendations for global public health guidelines, which is important because current public health guidelines for sedentary behavior are highly unspecific (Ministry of Health, 2018; Stamatakis et al., 2018). In our fifth work (Giurgiu et al., 2019), we have shown that breaking up sedentary behavior frequently and intensively, for example by walking instead of standing, may be most beneficial. Such ecologically valid findings can serve as a starting point to inform public health recommendations. However, to substantiate a causal inference, further studies with appropriate designs are needed. We would now like to introduce the within-person encouragement design (Schmiedek & Neubauer, 2019). This novel design can be categorized under the umbrella term of AAI and is a promising approach to examining, e.g., whether a break from sedentariness causes a mood enhancement.

The within-subject encouragement design combines methodological approaches from different research traditions: i) within-subject analyses using multilevel models, ii) experimental manipulation of a treatment variable, and iii) random encouragements used as an instrumental variable to induce exogenous experimental variation when strict treatment adherence is unrealistic. Each of these traditional approaches has strengths and limitations, but in combination they could overcome their limitations and provide a compelling study design. In particular, Schmiedek and Neubauer (2019) describe how to combine these approaches and suggest to consider the following four steps while planning and conducting a study with a within-person encouragement design. We transfer these planning steps to the research question of our fifth work (Giurgiu et al., submitted), aiming to substantiate a causal inference between sedentary break patterns and mood. Step 1: Define outcome and target population. The outcome must show within-subject fluctuations. Our example includes the outcome mood, which underlies temporal variations in daily life (Ebner-Priemer & Trull, 2009). Furthermore, we would recommend using a population that is prone to be highly sedentary in daily life, such as office workers (Clemes, O'Connell & Edwardson, 2014; van Dommelen et al., 2016). Step 2: Define a treatment behavior and the population of situations in which it can be shown. At this point, we must identify the behavior that should be manipulated by encouragements. In our case, it would be the "breaking-up behavior" of sedentariness. Furthermore, we could ensure that participants are free in their choice of breaking up sedentary behavior or not, and thus the second step is quite practicable. Step 3: Recruit participants and negotiate an intervention regime. According to the simulations of Schmiedek and Neubauer (2019), a total observation of 2,000 or larger (e.g., 100 participants with 20 assessments) is sufficient to obtain an unbiased estimation and adequately powered models to detect at least medium-sized treatment effects. Further, participants should be instructed about the treatment regime, e.g., break up sedentary behavior and walk with moderate intensity for three minutes. Step 4: Implement the intervention. As set up in step 3, participants received at a random subset of situations an encouragement to indicate the desired target behavior, e.g., a walking break after a selected amount of prolonged sedentary behavior such as ≥ 30 minutes. This encouragement could be provided via a smartphone application.

Lastly, to sum up, Reininghaus and colleagues (2015) concluded that (i) AAI is powerful in generating evidence on several causal criteria simultaneously, such as association, time order, and direction, and (ii) AAI provides robust evidence as to whether the type of intervention is useful. Since the implementation of AAI is at a very early stage in the field of physical behavior research, we call for future research work to climb to the second level of the ladder of causality.

Issue 3: The psychophysiological response to sedentary behavior – how to examine in daily life?

In chapter I, we introduced the theoretical framework of our work – a modified version of the Bouchard and colleagues (2012) model – which describes the complex relationship among physical behavior, health-related fitness, and health status. Our study presented in the third and fourth works (Giurgiu et al., 2019; Giurgiu et al., submitted) focused primarily on the reciprocal relationship between sedentary behavior and mood (gray paths in Figure 3). However, other paths of the relation are possible and may provide further insights into the association between sedentary behavior and mental health outcomes such as mood. For example, future researchers may be interested in examining the psychophysiological response to sedentary behavior in daily life. In other words, in examining whether sedentary behavior is associated with physiological markers and how this association may influence mood (black path in Figure 3). Accordingly, the theoretical framework indicates that there might be a physiological response to sedentary behavior that is associated with mood changes. However, few studies have investigated the associations between sedentary behavior and mood (Aggio et al., 2017; DeMello et al., 2018; Elavsky et al., 2016; Ellingson, Kuffel, Vack & Cook, 2014; Ellingson et al., 2018; Endrighi, Steptoe & Hamer, 2016; Kim et al., 2019). Thus, the research field had only begun to understand the possible psychophysiological responses to sedentariness. In the following section, we discuss i) how the psychophysiological response to sedentary behavior may look like and ii) whether it is possible to unravel a psychophysiological response to sedentary behavior in daily life.

Since only very few studies have examined the association between sedentary behavior and mood, there is insufficient evidence to explain how exactly a psychophysiological response may look like. Therefore, as a first step, we focus on the left path (see Figure 3), i.e., the association between sedentary behavior and physiological markers. One of the first studies on the topic, Hamilton and colleagues (2008) concluded that "too much sitting" is a serious health hazard involving unique biological mechanisms. In retrospect, this study can be seen as a starting point for the subsequent extensive research on the cardiometabolic health consequences of sedentary behavior. For example, several studies investigated the associations between sedentary time and physiological markers such as triglycerides, insulin, blood pressure, glucose plasma or total cholesterol. According to several systematic reviews (Brocklebank, Falconer, Page, Perry & Cooper, 2015; Loh, Stamatakis, Folkerts, Allgrove, & Moir, 2019; Powell, Herring, Dowd, Donnelly & Carson, 2018; Skrede, Steene-Johannessen, Anderssen, Resaland & Ekelund, 2019), the evidence of sedentary behavior´s influence on physiological response varies from marker to marker. We briefly summarize below the current state of research on the association between sedentary behavior and various physiological markers.

Lipid profiles: The majority of previous studies reported no association between sedentary behavior and low-density-lipoprotein cholesterol (LDL cholesterol) and between sedentary behavior and total cholesterol (TC). In contrast, the association between sedentary behavior and high-density-lipoprotein cholesterol (HDL cholesterol) is inconclusive. While some studies reported a negative association, others found no association. Similar mixed findings were found for the association between sedentary time and triglycerides (TG) (Brocklebank et al., 2015; Powell et al., 2018). Notably, Loh and colleagues' (2019) meta-analyses revealed small effects in terms of differences between physically active breaks and prolonged sitting on triacylglycerol levels. **Cytokines:** Compared to other physiological biomarkers, the association between sedentary behavior and circulating pro-inflammatory cytokines and chemokines such as interleukin (IL)-6, IL-8, IL-1β, and tumor necrosis factor (TNF) α has been examined less. However, at first glance studies have found some evidence of an association (Dogra et al., 2019; Healy, Matthews, Dunstan, Winkler & Owen, 2011; Henson et al., 2013). For example, Henson and colleagues (2013) have shown that sedentary time is positively associated with IL-6 levels.

Glucose: Brocklebank and colleagues' (2015) review revealed no evidence of an association between sedentary time and fasting plasma glucose but inconclusive evidence of an association between sedentary time and 2-hour plasma glucose. In contrast, Powell and colleagues (2018) reported inconclusive evidence of the association between sedentary behavior and fasting glucose as well as between sedentary behavior and 2-hour glucose. Notably, Loh and colleagues' (2019) meta-analyses revealed moderate effects in terms of differences between physically active breaks and prolonged sitting on glucose levels. **Insulin:** Most previous studies reported some evidence of an unfavorable association between total sedentary time and fasting insulin as well as between sedentary time and insulin resistance (HOMA-IR) and between sedentary time and insulin sensitivity (Brocklebank et al., 2015; Powell et al., 2018). Notably, Loh and colleagues' (2019) meta-analyses revealed moderate effects in terms of differences between physically active breaks and prolonged sitting on insulin levels.

Blood pressure (BP): Lee and colleagues (2015) concluded that only self-reported but not device-based assessed time spent in sedentary behaviors was associated with blood pressure. Furthermore, Powell and colleagues (2018), as well as Skrede and colleagues (2018), evaluated the evidence as being inconsistent with at least low effects. **Heart rate variability (HRV):** None of the reviews included studies focusing on the association between sedentary behavior and HRV. To the best of our knowledge, very few studies investigated the association between sedentary behavior and HRV (Hallman, Ekman & Lyskov, 2014; Miyagi, Sasawaki & Shiotani, 2018). For example, Hallmann and colleagues' (2014) findings revealed that occupational sitting was associated with reduced nocturnal HRV.

As an overall summary, Figure 3 visualizes the current state of research on the association between sedentary behavior and various physiological markers. Based on the findings of different systematic reviews and meta-analyses, we categorized evidence of the association between sedentary behavior and physiological markers into none-to-low association (dash line), low-to-medium association (thin line) and moderate-to-strong association (fat line).

Overall the association between sedentary behavior on various physiological markers is mostly low or even nonexistent. Furthermore, given the small number of studies addressing the psychophysiological response to sedentary behavior in terms of mood changes, we can only roughly guess how the response may look like or which markers could be involved. A likely explanation might be the involvement of inflammatory markers such as IL-6, IL-8 or TNF α. Some previous cross-sectional studies have shown that sedentary behavior is associated with inflammatory markers (Hamer, Poole & Messerli-Bürgy, 2013; Pinto Pereira, Ki & Power, 2012; Stamatakis, Hamer, & Dunstan, 2011). Moreover, Endrighi and colleagues (2016) examined under free-living conditions the influence of experimentally induced sedentary time on mood while assessing various physiological markers such as blood pressure and interleukin (IL-6). Their findings revealed that two weeks of more free-living sedentary time resulted in mood disturbances. Contrary to their expectation, there was limited evidence that sedentary behavior results in heightened psychophysiological responses. However, they have shown that negative mood is associated with pro-inflammatory IL-6 response. In line with this result, previous studies have shown that pro-inflammatory cytokines are linked with negative moods (Miller, Maletic & Raison, 2009). For example, Wright and colleagues (2004) found that cytokine-induced stimulus decreased mood. Therefore, although Endrighi and colleagues (2016) did not find that sedentary time resulted in a heightened psychophysiological response, we assume that more studies are needed to clarify this issue.

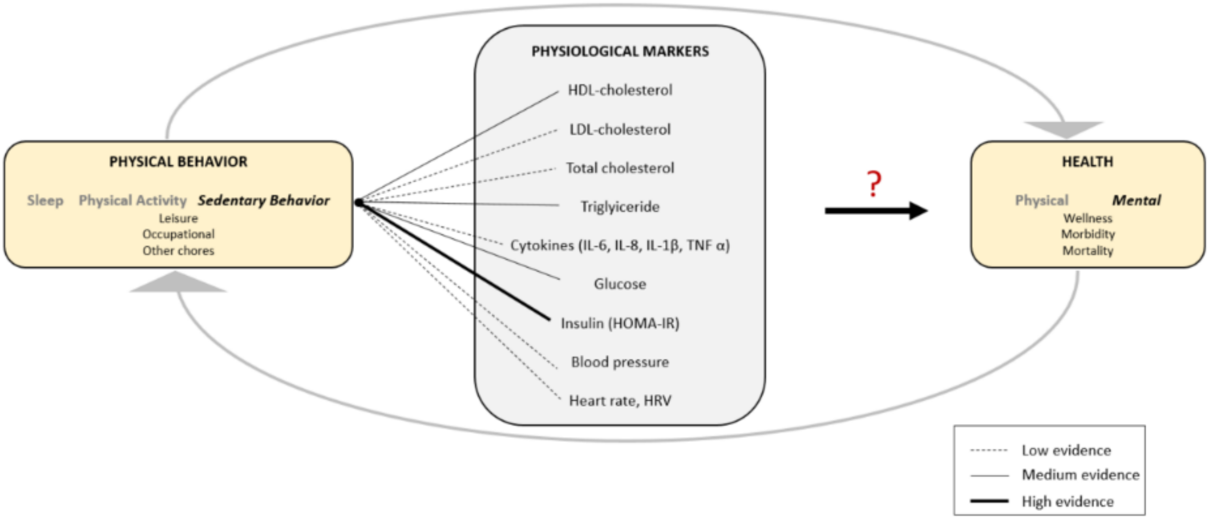

Figure 3. Associations between sedentary behavior and physiological markers.

Last, we would like to discuss how we might integrate repeated measurements of physiological markers such as cytokines into everyday life. As shown in our third and fourth works (Giurgiu et al., 2019; Giurgiu, et al., submitted), the association between sedentary behavior and mood underlies a time-sensitive within-subject relationship. Thus, if we are interested to detect the psychophysiological response of such a time-sensitive relationship, we must assess physiological markers more than twice as much as is usually done in traditional pre-post designs. Optimally, it is possible to assess physiological markers ambulatory with a high-resolution, i.e., optimally a continuous assessment for 24 hours. If continuous measuring is not possible, alternatively physiological measures should be assessed as often as possible, e.g., multiple times per day or at least once per day. The number of required assessments depends on the temporal course of the psychophysiological response, which is unclear in the context of sedentary behavior and thus elicits another interesting research question.

Most of previous studies investigating the associations between sedentary behavior and physiological markers collected fasting or nonfasting blood samples under laboratory conditions. However, some challenges make it practically infeasible to sample blood repeatedly in daily life. In particular, (i) blood sampling requires trained medical staff; (ii) blood sampling is invasive and may cause discontent in the participants; (iii) blood samples should be processed immediately to avoid hemolysis; and (iv) storage requires special conditions (-80 °C) (Cristi-Montero et al., 2019; Yoshizawa et al., 2013). Here, the development of salivary assay techniques provides a valuable and convenient ambulatory alternative. In particular, saliva can be sampled by chewing on a cotton wad for a couple of minutes and then kept in a special test tube (Smyth & Stone, 2003). Yoshizawa and colleagues (2013) summarized some advantages of saliva assessment. First, the collection is undemanding and can be carried out by anyone or by oneself. Second, the procedure is noninvasive and painless. Third, samples are easier to ship and store. Moreover, several biomarkers such as cytokines (e.g., IL-6 or IL-8) can be extracted from saliva samples. For instance, Dogra and colleagues (2019) used enzyme-linked immunosorbent assays to determine the level of cytokines. Of course the repeated assessment of saliva brings its own challenges. For example, Schlotz (2019) recommends storing saliva samples in a home freezer and returning them to the laboratory as soon as possible. Moreover, the quality of data depends strongly on the attendance of participants. Since missing assessments is a common problem in AA studies, inaccurate sampling times can substantially bias resulting saliva data. A possible solution is to record the time of sampling using containers with electronic caps (Kudielka, Gierens, Hellhammer, Wüst & Schlotz, 2012; Schlotz, 2019). In short, the ambulatory assessment of saliva might be an interesting approach to examining the psychophysiological response to sedentary behavior in daily life. In particular, it would be interesting to test whether cytokines such as IL-6 or IL-8 are influenced by sedentary behavior and whether this may result in mood changes.

Furthermore, since the temporal course of the associations between sedentary behavior and physiological markers is highly understudied in everyday life, it might be reasonable to take different markers into account. A promising approach is the use of new technologies such as portable biosensors. In the same vein as HR-monitors (von Haaren et al., 2016), biosensors can either continuously or frequently measure physiological markers (Li et al., 2017; Turner, 2013). Liao and Schembre (2018) have shown that a continuous glucose monitor (CGM) achieved high acceptability for use in daily life. Inserted under the skin, the CGM measures the concentration of glucose in real time. Supplied with a sensor, transmitter and receiver, the CGM indicates the rate of change and the glucose trend over the past 24 hours. Moreover, the receiver has the opportunity to mark (time-stamp) special events such as meals or exercise sessions. Further studies using different study populations are needed to verify Liao and Schembre's (2018) preliminary findings.

Last, unraveling the psychophysiological response to sedentary behavior is possible and, as a first hypothesis, we can anticipate that cytokines such as IL-6 or IL-8 are influenced by sedentary behavior and may cause mood changes. However, integrating physiological measures in daily life is a challenging task and depends more than usual on the individual's willingness to participate and to follow study instructions. Nevertheless, as shown in this section, the ambulatory monitoring of various physiological markers can be integrated into daily life. We expect that in the context of sedentary behavior research, the number of studies using the ambulatory monitoring of physiological markers will increase.

Perspective

One decade later, while researchers have shown that "too much sitting" is detrimental to human health, research on sedentary behavior is still at an early stage. Given the growing number of studies per year (see chapter I), we assume from a public health perspective that studies addressing sedentary behavior will continue to be a research focus. The work presented here contributes to this research field in a number of ways. We expand our knowledge of methodological assessments (see chapter II); we introduced a novel algorithm to capture "just in time" social and environmental information (see chapter III); we examined the reciprocal relationship between sedentary behavior and mood in daily life (see chapters IV and V) and we focused on the positive effects of sedentary breaks on mood (see chapter VI). Our work is a small step toward a better understanding of the antecedents and consequences of sedentary behavior in daily life. However, more studies using different populations are needed to increase ecological validity and to complete the picture of the possible associations between sedentary behavior and physical and mental health outcomes. In our last chapter, we mentioned three issues that might be relevant for future research endeavors. In particular, we assume that the simultaneous assessment and analysis of all aspects of physical behavior (i.e., sleep, sedentary behavior and physical behavior) will become increasingly important to understanding the interrelatedness of health effects. Furthermore, we assume that researchers will find solutions to answer the question of causality, which is crucial for the development of individually tailored interventions. Lastly, we suppose that the number of studies using ambulatory monitoring of physiological markers will increase, which will help to identify the psychophysiological response to sedentary behavior. We have included these perspectives in an extended version of the theoretical framework of the association among physical behavior, health-related fitness, and health status (see Figure 4).

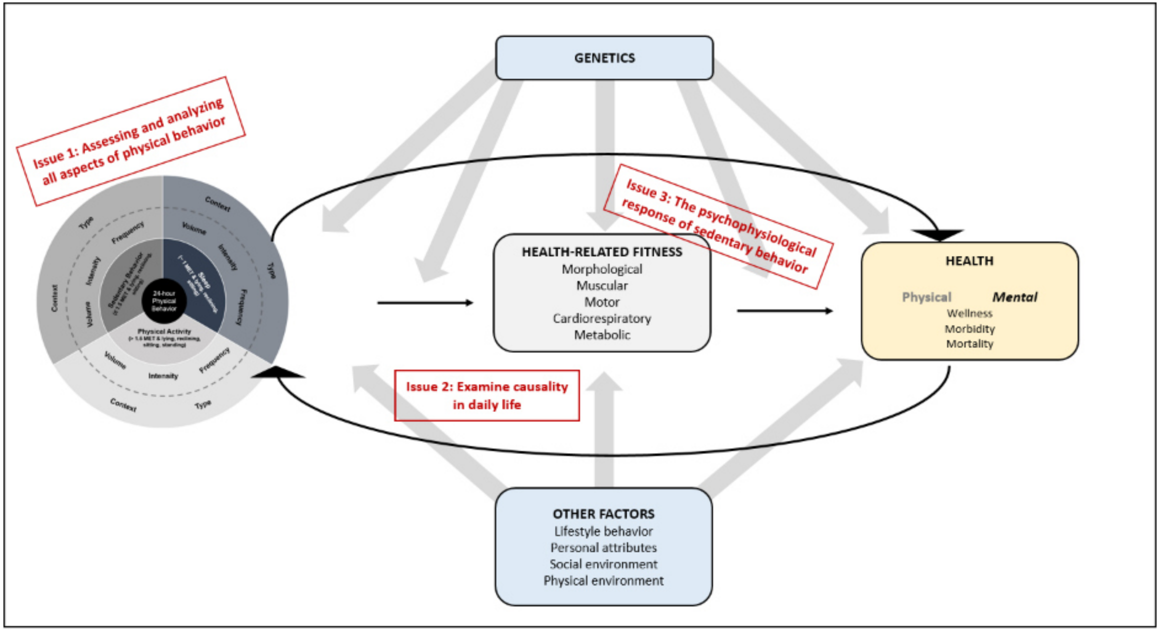

Figure 4. Associations between physical behavior, health-related outcomes, and health status.

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