The Association between Physical Behavior and Affective Well-being: The Impact of Social Contacts and Environmental Factors

Der Zusammenhang zwischen Bewegungsverhalten und mentalem Wohlbefinden: Einfluss von sozialen Kontakten und Umweltfaktoren

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Summary

There is strong evidence supporting the benefits of physical activity for both physical and mental health. Despite this, nearly a third of adults worldwide do not meet recommended activity levels, leading to increased risks of chronic conditions such as diabetes, hypertension, and obesity, as well as mental health issues and higher mortality rates. To fully understand the dynamics of adopting and maintaining an active lifestyle, it is crucial to recognize the broader concept of physical behavior, which encompasses both physical activity and sedentary behavior. Physical activity thereby includes everyday activities such as climbing stairs, cycling to work, or gardening. Sedentary behavior, on the other hand, is characterized by a reclining, lying, or sitting posture and a low movement intensity of ≤ 1.5 metabolic equivalents (METs). Understanding and promoting physical activity in daily life requires a comprehensive approach, often provided by socio-ecological models. Socio-ecological frameworks emphasize that individuals are influenced by a variety of factors on multiple levels in their daily lives, shaping their physical activity behavior. These frameworks highlight that behavioral, psychosocial, and environmental factors interact within complex social systems to influence physical activity levels. For example, momentary affective well-being influences subsequent physical activity. The umbrella term affective well-being includes core affect, describing a neurophysiological state of simple, primitive affective feelings represented in the circumplex model. It is a subcomponent of human subjective well-being, characterized by both trait and state components, as well as domain-specific and general valuations. Recognizing these interconnected relationships between physical behavior and affective well-being underscores the importance of designing environments that support and encourage active living across various levels of influence.

Previous studies investigating the connection between affective well-being and physical behavior have often been conducted in laboratory settings under experimental conditions. Much remains unknown due to the predominance of laboratory studies and a lack of within-subject perspectives. Over the past decades, laboratory research has provided in-depth insights into the associations between physical activity and affective well-being, as summarized in several reviews and meta-analyses. However, the everyday life perspective on the relationship between physical activity and affective well-being has not been studied extensively. This neglect may be due to the challenges of capturing physical activity and affective well-being during daily activities, such as shopping, gardening, or commuting. This can be overcome by ambulatory assessment, representing the state-of-the-art methodology for evaluating within-subject associations between physical behavior and affective well-being. Ambulatory assessment enhances the validity of data and minimizes recall biases by using device-based physical behavior measurement via accelerometers and repeated self-reports via electronic diaries (e-diaries) on smartphones for assessing affective well-being. This approach allows for the exploration of dynamic patterns within individuals over time, which is critical for understanding the complex associations between daily physical behavior and affective well-being. Recent ambulatory assessment studies have investigated the relationship between daily physical behavior and affective well-being, but findings have been inconsistent, likely due to context-specific effects. This inconsistency suggests that influences on physical behavior should be examined within a multi-layered framework. The primary purpose of this thesis is to provide insights into how various layers of the socio-ecological model (individual, interpersonal, and environmental factors) interact as determinants of physical behavior.

In the first paper, we aimed to enhance the understanding of time-dynamic associations between physical behavior and psychological antecedents and consequences in natural settings. We conducted a systematic literature review to compile current evidence on the relationship between physical behavior and affective well-being. Our focus was on understanding how automatic affective responses resulting from physical activity and vice versa contribute to maintaining an active lifestyle. These processes, often referred to as ‘micro-temporal within-subject processes’, are considered a promising research path for understanding the drivers of regular physical activity engagement. The systematic review specifically investigates intrapersonal behavioral reciprocal processes influencing physical behavior. We included studies that utilized intensive longitudinal data, combining device-based measurements of physical behavior (e.g., accelerometers, smartwatches) with affective well-being assessments via e-diaries, to focus on within-subject associations. Our literature search across three databases resulted in a final selection of 66 studies. The synthesis of study findings showed that associations of physical behavior with feelings of energy were homogeneous across nearly all studies, implying a dominant role of subjective energy in interaction with physical behavior in humans’ everyday lives. This extends the World Health Organization's notion “every move counts”, to be applicable not only to foster physical health but also to enhance affective well-being in everyday life. Overall, the evidence reviewed on physical behavior and affective well-being associations under ecologically valid conditions was heterogeneous. This suggests that physical behavior and affective well-being are not universally related in every situation or for all individuals, but rather depend on contextual factors such as psychosocial or environmental influences. These findings support the use of multilayered approaches in research, leading us to investigate environmental interac-

tions in the relationship between affective well-being and physical behavior in our second study.

In our seconPaper 1: The Within-Subject Association of Physical Behavior and Affective Well-Being in Everyday Life: A Systematic Literature Reviewd paper, we examined the psychosocial layers within the socio-ecological framework, focusing on whether social context (e.g., family, friends) influences subsequent physical behavior and if affective well-being mediates the association between social contact and physical behavior. Previous studies have highlighted the positive effects of social contact on affective well-being and its role in promoting physical activity. For our analyses, we recruited a sample of employees between July 2021 and March 2022. The assessment took place over a minimum of five consecutive days. Utilizing ambulatory assessment, 64 participants completed e-diaries about their affective well-being up to ten times a day, while their physical behavior was simultaneously recorded via accelerometers positioned at the hip and thigh. Participants also answered e-diary prompts about their current social environments, specifying who they were surrounded by (e.g., partner, family, friends, colleagues, acquaintances, strangers, others, or nobody). Our multilevel mediation analyses revealed that affective well-being partly mediated the association between social context and physical activity as well as between social contact and sedentary behavior. These findings suggest that incorporating peer relationship-building activities into interventions could foster a supportive environment, thereby encouraging physical activity and helping individuals overcome barriers to being active.

In our third paper, we explored how momentary affective well-being and environmental factors, i.e., weather conditions interact to influence everyday physical behavior. Our study involved a sample of university students and employees in Germany, recruited from September 2019 to March 2020. Using ambulatory assessment, 79 participants completed e-diaries about their affective well-being up to six times daily over five days, while their physical behavior was simultaneously recorded via accelerometers. We used a mixed sampling strategy, combining activity-triggered-, sedentary-triggered-, and randomly triggered assessments. Meteorological data were retrieved from a publicly available dataset from the Climate Data Center of the German Weather Service. Specifically, we obtained hourly values for temperature [°C] and precipitation [mm] from a weather station in Rheinstetten. To examine the within-person effects on subsequent physical behavior outcomes, we conducted multilevel models. Our results showed a significant positive association between temperature and physical activity intensity; higher temperatures led to increased physical activity intensity. We also investigated the additive effect of weather on the relationship between affective well-being and physical behavior. Specifically, temperature positively moderated the association between

valence and physical activity, meaning that higher temperatures strengthened the positive effect of valence on physical activity intensity. Additionally, temperature negatively moderated the association between valence and sedentary behavior; the reduction of sedentary behavior due to positive valence was more pronounced at higher temperatures. The effect of calmness on physical activity was similarly moderated by temperature, with the negative impact of calmness on physical activity diminishing as temperatures rose. Our findings emphasize the significant impact of temperature on physical activity levels, suggesting that environmental factors such as weather conditions should be considered when developing physical activity promotion programs. Despite the positive effects of pleasant weather on physical activity, it is crucial to develop strategies that encourage physical activity even under less favorable weather conditions. This can include strategies such as promoting indoor physical activities, tailoring physical activity goals to accommodate seasonal changes, or leveraging real-time weather data in Just-in-time adaptive Interventions to provide timely and context-specific encouragement.

Our studies demonstrate that both environmental and psychosocial factors can interactively influence the association between affective well-being and physical behavior, emphasizing the need for a multifaceted approach to promoting physical activity. Our findings contribute significantly to the current body of research on affective well-being and physical behavior: Firstly, our systematic review underscores the prominent role of the feeling of energy in individuals' daily interactions with physical behavior. The high heterogeneity in the results of the included studies suggests the influence of additional contextual factors on this relationship. Second, therefore, addressing these contextual factors, as one of the first studies we examined how social contact, as a layer of the socio-ecological model, impacts the affective well-being-physical behavior relationship. Our findings indicate that, beyond intraindividual factors, the psychosocial layer plays a crucial role in promoting and maintaining an active lifestyle. To enhance the effectiveness of future interventions, it is essential to integrate psychosocial elements by incorporating activities that for example, build peer relationships. This approach aims to establish a supportive environment that promotes physical activity and assists individuals in overcoming obstacles to staying active. Third, we explored environmental layers and were among the first studies to use ambulatory assessment combined with device-based physical behavior measurement, objective weather data, and a triggered design. Our study demonstrates that temperature variations significantly influence physical activity, a research area that has received little attention in physical activity promotion so far. Overall, our research shows that environmental and psychosocial factors can have an additive effect on the association between affective well-being and physical

behavior, and serve as important moderators and mediators influencing individuals in adopting or maintaining an active lifestyle.

With these findings in mind, several key issues warrant further exploration, which are addressed in the discussion section of this work. We seek to understand how individuals are embedded within and influenced by various contextual layers of the socio-ecological model. We assume that the integration of dual process models, such as the Affective-Reflective Theory, into the socio-ecological framework will facilitate a more comprehensive understanding of the interplay between affective and reflective processes across intrapersonal, interpersonal, and environmental levels, and their influence on physical behavior.

Future research would be enhanced by a focus on identifying how affective and reflective pathways interact across the model's layers and whether interventions targeting these pathways can improve physical activity engagement. Additionally, at the intrapersonal level, we assume that variables such as glucose levels, circadian rhythms, and physical activity self-efficacy could serve as moderators or mediators of the association between physical behavior and affective well-being. Understanding the dynamics of these variables can guide the development of personalized, adaptive interventions. Furthermore, at the interpersonal layer, we assume that assessing and analyzing dyadic interactions or social support networks in real-time will become increasingly important to explain how social relationships can be optimized to promote physical activity. Lastly, we assume that environmental factors such as air pollution, walkability, and climate conditions will become an increasing focus of research concerning how these environmental constraints interact and profoundly affect physical activity. By integrating these multi-layered moderators and mediators of physical behavior and affective well-being into adaptive interventions, this approach will contribute to the development of effective, context-sensitive strategies to combat sedentary lifestyles and promote overall health and well-being.

Zusammenfassung

Die Vorteile von körperlicher Aktivität sowohl für die physische als auch die psychische Gesundheit sind hinreichend belegt. Dennoch erreicht weltweit fast ein Drittel der Erwachsenen nicht das empfohlene Aktivitätsniveau, was zu einem erhöhten Risiko für chronische Erkrankungen wie Diabetes, Bluthochdruck und Adipositas sowie zu psychischen Erkrankungen und höheren Sterblichkeitsraten führt. Um die Dynamiken der Aufnahme und Aufrechterhaltung eines aktiven Lebensstils vollständig zu verstehen, ist es wichtig, das übergeordnete Konzept des physischen Bewegungsverhaltens zu erkennen, welches sowohl körperliche Aktivität als auch sedentäres Verhalten umfasst.

Der Begriff "körperliche Aktivität" umfasst dabei alltägliche Aktivitäten wie Treppensteigen, die Fahrt zur Arbeit mit dem Fahrrad oder Gartenarbeit. Demgegenüber ist "sedentäres Verhalten" durch eine überwiegend sitzende, zurückgelehnte oder liegende Körperhaltung mit einer geringen Bewegungsintensität von maximal 1,5 metabolischen Äquivalenten (MET) gekennzeichnet. Um die körperliche Aktivität im Alltag zu verstehen und zu fördern, ist ein umfassender Ansatz erforderlich, der häufig in sozio-ökologischen Modellen seinen Ausdruck findet.

Sozio-ökologische Modelle betonen, dass das Bewegungsverhalten im alltäglichen Leben von einer Vielzahl von Faktoren auf unterschiedlichen Ebenen beeinflusst wird. Innerhalb dieser Modelle interagieren verhaltensbezogene, psychosoziale und umweltbezogene Faktoren in komplexen sozialen Systemen, um das Ausmaß körperlicher Aktivität zu beeinflussen. Zum Beispiel beeinflusst die momentane Stimmung die nachfolgende körperliche Aktivität. Der Oberbegriff des affektiven Wohlbefindens umfasst den Kernaffekt, der einen neurophysiologischen Zustand einfacher und primitiver affektiver Gefühle beschreibt, wie er im Circumplex-Modell dargestellt wird. Bei diesem handelt es sich um eine Subkomponente des menschlichen subjektiven Wohlbefindens, gekennzeichnet durch trait- und state-Komponenten sowie domänenspezifische und generelle Bewertungen. Die Wahrnehmung dieser miteinander verbundenen Beziehungen hebt die Bedeutung für die Gestaltung von äußeren Bedingungen hervor, die die Möglichkeiten bieten sollten, ein körperlich aktiven Lebensstil auf verschiedenen Einflussebenen zu unterstützen und zu fördern. Vorherige Studien, die die Verbindung zwischen affektivem Wohlbefinden und Bewegungsverhalten untersuchten, wurden häufig unter Laborbedingungen durchgeführt. In den letzten Jahrzehnten haben Laborstudien detaillierte Einblicke in die Zusammenhänge zwischen körperlicher Aktivität und affektivem Wohlbefinden geliefert, welche in mehreren Reviews und Meta-Analysen bereits umfassend zusammengefasst wurden. Die Alltagsperspektive auf die Beziehung zwischen körperli-

cher Aktivität und affektivem Wohlbefinden wurde jedoch kaum untersucht. Dies kann u.a. auf die Herausforderungen der Erfassung von körperlicher Aktivität und affektivem Wohlbefinden während Alltagsaktivitäten wie Einkaufen, Gartenarbeit oder Pendeln zurückzuführen sein.

Durch technologischen Fortschritt und der innovativen Methodik des Ambulanten Assessments, können intraindividuelle Zusammenhänge zwischen dem Bewegungsverhalten und affektivem Wohlbefinden untersucht werden. Das Ambulante Assessment erhöht die Datenvalidität und minimiert Erinnerungsverzerrungen durch gerätebasierte physische Verhaltensmessung mittels Beschleunigungssensoren und wiederholte Selbstberichte mittels elektronischer Tagebücher (e-diaries) auf Smartphones zur Bewertung des affektiven Wohlbefindens. Dieser Ansatz ermöglicht die Untersuchung dynamischer Muster innerhalb von Individuen über die Zeit hinweg, was entscheidend für das Verständnis der komplexen Beziehungen zwischen täglichem Bewegungsverhalten und affektivem Wohlbefinden ist.

Ambulante Assessment Studien haben bereits die Beziehung zwischen täglichem physischem Verhalten und affektivem Wohlbefinden untersucht, allerdings mit heterogenen Ergebnissen, die auf kontextspezifische Einflüsse zurückzuführen sind. Diese Inkonsistenz deutet darauf hin, dass Einflüsse auf das alltägliche Bewegungsverhalten innerhalb eines mehrschichtigen Modells untersucht werden sollten. Das Ziel dieser Arbeit ist es, Einblicke zu geben, wie verschiedene Ebenen des sozio-ökologischen Modells (individuelle, interpersonelle und Umweltfaktoren) als Determinanten des Bewegungsverhalten interagieren.

In der ersten Arbeit zielten wir darauf ab, zeitdynamische Zusammenhänge zwischen Bewegungsverhalten und psychologischen Abläufen in natürlichen Settings zu untersuchen. Wir führten eine systematische Literaturübersicht durch, um die aktuelle Evidenz zur Beziehung zwischen Bewegungsverhalten und affektivem Wohlbefinden zu kompilieren. Unser Fokus lag dabei auf dem Verständnis, wie automatische affektive Reaktionen, die aus körperlicher Aktivität resultieren, zur Aufrechterhaltung eines aktiven Lebensstils beitragen können. Diese Prozesse, die auch als „mikrotemporale Within-Subject-Prozesse“ bezeichnet werden, gelten als vielversprechender Forschungsansatz, um die Mechanismen für eine regelmäßige Betätigung in körperlicher Aktivität zu verstehen. Die systematische Übersichtsarbeit untersucht dabei intrapersonale, reziproke Verhaltensprozesse, die das Bewegungsverhalten beeinflussen. Wir inkludierten Studien, die intensive Längsschnittdaten verwendeten und gerätebasierte Messungen des Bewegungsverhalten (z. B. durch Beschleunigungssensoren oder Smartwatches) mit Erhebungen des affektiven Wohlbefindens mittels elektronischer Tagebücher kombinierten, um intraindividuelle Zusammenhänge zu analysieren. Unsere Literaturrecherche in drei Datenbanken ergab eine finale Auswahl von 66 Studien. Die Synthese der Studienergebnisse zeigte, dass die Zusammenhänge zwischen Bewegungsverhalten und dem Gefühl von Energiegeladenheit in nahezu allen Studien homogen waren, was auf eine dominierende Rolle subjektiver Energie in der Interaktion mit Bewegungsverhalten im Alltag von Menschen hindeutet. Dies erweitert die Aufforderung der Weltgesundheitsorganisation „Jede Bewegung zählt" dahingehend, dass sie nicht nur auf die Förderung der körperlichen Gesundheit, sondern auch auf die Steigerung des affektiven Wohlbefindens im Alltag anwendbar ist. Insgesamt waren die Ergebnisse der systematischen Übersichtsarbeit zu den Zusammenhängen zwischen Bewegungsverhalten und affektivem Wohlbefinden unter ökologisch validen Bedingungen heterogen.

Dies deutet darauf hin, dass Bewegungsverhalten und affektives Wohlbefinden nicht universell in jeder Situation oder für alle Personen in Beziehung stehen, sondern vielmehr von kontextuellen Faktoren wie psychosozialen oder umweltbedingten Einflüssen abhängen. Diese Erkenntnisse unterstützen die Anwendung mehrschichtiger Modellansätzen in der Forschung, was uns dazu führte, in unserer zweiten Studie Umweltinteraktionen in der Beziehung zwischen affektivem Wohlbefinden und Bewegungsverhalten zu untersuchen.

In unserer zweiten Arbeit untersuchten wir die psychosozialen Ebenen innerhalb des sozio-ökologischen Modells, mit einem Schwerpunkt darauf, ob der soziale Kontext (z. B. Familie, Freunde) das nachfolgende körperliche Verhalten beeinflusst und ob das affektive Wohlbefinden die Verbindung zwischen sozialem Kontakt und körperlichem Verhalten mediiert. Vorherige Studien haben die positiven Effekte sozialen Kontakts auf das affektive Wohlbefinden und dessen Rolle bei der Förderung körperlicher Aktivität hervorgehoben. Für unsere Analysen rekrutierten wir eine Stichprobe von Angestellten zwischen Juli 2021 und März 2022. Die Erhebung fand über mindestens fünf aufeinanderfolgende Tage statt. Mit Hilfe der Datenerhebung des Ambulanten Assessments wurden 64 Teilnehmende erfasst, die mittels elektronischer Tagebuchbefragungen ihr affektives Wohlbefinden bis zu zehnmal täglich dokumentierten, während ihr Bewegungsverhalten zeitgleich durch am Hüft- und Oberschenkel angebrachte Beschleunigungssensoren erfasst wurde. Zudem beantworteten die Teilnehmenden über das elektronische Tagebuch Abfragen zu ihrem aktuellen sozialen Umfeld, und spezifizierten, von wem sie gerade umgeben waren (z.B. Partner, Familie, Freunde, Kollegen, Bekannte, Fremde, andere oder niemand).

Unsere Multilevel-Mediationsanalysen zeigten, dass affektives Wohlbefinden die Assoziation zwischen sozialem Kontext und körperlicher Aktivität sowie zwischen sozialem

Kontakt und sedentärem Verhalten teilweise mediiert. Diese Ergebnisse legen nahe, dass die Integration von Aktivitäten zum Aufbau von sozialen Beziehungen in Interventionen ein unterstützendes Umfeld schaffen könnte, welches die körperliche Aktivität fördert und den Einzelnen hilft, Barrieren zu überwinden, um nachhaltig aktiv zu bleiben.

In unserer dritten Arbeit untersuchten wir, wie momentanes affektives Wohlbefinden und Umweltfaktoren, insbesondere Wetterbedingungen, in ihrem Einfluss auf das tägliche körperliche Verhalten interagieren. Unsere Studie umfasste eine Stichprobe von Universitätsstudierenden und Mitarbeitenden, die zwischen September 2019 und März 2020 rekrutiert wurden. Mit Hilfe der Datenerhebung des Ambulanten Assessments führten 79 Teilnehmende elektronische Tagebücher, in denen sie ihr affektives Wohlbefinden bis zu sechsmal täglich über fünf Tage hinweg dokumentierten, während ihr körperliches Verhalten zeitgleich mit Beschleunigungssensoren erfasst wurde. Wir verwendeten ein Studiendesign, welches aktivitäts-getriggerte, sedentär-getriggerte und zufällig getriggerte Assessments kombinierte. Meteorologische Daten wurden aus einem öffentlich verfügbaren Datensatz des Klimadatenzentrums des Deutschen Wetterdienstes gewonnen. Die Daten für die stündliche Werte für Temperatur [°C] und Niederschlag [mm] bezogen wir von der Wetterstation in Rheinstetten. Um die Effekte innerhalb von Personen auf nachfolgende körperliche Aktivität zu untersuchen, führten wir Mehrebenenmodell-Analysen durch. Unsere Ergebnisse zeigten eine signifikant positive Assoziation zwischen Temperatur und der Intensität körperlicher Aktivität; höhere Temperaturen führten zu erhöhter körperlicher Aktivitätsintensität. Zudem untersuchten wir den additiven Effekt von Wetter auf die Beziehung zwischen affektivem Wohlbefinden und Bewegungsverhalten. Dabei moderierte die Temperatur die Assoziation zwischen Valenz und körperlicher Aktivität positiv, d.h. höhere Temperaturen verstärkten den positiven Effekt von Valenz auf die Aktivitätsintensität. Zusätzlich moderierte die Temperatur die Beziehung zwischen Valenz und sitzendem Verhalten negativ; die Reduktion von sitzendem Verhalten aufgrund positiver Valenz war bei höheren Temperaturen stärker ausgeprägt. Ähnlich wurde der Effekt von Ruhe auf körperliche Aktivität durch Temperatur moderiert: Der negative Einfluss von Ruhe auf körperliche Aktivität nahm bei steigenden Temperaturen ab. Unsere Ergebnisse zeigen, dass Temperatur einen signifikanten Einfluss auf körperliche Aktivität hat und legen nahe, dass Umweltfaktoren wie Wetterbedingungen bei der Entwicklung von Interventionsprogrammen zur Förderung körperlicher Aktivität berücksichtigt werden sollten. Trotz der positiven Auswirkungen angenehmen Wetters auf körperliche Aktivität ist es entscheidend, Strategien zu entwickeln, die körperliche Aktivität auch unter weniger günstigen Wetterbedingungen fördern. Dies kann Strategien wie die Förderung von

Indoor-Aktivitäten, die Anpassung von Aktivitätszielen an saisonale Veränderungen oder die Nutzung von Echtzeit-Wetterdaten in sogenannten „Just-in-Time-adaptiven Interventionen“ umfassen, um zeitnahe und kontextspezifische Motivation zu bieten.

Unsere Studien zeigen, dass sowohl Umwelt- als auch psychosoziale Faktoren die Assoziation zwischen affektivem Wohlbefinden und Bewegungsverhalten beeinflussen können und unterstreichen die Notwendigkeit eines facettenreichen Ansatzes zur Förderung körperlicher Aktivität. Unsere Ergebnisse leisten einen bedeutenden Beitrag zum aktuellen Forschungsstand zu affektivem Wohlbefinden und Bewegungsverhalten: Erstens zeigt unsere systematische Übersichtsarbeit, dass Energiegeladenheit das Bewegungsverhalten im alltäglichen Leben von Individuen beeinflusst. Die hohe Heterogenität in den Ergebnissen der eingeschlossenen Studien deutet darauf hin, dass zusätzliche Kontextfaktoren diese Beziehung beeinflussen könnten. Zweitens, um diese kontextuellen Faktoren zu adressieren, untersuchten wir als eine der ersten Studien, wie sozialer Kontakt, als psychosoziale Ebene des sozio-ökologischen Modells, die Beziehung zwischen affektivem Wohlbefinden und Bewegungsverhalten beeinflusst. Unsere Ergebnisse zeigen, dass über intraindividuelle Faktoren hinaus, die psychosoziale Ebene eine entscheidende Rolle bei der Förderung und Aufrechterhaltung eines aktiven Lebensstils spielt. Um die Effektivität zukünftiger Interventionen zu steigern, sollten psychosoziale Elemente integriert werden; beispielsweise Aktivitäten, die den Aufbau von sozialen Beziehungen fördern. Dieser Ansatz zielt darauf ab, ein unterstützendes Umfeld aufzubauen, das körperliche Aktivität fördert und Individuen hilft, Hindernisse für körperliche Aktivität zu überwinden.

Drittens gehörten wir zu den ersten Studien, die Ambulantes Assessment in Kombination mit gerätebasierter physischer Verhaltensmessung, objektiven Wetterdaten und einem getriggerten Design verwendeten und dabei die Umweltebene des sozio-ökologischen Modells bedienten. Unsere Studie zeigt, dass Temperaturvariationen einen erheblichen Einfluss auf die körperliche Aktivität haben – ein Bereich, der in der Förderung von körperlicher Aktivität bisher wenig Beachtung fand. Insgesamt zeigt unsere Forschung, dass Umwelt- und psychosoziale Faktoren einen additiven Effekt auf die Assoziation zwischen affektivem Wohlbefinden und physischem Verhalten haben können und als wichtige Moderatoren und Mediatoren fungieren, die Individuen bei der Annahme oder Aufrechterhaltung eines aktiven Lebensstils beeinflussen.

Vor diesem Hintergrund bedürfen mehrere zentrale Themen einer weiteren Erforschung, die im Diskussionsabschnitt dieser Arbeit adressiert werden. Wir möchten verstehen, wie Individuen in verschiedene kontextuelle Ebenen des sozio-ökologischen Modells eingebettet sind und von diesen beeinflusst werden. Wir gehen davon aus, dass die Integration dualer Prozessmodelle wie der Affective-Reflective-Theorie in das sozio-ökologischen Modell ein umfassenderes Verständnis des Zusammenspiels zwischen affektiven und reflektiven Prozessen auf intrapersonalen, interpersonalen und umwelt-bezogenen Ebenen, und deren Einfluss auf das Bewegungsverhalten fördern wird. Zukünftige Forschung würde davon profitieren, zu verstehen, wie affektive und reflektive Prozesse auf den verschiedenen Ebenen des Modells miteinander interagieren und ob Interventionen, die diese Prozesse ansprechen, das Engagement in körperlicher Aktivität verbessern können.

Zudem gehen wir auf der intrapersonalen Ebene davon aus, dass Variablen wie der Glukosespiegel, zirkadianer Rhythmus und physische Aktivitäts-Selbstwirksamkeit als Moderatoren oder Mediatoren der Assoziation zwischen Bewegungsverhalten und affektivem Wohlbefinden beeinflussen könnten. Das Verständnis der Dynamiken dieser Variablen kann die Entwicklung personalisierter, adaptiver Interventionen voranbringen.

Darüber hinaus gehen wir auf der interpersonalen Ebene davon aus, dass die Bewertung und Analyse dyadischer Interaktionen oder sozialer Unterstützungsnetzwerke in Echtzeit zunehmend wichtig werden, um zu erklären, wie soziale Beziehungen dazu beitragen können, körperliche Aktivität zu fördern. Schließlich gehen wir davon aus, dass auf der Umweltebene Faktoren wie Luftverschmutzung, eine freundliche Umgebung und Klimabedingungen zunehmend in den Fokus der Forschung rücken werden um zu verstehen, wie diese Umweltfaktoren miteinander interagieren und das Bewegungsverhalten nachhaltig beeinflussen. Durch die Integration dieser vielschichtigen Moderatoren und Mediatoren des Bewegungsverhaltens und des affektiven Wohlbefindens in adaptive Interventionen wird dieser Ansatz dazu beitragen, effektive, kontextsensitive Strategien zu entwickeln, die dabei helfen, sedentäres Verhalten zu verringern und das allgemeine Wohlbefinden sowie die Gesundheit zu fördern.

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Chapter I

General Introduction

The prevalence of physical inactivity is rising worldwide, concerning not only adults but extending across all age ranges. According to the World Health Organization (WHO), nearly one-third (31%) of adults worldwide, approximately 1.8 billion people, did not meet the recommended levels of physical activity in 2022 (Strain et al., 2024). Decreases in physical activity accompanied by increases in sedentary behavior (such as long, uninterrupted periods of sitting) lead to the risk of cardiovascular diseases, diabetes, obesity, depression, and anxiety, and continuous sedentary behavior (such as sitting for long periods of time) are associated with abnormal glucose metabolism and cardiometabolic morbidity, as well as overall mortality (Blair, 2009). Given the fact that in times of the COVID-19 pandemic, everyday physical activity patterns change (Brand et al., 2020), for example, due to the elimination of daily commutes, company health sports or activity breaks, etc., sedentary behavior has already become one of the leading global risk factors for both somatic and mental health (Fried et al., 2020; Pratt et al., 2020; Qin et al., 2020). Thus, the literature indicates that health-related research must not only focus on physical activity and its guidelines but also on sedentary behavior.

Thereby physical behavior encompasses both physical activity and sedentary behavior. In this paper, we will use and propose the term physical behavior as an umbrella term, which includes the behavior of a person in terms of body postures, movements, and/or daily activities in his/her own environment (Bussmann & van den Berg - Emons, 2013). Physical activity leads to an increase in energy expenditure (EE) and is performed by any skeletal muscle effort (Caspersen et al., 1985). Physical activity is defined as any bodily movement produced by skeletal muscle that requires energy expenditure (Caspersen 1985). It can be undertaken in many different ways: walking, cycling, sports, and active forms of recreation (such as yoga). Physical activity can also be undertaken as part of work (lifting, carrying, or other active tasks), and as part of paid or unpaid domestic tasks around the home (cleaning, carrying, and care duties) (World Health Organization, 2018). Exercise differs from physical activity insofar as it is a planned and structured physical activity in daily life, characterized by high demands of energy consumption (Kanning et al., 2013).

Sedentary behavior, on the other hand, is not just the counterpart to physical activity (Lord et al., 2011; Owen et al., 2010; Wilmot et al., 2012). For example, a person cannot be “active” and “sedentary” at the same moment, but he/she can have an “active lifestyle” from the perspective of physical activity or energy expenditure, and simultaneously be characterized by having a sedentary lifestyle because of long periods of sitting or reclining with low levels of energy expenditure. Sedentary behavior is characterized by an energy expenditure lower than 1.5 metabolic equivalents (METs) while the person is in a sitting or reclined position (not during sleep) (Sedentary Behaviour Research Network, 2012). Physiological studies have identified the unique mechanisms and characteristics of sedentary behavior, and thus suggest sedentary behavior being considered an independent behavior with its own characteristics, not only an absence of physical activity (Hamilton et al., 2007).

The general positive effects of physical activity and affective well-being associations have already been described by Socrates about 430 BC (Xenophon, 1864). Physical activity is evidenced to help prevent and treat somatic and psychiatric disorders, such as cardiovascular diseases, diabetes, obesity, depression, and anxiety (Warburton, 2006). Studies have shown that physical activity can counteract non-communicable diseases (NCD) (Trost et al., 2002), promote mental well-being (Fox, 1999; Sánchez-Oliva et al., 2019; van Woudenberg et al., 2020), and reduce psychiatric symptoms (Mata et al., 2012), e.g., in eating disorders (Reichert, Schlegel, et al., 2020). In addition, even brief interruptions from sedentary behavior have positive effects on affective states (Giurgiu et al., 2019; Reichert, Braun, et al., 2020). Therefore, breaking up sedentary behavior and promoting a physically active lifestyle should be addressed as a major health priority (Giurgiu et al., 2019; Owen et al., 2010).

Simultaneously, affective well-being processes are known to promote physical activity. Preliminary evidence suggests that mood drives physical activity within-persons’ everyday life (for an overview refer to Liao et al., 2015). By definition, affective well-being is a subcomponent of human subjective well-being (Lischetzke & Eid, 2006), e.g., characterized by trait vs. state components and domain-specific vs. general valuations. For example, the umbrella term affective well-being includes core affect, a measure describing a neurophysiological state of an elementary simple primitive affective feeling represented in the circumplex model (Russell, 1980, 2017).

In the past decades, laboratory research produced in-depth insights on physical activity and affective well-being associations summarized in several reviews and meta-analyses (Biddle, 2016; Kelly et al., 2018; Reed & Buck, 2009; Reed & Ones, 2006; White et al., 2017), the everyday life perspective on the physical activity and affective well-being association has been neglected for a long time. Part of this neglect may lie in difficulties in capturing physical activity and affective well-being in the everyday life of humans.

This can be overcome by ambulatory assessment methods: To explore the dynamic relationship between affective well-being and physical activity in real-world settings, researchers employ the ambulatory assessment methodology (Ebner-Priemer & Trull, 2009; Trull & Ebner-Priemer, 2013). Ambulatory assessment is a state-of-the-art approach that involves the continuous and real-time monitoring of individuals' behaviors and experiences in their natural environments. This method combines device-based measurements of physical behavior, such as accelerometers, with repeated self-reports of affective well-being through electronic diaries (e-diaries) on smartphones (Reichert, Giurgiu, et al., 2020). Ambulatory assessment allows for the collection of high-frequency data in everyday contexts, which enhances the ecological validity of the findings (Adamo et al., 2009; Prince et al., 2008). Unlike traditional laboratory-based methods, ambulatory assessment minimizes recall biases and captures real-time variations in affective states and behaviors (Fahrenberg et al., 2007; Stone & Shiffman, 2002). This real-world assessment is important for identifying nuanced and temporal everyday life patterns of human physical activity behavior. This is possibly through the examination of within-subject processes, which enables us to analyze how fluctuations in an individual's mood influence their physical activity levels throughout the day (so-called "intensive longitudinal methods" (Bolger & Laurenceau, 2013; Mehl et al., 2014). By employing advanced statistical techniques such as multilevel modeling, these within-subject effects are methodologically, statistically, and empirically distinct from between-subject associations (Kamarck et al., 2003; Zawadzki et al., 2017).

In recent years, applying ambulatory assessment to research the physical behavior-affective well-being association is gaining tremendous interest to uncover the factors that drive individuals to be physically active and how these behaviors dynamically interact with affective processes in everyday life, as evidenced by the increasing number of studies on physical behavior-affective well-being associations across the past years (see Figure 1).

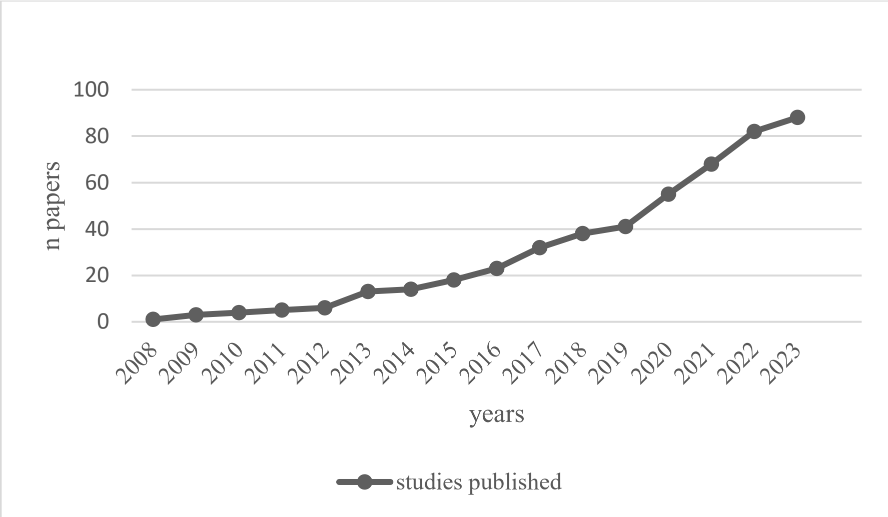

Figure 1: Accumulated number of ambulatory assessment studies that researched the association of physical behavior and affective well-being, by year of publication.

In 2015, a review summarized the current state of research on within-subject associations between physical behavior and affective well-being (Liao et al., 2015). However, the findings from this review are mixed, showing inconsistencies and gaps in the existing evidence. Therefore, to address these inconsistencies and provide a more comprehensive understanding of this relationship, we conducted an updated systematic review to compile and synthesize the latest evidence on physical behavior and affective well-being associations based on studies that collected data continuously and repeatedly within persons in naturalistic settings through ambulatory assessment. Given the methodological heterogeneity in the included studies, we also developed a modified quality assessment tool to evaluate the risk of bias in the studies. This tool was designed following established guidelines for quality assessment frameworks (National Institutes of Health, 2020; Page et al., 2021) and adapted to the unique challenges of ambulatory assessment research. Our systematic review fills the gap in the literature by providing a comprehensive synthesis of the current state of research concerning physical behavior-affective well-being associations in real life.

Topic 1: Within-Subject Association of Physical Behavior and Affective Well-Being

In this systematic literature review, we explored the within-subject associations between physical behavior and affective well-being in everyday life to understand micro-temporal within-subject processes (Dunton, 2018). We included studies that used ambulatory assessment methods (e.g., device-based physical behavior assessments, and studies using momentary self-reported affective well-being assessments), comprising studies in all available populations and across age groups, covering the relationship between physical behavior and valence, energetic arousal, calmness, energy, and fatigue as affective well-being components.

The present review across 66 studies showed that physical behavior is generally associated with increased feelings of energy (Timm et al., 2024). The review of findings showed that in general, already short physical activity bouts in everyday life, which clearly differ from structured exercise sessions, are positively associated with affective well-being. However, the associations between physical behavior and other dimensions of affective well-being showed more variability across studies. We showed that the reviewed evidence on physical activity-affective well-being associations in everyday life is ambiguous, e.g., no clear patterns of directions and strengths of physical activity-affective well-being relationships depending on physical activity and affective well-being components (such as intensity, emotions, affect, and mood) emerged.

We also developed a new Quality Assessment tool to assess the risk of bias in the included studies. The QA revealed that, overall, there is a moderate risk of bias across studies examining the relationship between physical behavior and affective well-being. However, significant methodological heterogeneity exists in the assessment of both affective well-being and physical behavior. For affective well-being, studies utilized multiple questionnaires or items, with 19 studies employing a short version of the Multidimensional Mood Questionnaire (Wilhelm & Schoebi, 2007). Additionally, 19 studies based their items on existing non-ambulatory assessment questionnaires, such as versions of the Positive and Negative Affect Schedule (Watson et al., 1988), assessing dimensions of positive and negative affect. Other studies applied different models, including the circumplex model (Russell, 1980), the Profile of Mood States (McNair et al., 1971), and the Depression and Anxiety Mood Scale (Fukui, 1997). Notably, some studies developed their items not based on standardized questionnaires or did not report their sources. The assessment of physical behavior also demonstrated considerable variation in methodological approaches. Physical behavior was parameterized using different measures, including movement-based volume variables like raw acceleration data and activity counts, time-based amount variables such as minutes spent in moderate to vigorous physical activity (MVPA), energy expenditure variables like metabolic equivalents (METs), and postural and activity-based variables, such as standing and stepping. This variability underscores the need for more standardized and detailed reporting of methods in future research. Overall, the heterogeneity of the findings underscores the need for further research. The findings suggest that context-specific factors play a significant role in influencing these associations.

Theoretical Foundations: Socio-Ecological Models in Understanding Physical Behavior

Our review suggests, that in the future, to better understand the processes that lead to the dynamics of adopting and maintaining an active lifestyle, the influence of intrapersonal, psychosocial, and environmental factors should be considered. The socio-ecological model offers a robust framework for this investigation, as it posits that individual health behavior is shaped by the interaction of multiple levels of influence, including intrapersonal, social,- built,- and natural environmental factors (Stokols, 1992). Interest in socio-ecological models has grown due to their potential as a more effective framework for promoting physical activity (Sallis et al., 2006). This framework demonstrates how environmental and social factors converge and possibly interact through multi-directional pathways, influencing health and well-being throughout an individual's everyday life (Olvera Alvarez et al., 2018). The relationship between affective well-being and physical behavior is consequently embedded in a larger system, which is consistently influenced by dynamic processes. Socio-ecological models are unique in their explicit consideration of various environmental factors that are presumed to impact physical behavior, encompassing a wide array of influences across multiple levels (Sallis et al., 2006). These levels typically include intrapersonal (psychological e.g. mood), interpersonal (social factors), and physical environment (both built and natural) (Sallis et al., 2006). In short, the model illustrates reciprocal dependencies among the health behavior of an individual which are influenced by different personal attributes or physical and social environmental conditions (Booth et al., 2001; Sallis et al., 2012).

Examining the layers of the socio-ecological model reveals distinct mechanisms by which various factors influence the relationship between physical activity and affective well-being. Taking a closer look at the different layers in the model, the intrapersonal layer involves understanding how momentary affective well-being influences physical activity patterns. For instance, examining how feelings of positive affect or fatigue impact one's likelihood to engage in physical activity can provide insights into the immediate, within-subject dynamics between physical activity and affective well-being. We showed in our systematic literature review that in the intrapersonal layer, feelings of energy, mostly relate to higher physical activity levels (Timm et al., 2024).

Moving to the interpersonal level, social interactions and relationships emerge as critical factors influencing both physical activity and affective well-being. Social support from family, friends, or colleagues, as well as the presence of others during physical activity, can boost affective states and encourage engagement in physical activity, showing the importance of social contexts in promoting an active lifestyle. To explore these dynamics, our second study focused on the psychosocial layers of the socio-ecological framework. Specifically, we examined whether social contact (e.g., spending time with family or friends) influenced subsequent physical behavior and whether affective well-being mediated the relationship between social contact and physical behavior within real-life contexts (Timm et al., submitted).

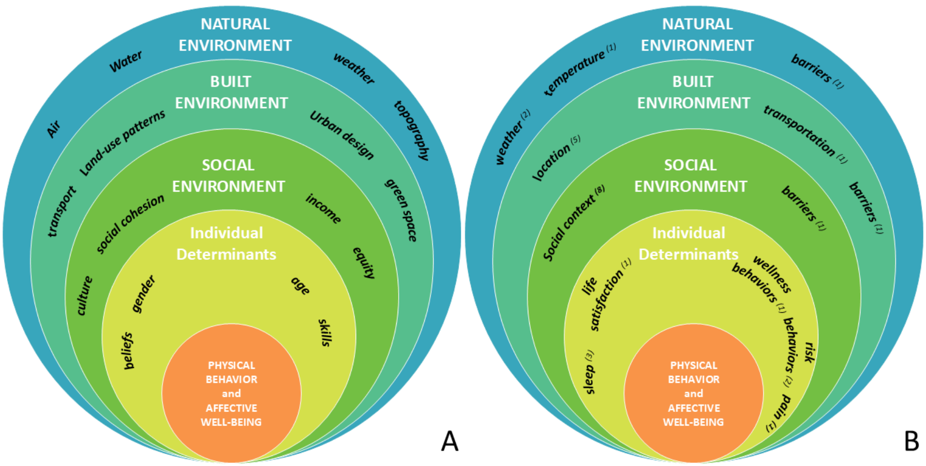

Figure 2: **A)** The socio-ecological model of physical activity and active living adapted from (Bornstein & Davis, 2014; Sallis et al., 2006). **B)** The socio-ecological model of physical behavior and affective well-being. Numbers in brackets show how many ambulatory assessment studies included in the systematic review considered variables from the socio-ecological model.

Topic 2: Physical Behavior and Social Contact: Exploring Psychosocial Factors

Recent years have underscored the significant impact of social contact on both psychological and physical well-being, highlighted further during the COVID-19 pandemic (Eshelby et al., 2022; Galea et al., 2020; Monninger et al., 2022). Social contact influences health behaviors such as physical activity, whereas being alone or socially isolated can increase sedentary time (Benedyk et al., 2024). Increased inactivity has adverse consequences for the healthcare system, contributing to chronic conditions like diabetes, hypertension, obesity, and depression (Ding et al., 2016; Katzmarzyk et al., 2022). Studies have shown that social interaction encourages everyday physical activity and reduces the risk of mortality and non-communicable diseases (Brand et al., 2020; Fried et al., 2020; Pratt et al., 2020). For example, previous studies have highlighted the positive effects of social contact on affective well-being and its role in promoting physical activity (Lindsay Smith et al., 2017; Papini et al., 2020). Despite recognizing the association between social contact and physical behavior (Bourke et al., 2021b, 2021a; Liao et al., 2015; Rhodes & Kates, 2015), the potential mediating role of affective processes has been less explored. In particular, no ecological momentary assessment study has explored the mediated mechanisms of affective well-being in the short-term dynamic relationship between momentary social contact and physical behavior. Therefore, in our second work (Timm et al., submitted), we conducted an ambulatory assessment study of the everyday life of 64 employees over six days. We continuously measured physical behavior via accelerometers and repeatedly assessed affective well-being (i.e., valence) ten times each day on smartphone e-diaries. Participants also answered e-diary prompts about their current social environments, specifying who they were surrounded by (e.g., partner, family, friends, colleagues, acquaintances, strangers, others, or nobody). Our multilevel mediation analyses revealed that affective well-being partly mediated the association between social contact and physical activity as well as between social contact and sedentary behavior. These findings suggest that incorporating peer relationship-building activities into interventions could foster a supportive environment, thereby encouraging physical activity and helping individuals overcome barriers to being active (Morrissey et al., 2015).

The next level of the socio-ecological model encompasses broader environmental factors such as air pollution, walkability, availability of recreational spaces, or weather factors. These environmental variables play a central role in shaping individuals' physical activity patterns and affective well-being. Investigating these factors in the context of physical activity promotion can uncover critical environmental determinants. Therefore, in our third paper, we closely looked at natural environmental factors and their potential interactions with physical behavior and affective well-being processes.

Topic 3: Momentary Associations of Affective Well-being, Physical Behavior, and Weather Conditions

In our third work, we introduce sedentary as well as physical activity-triggered ecological momentary assessment as a methodological advancement in the field of physical behavior research (Timm et al., 2023). Triggered e-diaries are able to maximize within-subject variance of the parameter of interest while minimizing participant burden. Unlike traditional time- or event-based designs, triggered e-diaries are connected for example via Bluetooth low energy (BLE) to accelerometers, and therefore offer the possibility to prompt participants in situations of interest (Ebner-Priemer et al., 2013). The algorithm is designed to focus on situations where a certain activity level is exceeded, as well as on episodes with a certain period of continuous sedentary behavior (Giurgiu et al., 2020).

We examined momentary affective well-being, weather conditions (i.e., precipitation and temperature), and physical behavior in a sample of healthy adults, to better understand how the interplay between affective states and weather conditions shape our everyday physical behavior. From September 2019 to March 2020, we recruited a sample of university students and employees in Germany. Using ambulatory assessment, 79 participants completed e-diaries about their affective well-being up to six times a day for five days. At the same time, their physical behavior was recorded using accelerometers. We used a mixed sampling strategy, combining activity-triggered, sedentary-triggered, and randomly triggered assessments. The thigh sensor analyzed and transmitted real-time body position and motion acceleration data to the smartphone via Bluetooth. With regard to external environmental factors, objective meteorological data have been integrated into our multilevel model. These data were obtained from the publicly accessible data repository of the German Weather Service (Kaspar et al., 2013). In particular, hourly values for temperature (in degrees Celsius) and precipitation (in millimeters) were sourced from a weather station in Rheinstetten (Brückel, 2019). The results demonstrated a positive correlation between temperature and physical activity intensity, indicating that elevated temperatures were associated with increased levels of physical activity intensity.

Furthermore, we integrated weather as a moderating factor in the relationship between affective well-being and physical activity into our analysis. We could show that temperature exerted a positive moderating effect on the relationship between valence and physical activity, indicating that higher temperatures enhanced the positive influence of valence on physical activity intensity. Furthermore, temperature was identified as a moderating factor in the association between valence and sedentary behavior, whereby the reduction in sedentary behavior attributable to positive valence was observed to be more pronounced in environments characterized by higher temperature. The impact of calmness on physical activity was similarly moderated by temperature, with the negative effect of calmness on physical activity becoming less pronounced as temperatures increased. The study's findings highlight that temperature is another factor embedded in the socio-ecological model, which is able to influence the association of affective well-being and subsequent physical behavior. Incorporating environmental factors like weather into physical activity promotion programs can mitigate the deterrent effect of adverse weather, and support a physically active lifestyle year-round. The results of our studies reveal that both environmental and psychosocial factors from the socio-ecological model can interactively influence the association between affective well-being and physical behavior. This underscores the necessity of employing a multifaceted strategy to encourage physical activity.

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Preface

Paper 1

Timm, I., Giurgiu, M., Ebner-Priemer, U., & Reichert, M. (2024). The Within-Subject Association of Physical Behavior and Affective Well-Being in Everyday Life: A Systematic Literature Review. *Sports Medicine*, *54*, 1667-1705. https://doi.org/10.1007/s40279-024-02016-1

Paper 2

Timm, I., Sers, S., Reichert, M., Reinhard, I., Ebner-Priemer, U. W., & Giurgiu, M. How social contact shapes physical behavior in everyday life: Evidence for affective well-being as a within-person mediator (*submitted*).

Paper 3

Timm, I., Reichert, M., Ebner-Priemer, U. W., & Giurgiu, M. (2023). Momentary within-subject associations of affective states and physical behavior are moderated by weather conditions in real life: An ambulatory assessment study. *International Journal of Behavioral Nutrition and Physical Activity*, *20*(1), 117. https://doi.org/10.1186/s12966-023-01507-0

Chapter II

Paper 1: The Within-Subject Association of Physical Behavior and Affective Well-Being in Everyday Life: A Systematic Literature Review

Timm, I., Giurgiu, M., Ebner-Priemer, U., & Reichert, M. (2024). The Within-Subject Association of Physical Behavior and Affective Well-Being in Everyday Life: A Systematic Literature Review. *Sports Medicine*, 54(6), 1667–1705. https://doi.org/10.1007/s40279-024-02016-1

Abstract

Background: The interplay of physical activity (PA) with affective well-being (AWB) is highly critical to both health behaviors and health outcomes. Current prominent theories presume AWB to be crucial for PA maintenance, and PA is evidenced to foster mental health. However, thus far, PA-AWB associations have mainly been researched in laboratory settings and with interventional designs, but the everyday life perspective had not been focused on, mostly due to technological limitations. In the course of digitization, the number of studies using device-based methods to research the within-subject association of physical activity and affective well-being (PA-AWB) under ecological valid conditions increased rapidly, but a recent comprehensive systematic review of evidence across populations, age groups, and distinct AWB components remained inconclusive.

Objectives: Therefore, we aimed to firstly review daily-life studies that assessed intensive longitudinal device-based (e.g., electronic smartphone diaries and accelerometry) and real-time PA-AWB data, secondly to develop and apply a quality assessment tool applicable to those studies, and thirdly to discuss findings and draw implications for research and practice.

Methods: To this end, the literature was searched in three databases (Web of Science, PubMed, Scopus) up to November 2022. The systematic review followed the PRISMA

guidelines and had been pre-registered (PROSPERO id: CRD42021277327). A modified quality assessment tool was developed to illustrate the risk of bias of included studies.

Results: The review of findings showed that, in general, already short PA bouts in everyday life, which clearly differ from structured exercise sessions, are positively associated with AWB. In particular, feelings of energy relate to incidental (nonexercise and unstructured) activity, and PA-AWB associations depend on population characteristics. The quality assessment revealed overall moderate study quality; however, the methods applied were largely heterogeneous between investigations. Overall, the reviewed evidence on PA-AWB associations in everyday life is ambiguous; for example, no clear patterns of directions and strengths of PA-AWB relationships depending on PA and AWB components (such as intensity, emotions, affect, mood) emerged.

Conclusions: The reviewed evidence can fuel discussions on whether the World Health Organization's notion "every move counts" may be extended to everyday life AWB. Concurrently, the PA-AWB relationship findings endorse prominent theories highlighting the critical role of AWB in everyday PA engagement and maintenance. However, the review also clearly highlights the need to advance and harmonize methodological approaches for more fine-grained investigations on which specific PA/AWB characteristics, contextual factors, and biological determinants underly PA-AWB associations in everyday life. This will enable the field to tackle pressing challenges such as the issue of causality of PA-AWB associations, which will help to shape and refine existing theories to ultimately predict and improve health behavior, thereby feeding into precision medicine approaches.

Key Points:

- The number of daily life studies using device-based methods (e.g., electronic smartphone diaries and accelerometry) to research the within-subject association of physical activity and affective well-being (PA-AWB) in everyday life increased rapidly across the last 15 years.
- Already short PA bouts in everyday life relate positively to AWB, feelings of energy appear to play a dominant role, and PA-AWB associations depend on population characteristics. However, overall, the reviewed evidence on PA-AWB association characteristics in everyday life is ambiguous.
- The quality assessment revealed overall moderate risk of bias; however, methods applied were largely heterogeneous between studies. Therefore, future research in the PA-AWB field should advance and harmonize methodological approaches to overcome challenges in the interpretation of heterogeneous study outcomes.

1 Introduction

Physical activity is indispensable for human health, but worldwide and across ages physical activity is declining [1,2]. Therefore, to foster prevention and treatment of physical and mental disorders, the World Health Organization addresses the prevention of physical inactivity as a major health priority [3,4]. Towards this aim, a key role is attributed to the within-subject associations of physical activity and human affective well-being in everyday life. This association is critically involved in both physical and mental health processes for motivating, maintaining and reinforcing physical activity and affective well-being [5–7]. Both immediate emotional responses to physical activity and rationale thinking about its benefits are important for initiating and maintaining a physically active lifestyle. The relevance of these associations between physical activity and affective well-being has recently progressed toward dual-process models and hedonism theories [8] for research on behavioral processes. In contrast to traditional health behavior theories that mainly focused on the role of cognitive aspects as physical activity drivers, these recent theories suggest within-subject variance of human well-being in everyday life to be of critical importance for physical activity engagement [9–11]. For example, positive emotional responses that automatically occur as a result of physical activity, along with emotionally-driven motivational states, are hypothesized to contribute to the maintenance of an active lifestyle [12,13]. In this context, these behavioral processes are often described as 'micro-temporal within-subject processes' and they are currently being considered as a highly promising research-path to understand the drivers of regular physical activity engagement [5]. Similarly, the importance of physical activity and affective well-being associations for human mental health appears face valid, e.g., with major depression disorder patients exhibiting both diminished mood and psychomotor retardation. Epidemiological studies clearly evidence physical activity to decrease the incidence of several mental disorders in the general population (e.g., [14,15]). Randomized clinical trials show physical activity to improve treatment outcomes, with most prominent effects in affective disorders [16], and particularly when combined with pharmacotherapy and psychotherapy [17]. While it is still poorly understood how physical activity relates to emotional well-being, recent studies showed that staying physically active can be especially beneficial for people at risk of mental disorders and for those with conditions like bipolar disorder [18]. Importantly, these benefits may be linked to the way exercise affects specific brain structures associated with mental disorders [19]. In other words, regular physical activity could potentially improve the health of these vulnerable brain areas, reducing the likelihood of experiencing mental disorders.

Within the last decades, laboratory research produced in-depth insights into physical activity and affective well-being associations summarized in several reviews and meta-analyses [20–24], but the everyday life perspective on the physical activity and affective well-being association has not been focused on for a long time. Part of this neglect may lie in difficulties to capture physical activity and affective well-being in everyday life of humans (e.g., data captured during daily activities e.g., while shopping, gardening, or commuting).

In recent years, this obstacle has been overcome through a group of methods often times called Ambulatory Assessment (AA) [25,26]. This capitalizes on device-based physical activity measurement via accelerometers and self-reports via electronic diaries (e-diaries) on smartphones for affective well-being assessment [25,26]. It allows to capture multiple assessments within a person over time [27], to track data near real-time therewith increasing ecological validity of data yet reducing retrospective biases [28–30]. A major strength of AA lies in the focus on within-subject variance through the use of intensive longitudinal methods drawing from multiple assessments within persons [31].

In these studies, physical activity (PA) and sedentary behavior (SB) form the superordinate category physical behavior (PB). Energy expenditure-increasing activities performed by any skeletal muscle effort are called PA [32]. In contrast, activities at an energy expenditure <1.5 metabolic equivalents while remaining in a sitting or reclined position but not during sleep is mainly understood as SB [33]. By definition, affective well-being is a subcomponent of human subjective well-being [34], e.g., characterized by trait vs. state components and domain-specific vs. general valuations. For example, the umbrella term *affective well-being* includes core affect, a measure describing a neurophysiological state of an elementary simple primitive affective feeling represented in the circumplex model [35,36]. Existing studies applied different questionnaires with established psychometric properties to quantify different components of affective well-being, such as the two-dimensional Positive And Negative Affect Scale (PANAS) [37] and the three-dimensional Multi Dimensional Mood Questionnaire [38]. Extensive discussions and empirical analyses on the advantages and limitations of different PA, SB and affective well-being quantifications can be found elsewhere (see, e.g., [11,34,39,40]). In this review, we refer to the intricate, two-way relationships between physical behavior (which includes physical activity and sedentary behavior) and indicators of affective well-being (measures of emotional health and mood) as "physical behavior - affective well-being (PB-AWB) associations".

In the past decade, applying AA to research the PB-AWB association is gaining tremendous interest as evidenced by the increasing number of studies on PB-AWB associations across the past years (see Electronic Supplementary Material (ESM) 1). While this increase in knowledge can, in principle, provide valuable insights into the understanding of within-subject associations of PB and psychological antecedents and consequences in natural settings, a recent comprehensive systematic review of evidence across populations, age groups and distinct AWB components is not available thus far. There are two prior works that reviewed the relationship between PB-AWB in daily life; that is, the narrative review across a total of 14 studies conducted by Liao and colleagues [41], as well as the very recent systematic review across 10 studies by Bourke and colleagues [42]. Against the background of these prior works, the present review across 66 studies significantly extends the state of knowledge by including studies published after 2015 (resulting in an additional 60 studies compared to the review conducted by Liao et al. [41]); comprehensively covering the relationship between physical activity valence, energetic arousal, calmness, energy, and fatigue as AWB components (prior work by Liao and colleagues focused on positive and negative affect [41]); comprising studies in all available populations and across age groups (thereby extending the focus on children and adolescents in Bourke et al.'s work [42]); including studies using state-of-the-art AA methods (e.g., device-based PB assessments; prior work by Liao and colleagues included studies using retrospective PB assessments [41]); and finally, our review offers a very comprehensive and detailed analysis, providing an in-depth exploration of PB-AWB effects in everyday life.

To this end, we summarized findings of studies that collected data continuously and repeatedly within persons and in real-life (so-called "intensive longitudinal methods" [29,43]). We also developed a modified quality assessment (QA) tool to be used against the background of the large heterogeneity of methods applied in the recent field of AA research on PB-AWB associations following established guidelines for QA tools [44,45]. Finally, we discuss the findings and draw implications for future real-life studies on PB-AWB associations.

2 Methods

The review followed established procedures (PRISMA checklist [46]; for details, see ESM 2) and was registered (PROSPERO id: CRD42021277327).

2.1 Literature Search Strategy

The electronic databases Web of Science, PubMed, and Scopus were systematically searched by selecting the fields' title and/or abstract and keywords. The terms “ecological momentary assessment”, “mood”, “physical activity” and “sedentary behavior” as well as their synonyms were searched as follows: "physical activity" or "exercise" or "sedentary behavior" or "sedentariness" or "physical inactivity" plus "mood" or "emotion" or "affect" or "affective states" or "valence" or "calmness" or "energetic arousal" plus "ambulatory assessment" or "ecological momentary assessment" or "experience sampling method" or "electronic sampling method" or "ambulatory monitoring" or "accelerometry" or "physical activity monitoring" or "interactive assessment" or "e-diary" or "electronic diary". We applied the same search strategy for all three databases, and therefore boolean operators etc. were adapted to the specific requirements (see ESM 3 for the comprehensive search term). The last search was run in November 2022. We also searched the reference lists of all eligible studies (backward search) to identify further studies.

2.2 Study Eligibility

Studies applying intensive longitudinal device-based and real-time assessments to investigate PB-AWB associations were eligible for this review, and, in particular, articles were included if: (a) PB was captured via device-based measurements (e.g., with accelerometers), the rationale for this being to capture features as objectively as possible, i.e., without (retrospective) distortions from cognitive heuristics [28], (for detailed advantages and disadvantages of device-based versus self-reported PB methods, see [47,48]; and (b) afective states were self-reported and assessed using an electronic device (e.g., via e-diaries), the rationale for this being that repeated real-life self-reports on electronic devices are the state-of-the-art procedure for a most reliable and ecologically valid assessment of psychological state, e.g., bypassing limitations of traditional paper–pencil diaries [28]; (c) the assessment duration, i.e., the number of days over which the study period extended, was equal to or greater than 1 day (24 h), the rationale for this being to enhance reliability of PB-AWB efects determined and minimize confounding, for example, through well-known diurnal patterns of AWB [49]; (d) momentary (short-term) relationships of PB and AWB had been analyzed (i.e., the aggregated time frames must not extend beyond 24 h; e.g., this criteria includes a study using PB within the last hour of an e-diary prompt as a predictor of AWB, but excludes a study using PB across the evening as a predictor of next-day AWB), the rationale for this being that against the background of well-known recall bias efects [28], we focused on studies investigating PB-AWB associations within 24 h: of note, we did not specify a minimum number of e-diary prompts per day; and (e) people with and without diseases of all ages were included, the rationale being that we aimed to provide a comprehensive review of PB-AWB associations across age groups and populations. Studies were excluded if: (a) PA or SB was captured in controlled (artificial) conditions (e.g., laboratory or research setting or interventions); (b) retrospective questionnaires (e.g., retrospective paper-pencil questionnaires on PB or AWB) were used, and (c) measurements had been taken at a single point in time only (e.g., for cross-sectional PB-AWB analyses). The search was limited to articles published in the English language but conducted independently of the year of publication of the papers. We excluded grey literature (e.g., unpublished manuscripts or dissertation studies) within our PROSPERO registration to ensure consistency in reporting and quality standards; peer-review ensures high quality standards, but including grey literature, where quality standards are not uniformly assessed, could introduce bias into the interpretation of results when mixing peer-reviewed with non-peer-reviewed studies [50,51].

2.3 Study Selection

First, study selection was based upon the title initially screened. Second, title and abstract of potentially eligible studies were screened independently by two researchers (MG, IT). Of the remaining relevant articles, the full text was read to assess potential eligibility. In case of decision standoff between the two researchers (IT, MG), a third reviewer (MR) was involved to receive a final decision on study inclusion. The selection process is depicted in Fig. 1.

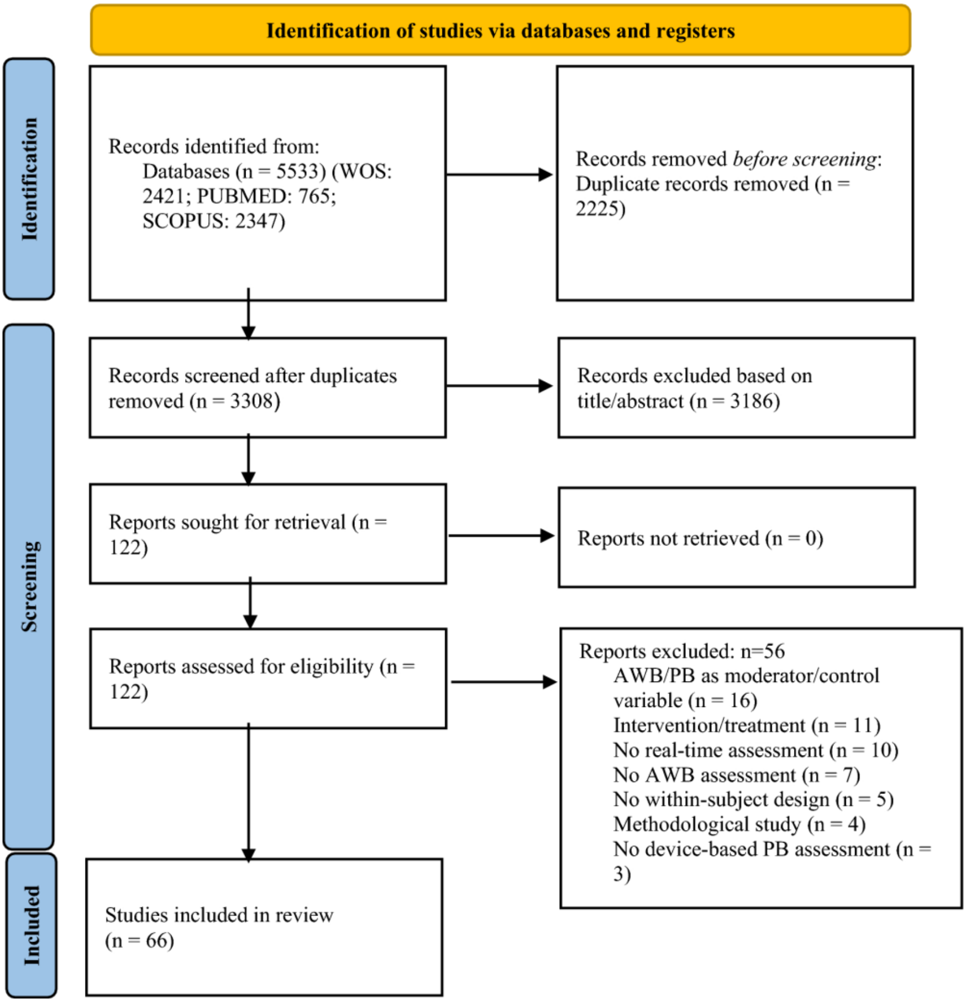

Figure 1: PRISMA flow diagram of the systematic search process [46]. *AWB* affective well-being, *PB* physical behavior

2.4 Data Extraction

A data extraction template was developed to extract data from each study systematically (see Table 1). The data extraction was custom-developed to capture all relevant characteristics of the studies included, applying the following categories: study, country, sample size, sex, age, detailed participant characteristics, ABW assessment, PB assessment, assessment duration, sampling design. To indicate the total time frame of the AA study conduct, we use the term "assessment duration". In particular, this defines the total time in which participants wore accelerometers and repeatedly answered e-diary prompts in their everyday life. For example, in several studies reviewed, the “assessment duration” covered a 1-week period. To indicate the time frame of PA aggregation for the statistical analysis, we adhered to the term “aggregated time frame”. In particular, this describes the time frame used for parameterization of PA, which does not automatically reflect a continuous bout of the same activity but rather an aggregation of all activities from being sedentary to highly PA. For example, in several studies reviewed, “aggregated time frame” equaled 15 min before and/or after the e-diary prompts. Accordingly, in these studies, researchers investigated associations of PA occurring 15 min before and/or after the e-diary rating with AWB. Details from each study included in the systematic review were extracted by two authors (IT, MG) independently. Thereafter, the two data extraction files were merged. Any discrepancies were discussed among the authors until consensus was reached, and in cases of non-agreement between the two researchers (IT, MG) the vote of a third reviewer (MR) was considered to reach a decision.

2.5 Quality Assessment/Risk of Bias Assessment

Following the guidelines for QA measure of PRISMA and the National, Heart, Lung, and Blood Institute [44,45], our modified QA primarily aimed to assess the “risk of bias” [46] of studies included to give an estimate of how likely certain study features may have led to ambiguous results, but the QA also includes a valuation of the comprehensiveness of information given to enable replication of results. For example, and in particular, in studies of PB-AWB associations in everyday life aiming to assess associations of sedentariness and AWB, a well-known risk of bias is the (lack of reporting of the) body position of the accelerometer device [47], which may place a study at enhanced likelihood for misleading results, for example, devices attached to the hip are limited in their validity of capturing sitting versus standing postures [52]. However, according to recent guidelines [45], our QA is not primarily intended to reflect the hierarchical quality of studies, for example, via between-study rankings, but rather to detect potential flaws and thus better reflect the internal validity of studies for the risk of bias assessment. Therefore, this QA is not well suited to judge absolute discrepancies between studies. To capture all relevant features of intensive longitudinal device-based and real-time assessment studies on PB and AWB, we built upon the Checklist for Reporting EMA Studies (CREMAS) [53], reporting guidelines for AA studies in psychopathology research [54], and the National Institute of Health Study Quality Assessment Tools [44]. For example, our modified QA tool included categories such as accelerometer technology used, e-diary sampling schema applied, and compliance rates received (for details, see ESM 4). In line with the PRISMA guidelines and an established scoring approach [55], we set up three evaluation levels: high, moderate, and low risk of bias. The modified QA consists of 16 questions, with a total score of 16. In particular, a score in the range of 16–12 indicates a strong quality (i.e., low risk of bias), a score in the range of 11–6 reflects moderate quality (i.e., moderate risk of bias), and a score in the range of 5–0 indicates weak quality (i.e., high risk of bias). For details on the evaluation process, see ESM 4. Following established procedures [56], we calculated the inter-rater reliability based on a single-rating, absolute agreement, two-way mixed-effects model with two raters across 66 studies (subjects), which indicated good reliability (intraclass correlation coefficient (ICC)=0.777; confidence interval (CI): 0.52–0.88). Each article's quality was assessed independently by two researchers (MG, IT). Any discrepancies were discussed among the authors until consensus was found.

3 Results

3.1 Study and Sample Characteristics

After removing duplicates, the systematic literature search yielded a total of 2225 relevant studies and 66 studies remained in the final selection (see Figure 1). The additional reference screening did not yield any further studies to be included. Of these 66 studies, 62 drew from independent datasets. Participants were recruited from 11 different countries, mainly from the US (26) and Germany (24). The mean age of participants in the studies ranged from 9.51 to 72.4 years. The total sample size of the selected studies varied between 10 and 805 participants. For an overview, see Table 1.

Table 1: Data extraction of the studies included in the review

Study	Country	*n*	Female %	Age (mean, range)	Participants characteristics sample; (study name)	Affect assessment AWB items (software, device); prompts/day	Physical behavior assessment (unit; time frame; direction; device; placement)	Assessment duration; sampling design (random, fixed, event-based, mixed)	Quality assessment
Bai et al. [189]	US	805	71.3	NR (18-25)	Adults (students)	Mood (WE study app, iPhone); 1 prompt/day	PA (metric); 1440 min; before; Apple Watch Series 0 or 1; wrist	50-216 days, fixed	8.5
Bossmann et al. [155]	GER	62	14,5	21.4 (19-30)	Adults (students)	Valence, energetic arousal, calmness (MyExperience, study smartphone); Every hour after waking up	PA (metric); 10 min; before; Movisens Move 1; chest	1 day, fixed	10
Bourke et al. [190]	AU	119	46,4	14.7 (NR)	Adolescents	Valence, energetic arousal, calmness (Qualtrics, participants' smartphone); 5 (weekdays) or 9 (weekend days) prompts/day	PA (MVPA); 15 min; before; ActiGraph GT3X+; dominant wrist	4 days, NR	11
Bourke et al. [191]	AU	119	46,4	14.7 (13-17)	Adolescents	Valence, energetic arousal, tense arousal (Qualtrics, participants' smartphone); 5 (weekdays) or 9 (weekend days) prompts/day	PA (MVPA); 15 min; before; ActiGraph GT3X+; dominant wrist	4 days, fixed with random component	14
Cabrita et al. [135]	NL	10	60	68.7 (65-83)	Elders	Pleasure (Activity Coach, study smartphone); 12 prompts/day	PA (metric); 10 min; before (accelerometer (NR); hip)	30 days, fixed	8.5
Curtiss et al. [192]	US	34	73.53	28.97 (18-55)	Adults (MDD, anxiety)	Positive affect, negative affect (Ethica App, participants' smartphone); 5 prompts/day	PA (NR); 0 min; NR; NR; NR	14 days, NR	4.5
Cushing et al. [129]	US	26	42.3	15.96 (13-18)	Adolescents	Positive affect, negative affect, fatigue, energy (PETE app, study smartphone); 4 prompts/day	PA (MVPA) and SB; 30 min; bidirectional; ActiGraph wActi Sleep-BT; nondominant wrist	20 days, fixed	11
Cushing et al. [81]	US	26	42,3	15.67 (13-18)	Adolescents	Anger, anxiety, depression (PETE app, study smartphone); 4 prompts/day	PA (MVPA); 30 min; bidirectional; ActiGraph wActi Sleep-BT; nondominant wrist	20 days, fixed	9.5

Study	Country	*n*	Female %	Age (mean, range)	Participants characteristics sample; (study name)	Affect assessment AWB items (software, device); prompts/day	Physical behavior assessment (unit; time frame; direction; device; placement)	Assessment duration; sampling design (random, fixed, event-based, mixed)	Quality assessment
DeMasi et al. [193]	US	53	49	19.83 (NR)	Adults (students)	Mood, energy (Open Sensing Framework App, participants' smartphone); 4 prompts/day	PA (metric); 1440 min; before; smartphone's accelerometer; no fixed position	56 days, random	9
Difrancesco et al. [194]	NL	359	63.7	49.5 (NR)	Adults (MDD, anxiety)	Positive affect, negative affect (NR, participants' or study smartphone); 5 prompts/day	PA (LPA, MVPA) and SB; 180 min; bidirectional; GENEActive; nondominant wrist	14 days, fixed	7
Dunton et al. [162]	US	119	52	NR (9-13)	Children (Healthy PLACES)	Positive affect, negative affect (MyExperience, study smartphone); 3-7 prompts/day	PA (MVPA); 30 min; bidirectional; ActiGraph GT2M; right hip	8 days (2 waves a 4 days), fixed with random component	10
Elavsky et al. [195]	US	121	100	51.5 (40-60)	Adults	Positive affect, negative affect (Purdue Momentary Assessment Tool, PDA); 4 prompts/day	SB; 180-360 min; bidirectional; ActiGraph GT1M; nondominant hip	15 days, mixed	10
Giurgiu et al. [90]	AU; GER	92	63	33.7 (22-62)	Adults (university employee)	Valence, energetic arousal, calmness (movisensXS, study smartphone); 8-21 prompts/day	PA (metric) and SB; 15-30 min; before; Movisens Move 3; chest, hip, thigh	5 days, mixed	13
Giurgiu et al. [86]	AU; GER	92	65	33.73 (22-62)	Adults (university employee)	Valence, energetic arousal, calmness (movisensXS, study smartphone); 8-21 prompts/day	PA (metric); 80 min; before; Movisens Move 3 + EcgMove 3; chest, hip, thigh	5 days, mixed	12.5
Giurgiu et al. [94]	AU; GER	92	65	33.88 (22-62)	Adults (university employee)	Valence, energetic arousal, calmness (movisensXS, study smartphone); 8-21 prompts/day	SB; 30 min; after; Movisens Move 3 + EcgMove 3; chest, hip, thigh	5 days, mixed	14
Giurgiu et al. [89]	GER	103	55.1	22.1 (19.3-24.9)	Adults (students)	Valence, energetic arousal, calmness (movisensXS, study smartphone); 6 prompts/day	PA (LPA, MVPA) and SB; 60 min; Movisens Move 4; wrist, hip, thigh	5 days, mixed	12.5
Haaren et al. [156]	GER	29	NR	21.3 (NR)	Adults (students)	Valence, energetic arousal, calmness (My Experience, PDA); 5 prompts/day	PA (metric, LPA) and SB; 15/-30 min; before; Movisens Move 2; chest	2 days, fixed with random component	11.5

Study	Country	*n*	Female %	Age (mean, range)	Participants characteris-tics sample; (study name)	Affect assessment AWB items (software, device); prompts/day	Physical behavior assessment (unit; time frame; direction; device; placement)	Assessment duration; sampling design (random, fixed, event-based, mixed)	Quality assessment
Hevel et al. [196]	US	103	62.5	72.4 (60-98)	Adults	Positive affect, negative affect, energy (movisensXS, study smartphone); 6 prompts/day	PA (metric); 15/-30 min; bidirectional; ActivePAL; thigh	10 days, fixed with random component	10.5
Jeckel & Sudeck [112]	GER	46	54,4	32 (21-59)	Adults	Valence, energetic arousal, calmness (MyExperience, study smartphone); 4 prompts/day and before and after activity	PA (metric); 15/-720 min; before; Movisens EcgMove; chest	6 days, mixed	12
Jeckel & Sudeck [197]	GER	46	54,4	32 (21-59)	Adults	Valence, energetic arousal, calmness (MyExperience, study smartphone); Activity-triggered prompts	PA (metric); 15 min; bidirectional; Movisens EcgMove; chest	6 days and 15h, event	11
Kanning et al. [198]	GER	44	47,7	26.2 (NR)	Adults (students)	Valence, energetic arousal, calmness (Izybuilder, PDA); 19 prompts/day	PA (metric); 10 min; before; Becker Meditech Varioport-e; hip	1 day, fixed with random component	9.5
Kanning [199]	GER	87	54	24.6 (NR)	Adults (students)	Valence, energetic arousal, calmness (Izybuilder, PDA); 19 prompts/day	PA (metric); 10 min; before; Becker Meditech Varioport-e; hip	1 day, fixed with random component	10.5
Kanning et al. [154]	GER	74	49	60.1 (50-70)	Adults	Valence, energetic arousal, calmness (MyExperience, study smartphone); Activity-triggered prompts only (mean 6.4)	PA (metric); 10 min; before; Becker Meditech Varioport-e; hip	3 days, mixed	11
Kanning & Schoebi [87]	GER	65	57	24.6 (NR)	Adults (students)	Valence, energetic arousal, calmness (Izybuilder, PDA); Every 45 min during pre-defined 14h period)	PA (metric); 5-/45 min; after; Becker Meditech Varioport-e; hip	1 day, fixed	10.5
Kanning et al. [173]	GER; US	202	100	41 (24-57)	Adults (mothers of 8 to 12-year-old children)	Happy, calm, stressed, angry, sad/depressed (NR, study smartphone); 4 (weekdays) or 8 (weekend days) prompts/day	PA (MVPA); 120 min; before; ActiGraph GT3X; hip	8 days, fixed with random component	9.5
Kanning et al. [200]	GER	308	50.3	27.4 (17-66)	Adults (students and	Valence, calmness, energetic arousal (movisensXS, study smartphone); Sedentary-	SB; 30 min; before; Movisens Move 3 or Move 4; thigh	4-5 days, mixed	11.5

Study	Country	*n*	Female %	Age (mean, range)	Participants characteristics sample; (study name)	Affect assessment AWB items (software, device); prompts/day	Physical behavior assessment (unit; time frame; direction; device; placement)	Assessment duration; sampling design (random, fixed, event-based, mixed)	Quality assessment
					employees)	triggered prompts			
Kim et al. [125]	JP	113	28,3	13.6 (NR) undergraduates: 21.6 (NR) office workers: 41.0 (NR)	Adolescents, adults (undergraduates and office workers)	Depressive mood (NR, wristwatch); 5 (adolescents), 6 (office workers) or 10 (undergraduates) prompts/day	PA (metric); 60 min; before; wristwatch computer (Ruputer); nondominant wrist	2-7 days, mixed	11.5
Kim et al. [126]	JP	57	EG: 14,3 HC: 0	EG: 34 (22–42) HC: 40.7 (23-58)	Adults (with and without MDD)	Depressive mood (NR, wristwatch); 6 prompts/day	PA (metric); 60 min; before; wristwatch computer (Ruputer); nondominant wrist	EG: 18-67 days; HC: 7 days, mixed	10.5
Kim et al. [175]	JP; US	122	76.4	41.3 (19-63)	Adults	Valence, energetic arousal (NR, PDA); 6 prompts/day	PA (metric) and SB; 5-/60-/120 min; bidirectional; ActiHeart; chest	3 days, fixed with random component	9.5
Koch et al. [93]	GER	113	48	15.02 (12-17)	Adolescents (URGENY)	Valence, energetic arousal, calmness (MovisensXS, study smartphone); 4-7 (weekdays) or 8-17 (weekend days) prompts/day	PA (metric), 10 min; after; Movisens Move 2 + Move 3; right hip	7 days, mixed	13.5
Koch et al. [91]	GER	113	48	15.02 (12-17)	Adolescents (URGENY)	Valence, energetic arousal, calmness (MovisensXS, study smartphone); 4-7 (weekdays) or 8-17 (weekend days) prompts/day	PA (metric), 15 min; before; Movisens Move 2 + Move 3; right hip	7 days, mixed	12
Koch et al. [80]	GER; ESP; GB; NL	185	54.1	(14-45)	Adolescents, adults (with and without ADHD)	Positive and negative affect (movisens XS, NR); 12 prompts/day	PA (metric); 10 min; before; Movisens LightMove 3; non-dominant wrist	4 days, random	7.5
Kracht et al. [201]	US	284	54	12.6 (10-16)	Adolescents (TIGER Kids study)	Positive affect (LifeData Corporation App, study device) or participants' smartphone); 2 (weekdays) or 6 (weekend days) prompts/day	SB; 30 min; before; ActiGraph GT3X+; hip	7 days, fixed with a random component	13.5

Study	Country	*n*	Female %	Age (mean, range)	Participants characteris-tics sample; (study name)	Affect assessment AWB items (software, device); prompts/day	Physical behavior assessment (unit; time frame; direction; device; placement)	Assessment duration; sampling design (random, fixed, event-based, mixed)	Quality assessment
Kuehnhausen et al. [202]	GER	82	45	117.2 (97-132) months	Children (FLUX)	Pleasantness, unpleasantness, activation, deactivation (NR, study smartphone); 4 prompts/day	PA (MVPA); 1440 min; before; ActiGraph GT3X+; hip	28 days, NR	6.5
Langguth et al. [127]	GER	72	37	17.36 (12-26)	Adoles-cents	Depression (NR, paper-pencil or online diaries); 3 prompts/day	PA (MVPA); 1440 min; before; ActiGraph GT3X+; hip	7 days, mixed	11.5
Le et al. [203]	AU	361	72.5	22.79 (NR)	Adults	Positive affect, negative affect, affective arousal (MetricWire, NR); 3-4 prompts/day	PA (LPA, MVPA) and SB; 1140 min; NR; ActiGraph wGT3X-BT; wrist	7-15 days, fixed with a random component	7.5
Li et al. [204]	UK	78	71.79	25.46 (NR)	Adults	Positive affect, negative affect, depression (mo-visensXS or Qumi, partici-pants' smartphone); 5 prompts/day	PA (LPA, MVPA) and SB; 0-180 min; Movisens EcgMove 3; chest	14 days, fixed with a random component	10
Liao et al. [205]	US	117	72.5	40.4 (NR)	Adults (MOBILE)	Positive affect, negative affect, energy, fatigue (MyExperience, study smartphone); 8 prompts/day	PA (MVPA, LPA); 15-/30 min; bidirection-al; ActiGraph GT2 M; hip	4 days, fixed with random component	13.5
Liao et al. [206]	US	117	73	39.8 (NR)	Adults (MOBILE)	Positive affect, negative affect, energy, fatigue (MyExperience, study smartphone); 8 prompts/day	PA (MVPA); 6-12 months; after; ActiGraph GT2 M; NR	4 days a 3 waves, random	6
Madden et al. [95]	US	21	76,2	49 (NR)	Adults (MDD, bipolar, schizo-phrenia)	Positive affect, negative affect, energy, fatigue (custom software phone application, study smartphone); 7 prompts/day	PA (MVPA); 30 min; bidirectional; ActiGraph wGT3x-BT; right hip	4 days, fixed with random component	12
McLean et al. [207]	US	75	63	31 (NR)	Adults	Valence (Personal Analytics Companion, participants' smartphone); 6 prompts/day	PA (metric); 60 min; before; Fitbit Flex; wrist	7 days, fixed with random component	9.5
Merikangas et al. [18]	US	242	61.9	48 (NR)	Adults (MDD, bipolar) (NIMH)	Mood, energy (NR, PDA); 4 prompts/day; 4 prompts/day	PA (metric); 240 min; bidirectional; Respironics and Actiwatch; nondominant wrist	14 days, fixed	6

Study	Country	*n*	Female %	Age (mean, range)	Participants characteristics sample; (study name)	Affect assessment AWB items (software, device); prompts/day	Physical behavior assessment (unit; time frame; direction; device; placement)	Assessment duration; sampling design (random, fixed, event-based, mixed)	Quality assessment
Michalak et al. [208]	GER	71	60.6	39.33 (NR)	Adults (MDD)	Mood and depressive symptoms (Palm Tungsten T3, NR); 14 prompts/day	PA (metric); 60 min; before; Vitamove; trunk, right thigh	2 days, fixed	8.5
Pannicke et al. [209]	AT	37	75.7	23.5 (19-28)	Adults	Positive affect, negative affect (NR, participants' smartphone); 6 prompts/day	PA (MVPA) and SB; 150 min; before; Actiheart; sternum, chest	7 days, fixed	11.5
Pinto et al. [210]	US	22	100	51.5 (NR)	Adults (breast cancer survivors)	Affective valence, sadness, anxiety, stress, fatigue (mEMA ilumivu, participants' smartphone); 5 prompts/day	SB; 1440 min; after; ActiGraph GT3X; right hip	7 days a 5 waves, mixed	9.5
Poppe et al. [211]	BE	38	34.2	63.18 (50-81)	Adults (with type 2 diabetes mellitus)	Stress, sadness, fatigue (LimeSurvey, participants' computer or tablet); 1 prompt/day	PA (LPA, MVPA) and SB; 1440 min; after; ActiGraph GT3X+; right hip	10 days, event	11.5
Powell et al. [212]	UK	29	36	71.4 (46-85)	Adults (after joint replacement surgery)	Positive affect, negative affect (NR, PDA); median of 6 prompts/day	PA (metric); 60-/1440 min; bidirectional; Vitaport 3 system; thigh, chest	1 day, fixed with random component	11.5
Reichert et al. [92]	GER	106	62.4	23.4 (18-27)	Adults (URGENCY)	Valence, energetic arousal, calmness (movisensXS, study smartphone); 9-22 prompts/day	PA (metric); 10 min; after; Movisens Move 2; hip	7 days, mixed	13
Reichert et al. [88]	GER	106	62.4	23.4 (18-27)	Adults	Valence, energetic arousal, calmness (movisensXS, study smartphone); 9-22 prompts/day	PA (metric); 15/1440 min; before; Movisens Move 2; hip	7 days, mixed	11.5
Ruissen et al. [85]	CA	126	48.4	27.71 (18-40)	Adults	Positive affect, negative affect (MetricWire, participants' smartphone); 6 prompts/day	PA (MVPA); n.a.*; bidirectional; Fitbit Blaze; wrist	14 days, fixed with random component	10.5
Schwerdtfeger et al. [83]	GER	124	51,6	31.67 (18-73)	Adults	Positive affect, negative affect (DialogPad, PDA); 13 prompts/day	PA (metric, MVPA, LPA) and SB; 1-30 min; after; ActiGraph GT1M; ankle	12 h, fixed with random component	13.5
Shin et al. [213]	KR	27	29.6	NR (19-44)	Adults	Joyful, good, nervous, tired, depressed, annoyed, upset (Google Forms, participants'	PA (metrics); 1440 min; after; Fitbit; NR	5 days, fixed	6.5

Study	Country	*n*	Female %	Age (mean, range)	Participants characteristics sample; (study name)	Affect assessment AWB items (software, device); prompts/day	Physical behavior assessment (unit; time frame; direction; device; placement)	Assessment duration; sampling design (random, fixed, event-based, mixed)	Quality assessment
						smartphone); 2 prompts/day			
Smith et al. [131]	US	17	58.8	10.59 (NR)	Children (with over-weight/obesity)	Negative affect, positive affect (ReTAINE, smartphone NR); 4-6 prompts/day and after meals	PA (LPA, MVPA) and SB; 30-/60-/120 min; bidirectional; Philips Actiwatch 2; wrist	14 days, mixed	9.5
Smith et al. [214]	US	77	41.6	15.36 (13-17)	Adolescents (with and without over-weight)	Negative affect, positive affect (NR, study smartphone); 4 (weekdays) or 7 (weekend days) prompts/day	PA (metric, MVPA); 60 min; bidirectional; ActiGraph (NR); waist	7 days; fixed	10
Stavrakakis et al. [157]	NL	20	70 (each group)	depressed: 36.4 (22-49) nondepressed: 36.7 (24-46)	Adults (with and without MDD) (MOOVD)	Negative affect, positive affect (PsyMate, NR); 3 prompts/day	PA (metric); 360 min; bidirectional; Respironics ActiCal; nondominant wrist	30 days, fixed	10
Stevenson et al. [82]	(NR)	25	56	40 (NR)	Adults (alcohol use disorder)	Positive affect, negative affect (ilumivu, participants' smartphone); 4 prompts/day	PA (metric); 60-/1440 min; before; Fitbit Charge; wrist	21 days, fixed with random component	10.5
Sudeck et al. [215]	GER	64	58.3	35.18 (20-63)	Adults	Valence, energetic arousal, calmness (movisensXS, study smartphone); 4 prompts/day	PA (metric); 15 min; before; Movisens Move 3; hip	4 days, fixed with random component	11.5
Takano et al. [216]	JP	41	22	NR	Adults (under-graduate students)	Positive affect, negative affect (NR, participants' smartphone); 8 prompts/day	PA (metric); 15 min; before; Respironics Actiwatch; wrist	7 days, fixed with random component	11
Vetrovsky et al. [217]	CZ	28	75	68 (NR)	Adults	Fatigue (NR, participants' smartphone); 1 prompt/day	PA (metric, MVPA); 720 min; after; ActiGraph wGT3X-BT; right hip	28 days, fixed	11.5
Walsh et al. [218]	US	111	60.36	22.01 (18-27)	Adults (bipolar)	Depression (NR, NR); 3 prompts/day	PA(MVPA) and SB; 1440 min; before; Philips Actiwatch Spectrum; nondominant wrist	20 days, fixed with random component	7
Wen et al. [132]	US	202	51.67	9.6 (8-12)	Children	Positive affect, negative affect	PA (MVPA) and SB;	7 days, random	11.5

Study	Country	*n*	Female %	Age (mean, range)	Participants characteristics sample; (study name)	Affect assessment AWB items (software, device); prompts/day	Physical behavior assessment (unit; time frame; direction; device; placement)	Assessment duration; sampling design (random, fixed, event-based, mixed)	Quality assessment
					(MATCH)	(NR, study or participants' smartphone); 3-7 prompts/day	30-/, 60 min; bidirectional; ActiGraph GT3X; right hip		
Wilhelm et al. [136]	CA	123	63	71.83 (64-85)	Elders	Negative affect (NR, paper-pencil); 3 prompts/day	PA (metric); 1440 min after; ActiGraph GT3X; hip	10 days, fixed	10
Williams et al. [219]	US	194	71	40.72 (20-74)	Adults	Positive affect, negative affect (online survey, NR); 1 prompt/day	PA (metric); 1440 min; after; Fitbit Charge; NR	100 days, fixed	7
Yang et al. [79]	US	185	Mothers: 100; Children: 53	Mothers: 41.03 (NR); children: 9.51 (NR)	Children, adults (MATCH)	Positive affect, negative affect (NR, participants' or study smartphone); mothers: 4 (weekdays) or 8 (weekend days) prompts/day; children: 3 (weekdays) or 7 (weekend days) prompts/day	PA (MVPA) and SB; 45 min; bidirection-al; ActiGraph GT3X or WGT3X-BT; hip	7 days, fixed with random component	11.5
Zenk et al. [78]	US	128	100	NR (25-64)	Adults	Positive affect, negative affect (NR, study smartphone); 5 prompts/day	PA (MVPA) and SB; 1440 min; bidirectional; ActiGraph GT1M; hip	7 days, fixed with random component	10
Zhaoyang & Martire [77]	US	152	58.04	65.39 (NR)	Elders (knee osteoar-thritis)	Positive affect, negative affect (NR, hand held computer); 2 prompts/day	PA (MVPA) and SB; 1440 min; bidirectional; ActiGraph GT1M or GT3X; hip	22 days, fixed	7.5

After affective well-being prior to physical behavior, *Before* physical behavior prior to afective well-being, *Bidirectional* physical behavior prior to and after affective well-being, *Event-based* self-initiated prompts, *Fixed with random component* random prompts within pre-established intervals or semi-random prompts, *Fixed* fxed prompts, *LPA* light physical activity, *MDD* major depression disorder, *Metric* e.g., milli-g, acceleration counts, steps, posture, *min* minimum, *max* maximum, *Mixed* e.g., activity- or sedentary-triggered prompt, combined with random prompts, *MVPA* moderate to vigorous physical activity, *NR* not reported, *PDA* personal digital assistant, *Random* random prompts, *SB* sedentary behavior

[a]Due to its novel statistical approach, this study could not be reviewed within the data extraction framework which we custom-developed to the methods applied by most of the AA studies in the PB-AWB feld

3.2 Quality Assessment/Risk of Bias Assessment

For AA categories, one study was classified at high risk of bias, 50 studies showed moderate risk of bias, and 15 studies showed a low risk of bias. The mean risk of bias score was 10.27 (SD=2.14; min=4.5, max=14) within a range of 0–16. Comprehensive information was provided for prompt frequency (i.e., 65/66 studies), further sampling design details, and parameterization of accelerometer data (see Fig. 2); thus, most of the information was provided for technical details such as PA epoch lengths. The epoch length choice in accelerometer studies influences activity classification accuracy. Longer epoch length may misclassify short vigorous activities as moderate. Modern technology allows for shorter epoch lengths than 60 s, which are recommended, while the ideal epoch length for health outcomes remains unclear [47]. Conversely, more than half of the studies (40/66) did not report details regarding the accelerometer sampling frequency. The sampling frequency is crucial for accelerometer data accuracy. It should be at least twice as high as the highest movement frequency component to prevent aliasing effects; for further discussion see [57,58]. Most of the studies (48/66) did not detail how accelerometer data had been filtered, with only 18 out of 66 studies reporting whether a high- or low-pass filter were set, i.e., critical information for risk of bias assessment [47]. Before converting raw data, filters are commonly applied to remove non-human movement acceleration frequencies. Different filters are available for data processing, and their selection significantly affects the results. Providing information on the specific filters used is crucial since there are no internationally accepted standards for signal processing [59]. This lack of standardization makes direct comparisons of outcome metrics across devices difficult [60]. Moreover, nearly half of the studies (32/66) did not report details on non-wear time definition applied, and most of the studies only sparsely reported on compliance rates, missing data and latency (Fig. 2). For a detailed rating see ESM 5.

Category	Description	Number of studies (n=66) fulfilling the criteria
Title	AA or EMA is included in title	25
Rationale	The concept of AA is briefly introduced and reasons for utilization are provided	51
Participant Training	Indicate if and by what methods participants were trained for the AA protocol and use of the accelerometer (i.e., how to wear the device properly)	44.5
AA Technology	Technology description for AWB assessment (e.g., device, model, operating system, AA program)	45.5
ACC Technology	Technology description of ACC used (brand, model, operating system, placement, frequency, axes, filter)	39.5
Monitoring period	Number of days each wave of the study lasted and how many weekdays vs. weekend-days for AWB and ACC	48.5
AA prompting design	Prompting strategy (event-based, interval-based or combined strategy)	63
AA prompt frequency	Intended prompts per day (including weekdays vs. weekend-days)	65
Parameterization	Source of AWB-items (e.g., existing questionnaire) and ACC-metric including epoch length (e.g., steps per hour)	57.5
Design features	Features addressing potential sources of bias or participant burden	34
Statistical methods	Psychometric properties of AWB-items, model description including centering, random vs. fixed effects and significance-measurement	51
Exclusion criteria	Criteria to exclude AWB-responses or ACC-data	31.5
Latency	Amount of time from prompt signal to answering the prompt	9
Delay possibility	Ability to delay or suspend responses	31
Compliance rate & missing data	Number of answered AA prompts in total and on average per person; wear-time of ACC overall and on average per person; indication of reasons for non-compliance	24
Limitations	Sources of potential bias while using AA methods	57

Figure 2: Quality Assessment (QA) description and number of studies fulfilling the criteria. The modified QA is displayed with 16 different categories. The number of studies that report information on the respective category are listed on the right. *AA* ambulatory assessment, *EMA* ecological momentary assessment, *AWB* affective well-being, *ACC* accelerometry.

3.3 Physical Behavior and Affective Well-being Assessment

Physical behavior To obtain PB measurements, the majority of the included studies (24) used accelerometer devices of the manufacturer “ActiGraph” [61], followed by 16 studies using devices from the “movisens GmbH” [62], as well as other accelerometers (e.g., “varioport-e” [63]; 4) and smartwatches (e.g., “Fitbit” [64]; (5)). The devices were mainly placed on the participants hip (30), followed by wrist (18) and chest (11). Seven studies used multiple placement positions. The parameterization of PB included movement-based volume variables (i.e., raw acceleration data; (13); activity counts; (12)), time-based amount variables (e.g., minutes spent in Moderate-to-Vigorous-Physical-Activity (MVPA); (27)), energy expenditure variables (e.g., metabolic equivalent; (6)), as well as postural and activity-based variables (e.g., standing, stepping; (11)).

Affective well-being The assessment of AWB (mainly implemented on smartphone e-diaries) differed between studies; 19 studies used a short version of the Multidimensional Mood Questionnaire (MDMQ; [65]). This questionnaire has been specifically adapted and validated for AA studies [38], and captures the three dimensions valence, energetic arousal and calmness; 19 studies based their items on existing (non-AA) questionnaires like some form of the Positive and Negative Affect Schedule (PANAS; [37,66–69]), mostly assessing the two dimensions positive and negative affect; three studies applied the circumplex model [70], two studies the Profile of Mood States (POMS; [71]), and two studies the depression and anxiety mood scale (DAMS; [72]). Nineteen studies used self-developed items which were not based on standardized questionnaires, or no source was reported (see ESM 6).

3.4 Assessment Duration and Frequency

Physical behavior The PB assessment duration differed among studies; mainly short periods of time were recorded, i.e., up to seven days (42). Most of the studies aggregated PB across 30 minutes time frames (16), 1440 minutes (16), or 15 minutes (13) before or after the e-diary prompt for their statistical analyses on the PB-AWB association. Of note, “aggregated time frame” refers to the time frame of PA aggregation for the statistical analysis, describing the time frame used for parameterization of PA (see Sect. 2.4 for details).

Affective well-being The majority of the studies (23) used a time-based sampling strategy with random components such as prompts occurring at random times within pre-established intervals or semi-random prompts. Sixteen studies chose a fixed time interval. In 2 studies, participants were responded to self-initiated queries (similar to an event-based sampling strategy). A combination of an event-based sampling strategy together with random or fixed prompts was applied in 6 studies. One study used an activity-triggered sampling scheme, while 3 studies utilized a sedentary-triggered design including fixed and random prompts. Two studies employed a geolocation-triggered sampling scheme including fixed and semi-random prompts. Three studies did not report the sampling schema applied. In line with the study inclusion criteria (d) (for details see Sect. 2.2), the number of prompts per day ranged from 1 to 23 times. Most studies applied a prompt frequency of 1 to 7 prompts per day (42) and had an assessment duration of 1 to 7 days (52).

3.5 Populations Studied

Most studies reviewed researched adult populations (50), followed by investigations of children and adolescents (16; aged 8–26 years) and elderly persons (3; aged 64–85 years). The total number of participants was 7441. Most of the reviewed studies (36) investigated healthy adult populations. They comprised a total of 4,388 participants. Interestingly, only a few studies were conducted in patient groups, for example, major depressive disorder (7), bipolar disorders (3), anxiety disorders (2), alcohol disorders (1), or attention deficit hyperactivity disorder (1), with a total of 1,104 participants. The studies that solely examined elderly people (60 years and older) had an age range of 64–85 years and a total of 285 subjects (3). In this cohort, there were other physical diseases such as knee osteoarthritis. Studies examining children (5) included participants across an age range of 8–13 years. In total, 518 subjects were studied. The studies that examined adolescents (11) included participants across an age range of 10–26 years, with a total of 1020 subjects being studied. A limited number of studies focused on participants with physiological health impairments. In particular, two were conducted in overweight or type 2 diabetes participants, one study investigated participants after joint replacement surgery, and one study dealt with breast cancer survivors or low active participants (2).

3.6 Schematic Overview of the Findings

We created a series of figures that enable a graphical review of the multilayered findings on the association of PB and affective well-being in everyday life (Figures 3-6, see Sect. 3.7). Figure 3 introduces this methodological approach applied to review the studies’ findings. In particular, the affective well-being subcomponent quantifications most often used in the studies reviewed (i.e., positive affect, negative affect, valence, energetic arousal, and calmness, energy, fatigue/tiredness) are displayed at the center of Fig. 3. For each of these affective well-being subcomponents, their respective associations with PA and SB are visualized through colored arrows.

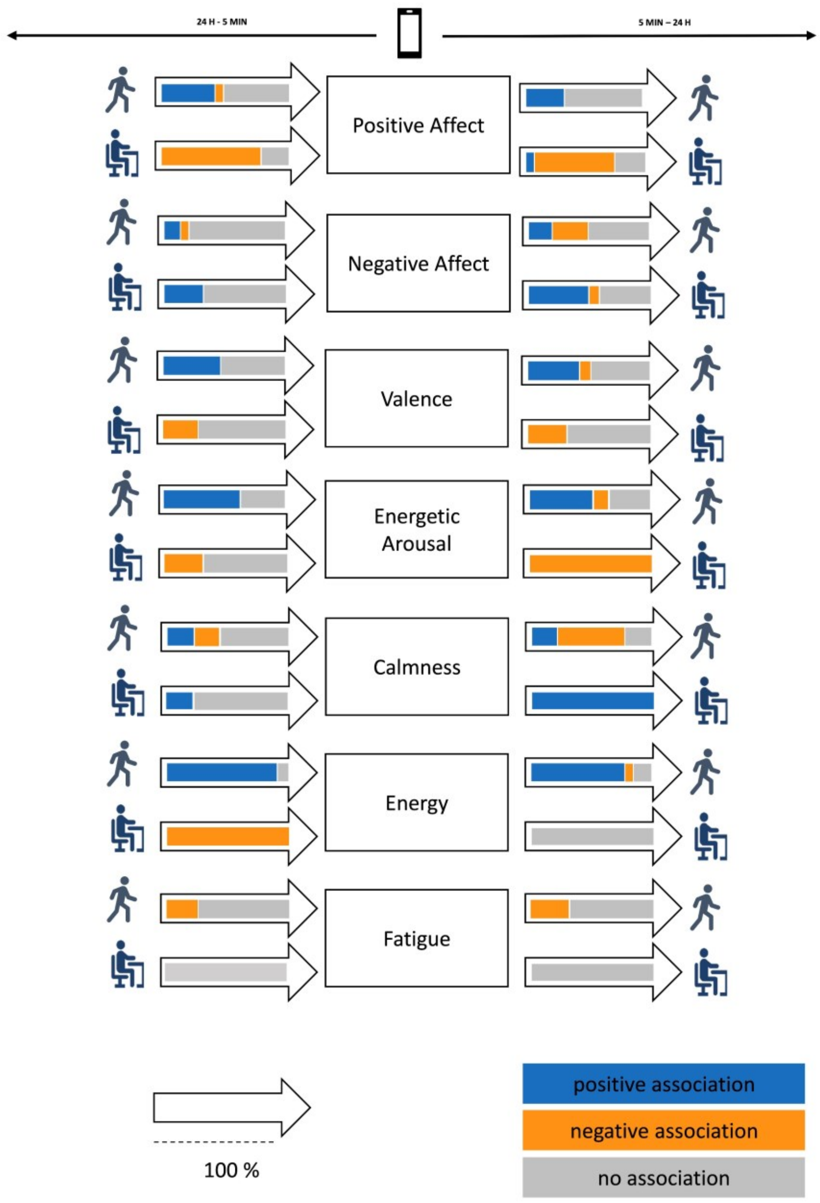

Figure 3: Graphical overview across the multilayered study findings reviewed. The direction of the arrows indicates the nature of the association (i.e., PA and SB being associated with subsequent affective well-being vs. affective well-being being associated with subsequent PA and SB). The color composition of the arrows represents the direction and statistical significance of the association in relation to the number of effects reviewed in percentage. That is, blue represents the relative number of effects revealing positive significant associations in % [positive beta coefficient and P value<0.05]; orange

indicates the relative number of effects showing negative significant associations [negative beta coefficient and P value<0.05]; and gray indicates the relative number of effects receiving non-significant associations [P value≥0.05]. For example, 45% of the effects in studies reviewed that investigated the association of PA with subsequent positive affect received a positive significant result (i.e., PA increased subsequent positive affect), 10% of the effects showed a significant negative result (i.e., PA decreased subsequent positive affect), and 45% of the effects showed a null finding (PA was not associated with subsequent positive affect); see the very top left arrow. *AWB* affective well-being, *LPA* light physical activity, *MVPA* moderate to vigorous physical activity, *PA* physical activity, *PB* physical behavior, *SB* sedentary behavior

3.7 Main Results

For a detailed review of the evidence, we summarized study results as a function of PB-AWB association features, i.e., the number of (non-) significant effects was plotted against their PB and AWB quantifications, their effect-directions, and their timing-orders. Some studies examined PB across multiple aggregated time frames within the same dataset. For data synthesis and to concentrate on the level of individual significant versus non-significant PB-AWB relationships found, various analyses within a study and across multiple aggregated time frames were incorporated into our results, which we called *investigated relationships* (and thus they were not summarized; e.g., a study that examined the relationship of PA and positive affect within the same data set for the aggregated time frames of 5, 10, and 60 min contributes three distinct investigated relationships into our Sect. 3). We also treated multiple effects from different studies (different papers) that used the same dataset individually, i.e., each result from each study (paper) counted as an individual investigated relationship in our results. More precisely, each investigated relationship from a study was treated as a distinct data point in our analysis, allowing us to maintain granularity in our examination of the relationships between PB and AWB. Translated into practice, some studies used the same data set to investigate different questions on the PB-AWB relationship in distinct papers; they counted as individual investigated relationships in our results, respectively. Of note, each PB-AWB association entered our analysis just once; i.e., while we included various investigated relationships from one data set reported in one paper or scattered across several papers, we did not include a single investigated relationship twice. The reviewed studies comprised a total of 242 investigated relationships for the PB-AWB direction, while less investigated relationships (i.e., 161) were available for the reverse AWB-PB association. The results are detailed in Figs. 4–6 (see also ESM 7). Moreover, to give an idea of the size of effects found in the studies reviewed, we provide a summary of practical effect sizes reported, a method also known as benchmarking and recommended for interpreting the PA effects seen in daily life [73] to indicate the meaningfulness of effects observed [74–76]. Of note, practical effect sizes had only been reported by a small portion of studies reviewed (14 studies).

3.7.1 Physical Behavior, Positive and Negative Affect

Figure 4a shows studies researching PB associations with positive affect. Most of the investigated relationships revealed either a positive association of PB with positive affect, i.e., higher PA was related to more positive affect (20/47), and more SB was related to less positive affect (7/9). Thirteen of 33 investigated relationships revealed a positive significant association of positive affect with PB, i.e., higher positive affect was related to more PA (13/33), and more positive affect was related to less SB (7/11). Sixty-nine of 102 investigated relationships in total showed nonsignificant associations. Only three investigated relationships showed opposite relationship directions [77–79]. Overall, this points to some evidence for a positive association of PB with positive affect in everyday life. Six studies reported practical effect sizes for the associations between PB and positive affect. In a study by Koch et al. [80], walking instead of sitting resulted in an increase of 3.2 points in positive affect on a scale with a range of 6-42. In Cushing et al.’s study, each one-unit increase in MVPA (minutes) beyond participants' usual level was associated with a 0.12-point increase in positive affect [81]. Additionally, every one-unit increase in sedentary time (minutes) beyond participants’ average level was linked to a decrease of 0.10 points in positive affect (scale 1-5) [81]. Similarly, Zhaoyang et al. [77] found days with an extra hour spent in sedentary behavior to be associated with a 0.1-point decrease in positive affect on a 7-point scale. If participants exceeded their daily average step count by 500 steps in Stevenson et al.’s study was linked to a 0.02 increase in positive affect on a scale of 0 to 10 [82]. Moreover, in Zenk et al.’s [78] study each one-minute increase in MVPA during the day was associated with a 2.2% higher likelihood of positive affect. Further findings by Schwerdtfeger et al. [83] suggest that a 3-point increase in positive affect (scale 6-30) corresponds to a 13-16% increase in bodily movement.

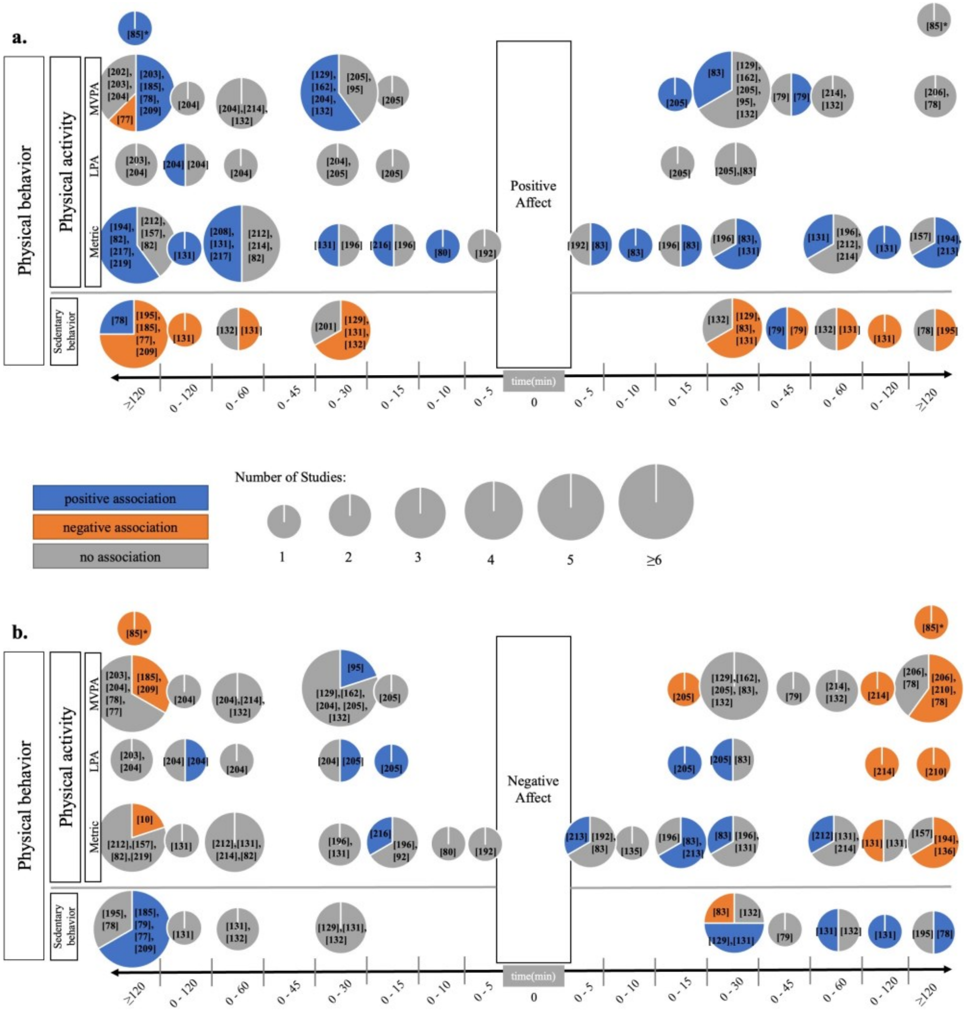

Figure 4: Associations of real-life PB and **a** positive affect and **b** negative affect. The x-axes depict the aggregated PB time frame in relation to the e-diary prompt, i.e., the time frame (in minutes) before vs. after the e-diary prompt across which PB had been aggregated (timing-order). The y-axes depict the PB categories applied, i.e., SB, PA parameterized in a metric unit (e.g., steps, counts, movement acceleration intensity), LPA, and MVPA. The pie charts contain three pieces of information. First, their total size represents the number of investigated relationships on the respective PB-AWB feature-combinations comprising PB and AWB quantifications, their direction, order, and timing of investigated relationships. Second, the color composition represents the investigated relationship directions, i.e., blue colors equal positive significant associations (positive beta coefficient and P value <0.05), and orange colors show negative significant associations (negative beta coefficient and P value<0.05) relative to all effects that investigated the respective feature combinations. Third, non-significant investigated relationships are colored grey (P value≥0.05). *Due to the novel statistical approach (for details see Sect. 4.5), this study could not be reviewed within the framework that we

custom-developed to the methods applied by most of the AA studies in the PB-AWB field. *AWB* affective well-being, *LPA* light physical activity, *MVPA* moderate to vigorous physical activity, *PA* physical activity, *PB* physical behavior, *SB* sedentary behavior.

Figure 4b depicts studies investigating PB associations with negative affect. Overall, the picture appears heterogeneous. In particular, 12/82 investigated relationships revealed a positive significant association between PA with negative affect, i.e., increased PA led to higher negative affect (5/42), and an increased negative affect led to more PA (7/39). Conversely, 14/82 investigated relationships showed the reverse direction of significant associations, i.e., increased PA led to lower negative affect (3/42) and higher negative affect led to less PA (11/39). SB was significantly and positively related to negative affect in 8/21 investigated relationships and one study showed the reverse investigated relationship-direction [83]. In 68/103 investigated relationships there was no significant PB–negative affect relationship found. In a comprehensive and important work, Ruissen and colleagues reviewed [84] custom-developed and applied methods to better take into account composition and timing aspects of PA provoking AWB, thereby overcoming some limitations of prior studies in the field (for details see Sect. 4.6 [85]). In the resulting first study applying these procedures, Ruissen et al. reported a “recursive relationship between incidental affective states and MVPA, which is particularly strong at 7–9 h time intervals” [85]. In particular, Ruissen et al. found that the strongest cross-lagged effects of high positive incidental affect and low negative incidental affect predicting subsequent MVPA occur approximately 8 h prior to an MVPA episode. A similar timing was observed in the reverse direction of MVPA predicting subsequent affect [85]. This study's use of continuous-time modeling represents an innovative approach that promises to offer more detailed insights into the interplay between AWB and PB. Due to its alternative and sophisticated statistical approach, this study could not be reviewed within the framework that we custom-developed to the methods applied by most of the AA studies in the PB-AWB field. Thus, this study has been highlighted with an asterisk in Fig. 4a, b. Three studies reported practical effect sizes for the associations between PB and negative affect. A 3-point increase in negative affect (scale 5–25) corresponded to a 14% increase in bodily movement (counts/minute) in a study by Schwerdtfeger et al. [83]. Furthermore, in a study by Zenk et al. [78], individuals reporting negative affect (dichotomized) experienced a subsequent 38.6% decrease in MVPA and a 33.2-min increase in SB. Additionally, in Zhaoyang et al.’s study [77], spending an additional hour in SB was associated with a 0.04-point increase in negative affect on a 7-point scale.

3.7.2 Physical Behavior, Valence, Energetic Arousal and Calmness

PB associations with valence are illustrated in Fig. 5a. Higher PA was significantly associated with more positively valenced mood (14/31) and more SB was significantly correlated with less positively valenced mood (5/11), or non-significant associations emerged (6/11). Two investigated relationships showed a reverse direction [86, 87]. Three of eight investigated relationships revealed a significant positive association of valence with PA, i.e., higher valence was related to more PA, and more valence was related to less SB (2/5). That is, overall, most of the investigated relationships revealed a significant positive association of PB with valence. Eight studies examined the practical effect sizes for PB associations with valence. Reichert et al.'s study [88] demonstrated that 2 h of exercise increased valence by 2.5 points on a 0–100 scale. Additionally, in the study by Giurgiu et al. [89], increasing MVPA by 20 min enhanced valence by 1.35 units. Conversely, decreasing SB by 20 min enhanced valence by 0.55 units, while increasing SB up to 20 min reduced valence by 1.12 units (scale 0–100) [89]. Being sedentary for 15 min instead of 5 min resulted in a decrease in valence by 3 units (scale 0–100) [90]. Breaking up SB with higher-intensity activities like moderate walking led to an average valence enhancement of 18.13 points, while low-intensity activities like standing enhanced valence by 8.29 points (scale 0–100) [86]. Furthermore, in Koch et al.'s study, choosing to walk instead of remaining seated or engaging in exercise resulted in an average increase in valence of 0.257 and 0.258, respectively, on a 1–7 scale [91]. In a reverse effect direction, a 10-point increase in valence (scale 0–100) resulted in a 4.5% increase in non-exercise activity [92]. Furthermore, a 1-point increase in a participant's valence on a 1–7 scale correlated with a substantial 19% rise in their non-exercise activity [93]. Additionally, higher valence ratings, as compared to lower ones on a 0–100 scale, were linked with reduced SB by 2.77 min [94].

For the association of PB with energetic arousal (see Fig. 5b), 18/28 investigated relationships showed that more PA correlated significantly with higher energetic arousal, and 10/28 investigated relationships were non-significant. Similarly, more SB was significantly correlated with lower energetic arousal (3/9), and 6/9 investigated relationships revealed no significant association between SB and energetic arousal. There was a positive association of energetic arousal with PA, i.e., higher energetic arousal was related to more PA (4/8), and more energetic arousal was related to less SB (4/4). Only one study showed a reverse investigated relationship direction [87]. Overall, this rather homogenous picture points toward a positive association between PB and energetic arousal. Eight studies reported practical effect sizes for PB associations with energetic arousal. In a study by Reichert et al. [88], there was an increase of 14.8 points on a 0–

100 scale in energetic arousal when participants walked 15 min instead of remaining seated. Koch et al. [91] found that choosing to walk instead of remaining seated resulted in an average increase in energetic arousal by 0.136 (scale 1–7), while engaging in sports decreased energetic arousal by − 0.574 points on a 1 to 7-point scale. Breaking up SB with low-intensity activities, like standing, enhanced energetic arousal by 11.69 points, while higher intensities, like moderate walking, enhanced energetic arousal by 25.58 points on a scale of 0–100 [86]. Furthermore, a 20-min increase in MVPA enhanced energetic arousal by 1.31 units on a scale of 0–100 [89]. Conversely, reducing SB by 20 min increased energetic arousal by 1.68 units, while increasing SB up to 20 min resulted in a decrease of 3.39 units (scale 0–100) in energetic arousal [89]. Moreover, being sedentary for 15 min instead of 5 min led to a decrease in energetic arousal by 7.6 units (scale 0–100) [90]. Reichert et al. [92] reported in their study that feeling 10 points more energized (scale 0–100) was associated with a 15.2% increase in non-exercise activity. Additionally, a 1-point increase (scale 1–7) in energetic arousal led to a 20% increase in non-exercise activity [93]. Furthermore, higher energetic arousal ratings (e.g., 90), compared to lower ones (e.g., 20) on a 0–100 scale, were associated with a reduction in sedentary time of about 4.45 min [94].

Figure 5c depicts a heterogeneous picture of the results of the studies investigating PB associations with calmness. In particular, 7/26 investigated relationships revealed a significant positive association of PA with calmness; five studies showed the reverse investigated relationship-direction. SB was significantly and positively related to calmness in 1/1 investigated relationship. In addition, 1/5 investigated relationships revealed a significant positive association between calmness and PA; 3/5 of the studies showed the reverse investigated relationship-direction. Calmness was significantly and positively related to SB in 1/1 investigated relationship. Twenty-one of 32 investigated relationships showed no significant PB-calmness relationship. Interestingly, thus far only few studies investigated correlations of calmness with subsequent PB compared to other PB-AWB feature-combinations. Six studies provided practical effect sizes for the associations between PB and calmness. In a study by Reichert et al. [88], participants experienced a decrease of 7.2 points in calmness when choosing to walk for 15 min instead of remaining seated; 2 h of exercise increased calmness by 2.4 points (scale 0–100). Furthermore, choosing to walk instead of remaining seated or engaging in exercise resulted in an average decrease in calmness by − 0.117 and − 0.280, respectively, on a 1–7 scale [91]. Breaking-up SB with low-intensity activities such as standing was associated with an increase in calmness by 7.65 points. Higher PA intensities such as moderate walking were related to enhanced calmness by 16.74 points on a 0–100 scale [86]. In their study, Reichert et al. [92] showed that a 10-point increase in calmness (scale 0–100) led to a decrease in non-exercise activity of 9.7%. Moreover, when participants felt 1-point more calm (scale 1–7), their subsequent non-exercise activity was decreased by 15% [93]. In addition, higher ratings of calmness compared to lower ratings on a 0–100 scale were associated with higher amounts of sedentary time of about 5.54 min [94].

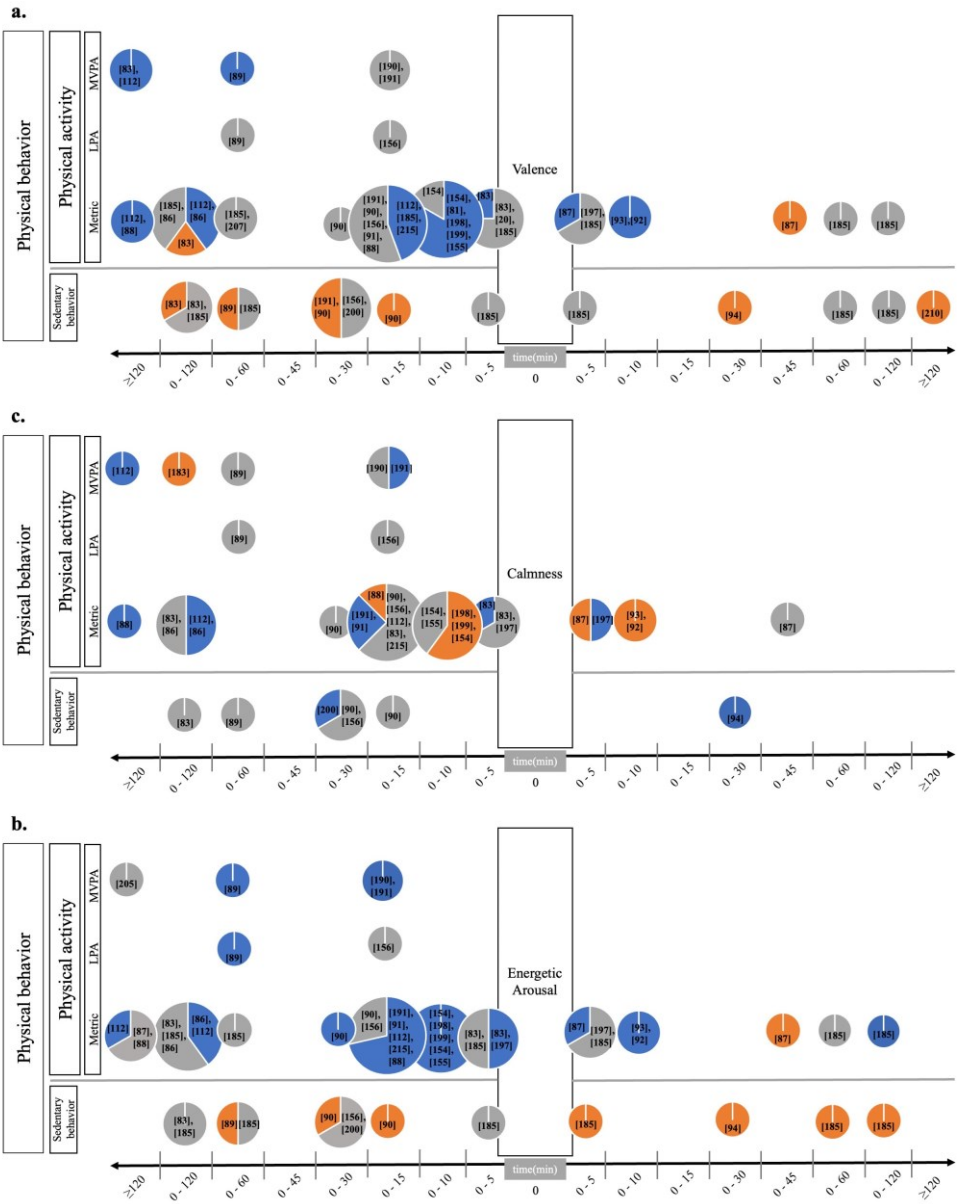

Figure 5: Associations of real-life PB and **a** valence, **b** energetic arousal, and **c** calmness. The x-axes depict the aggregated PB time frame in relation to the e-diary prompt, i.e., the time frame (in [minutes]) before vs. after the e-diary prompt across which PB had been aggregated (timing-order). The y-axes depict the PB categories applied, i.e., SB, PA parameterized in a metric unit (e.g., steps, counts, movement acceleration intensity), LPA, and MVPA. The pie charts contain three pieces of information. First, their total size represents the number of investigated relationships on the respective PB-AWB feature-combinations comprising PB and AWB quantifications, their direction, order, and timing of investigated relationships. Second, the color composition represents the investigated relationship directions, i.e., blue colors equal positive significant associations (positive beta coefficient and P value < 0.05), and orange colors show negative significant associations (negative beta coefficient and P value < 0.05) relative to all studies that investigated the respective feature combinations. Third, non-significant investigated relationships are colored grey (P value ≥ 0.05). *AWB* affective well-being, *LPA* light physical activity, *MVPA* moderate to vigorous physical activity, *PA* physical activity, *PB* physical behavior, *SB* sedentary behavior

3.7.3 Physical Behavior, Energy and Fatigue

The most homogenous picture appeared for associations of PB with energy (see Fig. 6a). That is, out of a total of 23 investigated real-life PB-energy relationships, 19 were significant. Most investigated relationships revealed PB to be significantly and positively correlated with feelings of energy; namely 8/9 investigated relationships showed higher PA to be associated with more energy, and 2/2 investigated relationships found that more SB was significantly related to less energy. In contrast, only 1/11 investigated relationships showed an opposite direction with more energy being significantly associated with less PA [95]. One study reported practical effect sizes on the association between PB and energy. It revealed that each one-unit increase in MVPA (minutes) beyond participants' usual level correlated with an increase of 0.06 units in energy (scale 1–5); for every one-unit increase in sedentary time (minutes) beyond participants' usual level, a decrease of 0.05 units in energy was observed [81].

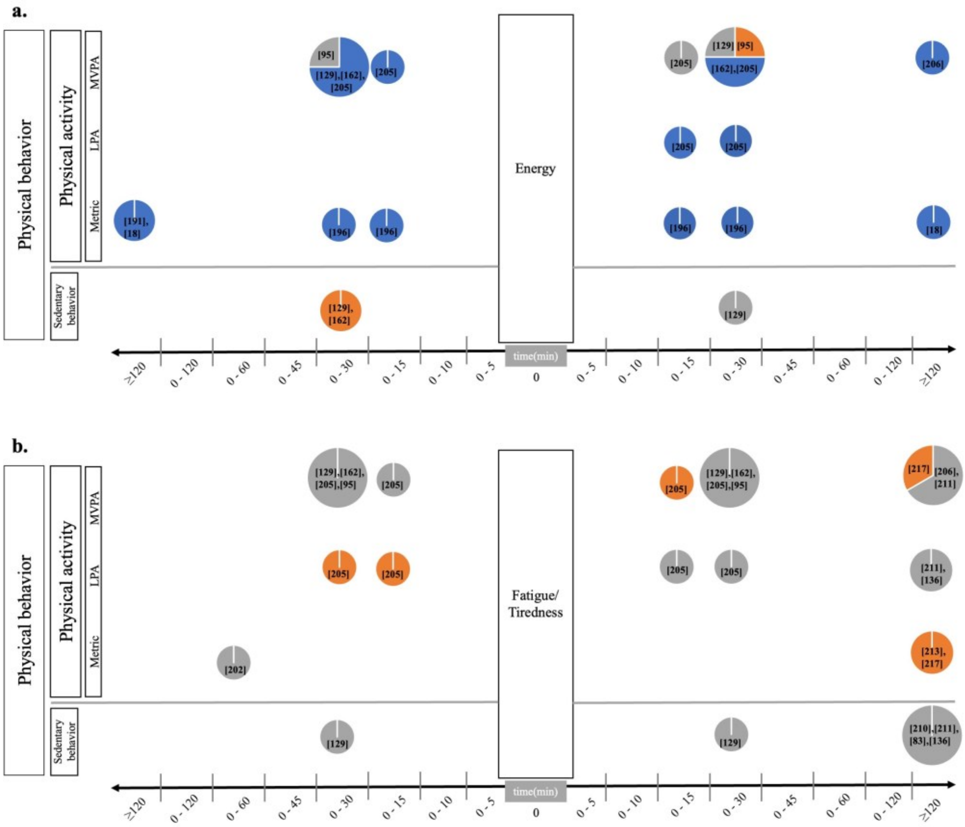

Figure 6: Associations of real-life PB and **a** energy and **b** fatigue/tiredness. The x-axes depict the aggregated PB time frame in relation to the e-diary prompt, i.e., the time frame (in minutes) before vs. after the e-diary prompt across which PB had been aggregated (timing-order). The y-axes depict the PB categories applied, i.e., SB, PA parameterized in a metric unit (e.g., steps, counts, movement acceleration intensity), LPA, and MVPA. The pie charts contain three pieces of information. First, their total size represents the number of investigated relationships on the respective PB-AWB feature-combinations comprising PB and AWB quantifications, their direction, order, and timing of investigated relationships. Second, the color composition represents the investigated relationship directions, i.e., blue colors equal positive significant associations (positive beta coefficient and P value < 0.05), and orange colors show negative significant associations (negative beta coefficient and P value < 0.05) relative to all studies that investigated the respective feature combinations. Third, non-significant investigated relationships are colored grey (P value ≥ 0.05). *AWB* affective well-being, *LPA* light physical activity, *MVPA* moderate to vigorous physical activity, *PA* physical activity, *PB* physical behavior, *SB* sedentary behavior

The studies on PB-fatigue/tired associations (Fig. 6b) showed either a significant negative investigated relationship direction, or non-significant associations (6/29). In particular, more PA was significantly related to less fatigue/tiredness (29), and more fatigue/tiredness was significantly related to less PA (4/15). All investigated relationships on SB and fatigue/tiredness showed non-significant relationships (0/5).

3.7.4 Physical Behavior and other AWB Quantifications

The results for the PB-AWB association for rare AWB quantifications (i.e., sad, depressed, pleasure, anxiety, anger) are detailed in ESM 7.

4 Discussion

4.1 State of Evidence

Our synthesis of study findings revealed hardly any systematic effect of PB intensity in daily life PB-AWB associations of both temporal directions, while the review of other PB characteristics (such as duration and type) was hampered by methodological limitations in the field, which are currently being tackled. However, most studies investigated primarily incidental and unstructured PB (e.g., climbing stairs [96]), and found positive PB-AWB and AWB-PB associations even for low intensities. Incidental activities are characterized by relatively low energy expenditure, for example, gardening (metabolic equivalent: 3.8 [97]), and differ from volitional and structured PA, for example, playing handball (metabolic equivalent: 8.0). In a similar vein, differentiating the reviewed studies by AWB characteristics (such as emotions, affective states, and mood captured via different questionnaires) did not result in a clear overarching pattern for the reciprocal PB-AWB associations in everyday life. However, associations of PB with feelings of energy were homogenous across nearly all investigated relationships, implying a dominant role of subjective energy in interactions with PB in everyday human life. Of note, PB-AWB associations of both temporal directions appear to be dependent on population characteristics. For example, in people susceptible to mental disorders, a high relative number of significant investigated PB-AWB relationships were found compared to other populations. However, overall, findings were heterogeneous across investigated relationships, and our review raises the question of potential sources for this heterogeneity. Numerous reviews and meta-analyses on correlational, experimental, and quasi-experimental studies concluded that PB and AWB are positively related (e.g., [23, 24, 98]. Nevertheless, the everyday life perspective on the PB and AWB association had not been addressed for an extended period of time. It is important to emphasize that there are inherent differences between studies conducted in controlled laboratory and/or intervention settings versus AA investigations that specifically focus on real-life scenarios in real time, bypassing distortions seen in the laboratory [99]. It is not only experimental control in laboratory and interventional studies that contrasts with ecological validity of real-life studies but, for example, also the primary subject being researched; that is, structured exercise sessions in laboratory/interventional studies versus incidental PA comprising exercises as one of many PA facets in real-life studies. Therefore, we will discuss to what degree PB and AWB are related to each other in everyday life, and in both temporal directions, for example, depending on PB/AWB characteristics, contextual factors, and biological determinants. While we found more daily-life investigations of PB investigated relationships on AWB (242 vs. 161 for AWB-PB) in the present literature search, both temporal sequences of the PB-AWB phenomena promise to hold high relevance for human physical and mental health; for example, recent dual-process models and hedonism theories [8] on behavioral processes acknowledge this potential. The following section discusses both temporal sequences against the background that the observational data reviewed precludes any causal conclusions.

4.2 Does the PB–AWB Association Differ Depending on PB Characteristics?

Physical behavior intensity In our review, we found heterogeneous associations between PB characteristics (e.g., activity intensity, duration, volume) and AWB. From a theoretical perspective, for example, one could have expected distinct influences of PB intensity on AWB. For example, the prominent inverse-U hypothesis [100, 101] suggests that especially moderate intensities provoke positive AWB in contrast to vigorous intensities, which are hypothesized to be associated with negative AWB. However, in general, our review showed no clear pattern of distinct effects of different PB intensities in the PB-AWB associations across daily real-life studies (e.g., comparing SB vs. LPA vs. MVPA).

Reviewing recent empirical evidence, the most prominent meta-analysis examining acute aerobic exercise on positive activated affect in the laboratory found positive affective responses at lower intensities compared to moderate or high-intensity exercise [24]. In contrast, in a meta-analysis examining regular aerobic exercise, the strongest positive effects occurred at low but also in highest intensities [23]. In line with these heterogeneous empirical findings, in a very recent meta-analysis compiling all correlational, experimental, and quasi-experimental studies investigating effects of PA on subjective well-being, activity intensity did not qualify as a significant moderator of effects [98].

We could not clearly determine a moderating role of activity characteristics on PB-AWB associations in the reviewed real-life studies via visual inspection, which is in line with other works that summarize laboratory, correlational, experimental, and quasi-experimental studies as outlined above. The heterogeneity of findings and the missing moderating role of activity intensity may be linked to a wealth of confounders. For example, following the dual-mode theory, fitter individuals may be more likely to benefit from high-intensity exercise [102].

The different results regarding the intensity of exercise are possibly due to the individual perception of the exertion of PA with the associated phenomena such as increased heart rate and rise in blood lactate [103,104,105]. These physiological responses to PA stimuli are dependent on the individual's fitness state and thus contribute to the degree of fatigue perceived during PA [102, 106, 107]. Untrained individuals will perceive the physical processes as more fatiguing than more trained individuals and thus generate a differentiated affective response [108, 109]. Therefore, one may be tempted to speculate that in studies including participants with heterogeneous fitness levels, not controlling for those may confuse effects, and similarly in real-life studies [110, 111].

In support of the idea that a wealth of confounders hide intensity effects within the PB-AWB associations, two real-life studies contrasting extreme forms of PB intensities found distinct effects on AWB. In particular, opposing incidental PA versus volitional PA revealed both in an investigation by Koch et al. [91] and an independent study by Jeckel and Sudeck [112] distinct effects, that is, volitional PA increased affective valence and calmness, but incidental PA increased energetic arousal. However, of course, one has to acknowledge that unstructured PA activity versus structured PA do also differ, in motives, duration, and social interaction, which limits our conclusion.

Physical behavior duration At a theoretical level, there are assumptions of an optimal PB duration for mood-enhancing effects. For example, a minimum PB duration to provoke effects on the central nervous system has been hypothesized to be necessary to improve AWB [113]. Conversely, extended durations of high-intense PA have been suggested to potentially induce fatigue, leading to a decline in AWB [114]. Distinct behavioral (e.g., stress response), neurophysiological (e.g., activity in prefrontal cortex or hippocampus [115, 116]), and neurochemical (e.g., lactate, cortisol, neurotrophins [117]) processes [104] have been researched and discussed as relevant for potential duration effects on the PB-AWB association.

Studying recent empirical evidence, a review including 38 studies showed such saturation effects between PB and AWB [118]. The tendency of the included studies showed that 10–30 min of PA had sufficient positive effects on AWB and longer sessions do not necessarily lead to additional benefits. This is in line with previous studies conducted in the laboratory regarding optimal affect response in terms of duration that have mainly been oriented towards short, 20-min PA periods [113]. In a prominent study that investigated duration effects, Ekkekakis et al. found an inverted-U dose–response relationship between PA duration and affect [100]. However, a meta-analysis examining effects of regular aerobic exercise could not find a specific exercise duration that was especially relevant to increase positive activated affect [23]. Similarly, in another meta-analysis across 158 laboratory studies focusing acute aerobic exercise on positive activated affect, the authors concluded that the reviewed evidence provides "support for the hypothesis of no differential effect of exercise duration on post-exercise positive activated affect" [24]. The interpretation of PB duration effects of studies reviewed in the present work must be viewed against the background that the investigation of the role of specific PB components (such as duration, intensity, and type of PA) and the aggregated time frames of effects within the PB-AWB associations in everyday life are known methodological challenges in the field, which is especially prominent with regard to the duration component (for details see Sect. 4.6 below). Accordingly, we could not draw general statements within this review, for which duration of PA and in which time periods in everyday life an optimal relationship between PB and AWB emerged. While overall the dose–response relationships of the duration of activity on AWB are difficult to infer from laboratory studies to everyday activities, some daily-life studies did specifically investigate duration effects and give first insights. For example, a study by Giurgiu et al. [86] showed that the duration of interrupting SB had no effect on AWB. Moreover, in a recent work, Ruissen and colleagues reviewed [84] custom-developed and applied methods (i.e., Bayesian hierarchical continuous-time structural equation models) for overcoming methodological challenges [85]; in the resulting study applying these procedures, Ruissen et al. found a relationship between incidental affective states and MVPA, which is particularly strong at 7- to 9-h time intervals.

4.3 Does the PB-AWB Association Differ Depending on Affective Well-Being Characteristics?

PB may affect distinct components of AWB differently and vice versa. For example, there is evidence that effects of PA on positive affect are stronger than those on negative affect, at least in healthy populations [41]. However, reviewing the AA studies on a potential moderating role of the AWB dimension on the strengths of effects, we could not determine a clear overarching pattern. Of note, across the studies we reviewed, the quantification of AWB definitions fluctuates considerably: 28.8% used the MDMQ [38], 28.8% used the PANAS [37, 68], 4.6% used the circumplex model [70], 3% the POMS [71], 3% the DAMS [72], and 12.1% used self-developed questionnaires. In particular, the MDMQ quantifies affective well-being as a three-dimensional construct (i.e., valence, energetic arousal, calmness; for a detailed factor structure, empirical evidence, and discussion see [38]), while the PANAS builds upon an understanding of AWB as a two-dimensional construct. Within the reviewed studies using the PANAS as a basis, the items applied differed considerably even though they refer to PANAS as the same source (see ESM 6).

Most consistently, in this review, we found PB-AWB associations for the subjective energy dimension compared to all other AWB measures. Most of the PB-subjective energy associations investigated were statistically significant (19/23). Reviewing recent empirical evidence, in the meta-analysis of Reed and Ones [24], the effects found suggest that exercise led to increased positively activated affect—this was also evidenced for the effects of regular PA on positively activated affect [23]. Positive activated affect was described as a status of positive valence and activation [119], with the latter construct also being described as energy in previous studies [120]. That is, positive activated affect does not only capture affective components of valence but also comprises those of feeling energetic. For example, the PANAS questionnaire comprises the items "active, alert, …," which clearly belong to this domain. Therefore, as already discussed in the work of Reed and Ones [24], it remains unclear whether the increases seen in positive activated affect through PB originate from affective components of valence or rather from those of feeling energetic. Against this background and the additional evidence generated in our review, we argue that especially feelings of energy seem to play a dominant role in interaction with PB in everyday human life.

From a mental health perspective, this PB-energy association has been argued to play an especially important role for patients with affective disorders. For example, one study [18] investigated the relationship between motor activity and subjective feelings of energy in bipolar patients (bipolar disorder I, II) and people with major depressive disorder. Bidirectional correlations were found between motor activity and subjective energy levels, while the association with momentary mood was unidirectional, implying a major role of the PB-energy association within individuals. This suggests that interventions aimed at increasing energy and activity might be even more beneficial than treatments aimed solely at mood elevation or stabilization in bipolar disorder and major depressive disorder.

Taking a neurobiological perspective, a recent study investigated non-exercise activity's role in the regulation of AWB [19] and its neuronal correlates. Here, mean non-exercise activity levels were related to gray matter volume of the subgenual anterior cingulate cortex, a neuronal region shown to be involved in both affect regulation and risk for and recovery from mood disorders [19]. In everyday life and captured via AA methods, low subgenual anterior cingulate cortex gray matter volume predicted greater non-exercise activity vulnerability, leading to greater negative within-person influence of non-exercise activity on energy, while, in addition, the data indicated that people with low subgenual anterior cingulate cortex volumes also had greater energetic benefits when they achieved high levels of non-exercise activity. Put simply, participants showing neuronal risk markers for affective disorders compared to those with more resilient brain structures felt less energetic in their everyday life when being inactive but more energetic when engaging in PA. These momentary within-subject associations were related to trait well-being: for example, momentary subjective feelings of energy in real life predicted well-being captured via the established WHO-5 questionnaire and a range of other trait well-being indices [19, 121, 122]. These findings strengthen the conclusion that the PB-energy association may be of high value for prevention and treatment of affective disorders if such findings can be replicated in patient samples.

Moreover, in our review, 50 of 101 investigated relationships between PB and positive affect were statistically significant. As discussed above, these findings may be partly attributable to energy effects. Despite the different questionnaires and items used for positive affect quantification, evidence was found for associations between PA and subsequent within-subject positive affect, for example, when people were more active, they reported significantly higher levels of positive affect. For instance, after PA individuals felt more inspired, happy, and active. It seems worthwhile for future investigations to investigate effects of PB on positive affect components not linked to energy domains. First approaches to develop questionnaires specifically capturing affective responses to PA have already been developed [123]; however, to the best of our knowledge such instruments are not yet available for within-subject measurements.

Beyond positive affect, in our review, the evidence for PB affecting other domains of AWB and vice versa is mixed. For negative affect, only 34.3% (35/102) of investigated relationships were significant. These null findings are consistent with several other studies that found no significant within-subject association between PA and negative affect [41, 124]. However, some results indicated an inverse relationship between PA and depressive states [125,126,127]. Since only high negative values are entered in the PANAS questionnaire, information on low-activated negative states (e.g., fatigue) is not available [128]. Due to the null-findings between PB and negative affect, it might be advisable to split the construct of negative affect into single items (e.g., [129]) and thus allow low activation items.

Valence, a construct related to both positive affect and negative affect, however, is clearly different in its factor structure [38], for example, presenting no energy-related construct. In particular, associations between valence (e.g., feeling well and content) and prior time spent in PB or on subsequent PB were inconsistent; most investigated relationships were non-significant for PA predicting within-subject valence or valence predicting subsequent PA. Only 42.5% (17/40) of investigated relationships were significant. Concerning the link between PB and calmness, as a low activated positive AWB construct, the evidence was mixed and in part contradictory, i.e., some investigated relationships in our review were significant and revealed positive effects of PB on calmness (25.9%) while others revealed PB decreases calmness (18.5%) or vice versa. Concerning the link between PB and negative affect components, PA was not related to feelings of fatigue, tiredness, anger, anxiety, depressed feelings, or stress in most of the investigated relationships.

4.4 Does the PB-AWB Association Differ Depending on Subgroups Researched?

This review shows that despite community based-samples of adult and youth populations, subgroups such as clinical samples are under-represented. Taken together, the few existing studies on subgroups are currently too small to draw overarching conclusions. However, the few investigations on vulnerable samples yield the impression of an increased relevance of the PB-AWB interaction in everyday life compared to healthy populations, especially in the mental health domain. For example, AA studies provide first mechanistic insights into the importance of PB-AWB associations for affective disorders; PB-AWB relationships seem to play an especially critical role in people showing brain structure characteristics of vulnerability for affective disorders [19] and in patients with bipolar disorder [18], but the underlying behavioral mechanisms remain to be investigated in depth. For example, we found only one study researching the PB-AWB association in patients with attention deficit hyperactivity disorder. This is surprising since alterations in both the PB and the AWB domain are central diagnosis criteria of the disorder. In a similar vein, Koch et al. [80] uncovered interactions of attention deficit hyperactivity disorder types and PB-AWB interactions in everyday life. In particular, patients being inattentive and hyperactive showed stronger PB-AWB associations compared to patients being predominantly inattentive and compared to healthy controls. Similarly, negative affect was related to PB solely in participants with a combined presentation, but not in the other two groups, which may, taken together, point towards a mechanism reinforcing hyperactivity, if replicated.

Furthermore, 16 of 66 studies investigated the PB-AWB association in children and adolescents. In particular, three of these studies found evidence for a positive association of PA and subsequent positive affect in children [130,131,132], and two studies showed higher levels of positive affect positively influence subsequent PA [79, 131]. Especially children who are overweight or obese benefit from increased PA and reduced SB resulting in elevated positive affect [131], which in turn may provoke sustained PA behavior [111] and thus potentially foster long-term mental and physical health. Evidence on the within-subject associations between PB and affective states at the ages of 13–18 years is mixed and points towards an idiographic relationship in this target group, suggesting that the association is unique to each individual and varies based on personal experiences, environmental influences, genetic factors, and other factors [84, 133, 134]. Further studies in adolescent samples are necessary to determine which particular PB and AWB components are related to each other and under which contextual conditions. Towards this aim, a reviewed study involving adolescents has already demonstrated that various PA motives (competitive vs. non-competitive PA) can yield diverse effects on AWB components. For instance, participating in non-competitive PA, such as skating as a leisure activity, resulted in increased feelings of energy and positive affect. In contrast, engaging in competitive PA, such as a volleyball match, led to a decrease in subjective energy [91]. In the elderly, our literature search yielded only three studies [77, 135, 136]. These three investigations provided mixed findings and therefore we are unable to draw any specific conclusions. In sum, future research endeavors exploring the (change of the) PB-AWB association across the lifespan (e.g., via a cohort studies) are highly warranted.

4.5 Does the PB-AWB Association Differ Depending on Methodological Study Quality?

Based on our modified version of the QA, most studies were rated with a low or moderate risk of bias. Here we discuss selected categories from the QA such as PB measurement, AWB assessment, design features, compliance, and statistical modeling.

PB measurement in AA studies The terminology “physical behavior” (as discussed above, see Sect. 4.3), describes a recent scientific model [52] operationalizing highly complex human PB characterized by distinct features such as PB *type* (e.g., walking, standing, or sitting), *intensity* (e.g., LPA or MVPA), *purpose* (e.g., structured exercise or gardening), and *social-environmental context* (e.g., jogging alone through the city park or sitting with friends while watching movies). Here, various definitions and operationalizations exist while no consensus across disciplines has been reached thus far [137,138,139]. However, the variation of PB operationalization can influence the findings on PB-AWB associations [47]. In this review, we only included studies comprising a device-based PB measurement method to capture features as objectively as possible, i.e., without (retrospective) distortions from cognitive heuristics [28]. The detailed advantages and disadvantages of device-based versus self-reported PB methods are discussed elsewhere [47, 48]. Although accelerometry is broadly accepted as the gold-standard for device-based PB measurement methods in daily-life studies [47, 48, 52, 137], this method also comes with considerable degrees of freedom, challenges, and limitations in data assessment, preprocessing, and analyses, which lead to a wealth of different PB parametrizations that can influence the findings on PB-AWB associations [47].

In particular, as outlined in Sect. 3, the PB assessment design varied considerably between the studies reviewed within this work; for example, regarding (i) the *placement of the accelerometer* (e.g., hip-, wrist-, thigh-worn), (ii) the *devices used* (e.g., Actigraph, movisens Move), (iii) the *sampling frequency* (e.g., 10 vs. 30 Hz) defined, (iv) the *epoch length* installed (e.g., 1 vs. 10 vs. 600 s), (v) the *assessment duration* applied (e.g., 1 day to 3 weeks of accelerometry) and (vi) the *metrics or parameters* calculated with different software packages and distinct filtering algorithms, cut-offs, etc. (e.g., resulting in counts, movement acceleration intensity [milli-g], energy expenditure [metabolic equivalent], activity intensity [minutes spent in light, moderate, vigorous PA], body position/posture [sitting, standing, lying], activity patterns [activity breaks]).

As described earlier (see Sect. 3.3), the parameterization of PB included movement-based volume variables (i.e., raw acceleration data), time-based amount variables (e.g., MVPA), energy expenditure variables (e.g., metabolic equivalent), as well as postural and activity-based variables (e.g., standing, stepping). Each of these features has been shown to have an influence on PB quantification. For example, thigh-accelerometry has been shown to be most valid for SB assessment [52], length of measurement time frames have been associated with validity and reliability of data [140, 141], epoch lengths were recommended to be chosen as short as possible to represent spontaneous and short movement episodes adequately [142, 143], and the choice of cut-points should follow established recommendations to enable unbiased PB assessment [140, 144]. The influence of these features on PB quantification is discussed in a huge wealth of accelerometry literature (e.g., [145,146,147]. Therefore, obviously, the differences regarding these features of studies reviewed within this work may lead to heterogeneous findings on the PB-AWB association in both directions.

AWB assessment in AA studies There are extensive and ongoing discussions as well as empirical analyses on the advantages and limitations of different AWB quantifications, tackling constructs such as (core) affect, mood, and emotions. Beyond literature on these general conceptualizations, there is also considerable work on the application of AWB quantifications to the PB-AWB association. For example, in 2013 Ekkekakis summarized knowledge on this challenge in “A guide for health-behavioral research” [39], and just recently developed and validated an “Affective Exercise Experiences (AFFEXX) questionnaire” to enable the assessment of affective and motivational antecedents of PB [123]. However, this work mainly stems from laboratory and cross-sectional research, and its transfer into momentary, within-subject processes on the PB-AWB association that are central to this review is pending. In daily-life research and especially in the studies reviewed here, different questionnaires to quantify AWB, such as the two-dimensional PANAS [37] and the three-dimensional MDMQ [38], have been applied. For example, the often-used MDMQ for PA-AWB investigation in daily life, originally a German language questionnaire with 20 items, was specifically adapted for use in AA studies aiming to reduce the participant burden [38]. The resulting AA questionnaire was reduced to six bipolar items, representing the three mood dimensions valence, energetic arousal, and calmness validated to represent distinct mood components and showing high reliability for the assessment of mood changes on both the momentary within-subject (state-like) and between-subject (trait-like) level [38]. Recent work compared this MDMQ questionnaire with PANAS-like questionnaires on e-diaries, which were used in two studies reviewed. In particular, for the usage in these PA-AWB studies, the PANAS, which was not initially developed for AA studies and consisted originally of 20 items (10 positive affect/10 negative affect), had been reduced to the shorter form, for example, including 10 items (I-PANAS-SF). Such comparisons show the challenges that accompany the usage of different mood assessments. For example, the PANAS items forming the negative affect dimension offer hardly any variance in healthy samples, which can lead to ceiling effects and non-normally distributed residuals in multilevel analyses. On the one hand, this offers multiple insights into how distinct AWB components interact with PB and vice versa in everyday life. On the other hand, given that the number of studies applying the same AWB measurement is small, this precludes us from drawing overarching inferences from the studies reviewed. Therefore, beyond our call for more studies on distinct components of AWB, future investigations may be guided by key questions such as: (i) was the questionnaire developed for the purpose applied; (ii) is the questionnaire appropriate for the target group researched (e.g., clinical vs. community-based samples); (iii) is the questionnaire suitable for answering the research question (e.g., is one interested in energetic antecedents vs. tension responses of PB); and (iv) is the questionnaire validated for use in daily-life research (e.g., within-subject reliability on e-diaries). Here, the use of the "Experience Sampling Method Item Repository", an open database including all AWB items of published daily-life studies, their fit to already existing questionnaires and their psychometric properties, may guide future studies.

Design features, compliance issues, and statistical methods In daily-life research on PB-AWB associations, compliance is defined as the ratio of answered versus triggered e-diary prompts and of wear versus non-wear time of the accelerometers [48]. Compliance is a measure of participant adherence to the study protocol, in particular, to the sampling schema. Therefore, AA compliance obviously depends on both the sampling schema applied and participant motivation [148]. Of the studies reviewed, nearly half of the investigations did not provide details on compliance of the accelerometer measurement, and 26 did not report any details, although this information is crucial to assess the quality and representativeness [47]. For example, since the acceleration values between sitting still and not wearing the device are almost similar, it is important to differentiate between wear and non-wear time. Only two studies reported details about the total wear time across all participants, the total wear time per participant, and reasons for noncompliance. In the studies reviewed, the average e-diary compliance rate was 79.17% (mean; SD = 29.0), ranging from 58.6% to 95%. This falls within the range of sound compliance rates according to current method guidelines [54]. Moreover, only seven studies reviewed reported their latency, with latency being defined as the time window from the e-diary prompt to the participants answering the respective prompt. This non-reporting had already been criticized in previous reviews [53, 149, 150] and is critical since high latency (such as 1 h) reduces the ecological validity and increases the probability of retrospective biases. Therefore, we suggest future studies thoroughly report accelerometer wear time, e-diary compliance, and other adherence measures such as latency; for a detailed overview see current reporting guidelines for AA studies [54]. Additionally, in study conceptualization especially sampling schemes should be carefully designed. For example, a large proportion of adults worldwide fail to meet the recommended PA levels [1]. Consequently, their everyday life is characterized by a high prevalence of sedentary behaviors, possibly with only infrequent instances of moderate to high physical activity [151, 152], which leads to restricted within-subject variance of PA [153]. This appears critical to consider in research on PB-AWB associations, for example by using activity-triggered e-diaries to enhance within-subject variance of interest [153] in PB. To capture these phases of high PA, it can be useful to apply triggered e-diaries (e.g., *activity-, *GPS-, *sedentary-triggered [86, 88, 90, 92,93,94, 154]) beyond fixed or random sampling designs, which draw from technological advances of accelerometer-smartphone Bluetooth connections and real-time analyses including interactive algorithms to trigger participants in phases of low and high PA (for a detailed discussion, see [148]). Such challenges have been especially encountered in studies with older or inactive samples [126, 154,155,156,157]. Further measures to improve participant compliance in daily-life studies on PB-AWB are critical, such as study personnel increasing participant motivation (for a detailed discussion, see Reichert et al. [48]). Most reviewed studies (41/66) collected data over 7 or less days. While in general designing an AA study requires an appropriate assessment duration to collect sufficient data for the analysis of momentary within-subject processes, both the person level (i.e., the number of participants) and the prompt level (i.e., e-diary entries) data are critical to statistical power but of different importance depending on the analysis planned (e.g., at the same power and alpha level, within-subject direct effects require much less data compared to cross-level interaction effects) [158]. However, an in this context crucial but often unattended aspect is that the sampling frequency must fit the process of interest to produce univocal results [28, 48, 159], which often conflicts with long assessment durations, for example, high-frequency e-diary assessments such as every 15 min across 10 h a day (which equals 40 prompts a day) to appropriately capture AWB within-person variation across more than 1 day will obviously pose a huge burden on participants and lead to compliance issues [48, 159]. Against this background, to capture both PB-AWB short-term responses and long-term effects, we expect that future PB-AWB studies may be designed to collect data over longer assessment durations yet concurrently draw from high-frequency assessments, which is possible via so-called measurement burst designs combining sparse and intense sampling phases [160, 161]. Following standard procedures in AA, most of the studies reviewed conducted two-level multilevel modeling. Against the background of limitations to these models which we detail in Sect. 4.6, we expect that in future, the field will draw from advanced statistical approaches to unravel the timing of effects and PB compositions in detail. A review published by Ruissen and colleagues [84] provides a comprehensive overview of some dynamic measurement and modeling approaches applicable to AA-studies in the PB-AWB field [85].

4.6 Limitations

This review entails many strengths, but some aspects merit further discussion. First, in our work, we searched three databases, and thus it cannot be assured that some appropriate literature on PB-AWB associations has not been inadvertently missed. Moreover, we did not include unpublished work, or grey literature. We acknowledge that the exclusion of grey literature may represent a limitation of our review since this may have resulted in our literature overview not being fully comprehensive. However, the inclusion of grey literature, where quality standards are not uniformly assessed, into literature reviews is under debate [51]. Mixing peer-reviewed with non-peer-reviewed studies could introduce bias into the interpretation of results [51]. However, since we searched the most comprehensive and recognized databases, we do not expect the findings of our review to be critically biased by the search strategy. Second, the modified QA employed had been custom-developed, and should be further validated. Still, we would like to emphasize that our QA follows high standards, given that it was guided by and includes items of already existing and validated QAs [44, 53, 54] (see ESM 8). As such, we assume that we have covered relevant QA aspects. Of note, following established recommendations [45], our QA is not primarily intended to reflect the hierarchical quality of studies, for example, via between-study rankings, but rather to detect potential flaws and thus better reflect the internal validity of studies. Beyond a risk of bias rating, our modified QA was mainly guided by the concept to rate whether studies provided sufficient information for future studies to replicate the investigations conducted. Third, we did not include intervention studies, but rather only observational real-life investigations. This precludes causal conclusions and direct recommendations for interventions. However, since there are currently only very few intervention studies including daily life methods (e.g., combining experimental manipulation and ecological validity), this proposal should be substantiated by future reviews. Fourth, the studies reviewed did not report uniform standardized effect sizes. Critically, reliable effect sizes in intensive longitudinal data analyses must be informed by a wealth of statistical parameters (e.g., variances on the different analyses levels [158]). Therefore, it was not possible to conduct a meta-analysis solely with the information provided in the papers. However, to give hints on the meaningfulness of effects found in the studies reviewed, we provided readers with a summary of practical effect sizes reported. Future work on PB-AWB associations should include statistical parameters to enable uniform standardized effect size, or alternatively, researchers may aim for conducting individual participant data meta-analysis in a future open research framework. Fifth, in the studies reviewed, a large proportion of convenience samples were investigated (e.g., students or university employees), limiting generalizability. Sixth, most the AA studies aggregated PA across distinct time frames prior to and/or following the e-diary prompts, a parameterization we described as "aggregated time frames." For example, in several studies reviewed, aggregated time frame equaled 15 min before and/or after the e-diary prompts. Accordingly, in these studies, researchers investigated associations of PA occurring 15 min before and/or after the e-diary rating with AWB. Importantly, this does not give any information about the particular composition of PA conducted within the aggregated time frame. More precisely and drawing from a prominent example derived from the studies reviewed, if parameterizing PA as minutes of MVPA within the 15 min before an AWB rating, a value of 8 min MVPA may result from a person running 8 min in a row across 15 min, but also from this person achieving 8 MVPA min in total across 15 min through four interspersed MVPA bouts of 2 min each. If data entail values of 15 min of MVPA, this may even stem from exercising sessions by far exceeding 15 min. Of note, studies under investigation differed in their operationalizations of average PA within the aggregated time frames, for example, some used the parameters time spent in LPA, MVPA, or SB, while others were interested in metric operationalizations of PA (ESM 9). Moreover, the underlying parameterization does not give information on the type of PA, nor it does allow for a precise investigation of the timing of effects (e.g., at which time lag after being physically active is AWB being affected most). Accordingly, this way of parameterization of PA does not allow direct inferences on the PA composition provoking potential AWB effects. While many studies differentiated their analyses by PA intensity (e.g., LPA, MVPA), this challenge is particularly salient to the PA duration and timing of effects domains against the background of the aim of the present work to summarize existing studies. Hence, to receive more information on the underlying physical activity composition provoking potential AWB effects, the parameterization and related statistical modelling is a critical challenge to the field to be tackled in the upcoming years. Fortunately, in a comprehensive work, Ruissen and colleagues reviewed [84] custom-developed and applied methods (i.e., Bayesian hierarchical continuous-time structural equation models) for overcoming these limitations [85]. Seventh, the QA of methods used to study PB-AWB associations revealed large heterogeneity, which limits interpretability of the results (for an in-depth discussion, see Sect. 4.6). Therefore, researchers may streamline their methodological approaches and engage in a more detailed reporting of methods used (e.g., accelerometry data preprocessing procedures). Eighth, only a small proportion of the studies reviewed conducted a (post hoc) power analysis to estimate the appropriate sample size or did not report it. Therefore, some of the results may be underpowered which may have led to type-2 error inflation in our review.

5 Conclusions, Practical Recommendations, and Future Directions

Our search revealed that the number of daily-life studies on PB-AWB has increased rapidly. In sum, the reviewed evidence on PB-AWB associations under ecological valid conditions is heterogeneous, that is, the direction and strength of relationships is ambiguous across studies. Therefore, one might be tempted to speculate that PB and AWB are not related to each other in each and every situation and in all humans, but are dependent on contextual factors (such as time, situational, and social context, weather conditions), PB and AWB components (such as PB duration and intensity; emotions, affect, mood) and biological determinants.

Amalgamation of the findings revealed that PB intensity barely revealed any systematic effect on everyday life AWB and vice versa, while the review of other PB characteristics (such as PA duration and type) is hampered by methodological limitations in the field that are currently being tackled. However, in general, most studies investigated primarily incidental PB, and studies found positive AWB effects even for low intensities; these findings should be followed up by novel AA approaches to research PB characteristics, and they can fuel the discussion about whether the World Health Organization notion "every move counts" [1] may be extended to everyday-life AWB. Similarly, AWB characteristics (such as emotions, affective states, mood) do not fully explain variance of PB-AWB associations, but, importantly, PB relations with subjective energy were largely homogenous across studies. This points to a dominant role of feelings of energy, a reasonable finding against the evidence from mental health studies and previous meta-analyses on positive activated affect. A high relative amount of significant investigated PB-AWB relationships were found in people susceptible to mental disorders compared to other populations. We found a large heterogeneity of methods applied to study PB-AWB associations, which further complicates scrutiny of real-life evidence on PB-AWB associations. While overall the quality of studies reviewed was rated moderate to high, there is considerable room for improvements. In particular, PB measurement via accelerometry is considered the gold standard and was set as an inclusion criterion in this review, but the devices used and procedures applied show large variability. While repeated AWB assessment in real-time is at least in part conducted via questionnaires validated for AA purposes, barely any study of those reviewed used questionnaires specified for the individual everyday-life PB-AWB association purpose. AA sampling procedures were not always tailored to the PB-AWB process of interest, and compliance reporting was in part insufficient, especially for accelerometry. Therefore, over and above method improvements, streamlining of methodological procedures to investigate PB-AWB association, and especially more transparent reporting of methods, are critical for future investigations in the field.

Since the direction and strength of the PB-AWB associations vary across studies, this suggests that the association is not universally consistent but may amongst other influences (e.g., biological determinants) also depend on daily-life contextual factors. Contextual influences are known to be key determinants of human behavior and feelings [162]. In contrast to laboratory studies, real-life investigations offer the possibility of studying these moderation effects. For example, environmental factors (such as outdoor vs. indoor settings, nature vs. built environments, as well as air and noise pollution) are shown to influence both PB and AWB [162,163,164,165]. Accordingly, such environmental influences may also play a potential moderating role on the PB-AWB association, and their consideration should be a central aspect of future AA studies. Supporting this hypothesis, a study showed that PA being performed outdoors revealed higher affective benefits compared to indoor PA [135], a finding consistent with other studies [162, 166,167,168,169,170]. Another example of contextual influences is PB-AWB moderation effects by weather; poor weather conditions have been associated with lower levels of MVPA [78], while higher temperatures were linked to increased PA levels [171]. Moreover, situational contexts, such as work versus leisure environments, have also been found to influence the PB-AWB association [172]; for example, the frequency and intensity of sedentary breaks have a more pronounced effect on energetic arousal when individuals are at home compared to being at work [78, 86]. Furthermore, social contexts should be a focal point in future research, since influences on the PB-AWB real-life association are highly conceivable. For example, engaging in PA in social settings has been found to enhance AWB [135], to increase the duration of activities [164], and a study demonstrated influences of partner support on the interaction of SB and AWB [77]. These moderation effects could also extend to the complex contextual interactions within families and among friends [79, 132, 165, 167, 173,174,175]. In conclusion, contextual factors are integral to our understanding of PB-AWB associations, and we argue that investigating these interactions in future real-life settings is essential for gaining comprehensive insights. The PB-AWB association is highly relevant to both physical and mental health in humans as outlined above. This puts forward highly promising future follow-up research questions, which can be critically informed by this review. First, it emphasizes the ongoing need to tackle the issue of causality in more depth. For example, the reviewed studies show PB-AWB correlations in both temporal directions, which leads to the assumption of a circular relationship [85]. Second, the issue arises how the PB-AWB association can be exploited to proceed toward precision medicine approaches. For example, the specificity of PB-AWB associations for distinct populations found in this review can set the basis to build "acute dynamic process phenotypes" for the prediction of prospective health behavior [48, 176, 177]. Third, this includes the question of how the extracted knowledge can shape and refine existing health behavior theories and even promote novel health behavior models. For example, the strong PB-AWB link with feelings of energy in both directions found in the present synthesis of everyday-life studies perfectly fits with innovative health behavior theories hypothesizing PB engagement to be mediated by cravings for PA [13] and the affective-reflective theory [178].

To tackle these follow-up questions, future research can draw from methodological advancements. For example, sophisticated Granger causality [179] approaches have been suggested for intensive longitudinal data modeling [180, 181], and in future, experimental manipulations in everyday life (e.g., [182]) can help to approach issues of PB-AWB causality. Second, technological advancements such as high-resolution smartphone sensing (e.g., application-use, calls and text message tracking, voice pitch [150, 183,184,185,186]), physiology tracking in real-life (such as skin, heart rate), and combinations with laboratory testing (such as neuroimaging, intestinal microbes [19]; multiparametric sensor fusion [187, 188]), can be exploited to proceed towards precision medicine approaches. Third, meta-analytic strategies with individual participant data can scrutinize evidence to shape and refine existing health behavior theories and to inform novel health behavior models. Together, these insights will help to promote and develop (mobile) interventions for prevention and therapy of human physical and mental health.

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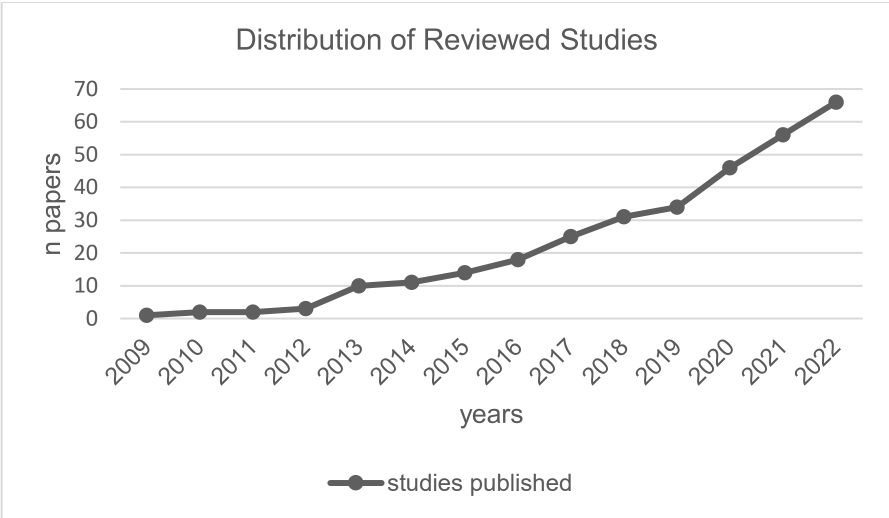
Supplementary Material

ESM 1



ESM Figure 1: Accumulated number of studies included in this review by year of publication.

ESM 2

ESM Table 2: PRISMA 2020 checklist for systematic literature reviews (Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71)

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Line 1
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Line 30-61
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Line 100-147
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Line 148-167
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Line 183-205
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Line 173-181
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	See ESM 3
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Line 207-210
Data collection	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investiga-	Line 216-229

Section and Topic	Item #	Checklist item	Location where item is reported
process		tors, and if applicable, details of automation tools used in the process.	
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	See Table 1
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	n.a.
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automa-tion tools used in the process.	Line 231-252
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presenta-tion of results.	See ESM 5
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	n.a.
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	n.a.
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	n.a.
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	n.a.
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	n.a.
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	n.a.
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	n.a.
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	n.a.

Section and Topic	Item #	Checklist item	Location where item is reported
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	See Figure 1
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	See Figure 1
Study characteris-tics	17	Cite each included study and present its characteristics.	Line 255-259, see Table 2
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Line 263-279
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	n.a.
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Line 263-279
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	n.a.
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	n.a.
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	n.a.
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	n.a.
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	n.a.

Section and Topic	Item #	Checklist item	Location where item is reported
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Line 531-815
	23b	Discuss any limitations of the evidence included in the review.	Line 817-865
	23c	Discuss any limitations of the review processes used.	Line 817-865
	23d	Discuss implications of the results for practice, policy, and future research.	Line 867-929
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Line 170-171
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Line 170-171
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Line 170-171
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Line 79-80
Competing interests	26	Declare any competing interests of review authors.	Line 81-83
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Line 84-85

ESM 3

ESM Table 3: Detailed search terms in three databases.

Database	Complete search term
Scopus:	TITLE-ABS-KEY ("physical activit*" OR exercis* OR "sedentary behav*" OR sedentar* OR "physical inactivit*") AND TITLE-ABS-KEY (mood* OR emotion* OR affect OR "affec* stat*" OR valence OR calmness OR "energetic arousal") AND TITLE-ABS-KEY ("ambulatory assessment" OR "ecological momentary assessment" OR "experience sampling method*" OR "electronic sampling method" OR "ambulatory monitoring" OR acceler* OR "physical activity monitoring" OR "interactive assessment" OR "e*diar*" OR "electronic diar*") AND (LIMIT-TO (LANGUAGE , "English"))
Web of Science:	((TS=("physical activit*" OR exercis* OR "sedentary behav*" OR sedentar* OR "physical inactivit*") AND TS=(mood* OR emotion* OR affect OR "affec* stat*" OR valence OR calmness OR "energetic arousal") AND TS=("ambulatory assessment" OR "ecological momentary assessment" OR "experience sampling method*" OR "electronic sampling method" OR "ambulatory monitoring" OR acceler* OR "physical activity monitoring" OR "interactive assessment" OR "e*diar*" OR "electronic diar*"))) AND LANGUAGE: (English)
PubMed:	((physical activity[Title/Abstract] OR exercise[Title/Abstract] OR exercises[Title/Abstract] OR sedentary behavior[Title/Abstract] OR sedentary behaviour[Title/Abstract] OR sedentariness[Title/Abstract] OR physical inactivity[Title/Abstract]) AND (mood[Title/Abstract] OR moods[Title/Abstract] OR emotion[Title/Abstract] OR emotions[Title/Abstract] OR affect[Title/Abstract] OR affects[Title/Abstract] OR affective state[Title/Abstract] OR affective states[Title/Abstract] OR affective-states[Title/Abstract] OR valence[Title/Abstract] OR calmness[Title/Abstract] OR energetic arousal[Title/Abstract])) AND (ambulatory assessment[Title/Abstract] OR ecological momentary assessment[Title/Abstract] OR experience sampling method[Title/Abstract] OR (("electronics"[MeSH Terms] OR "electronics"[All Fields] OR "electronic"[All Fields]) AND sampling method[Title/Abstract]) OR ambulatory monitoring[Title/Abstract] OR accelerometry[Title/Abstract] OR accelerometer[Title/Abstract] OR physical activity monitoring[Title/Abstract] OR interactive assessment[Title/Abstract] OR e-diary[Title/Abstract] OR ediary[Title/Abstract] OR ediaries[Title/Abstract] OR electronic diary[Title/Abstract] OR electronic diaries[Title/Abstract]) AND English[lang]

ESM 4

ESM Table 4: Adapted Quality Assessment Tool

Topic		Item	Description
Title			
	Title		
		1	a. Include ambulatory assessment or ecological momentary assessment in title
Introduction			
	Rationale	2	a. Briefly introduce the concept of AA and provide reasons for utilizing AA for this study or topic of interests (e.g., to examine time-varying predictors of unhealthy eating occasions in children's daily lives)
Methods			
	Participant Training	3	a. Indicate if, and by what methods, training of participants for AA protocol was used b. Indicate if, and by what methods, training of participants for accelerometer was used (how to wear device correctly; placement, wearing times, data protection and return of the device)
	AA Technology	4	Describe what technology, if any, was used. Include the following information: a. Device (e.g., mobile phone, portable computer), b. Model (e.g., Nexus 4), c. Operating system (e.g., android, windows), d. EMA program name
	ACC Technology	5	a. Sensor brand and model of ACC (e.g., Actigraph accelerometer GT1 M) b. Operating system (e.g., data merger movisens) c. Sensor placement (must indicate location and side of the body) d. Sampling frequency (Hz), e. Signal axes used (x, y, z) f. Filter (low, high, band, e.g., low-frequency extension filter)
	Assessment duration	6	a. AA: state the number of days each wave of the study lasted, b. AA: and how many weekdays versus weekend days c. ACC: State the number of days each wave of the study lasted

			d. ACC: and how many weekdays versus weekend days
	AA prompting design	7	a. Indicate the prompting strategy used for the study (e.g., event-based, interval-based, or a combination of the two). If using interval-based strategy, indicate what type of schedule is used (e.g., fixed, random, or hybrid interval)
	AA prompt frequency	8	a. Intended frequency of prompts per day. Break down by weekdays and weekend days if applicable
	Parameterization	9	a. AA: the origin of items: the source of items used in the AA (e.g., existing AA questionnaire, self-made) b. ACC: accelerometer signals “outcome metric” (counts, time, intensity, type of PB) c. ACC: epoch length used (sec, min, h)
	Design features	10	a. Describe any design feature to address potential sources of bias (e.g., reactivity; devices that display the archived activity) or participant burden (e.g., AA questions appearing in different orders)
	Statistical methods	11	a. Psychometric properties of items (Cronbach’s alpha, omega) b. Model description (formula and / or text) c. Centering (person, group, grand mean) d. Random versus fixed effects e. Measurements (p, Beta, effect size)
	Criteria for defining non-wear / non-wear-time definition (exclusion criteria)	12	a. Of AA (e.g., <30% responses to e-diary prompts) b. Of ACC (e.g., ≥60 min of continuous 0s)
Results			
	Latency	13	a. Report the amount of time from prompt signal to answering of prompt
	Delay possibility	14	a. Ability to suspend/delay responses

	Compliance rate and missing data	15	Describe final data set: a. Report total answered AA prompts across all subjects b. The average number of AA prompts answered per person/group (report compliance rate both by monitoring days and waves, if applicable) c. Indicate reasons for noncompliance, if known d. ACC: report total wear time across all subjects e. ACC: report total wear time per person f. Indicate reasons for noncompliance, if known (number of participants non-compliant or who had accelerometer malfunction issues)
Discussion			
	Limitations	16	a. Discuss sources of potential bias when using AA methods / ACC (e.g., reactivity, use of technology, sampling, …)

Abbreviations: AA = ambulatory assessment; ACC = accelerometry; PB = physical behavior; HZ = hertz; sec = seconds; min = minutes; h = hours

ESM Table 4a: Detailed valuation process:

1 item	true = 1 false = 0
2 items	2 true = 1 1 true / 1 false = 0,5 2 false = 0
3 items	3 true = 1 2 true / 1 false = 0,5 1 true / 2 false = 0 0 true /3 false = 0
4 items	4 true = 1 3 true = 1 2 true = 0,5 1 true = 0 0 true = 0
5 items	5 true = 1 4 true = 1 3 true = 0,5 2 true = 0 1 true = 0 0 true = 0
6 items	6 true = 1 5 true = 1 4 true = 1 3 true = 0,5 2 true = 0 1 true = 0 0 true = 0

ESM 5

ESM Table 5: Detailed quality assessment

	Bai et al. [189]	Bossmann et al. [155]	Bourke et al. [190]	Bourke et al. [191]	Cabrita et al. [135]	Curtiss et al. [192]	Cushing et al. [81]	Cushing et al. [129]	DeMasi et al. [193]	Difrancesco et al. [194]	Dunton et al. [162]	Elavsky et al. [195]	Giurgiu et al. [89]
1. Title	1	1	1	1	0	0	0	1	0	1	1	0	0
2. Rationale	0	1	0	0	1	0	1	0	1	1	0	1	1
3. Training	0	0.5	0.5	0.5	1	0.5	1	1	0	0	0	0.5	1
4. AA technology	1	1	0.5	0.5	0.5	1	1	0.5	1	0	1	1	1
5. ACC technology	0.5	1	1	1	0.5	0	1	1	0.5	0	0	0.5	1
6. Assessment duration	0.5	0.5	1	1	0.5	0.5	0.5	0.5	0.5	0.5	1	0.5	1
7. AA prompting design	1	1	1	1	1	0	1	1	1	1	1	1	1
8. AA prompt frequency	1	0	1	1	1	1	1	1	1	1	1	1	1
9. Parameterization	0.5	1	1	1	0.5	0	1	1	0.5	1	1	1	1
10. Design features	0	0	0	1	1	0	1	0	1	1	1	0	1
11. Statistical methods	0	1	1	1	0	0	1	1	0.5	0	1	1	1
12. Defining non-wear	1	0	0.5	1	0	0	0.5	0.5	1	0	0.5	1	1
13. Latency	1	0	0	1	0	0	0	0	0	0	0	0	0
14. Delay possibility	0	1	1	1	0	0	0	0	0	0	0	0	1
15. Compliance rate/missing data	0	0	0.5	1	0.5	0.5	0	0	0	0.5	0.5	0.5	0.5
16. Limitations	1	1	1	1	1	1	1	1	1	0	1	1	0
Total score	**8.5**	**10**	**11**	**14**	**8.5**	**4.5**	**11**	**9.5**	**9**	**7**	**10**	**10**	**12.5**

	Giurgiu et al. [90]	Giurgiuet al. [86]	Giurgiu et al. [94]	Haaren-Mack et al. [156]	Hevel et al. [196]	Jeckel & Sudeck [197]	Jeckel & Sudeck [112]	Kanning [199]	Kanning & Schoebi [87]	Kanning et al. [173]	Kanning et al. [198]	Kanning et al. [154]	Kanning et al. [200]
1. Title	1	0	0	1	1	0	0	0	0	0	1	0	1
2. Rationale	1	1	1	1	1	1	0	1	1	1	1	1	1
3. Training	1	1	1	1	1	1	1	0	0	0.5	0	1	0.5
4. AA technology	1	1	1	1	1	1	1	0.5	0.5	1	1	1	1
5. ACC technology	1	1	1	1	0	0.5	0.5	1	1	0	1	1	1
6. Monitoring period	1	1	1	0.5	0.5	1	1	1	1	0.5	0.5	1	1
7. AA prompting design	1	1	1	1	1	1	1	1	1	1	1	1	1
8. AA prompt frequency	1	1	1	1	1	1	1	1	1	1	1	1	1
9. Parameteriza-tion	1	1	1	1	1	1	1	1	1	1	1	1	1
10. Design features	0	1	1	0	0	0	1	1	0	0	0	1	1
11. Statistical methods	1	1	1	0	0.5	1	1	1	0.5	1	1	1	1
12. Defining non-wear	0.5	0	1	0	0.5	0	1	0	0.5	0.5	0	0	0
13. Latency	0	0	0	1	0	0	0	0	1	0	0	0	0
14. Delay possibility	1	1	1	1	1	1	1	1	1	1	0	0	0
15. Compliance rate/missing data	0.5	0.5	1	0	0	0.5	0.5	0	0	0	0	1	0
16. Limitations	1	1	1	1	1	1	1	1	1	1	1	0	1
Total score	**13**	**12.5**	**14**	**11.5**	**10.5**	**11**	**12**	**10.5**	**10.5**	**9.5**	**9.5**	**11**	**11.5**

	Kim et al. [175]	Kim et al. [125]	Kim et al. [126]	Koch et al. [80]	Koch et al. [93]	Koch et al. [91]	Kracht et al. [201]	Kuehnhausen et al. [202]	Langguth et al. [127]	Le at al. [203]	Li et al. [204]	Liao et al. [206]	Liao et al. [205]
1. Title	0	1	0	0	1	0	1	0	0	0	1	1	1
2. Rationale	1	1	1	1	1	1	1	1	0	0	0	1	1
3. Training	1	1	1	0	1	1	1	0	1	0	0.5	0	1
4. AA technology	0	0.5	0.5	0.5	1	1	1	0	0.5	0.5	1	0	1
5. ACC technology	0	1	1	1	1	1	0	1	1	0.5	1	0	0
6. Assessment duration	1	1	0.5	0.5	1	0.5	1	0.5	1	0.5	0.5	1	1
7. AA prompting design	1	1	1	1	1	1	1	0	1	1	1	1	1
8. AA prompt frequency	1	1	1	1	1	1	1	1	1	1	1	1	1
9. Parameterization	0.5	1	1	1	1	1	1	0.5	1	1	1	0.5	1
10. Design features	1	0	1	0	0	1	1	1	0	0	1	0	1
11. Statistical methods	1	0.5	1	1	1	1	1	0.5	1	0.5	1	0	1
12. Defining non-wear	0.5	0	0.5	0.5	0.5	1	1	0.5	1	0.5	0	0.5	1
13. Latency	0	0	0	0	0	0	0	0	1	1	0	0	0
14. Delay possibility	0	1	0	0	1	1	1	0	0	0	0	0	1
15. Compliance rate/missing data	0.5	0.5	0	0	1	0.5	0.5	0.5	1	0	0	0	0.5
16. Limitations	1	1	1	0	1	0	1	0	1	1	1	0	1
Total score	**9.5**	**11.5**	**10.5**	**7.5**	**13.5**	**12**	**13.5**	**6.5**	**11.5**	**7.5**	**10**	**6**	**13.5**

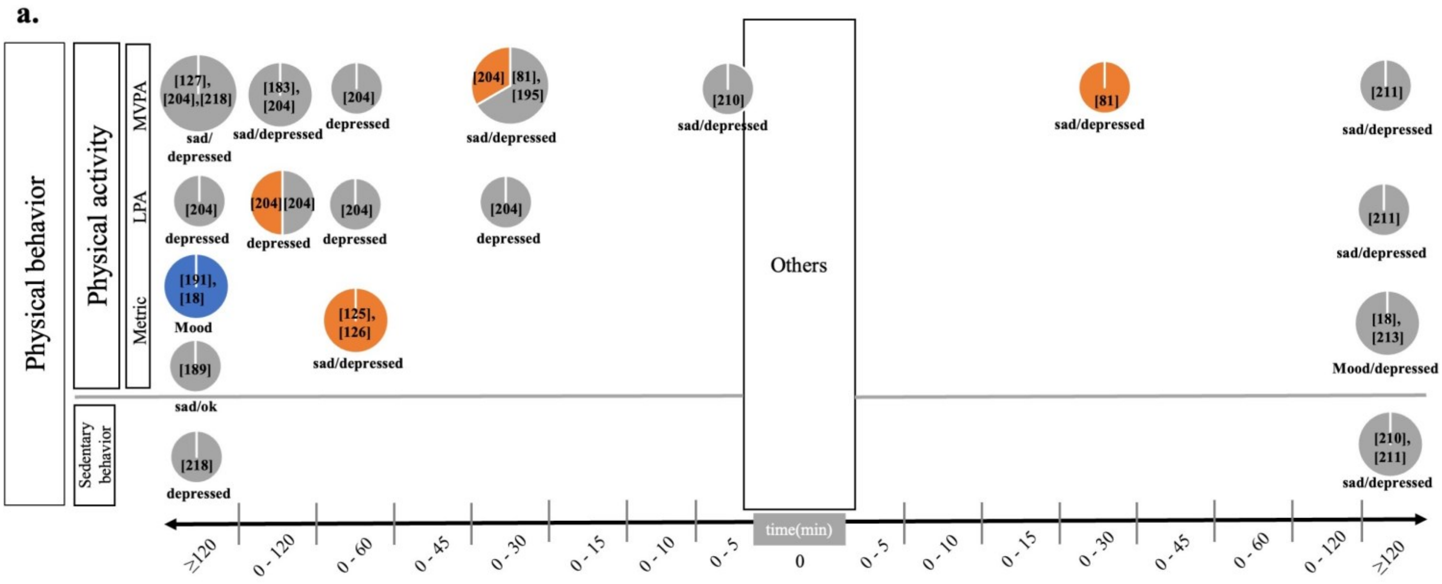
	Madden et al. [95]	McLean et al. [207]	Merikangas et al. [18]	Michalak et al. [208]	Pannicke et al. [209]	Pinto et al. [210]	Poppe et al. [211]	Powell et al. [212]	Reichert et al. [88]	Reichert et al. [92]	Ruissen et al. [85]	Schwerdtfeger et al. [83]	Shin et al. [213]
1. Title	0	0	0	0	0	1	0	0	0	1	0	1	0
2. Rationale	1	1	1	0	1	1	1	1	1	1	0	1	1
3. Training	1	1	0	0	1	1	0.5	1	1	1	1	1	0
4. AA technology	1	1	1	1	0	1	1	0.5	1	1	1	1	0.5
5. ACC technology	0	0.5	0	1	0	0	0.5	1	1	1	0.5	1	0
6. Monitoring period	0.5	0.5	0.5	0.5	1	1	0.5	0.5	0.5	0.5	0.5	1	1
7. AA prompting design	1	1	1	1	1	1	1	1	1	1	1	1	1
8. AA prompt frequency	1	1	1	1	1	1	1	1	1	1	1	1	1
9. Parameterization	1	0	0.5	1	1	1	1	0.5	1	1	1	1	0
10. Design features	1	1	1	1	1	0	1	0	0	0	1	1	0
11. Statistical methods	1	0	0	1	1	0	1	1	1	1	1	1	0
12. Defining non-wear	0.5	0.5	0	0	1	0	1	1	0.5	0.5	0.5	0.5	0
13. Latency	0	0	0	0	0	0	0	0	0	0	1	0	0
14. Delay possibility	1	0	0	0	1	0	1	1	1	1	0	1	1
15. Compliance rate/missing data	1	1	0	0	0.5	0.5	0	1	0.5	1	0	0	0
16. Limitations	1	1	0	1	1	1	1	1	1	1	1	1	1
Total score	**12**	**9.5**	**6**	**8.5**	**11.5**	**9.5**	**11.5**	**11.5**	**11.5**	**13**	**10.5**	**13.5**	**6.5**

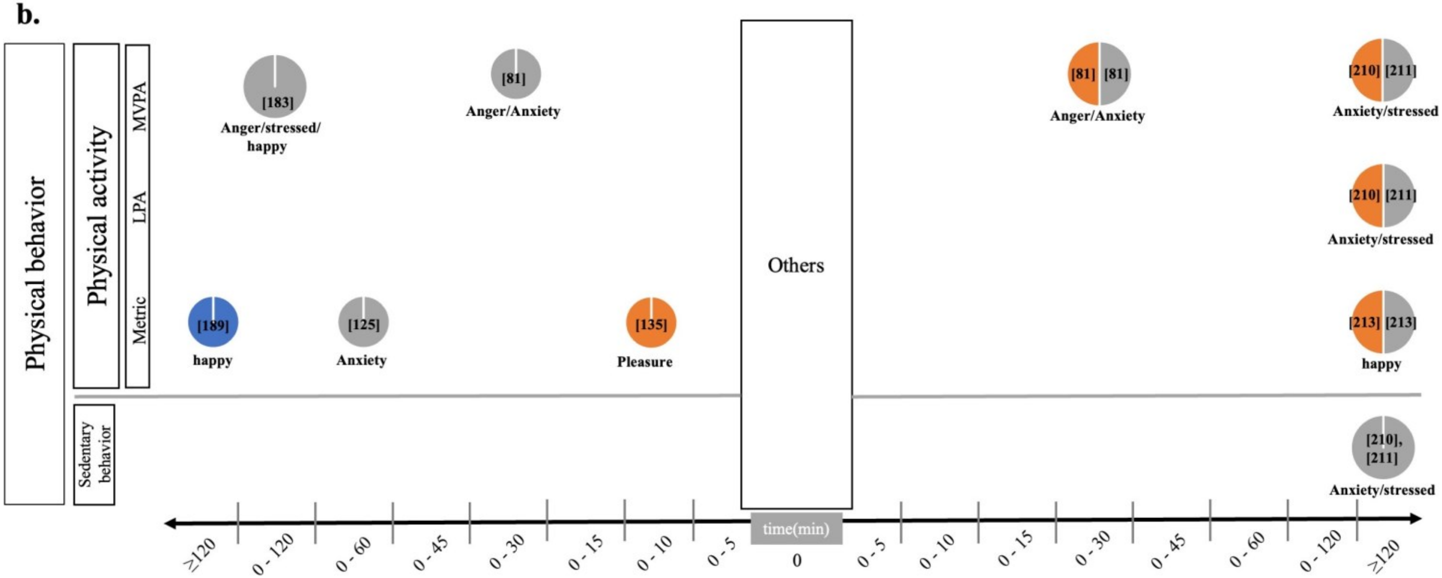
	Smith et al. [131]	Smith et al. [214]	Stavrakakis et al. [157]	Stevenson et al. [82]	Sudeck et al. [215]	Takano et al. [216]	Vetrovsky et al. [217]	Walsh et al. [218]	Wen et al. [132]	Wilhelm et al. [136]	Williams et al. [219]	Yang et al. [79]	Zenk et al. [78]	Zhaoyang & Martire [77]
1. Title	0	0	0	1	0	0	0	1	0	0	0	1	1	0
2. Rationale	1	1	1	0	1	0	1	0	1	1	1	1	1	1
3. Training	1	1	1	1	1	1	1	0	1	1	0.5	0	1	0.5
4. AA technology	0.5	0	0.5	0.5	1	0	0.5	0	1	0	0	1	0	0
5. ACC technology	0.5	0.5	0.5	0.5	1	1	1	0.5	0.5	0.5	0	0	0.5	0.5
6. Assessment duration	1	1	0.5	0.5	0.5	1	1	0.5	0.5	0.5	0.5	1	0.5	0.5
7. AA prompting design	1	1	1	1	1	1	1	1	1	1	1	1	1	0
8. AA prompt frequency	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9. Parameterization	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5
10. Design features	0	0	1	1	0	1	0	0	1	0	1	1	0	0
11. Statistical methods	0,5	1	0	1	1	1	0.5	1	1	1	1	1	1	1
12. Defining non-wear	0.5	0.5	0.5	0	0	0.5	1	0	0.5	1	0	0.5	1	1
13. Latency	0	0	1	0	0	1	0	0	0	1	0	0	0	0
14. Delay possibility	0	0	0	0	1	0	1	0	1	0	0	1	0	0
15. Compliance rate/missing data	0.5	1	0	1	1	0.5	0.5	0	0	0	0	0	0	0.5
16. Limitations	1	1	1	1	1	1	1	1	1	1	0	1	1	1
Total score	**9.5**	**10**	**10**	**10.5**	**11.5**	**11**	**11.5**	**7**	**11.5**	**10**	**7**	**11.5**	**10**	**7.5**

ESM 6

(see https://doi.org/10.1007/s40279-024-02016-1)

ESM 7





ESM Figure 7: Associations of real-life PB and further affective well-being items. The x-axes depict the aggregated PB time frame in relation to the e-diary prompt, i.e., the time frame (in [minutes]) before vs. after the e-diary prompt across which PB had been aggregated (timing-order). The y-axes depict the PB categories applied, i.e., SB, PA parameterized in a metric unit (e.g., steps, counts, movement acceleration intensity), LPA, and MVPA. The pie charts contain three pieces of information. First, their total size represents the number of investigated relationships on the respective PB-AWB feature-combinations comprising PB and AWB quantifications, their direction, order, and timing of investigated relationships. Second, the color composition represents the investigated relationship directions, i.e., blue colors equal positive significant associations [positive beta coefficient and P value < .05], and orange colors show negative significant associations [negative beta coefficient and P value < .05] relative to all studies that investigated the respective feature combinations. Third, non-significant investigated relationships are colored grey [P value ≥ .05]. *AWB* affective well-being; *LPA* light physical activity; *MVPA* moderate to vigorous physical activity; *PA* physical activity; *PB* physical behavior; *SB* sedentary behavior.

ESM 8

ESM Table 8: Overview of categories across quality assessment tools and ambulatory assessment guidelines.

QA – Timm et al.	CREMAS – Liao et al.	Guidelines AA – Trull & Ebner-Priemer
Title	Title	
Rationale	Rationale	Rationale
Training	Training	Training
AA Technology	AA Technology	Describe hardware and software
ACC Technology		
Assessment duration	Assessment duration	Assessment duration
Prompt design	Prompt design	Prompt design
Parametrization		Parametrization
Design features	Design features	Design feature
Statistic		Statistic
Inclusion criteria		
Latency	Latency	
Compliance/Missing data	Compliance/Missing data	Compliance/Missing data
Limitation	Limitation	
	Wave duration	Justify sample size
	Conclusion	

ESM 9

ESM Table 9: Data extraction.

Study	n	Female %	Age mean (range)	Participants characteristics sample (specifics)	Physical behavior assessment unit; timeframe; direction;	PB mean/day parameter in minutes/day or week: mean ± SD, range	PB within the aggregated time frame parameter and unit/timeframe: mean ± SD, range
Bai et al. [189]	805	71.3%	NR (18-25)	Adults (students)	Metric; 1440 min; before	Steps/d: NR ± NR, 8989-9566 (mo-fr); 8533 ± 286, NR (sa); 7327 ± 286, NR (su)	NR
Bossmann et al. [155]	62	14.5%	21.4 (19-30)	Adults (students)	Metric; 10 min; before;	NR	Milli-g/min: 62 ± 64.9, 12.8-765.2
Bourke et al. [190]	119	46.4%	14.7 (NR)	Adolescents	MVPA; 15 min; before	NR	MET/15 min prior prompt: 2.59 ± NR, NR (recreational PA); 2.46 ± NR, NR (active travel); 2.34 ± NR, NR (household PA)
Bourke et al. [191]	119	46.4%	14.7 (13-17)	Adolescents	MVPA; 15 min; before;	NR	MVPA min/15 min prior prompt: 2.23 ± 2.43, NR
Cabrita et al. [135]	10	60%	68.7 (65-83)	Elders	Metric; 10 min; before	NR	NR

Curtiss et al. [192]	34	73.53%	28.97 (18-55)	Adults (MDD, anxiety)	NR; 0 min; NR	NR	NR
Cushing et al. [129]	26	42.3%	15.96 (13-18)	Adolescents	MVPA; 30 min; bidirec-tional	MVPA min/d: 30.63 ± 28.75, NR	MVPA min/30 min prior prompt: 1.14 ± 2.79, NR; MVPA min/30 min after prompt: 1,20 ± 2,94, NR
Cushing et al. [81]	26	42.3%	15.67 (13-18)	Adolescents	MVPA; 30 min; bidirec-tional	MVPA min/d: 30.63 ± 28.75, NR	MVPA min/30 min prior prompt: 1.14 ± 2.79, NR; MVPA min/30 min after prompt: 1.20 ± 2.94, NR
DeMasi et al. [193]	53	49%	19.83 (NR)	Adults (students)	Metric; 1440 min; before	Activity min/d: 118.78 ± 32.67, NR	NR
Difrancesco et al. [194]	359	63.7 %	49.5 (NR)	Adults (MDD, anxiety)	LPA, MVPA; 180 min; bidirectional	NR	NR
Dunton et al. [162]	119	52%	NR (9-13)	Children (Healthy PLACES)	MVPA; 30 min; bidirec-tional	MVPA min/d: 22.24 min ± 14.43, 4.39 – 96.20	MVPA min/15min window: 0.75 min ± 2.13, 0–30
Elavsky et al. [195]	121	100%	51.5 (40-60)	Adults	SB; 180-360 min; bidirec-tional	SB h/d: 12.6 ± 1.7, NR	NR
Giurgiu et al. [90]	92	63%	33.7 (22-62)	Adults (university employee)	Metric, SB; 15-30 min; before	SB h/d: 7.2 ± 3.8, 5-22	PA milli-g/min: 65.03 ± 15.3, 31.7-95.5
Giurgiu et al. [86]	92	65%	33.73 (22-62)	Adults (university employee)	SB; 80 min; before	SB h/d: 7.6 ± 2.88, 0 – 16.09	NR
Giurgiu et al. [94]	92	65%	33.88 (22-62)	Adults (university employee)	SB; 30 min; after	SB h/d: 8.03 ± 2.71, 1.55 – 16.09	NR

Giurgiu et al. [89]	103	55.1%	22.1 (19.3-24.9)	Adults (students)	LPA, MVPA; 60 min; after	MVPA h/d: 1.15 ± 0.56, 0-3.53; LPA h/d: 5.02 ± 2.46, 0-13.91	LPA min/60 min prior prompt: 21 ± NR, NR; MVPA min/60 min prior prompt: 1 ± NR, NR
Haaren et al. [156]	29	NR	21.3 (NR)	Adults (students)	Metric, LPA; 15/-30 min; before	NR	MET across all 15 min episodes: 1.44 ± 0.42, NR. LPA min across all 15 min episodes: 1.62 ± 2.46, NR; MPA min across all 15 min episodes: 0.51 ± 1.38, NR; VPA min across all 15 min episodes: 0.04 ± 0.51, NR
Hevel et al. [196]	103	62.5%	72.4 (60-98)	Adults	Metric; 15/-30 min; bidirec-tional	Stepping min/d: 250.55 ± 119.36, NR; standing min/d: 90.72 ± 50.15, NR	Stepping min/15 min prior prompt: 1.49 ± 0.7, NR; Stepping min/15 min after prompt: 1.44 ± 0.65, NR; Stepping min/30 min prior prompt: 3.02 ± 1.36, NR; Stepping min/30 min after prompt: 2.94 ± 1.32, NR; Standing min/15 min prior prompt: 4.02 ± 1.58, NR;

							Standing min/15 min after prompt: 4.08 ± 1.63, NR; Standing min/30 min prior prompt: 8.02 ± 3.12, NR; Standing min/30 min after prompt: 8.06 ± 3.18, NR
Jeckel & Sudeck [112]	46	54.4%	32 (21-59)	Adults	Metric; 15/-720 min; before	MET/h: 5.41 ± 3.09, 0.64-13.96	NR
Jeckel & Sudeck [197]	46	54.4%	32 (21-59)	Adults	Metric; 15 min; bidirec-tional;	MET/h: 5.41 ± 3.09, 0.64-13.96	NR
Kanning et al. [198]	44	47.7%	26.2 (NR)	Adults (students)	Metric; 10 min; before	NR	Milli-g/min across all 10-min episodes: 77.3 ± 94.3, 0.8-994.4
Kanning [199]	87	54%	24.6 (NR)	Adults (students)	Metric; 10 min; before	NR	Milli-g/min: 84.4 ± NR, 0.4 – 994.4
Kanning et al. [154]	74	49%	60.1 (50-70)	Adults	Metric; 10 min; before	NR	Milli-g/10 min prior prompt: 105.5 ± 137.3, 0.01-1307.5
Kanning & Schoebi [87]	65	57%	24.6 (NR)	Adults (students)	Metric; 5-/45 min; after	NR	Milli-g/min: 90.25 ± 27.31, 0 – 1330.71 (between subject); 104.94 ± 47.42, 0-1330.71 (within subject)

Kanning et al. [173]	202	100%	41 (24-57)	Adults (mothers of 8 to 12-year-old children)	MVPA; 120 min; before	MVPA min/d: 21.35 ± 15.18, 1.56-86.56; LPA min/d: 198.52 ± 65.95, 29.06-397.75	NR
Kanning et al. [200]	308	50.3%	27.4 (17-66)	Adults (students and employees)	SB; 30 min; before	NR	Sedentary bouts of 30 min: 5.4 ± 2.7, 1.8-15.6 (study 1); 2 ± 0.5, 1-3.4 (study 2); Sedentary bouts of 20 min: 8.7 ± 4.6, 1.5-20.5 (study 3); 6.4 ± 3.78, 1-17 (study 4)
Kim et al. [125]	113	28.3%	adolescents: 13.6 (NR) undergraduates: 21.6 (NR) office workers: 41.0 (NR)	Adolescents, adults (undergraduates and office workers)	Metric; 60 min; bidirec-tional	NR	Locomotor activity/60 min around EMA: 144.44 ± 22.31, NR
Kim et al. [126]	57	MDD: 14.3% HC: 0%	MDD: 34 (22–42); HC: 40.7 (23–58)	Adults (with and without MDD)	Metric; 60 min; before	NR	Locomotor activity/60 min around EMA: 111.59 ± 5.08, NR (MDD); 132.61 ± 3.08, NR (HC)
Kim et al. [175]	122	76.4%	41.3 (19-63)	Adults	Metric; 5-/60-/120 min; bidirectional	NR	Activity counts prior prompt: 28.1–30.7 ± 16.3–19.5, 5.8–93.0; Activity counts after prompt: 25.2–29.9 ± 16.8–

							20.4, 1.4–116.3
Koch et al. [93]	113	48%	15.02 (12-17)	Adolescents (URGENY)	Metric; 10 min; after	Milli-g/participant/week: 40.86 ± 11.87, 13.32-74.78	NR
Koch et al. [91]	113	48%	15.02 (12-17)	Adolescents (URGENY)	Metric; 15 min; before	Milli-g/participant/week: 40.86 ± 11.87, 13.32-74.78	NR
Koch et al. [80]	185	54.1%	26.65 (14-45)	Adolescents, adults (with and without ADHD)	Metric; 10 min; before	NR	NR
Kracht et al. [201]	284	54%	12.6 (10-16)	Adolescents (TIGER Kids study)	LPA, MVPA; 30 min; before	NR	MVPA min/30 min prior prompt: 1.0 ± 2.3, NR; LPA min/30 min prior prompt: 7.6 ± 5.7, NR
Kuehnhausen et al. [202]	82	45%	117.2 (97-132) months	Children (FLUX)	MVPA; 1440 min; before	Activity min/d: 103 ± 81, NR; VPA min/day: 21 ± 24, NR	NR
Langguth et al. [127]	72	37%	17.36 (12-26)	Adolescents	MVPA; 1440 min; before	Activity hours: 1.28 ± 0.48, NR (weekday); 0.92 ± 0.75, NR (weekend)	NR
Le et al. [203]	361	72.5%	22.79 (NR)	Adults	LPA, MVPA; 1140 min; NR	MVPA h/d: 2.56 ± 1.01, NR; LPA h/d: 8.71 ± 1.37, NR;	NR
Li et al. [204]	78	71.79%	25.46 (NR)	Adults	LPA, MVPA; 0-180 min	NR	Milli-g/min/0-180 min prior prompt: 66.13–70 ± 22.09–27.09, NR; MET/min/0-180

							min prior prompt: 1.59–1.63 ± 0.19–0.25, NR; Milli-g/min/0-180 min after prompt: 64.34–68.94 ± 22.75–29.42 22.77, NR; MET/min/0-180 min after prompt: 1.58–1.62 ± 0.21–0.26, NR;
Liao et al. [205]	117	72.5%	40.4 (NR)	Adults (MOBILE)	MVPA, LPA; 15-/30 min; bidirectional	MVPA min/d: 26.79 ± 22.32, NR (basline); 20.84 ± 11.90, NR (wave 2); 22.21 ± 15.74, NR (wave 3)	NR
Liao et al. [206]	117	73%	39.8 (NR)	Adults (MOBILE)	MVPA, LPA; 15-/30 min; bidirectional	NR	MVPA min/15–30 min prior prompt: 0.36–0.72 ± 0.43–0.85, NR; LPA min/15–30 min prior prompt: 4.12–6.78 ± 1.35–2.54, NR; MVPA min/15–30 min after prompt: 0.33–0.7 ± 0.41–0.83, NR; LPA min/15–30 min after prompt: 3.49–7.19 ± 1.25–2.36, NR

Madden et al. [95]	21	76.2 %	49 (NR)	Adults (MDD, bipolar, schizophrenia)	MVPA; 30 min; bidirec-tional	NR	MVPA min/30 min prior prompt: 1.2 ± 3.0, NR; MVPA min/30 min after prompt: 1.0 ± 2.5, NR
McLean et al. [207]	75	63%	31 (NR)	Adults	Metric; 60 min; before	NR	Steps/60 min prior prompt: 532.81 ± 261.63, 162.44–1605.38
Merikangas et al. [18]	242	61.9%	48 (NR)	Adults (MDD, bipolar) (NIMH)	Metric; 240 min; bidirec-tional	NR	NR
Michalak et al. [208]	71	60.6%	39.33 (NR)	Adults (MDD)	Metric; 60 min; before	Acceleration (g): 0.09 ± 0.03 (MDD pa-tients); 0.09 ± 0.03 (controls)	NR
Pannicke et al. [209]	37	75.7%	23.5 (19-28)	Adults	LPA, MPA, VPA and SB; 150 min; before	MVPA min/d: 45.05 ± 42.29	LPA min/150 min: 21.37 ± 19.48, NR; MPA min/150 min: 6.76 ± 11.84, NR; VPA min/150 min: 0.63 ± 3.93, NR;
Pinto et al. [210]	22	100%	51.5 (NR)	Adults (breast cancer survivors)	MVPA; 1440 min; after	MVPA min/week: 30.18 ± 27.41, NR;	NR
Poppe et al. [211]	38	34.2%	63.18 (50-81)	Adults (with type 2 diabetes mellitus)	LPA, MVPA; 1440 min; after	LPA min/d: 35.54 ± 7.18, 21.57–51.91; MVPA min/d: 6.31 ± 2.82, 0.74–13.93	NR
Powell et al. [212]	29	36%	71.4 (46-85)	Adults (after joint replacement surgery)	Metric; 60-/1440 min; bidirectional	NR	Activity monitor past activity: 11.08 ± 9.31;

							activity monitor future activity: 12.34 ± 12.39
Reichert et al. [92]	106	62.4%	23.4 (18-27)	Adults (URGENCY)	Metric; 10 min; after	Exercise min/week: 186.2 ± 137.8, NR	Non-exercise activity in milli-g/min/participant: 36.3 ± 9.8, 14.3–58. 6
Reichert at al. [88]	106	62.4%	23.4 (18-27)	Adults	Metric; 15/1440 min; before	Exercise min/week: 188.8 ± 138, 20–570	Non-exercise activity in milli-g/min/participant: 36.3 ± 9.8, 14.3–58. 6
Ruissen et al. [85]	126	48.4%	27.71 (18-40)	Adults	MVPA; n.a.*; bidirectional	MVPA min/week: 189.11 ± 184.38, 0–1045.50; length of MVPA bouts: 17.91 ± 5.37, 10.00–43.50	NR
Schwerdtfeger et al. [83]	124	51.6%	31.67 (18-73)	Adults	Metric, MVPA, LPA; 1-30 min; after	NR	Counts/min/1-min-window: 542.18 ± 1285.21, 0–11838; counts/min/5-min-window: 654.02 ± 1236.97, 0–9771.80; Counts/min/15-min-window: 724.96 ± 1239.65, 0–10383.30; counts/min/30-min-window: 771.74 ± 1195.66, 0–9849.80

Shin et al. [213]	27	29.6%	NR (19-44)	Adults	Metrics; 1440 min; after	Steps/d: 9376 ± NR, 5467 – 16997	NR
Smith et al. [131]	17	58.8%	10.59 (NR)	Children (with overweight/obesity)	LPA, MVPA; 30-/60-/120 min; bidirec-tional	LPA min/d: 668.84 ± 148.96, 56.0–961.5; MVPA min/d: 14.31 ± 16.73, 0.0–116.0	MVPA min/60 min prior prompt: 0.25 ± 1.20, 0–14; LPA min/60 min prior prompt: 33 ± 15,81, 0–59; MVPA min/60 min after prompt: 0.14 ± 0.61, 0–8; LPA min/60 min after prompt: 33.03 ± 15.95, 0–60
Smith et al. [214]	77	41.6%	15.36 (13-17)	Adolescents (with and without overweight)	Metric, MVPA; 60 min; bidirectional	MVPA min/d: 23.38 ± 18.34, NR	MVPA min/60 min prior prompt: 1.42 ± 1.33, NR; MVPA min/60 min after prompt: 1.15 ± 1.33, NR; Activity counts 15s epochs/60 min prior prompt: 20231.65 ± 8504.27, NR; Activity counts 15s epochs/60 min after prompt: 17829.70 ± 8553.89
Stavrakakis et al. [157]	20	70% (each group)	depressed: 36.4 (22-49) nondepressed:	Adults (with and without MDD) (MOOVD)	Metric; 360 min; bidirec-tional	EE/day: 233 ± 77, 126-385 (depressed); 258 ± 69, 120-369 (non-	NR

			36.7 (24-46)			depressed)	
Stevenson et al. [82]	25	56%	40 (NR)	Adults (alcohol use disorder)	Metric; 60-/1440 min; before	Steps/d: 8183 ± 5560, 0–30279	Steps/60 min prior prompt: 553 ± 662, 0-5806
Sudeck et al. [215]	64	58.3%	35.18 (20-63)	Adults	Metric; 15 min; before	NR	Milli-g/min/15 min prior prompt: 76.24 ± 26.14, 18.86 – 171.62
Takano et al. [216]	41	22%	NR	Adults (undergraduate students)	Metric; 15 min; before	NR	Physical activity [log-transformed]: 5.10 ± 1.51, 0-8.32
Vetrovsky et al. [217]	28	75%	68 (NR)	Adults	Metric, MVPA; 720 min; after	MVPA min/d: 54 ± 38, NR	NR
Walsh et al. [218]	111	60.36%	22.01 (18-27)	Adults (bipolar)	LPA, MPA, VPA; 1440 min; before	LPA %/activity/day: 33.7 ± 7.75, NR; MPA %/activity/day: 40.12 ± 12.06, NR; VPA %/activity/day: 13.4 ± 5.35	NR
Wen et al. [132]	202	51.67%	9.6 (8-12)	Children (MATCH)	MVPA; 30-/, 60 min; bidirectional	NR	MVPA min/30 min prior prompt: 1.83 ± 3.93, 0-30; MVPA min/60 min prior prompt: 3.64 ± 7.16, 0-30; MVPA min/30 min after prompt: 1.78 ± 3.88, 0-30; MVPA min/60 min after prompt: 3.46 ± 6.94, 0-60;

Wilhelm et al. [136]	123	63%	71.83 (64-85)	Elders	Metric; 1440 min after	NR	Counts/min: 292.12 ± 151.65, 41-20-1315.60; Steps/min: 9.34 ±4.64, 0.8-35
Williams et al. [219]	194	71%	40.72 (20-74)	Adults	Metric; 1440 min; after	NR	NR
Yang et al. [79]	185	Mothers: 100%; Children: 53%	Mothers: 41.03 (NR); children: 9.51 (NR)	Children, adults (MATCH)	MVPA; 45 min; bidirec-tional	NR	MVPA min/45 min: 2.345 ± 4.125, 1–45 (children); 1.177 ± 3.057; 1–45 (adults);
Zenk et al. [78]	128	100%	NR (25-64)	Adults	MVPA; 1440 min; bidirec-tional;	MVPA min/d: 15.7 ± 11.2, NR;	NR
Zhaoyang & Martire [77]	152	58.04%	65.39 (NR)	Elders (knee osteoar-thritis)	MVPA; 1440 min; bidirec-tional	MVPA h/d: 1.16 ±0.72, NR;	NR

*Due to its novel statistical approach, this study cannot be reviewed within the data extraction framework which we custom-developed to the methods applied by most of the AA studies in the PB-AWB field. Abbreviations: d = day; EE = energy expenditure; h = hours; HC = healthy controls; LPA = light physical activity; MDD = major depressive disorder; MET = metabolic equivalent of task; min = minutes; MPA = moderate physical activity; MVPA = moderate to vigorous physical activity; NR = not reported; PA = physical activity; SB = sedentary behavior; SD = standard devia-tion; VPA = vigorous physical activity

Chapter III

Paper 2: How Social Contact Shapes Physical Behavior in Everyday Life: Evidence for Affective Well-Being as a Within-Person Mediator

Timm, I., Sers, S., Reichert, M., Reinhard, I., Ebner-Priemer, U., & Giurgiu, M. How Social Contact Shapes Physical Behavior in Everyday Life: Evidence for Affective Well-Being as a Within-Person Mediator. *Submitted*.

Abstract

Objective: Social contact is evidenced to benefit physical activity participation in several epidemiological studies, but the underlying behavioral mechanisms remain elusive. Recent health behavior models attribute a critical role to affective well-being potentially connecting social contact with physical behavior, yet this proposal needs to be tested by taking a within-person perspective in everyday life.

Methods: To examine whether momentary affective well-being mediates the association between social contact and subsequent physical behavior, we recruited 64 participants from July 2021 to March 2022. Participants completed up to 10 daily e-diary prompts over 6 days while continuously wearing accelerometers. Multilevel mediation models were used for data analysis.

Results: We found affective well-being to partially mediate the relationship between social contact and physical activity (p=.012), and sedentary behavior (p=.005), so that 7% of the effect of social contact on physical activity and 7.5% on sedentary behavior was mediated through AWB, respectively. That is, if a participant had been in company as they went about their daily routines, they reported enhanced affective well-being which was in turn related to increased physical activity and decreased sedentary behavior.

Conclusions: This intensive longitudinal within-subject study shows that a remarkable amount of the known relationship between social contact and physical activity is mediated by affective well-being; providing first mechanistic insights linking existing evidence both on the within-person association of social contact and physical behavior as well as of affective well-being and physical behavior. Therewith, our daily life study supports the current development of health behavior change models that attribute a critical role to momentary states of affective well-being and pours into public health initiatives informing on the high value of positive affective environments to encourage sustainable physical activity.

1 Introduction

Increasing inactivity rates in the population have far-reaching consequences for the healthcare system (Ding et al., 2016), and can cause sequelae such as diabetes, hypertension, obesity, and depression (Katzmarzyk et al., 2022). Addressing the question of how to effectively increase physical activity is therefore of critical importance. Social contact has emerged as a key factor in promoting physical activity, with evidence suggesting that being alone or socially isolated can increase the risk of prolonged sedentary behavior (Benedyk et al., 2024). Referring to social aspects of the environment, e.g., being in contact with somebody, has been an indicator in fostering everyday physical activity (Owen et al., 2000; Trost et al., 2002) and therefore reducing risk of mortality, and non-communicable diseases (Strain et al., 2024).

There is substantial evidence that social contact indeed positively influences physical activity: a recent review demonstrated that the presence of others, i.e. partners or family, was related to elevated physical activity levels (Papini et al., 2020). For instance, research findings suggest that individuals with higher levels of social interaction tend to engage in more physical activity (Smith et al., 2017). In the context of our current manuscript, we stick to the definition of physical activity by Caspersen, which refers to an increase in energy expenditure produced by any skeletal muscle (Caspersen et al., 1985). Results from a study involving 172 adults revealed that engaging in physical activity with a partner was associated with increased daily moderate-to-vigorous physical activity levels (Pauly et al., 2021). Conversely, sedentary behavior, characterized by prolonged periods of sitting or low levels of energy consumption (Tremblay et al., 2017) has been associated with reduced social engagement. The results of a study suggested that the neglected support of a spouse contributes to increased sedentary behavior (Zhaoyang & Martire, 2019).

However, how social contact influence physical behavior (i.e., physical activity and sedentary behavior) remains unclear, there are several models potentially explaining the mechanisms. In health behavior change theories, such as Social Cognitive Theory (Bandura, 1986), it has been explicated that additional contextual factors, such as the role of social influence, are pivotal determinants in subsequent behavioral outcomes, including physical activity engagement (Courneya et al., 2000). Drawing from socio-ecological models of health behavior, multifaceted layers i.e., individual, social, and environmental factors, can influence an individual and initiate or facilitate individual health behaviors (Sallis et al., 2006; Spence & Lee, 2003; Stokols, 1992). The socio-ecological framework emphasizes the dynamic relationships between individuals and their social environment, further highlighting the importance of social context in shaping health behaviors (McNeill et al., 2006). According to dual process theories, affective processes are intertwined with physical behavior, proposing that (other) affective components play roles in maintaining an active lifestyle (Brand & Ekkekakis, 2018). In the current transition to dual-process models, it is illustrated that affective processes and physical behavior mutually influence each other (Ekkekakis, 2003). In those models, affective well-being is most often defined as the basic construct of core affect, which comprises elementary primitive feelings corresponding to neurophysiological states, and is continuously retrievable by the conscious mind and therefore can be measured in the moment (Russell, 2017).

However, despite the recognition of the association between social contact and physical behavior, there is very limited evidence on the potential underlying behavioral mechanism and especially the mediating role of affective processes. This is surprising, considering that studies have already demonstrated the influence of affective well-being on physical behavior (Bourke et al., 2021a; Liao et al., 2015; Rhodes & Kates, 2015). For example, research has shown that higher levels of affective well-being can predict increased physical activity (Reichert et al., 2016) and reduced sedentary behavior (Giurgiu, Plotnikoff, et al., 2020), highlighting the critical role of affective well-being as antecedence to physical behaviors. In particular, a recent review showed that especially feelings of energetic arousal relate to elevated physical activity intensity levels (Timm et al., 2024).

The above-mentioned evidence and theories built upon cross-sectional research, but to investigate the interplay of social contact, affective well-being, and physical activity, one needs to consider within-person momentary dynamics in everyday life. Ambulatory

Assessment (AA), which combines real-time self-reports through ecological momentary assessments (EMA) (Stone & Shiffman, 1994) via e-diaries with device-based physical behavior recording via accelerometers, facilitates this process (*SAA – Society for Ambulatory Assessment*, n.d.). Intensive longitudinal data collection reveals fluctuations in the processes of interest (Shiffman et al., 2008), offering insights into the maintenance of physical behaviors. Using real-time tracking, within-subject variability can be adequately reflected, and retrospective biases can be minimized (Mehl et al., 2014; Thomas & Diener, 1990; Trull & Ebner-Priemer, 2013), simultaneously enhancing ecological validity (Bussmann et al., 2009; Prince et al., 2008). By utilizing accelerometers for physical behavior measurement, potential recall biases such as mood-congruent memory effects are mitigated (Reichert et al., 2020).

In sum, the evidence on positive effects of social contact on affective well-being and physical behavior, as well as the influence of affective well-being on physical behavior, is convincing, but the mechanisms underlying these associations remain unclear. Towards this end, we here for the first time set up an EMA study to explore the potential mediated mechanisms of affective well-being influencing the short-term dynamic relationship between momentary social contact and device-based assessed physical behavior, explaining intraindividual variance. Our hypotheses of the current study were: 1) that affective well-being mediates the relationship between social contact and physical activity; 2) that affective well-being mediates the relationship between social contact and sedentary behavior. That is, we expected a total effect on physical activity/sedentary behavior composed of the direct effect of social contact and the indirect effect of social contact via affective well-being.

2 Methods

2.1 Recruitment and Participants

A convenient sample of employees ≥18 years was recruited during the period from July 2021 to March 2022 in Germany. Eligible participants were included in the study if they were capable of performing daily activities without physical limitations, had no existing injuries, and reported no current mental disorders. A total of 64 participants were recruited. Participants were excluded if the e-diary compliance was less than 30% (n=6). All eligible participants were informed in writing and verbally about the study procedure before giving their written informed consent. All participants were free to withdraw from the study on any occasion. The study was performed in accordance with the Declaration of Helsinki and the Human Research Ethics Committee of the Karlsruhe Institute of Technology (KIT) approved this study.

2.2 Study Design and Procedure

Throughout the assessment period, participants were asked to wear two Move 4 accelerometers (movisens GmbH, Karlsruhe, Germany, movisens.com) continuously at two different positions (i.e., hip and thigh) for 24 hours and to respond to e-diary prompts via a study-provided smartphone (Nokia 6, Nokia Corporation, Espoo, Finland, nokia.com, android phones). The assessment took place over five to six working days during the week. Participants received personalized training to become acquainted with both the accelerometers and the provided smartphone. Following the training session, participants received the study smartphone and the accelerometers. Seven random prompts were distributed between 9 am and 8 pm on weekdays. To alleviate the participants' burden, time-out periods lasting 40 to 60 min were programmed, i.e., after responding to an e-diary prompt, participants would not receive another prompt for the subsequent 40 to 60 min. In case a prompt appeared at an inconvenient time, participants had the option to postpone it by 10 min. Additionally, participants were asked to complete a self-determined e-diary prompt in the morning, evening, and after work resulting in a maximum of ten responses per day. The sampling strategies and e-diary assessments were facilitated using movisensXS, version 0.7.47574 (movisens GmbH, Karlsruhe, Baden-Wuerttemberg, Germany, xs.movisens.com). Participant baseline characteristics including age, height, sex, and household size were assessed via an electronic survey provided on the smartphone and were completed before the start of the study period.

3 Measures

3.1 Ecological Momentary Assessment

3.1.1 Affective Well-Being

To assess momentary affective well-being, we employed the 6-item e-diary scale developed by Wilhelm and Schoebi (Wilhelm & Schoebi, 2007), which is designed specifically for e-diary research and has been rigorously evaluated. This scale is built on a three-dimensional concept of affective states, encompassing valence, energetic arousal, and calmness. The six bipolar items are distributed across three affect dimensions: valence (item 5: unwell to well; item 2: discontent to content), energetic arousal (item 4: without energy to full energy; item 1: tired to awake), and calmness (item 6: tense to relaxed; item 3: agitated to calm). The bipolar items were presented to participants in a mixed order and with reversed polarity. Participants could express the varying degrees of their current affective states using a visual analog scale ranging from 0 to 100. The scale demonstrated satisfactory psychometric properties, both in its original publication (Wilhelm & Schoebi, 2007) and in our dataset, with reliability coefficients at the within-person level ranging between 0.82 and 0.86.

3.1.2 Social Contact

In addition to the queries about affective states, participants were also asked to provide details about their current social context. Social contact was evaluated through a single question regarding who they were with at the moment (i.e., partner, family, friends, colleagues, acquaintances, strangers, others, or nobody). From these responses, a dichotomous variable was created for social contact, which includes friends, family, and partners, as opposed to "being alone".

3.2 Physical Behavior

The deployed Move 4 accelerometers, validated for measuring physical behavior (Anastasopoulou et al., 2014; Giurgiu, Bussmann, et al., 2020), capture triaxial acceleration within a ± 16 g range, sampling at 64 Hz with a 12-bit resolution. The two sensors were worn on the right thigh and on the hip. Raw data were stored on the device's internal memory card and subjected to band-pass filtering (0.25 to 11 Hz) to remove artifacts. Physical activity and sedentary behavior were derived from the accelerometer's raw files in 1-minute epochs using DataAnalyzer software (version 1.13.7; movisens.com, movisens GmbH). Physical activity was operationalized as the aggregated triaxial mean movement acceleration intensity in gravitational constant g (9.81 m/s^2) within 15-minute sections following each e-diary entry, based on established protocols (Koch et al., 2018; Reichert et al., 2016). Sedentary behavior was quantified as the total minutes of sedentary minutes within a 30-minute window following each e-diary entry (Giurgiu, Plotnikoff, et al., 2020).

3.3 Data Analysis

Physical activity and sedentary behavior data were merged with the assessments of the e-diary entries (DataMerger, version 1.8.0, movisens GmbH). The outcome parameter movement acceleration was logarithmized with a natural logarithm, as the distribution was right-skewed. Skew statistics was 5.58, after applying log-transformation to physical activity skewness reduced to -.42. Extending the classic mediation model which assumes independent observations (Baron & Kenny, 1986; Preacher & Hayes, 2004) a multilevel mediation analysis was performed accounting for clustered data (Bauer et al., 2006; Hayes & Rockwood, 2020; Tofighi & Thoemmes, 2014). In this approach, utilizing a lower-level mediation model (1-1-1), the effect of a lower-level predictor is mediated, with the mediator being a level 1 variable. This current model examined whether momentary affective well-being (valence - level 1 data) mediates the association between the independent (i.e., social contact - level 1 data) and the outcome variable (i.e., physical behavior - level 1 data). Level 1 covariates age [years], sex [female vs. male], and BMI [m/kg^2] were added into the model. Our models incorporated random intercepts and slopes and were estimated using restricted maximum likelihood (REML) and an unstructured covariance structure (Rockwood, 2017; Zhang et al., 2009). Standardized beta coefficients (stand. β) were calculated to compare the effects of each predictor, following established procedures (Hox et al., 2010). Our data were deemed suitable for detecting small within-subject effects and medium to large between-subject effects, based on established simulation studies towards multilevel power analysis (Arend & Schäfer, 2019).

The multilevel mediation analysis assessed direct, indirect and total effects, using social contact as predictor, affective well-being as mediator and physical activity / sedentary behavior as outcome (see figure 1). The indirect effect was calculated as the product of the paths a and b, and Monte Carlo method based on 10.000 samples was used to estimate the 95% confidence intervals for the indirect effect (Cerin & Mackinnon, 2009). The respective effect is significant for zero falling outside the interval. The proportion of mediation was calculated as the ratio of the indirect (a×b) and the total effect (c = a×b + c'). All data analyses were conducted with the software SPSS (IBM), version 28.0.0.0, and the level of statistical significance was set at $\alpha = 0.05$. Calculation and testing of indirect and total effects were carried out using MLmed macro for SPSS (Rockwood & Hayes, n.d.). The macro is available from https://njrockwood.com/mlmed.

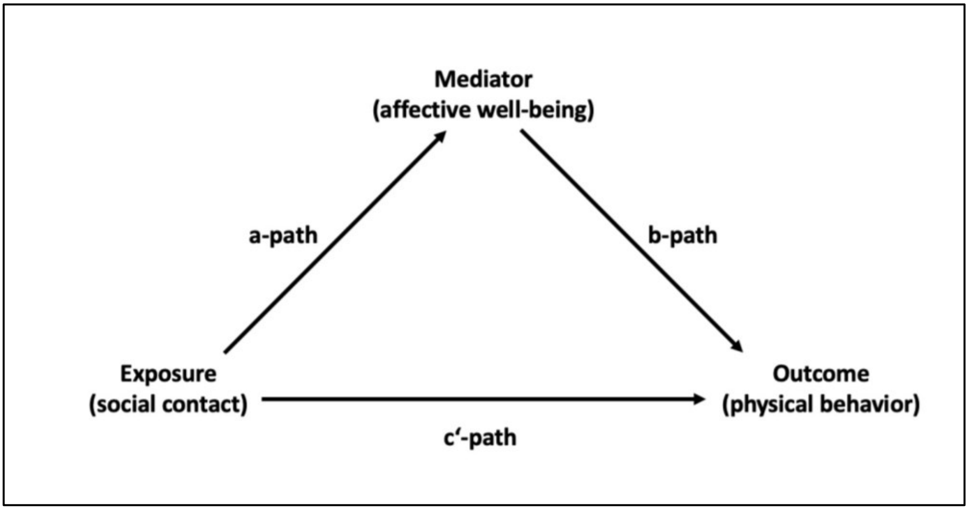


Figure 1: Proposed mediation by affective well-being on the associations between social contact and physical behavior. Path a represents the estimated association between social contact (predictor) and affective well-being (mediator). Path b illustrates the estimated association between affective well-being and physical behavior (outcome). Path c' shows the estimated direct association between social contact and physical behavior, controlling for affective well-being.

4 Results

4.1 Descriptive Statistics

Our final sample included 58 participants aged between 17 and 61 years (35.3 ± 9.8) (details see Table 1). The average scorte reported by the participants for valence was 67.75 (SD = 11.67) on a scale of 0–100. Throughout the study period, participants had an average response rate of 4.88 prompts, yielding an overall compliance rate of 60.37% (SD = 15.28). Participants wore accelerometers for an average of 15 hours per day (SD = 5.0). Additionally, the mean level of physical activity across participants was 49.56 mg (SD = 16.15), while the mean time spent in sedentary behavior was 10 hours per day (SD = 4.10).

Table 1: Descriptive statistics (n=58).

Variable	Mean (SD[1])/ %	Minimum	Maximum
Female	60.30	-	-
Age [yr]	35.31 (9.76)	17.00	61.00
BMI [kg/m^2]	22.98 (3.73)	17.63	35.42
Answered e-diary assessments [per day][a]	4.88 (1.20)	2.74	7.17
Valence [0-100][a]	67.75 (11.67)	42.65	99.29
Sedentary time [min/prompt][b]	17.51 (4.72)	0.19	24.83
Movement acceleration [mg/prompt][c]	47.91 (16.89)	18.73	103.74

[1] standard deviation
[a] assessed via e-diary, aggregated within participants
[b] average minutes per participant across e-diary prompts within a 30-minute timeframe
[c] average mg aggregated within participants across e-diary prompts within a 15-minute timeframe

4.2 Mediation Analysis

4.2.1 Affective Well-Being Mediates the Association Between Social Contact and Physical Activity (Hypothesis I)

Affective well-being was hypothesized to mediate the relationship between social contact and physical activity. Results from the multilevel mediation model indicated that social contact significantly influenced within-subject variations in physical activity intensity (see Figure 2). Specifically, being together with family, friends, or a partner positively influenced physical activity intensity with a direct positive effect of 0.244 ($p < .001$, path c') (see Table 2). Higher levels of affective well-being were associated with increased levels of physical activity, indicating a positive association between momentary affective ratings and subsequent movement acceleration within the 15 minutes following e-diary assessments ($\beta = 0.005$; $p = .001$, path b). The multilevel mediation model revealed that social contact was a significant predictor of affective well-being. Specifically, supportive contact, such as being with family and friends, was associated with heightened affective well-being ($\beta = 3.72$; $p = 0.001$, path a).

The indirect effect, calculated as the product of the beta coefficient of path a (social contact on affective well-being) and the beta coefficient of path b (affective well-being on physical activity), was 0.018 ($p = 0.012$). Thus, the total effect, which is the sum of the direct and indirect effect, sums up to 0.262. The results showed a partial mediation between social contact and physical activity via affective well-being. In support of hypothesis I, the indirect effect of 0.018 and the total effect of 0.262 gave a ratio of

0.070, which indicated that 7% of the effect of social contact on physical activity was mediated through affective well-being. It is important to note that all reported beta coefficients represent within-subject effects. Between-subject effects are not presented in this analysis as they are not the focus of the investigation.

Table 2: Results of the individual paths of the multilevel mediation model.

Outcome variable	Mediator	Direct effect Path c'		Path b		Path a		Indirect effect (a×b)		*Total effect* Path c (a×b + c')
		β (95%CI)	*p* value	β (95%CI)	*p* value	β (95%CI)	*p* value	β (95%CI)	*p* value	
Physical activity	affective well-being	0.244 (.134, .354)	<.001	.005 (.002, .008)	.0007	3.72 (1.816, 5.624)	.0001	.018 (.006, .034)	.0123	0.26
Sedentary behavior	affective well-being	-.093 (-.129, -.057)	<.001	-.002 (-.003, -.001)	<.001	3.72 (1.816, 5.624)	.0001	-.008 (-.013, -.003)	.005	-0.10

Abbreviations: CI, confidence interval. Path a represents the effect of social contact on affective well-being. Path b represents the effect of affective well-being on physical behavior (i.e., physical activity, sedentary behavior). Path c' represents the direct effect of social contact on physical behavior, controlling for affective well-being. The indirect effect (a×b) represents the effect of social contact on physical behavior mediated through affective well-being. The total effect (c) is the sum of the direct (c') and indirect (a×b) effects

4.2.2 Affective Well-Being Mediates the Association Between Social Contact and Sedentary Behavior (Hypothesis II)

Affective well-being was hypothesized to mediate the relationship between social contact and sedentary behavior. We investigated whether social contact predicted within-subject variations in sedentary behavior. The direct effect of social contact was negatively related to sedentary behavior in the multilevel mediation model. In particular, being in the company of family, friends, or a partner was significantly associated with reduced time spent in sedentary behavior ($\beta = -0.093$; $p < .001$, path c’). Higher levels of affective well-being significantly predicted reduced time spent sedentary in the 30 minutes following the e-diary prompt with a direct negative effect ($\beta = -0.002$; $p < .001$, path b). Again, the multilevel mediation model revealed that social contact was a significant predictor of affective well-being ($\beta = 3.72$; $p = 0.001$, path a). The indirect effect, namely the product of the beta coefficient of path a (social contact on affective well-being) and the beta coefficient of path b (affective well-being on sedentary behavior) was -0.0075 ($p = .005$). The results showed a partial mediation between social contact and sedentary behavior via affective well-being. In support of hypothesis II, the indirect effect of -0.0075 and the total effect of -0.1 gave a ratio of 0.075, which indicated that 7,5% of the effect of social contact on sedentary behavior was mediated through affective well-being.

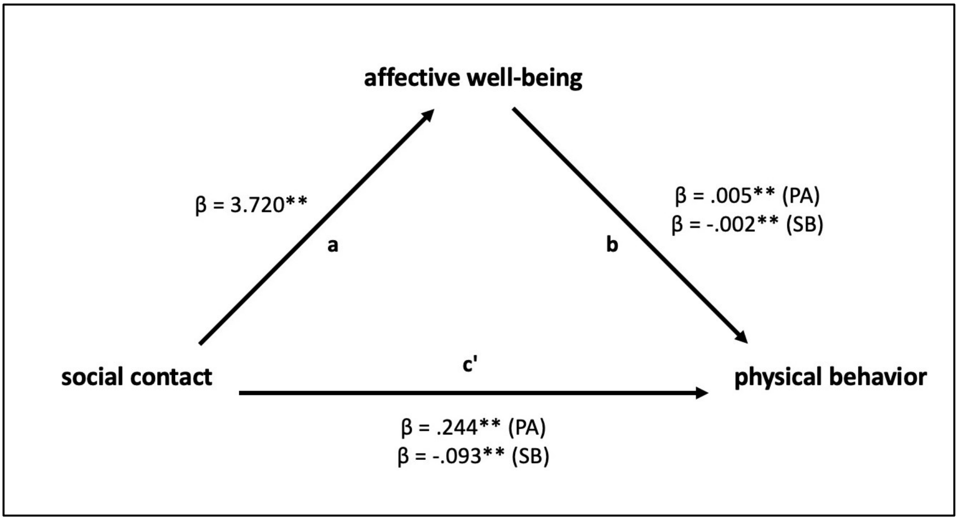


Figure 2: Mediation results by affective well-being on the associations between social contact and physical behavior (**p < .01). Abbreviations: PA, physical activity; SB, sedentary behavior.

5 Discussion

The present study uncovers a behavioral within-person mechanism linking social contact to physical behavior. While we could replicate direct positive effects of social contact on physical behavior, momentary associations of affective well-being with subsequent physical activity, as well as positive relationships of social contact on affective well-being seen in a wide range of epidemiological and correlational studies, our intensive longitudinal study for the first time accumulates evidence for a mediating role of affective well-being in the relationship between social contact and physical behavior in everyday life. In a sample of healthy adults, we found that the relationship between social contact and physical activity as well as sedentary behavior is partially but to a considerable degree mediated by affective well-being. Translated to practice, our results suggest that when participants are with others, their affective well-being improves, leading to increased physical activity entailing an additive effect of affective well-being on physical activity levels when individuals are socially engaged. This finding provides support for socio-ecological frameworks attributing a critical role to intraindividual processes, the social context of individuals, and physical behavior, and therewith contributes to closing the evidence gap on the short-term dynamics of everyday life that may underlie these associations.

Compared to prior studies that researched direct correlation of the three key variables investigated, one can see that there is a clear consistency with the existing literature. First, we found that the social environment has emerged as a critical determinant not only of everyday physical activity levels but also of sedentary behavior. Our findings show that momentary social contact positively influenced subsequent physical activity intensity, aligning with prior studies that show social context as a predictor of increased physical activity levels (Ball et al., 2001; Burke et al., 2006; Dunton et al., 2015). For example, being active with a partner has been shown to extend physical activity duration in low-active or overweight individuals (Boyle et al., 2020), while reductions in social contact have been linked to higher levels of sedentary behavior (Otaki et al., 2022; Tully et al., 2020). Second, we observed that higher ratings of momentary affective well-being are associated with increases in physical activity intensity and reductions in sedentary behavior, consistent with previous research using similar EMA methodologies (Giurgiu, Plotnikoff, et al., 2020; Liao et al., 2015; Reichert et al., 2016; Timm et al., 2024). Lastly, our findings supported the well-documented influence of social contact on affective well-being, with studies showing that affective well-being tends to decrease when individuals are alone and increase during social interactions (Bernstein et al., 2019; Kuczynski et al., 2022).

While prior research has not taken a comprehensive mechanistic view using mediation analyses, our findings are in line with EMA studies asking similar questions. For example, previous studies have shown that a lack of social support contributes to increased sedentary behavior and reduced positive affect (Zhaoyang & Martire, 2019), while higher positive affect is reported during physical activity with others (Dunton et al., 2015). Our research expands on Boyle et al. (Boyle et al., 2020), who found that affective responses during physical activity with a partner significantly mediate the impact of walking with a partner on physical activity behavior. Their study showed that engaging in physical activity with a partner and in positive environments (both physical and social) increases physical activity behavior through more positive affective responses. However, Boyle et al.'s study relied on self-reports of physical behavior and was limited to walking behavior. Dunton et al. explored whether activity levels moderated the relationship between being alone or with others and concurrent affect (Dunton et al., 2015). They found that physical activity with others led to greater positive affect compared to being alone, highlighting the significance of social context to the mood-enhancing effects of physical activity. Positive social interactions, like social support or companionship, likely explain these benefits (Vranceanu et al., 2009), supporting our finding that affective well-being in positively perceived social environments has an additive benefit on physical behavior. A moderation study on sedentary behavior found that older adults experienced higher negative affect when sedentary and alone compared to when they were not sedentary (Hevel et al., 2021). This suggests that solitary sedentary activities may contribute to the development of more negative affective experiences, reinforcing our mediation model indicating that when individuals are in the presence of another person, they experience greater levels of affective well-being and thus are less sedentary. In contrast, Bourke et al. (Bourke et al., 2021b) found no significant interaction between social context, MVPA levels, and affective well-being in adolescents. This discrepancy may arise from differences in how physical activity was operationalized; while our study used raw activity signals of everyday activity, Bourke et al. focused on MVPA levels. There are theoretical perspectives suggesting that high volumes of physical activity can negatively impact affect (Ekkekakis, 2003), and the study did not distinguish between supportive and non-supportive social interactions. Similarly, Cabrita et al. (Cabrita et al., 2017) found that while social contact didn't significantly interact with device-measured physical activity to predict pleasure in older adults, it remained consistently important since participants spent most of their time at home and alone. This context may explain the differences in how social contact moderates the relationship between physical activity and pleasure compared to our findings.

Our findings revealed that affective well-being mediated 7% of the association between social contact and physical behavior. We deem this variance explained as surprisingly high given the numerous influence on physical activity in daily life proposed by the socio-ecological model. For instance, physical activity can be influenced by environmental factors such as weather conditions (Bejarano et al., 2019; Timm et al., 2023), green space exposures (Tost et al., 2019), or whether an activity is performed outside or inside (Bourke et al., 2021b). Furthermore, individual factors such as autonomy may also play a role. For example, increased sedentary behavior and lower positive affect scores were mediated by low autonomy support from a relative (Zhaoyang & Martire, 2019). Autonomy has also been found to moderate the association between physical activity and affective states (Dunton et al., 2015; Kanning & Hansen, 2017). However, despite the wealth of influencing factors, we found that 7% of the association is mediated via affective well-being.

Our study comes with promising implications for practice and implications for future public health campaigns to emphasize the positive impact of social interactions on both mental and physical health, as both social contact and physical behavior impact overall mortality rates and health status (Foster et al., 2023; Holt-Lunstad, 2021). Recognizing the mediating role of affective well-being allows for future design of just-in-time adaptive interventions (JITAIs) that address not only social factors but also affective states influencing physical activity behavior. For example, in the context of being with others, JITAIs can leverage these situations to motivate physical activity through affect modulation. Creating a supportive environment that encourages physical activity can help individuals overcome barriers to being active. These effects could also be extended to mental health disorders. People with higher depressive symptoms experienced higher affective well-being when with others compared to being alone (Brown et al., 2011). A study showed that feelings of social isolation may cause individuals to withdraw from social interactions, further exacerbating the feeling of social isolation (Hevel et al., 2021). In particular, participants experienced increased negative affect when alone and sedentary compared to when they were with others and sedentary (Hevel et al., 2021). In being-alone situations, JITAIs can be used to lower barriers via affective well-being to being active, as a lack of social support and active peers are key barriers to being active (Arigo et al., 2023). Especially, in situations lacking social contact, loneliness may increase. Therefore, including partners in interventions can promote physical activity, as shown by a study where participants with partner involvement saw substantial increases in activity over time (Gellert et al., 2011). Future interventions should incorporate social components like group activities to address sedentary behavior and be tailored to also address functional and capability limitations, helping to reduce loneliness and social isolation (Tully et al., 2020). Web applications and social media can also facilitate physical activity meet-ups, connecting individuals (Arigo et al., 2023).

Despite numerous strengths, our study also has several limitations. First, this study is observational, precluding any conclusions about causality. Additionally, we cannot rule out reverse causality, where depression and loneliness may influence social interaction. For example, participants with higher rates of depressive symptoms were more likely to be alone at the time of the e-diary prompt (Brown et al., 2011). However, we applied multilevel mediation analysis, which represents a significant step closer to understanding causal relationships compared to previous correlational studies. In future studies, it would be beneficial to utilize a within-person encouragement design. Second, we collected data during the COVID-19 pandemic when nationwide restrictions (i.e., the "3G rule") were enforced in Germany. Future studies should replicate our findings under post-pandemic conditions to determine if the results are specific to the pandemic's social contact structure or generalize to typical periods in everyday life. Third, participants were instructed to remove the accelerometer during activities such as swimming and in extreme heat conditions like saunas. Given that these activities are infrequent in daily life, this limitation is considered minor.

6 Conclusion and Future Directions

The findings from our intensive longitudinal study revealed that affective well-being partially mediates the association between social contact and subsequent physical activity and sedentary behavior in everyday life. Using multilevel mediation analysis, we identified a behavioral within-person mechanism linking social contact to physical behavior. Practically, our findings suggest that social engagement enhances affective well-being, which in turn increases physical activity levels, demonstrating an additive effect of affective well-being when individuals are socially engaged. These results lend further support to the socio-ecological framework that attributes a critical role to intraindividual processes, the social context of individuals, and physical behavior. This, in turn, contributes to narrowing the evidence gap on the short-term dynamics in daily life that may drive these associations. Our findings suggest that promoting physical activity through social contexts and affective well-being appears to be a promising approach. These insights can be incorporated into JITAIs to encourage active lifestyles in real-time, emphasizing the critical role of social contact and affective well-being enhancement in motivating physical activity. Based on the socio-ecological model, future studies should integrate diverse context-related assessments via passive technology sensing, geolocation tracking, and advanced GPS-triggered designs (Koch et al., 2018; Reichert et al., 2017) to gain insights into contextual factors and detailed social contexts. In addition, subjective perceptions of the physical environment, such as walkability, traffic safety, and neighborhood aesthetics, should be included in EMA studies due to their potential impact on behavior (Papini et al., 2020). Furthermore, data on the qualitative dimensions of physical behavior should be collected including domains in which physical behavior occurred (e.g., transport, work, household, leisure) (Giurgiu, Niermann, et al., 2020). Considering these domains may be important for a full understanding of the determinants of physical behavior in everyday life. It would be beneficial for future studies to consider incorporating passive sensing technologies to validate social contact reports. One promising approach is the use of Bluetooth Low Energy (BLE) beacons to detect proximity and interactions with others (Girolami et al., 2020). Additionally, social network analyses can be employed to identify significant others in participants' lives and to understand the structure and dynamics of their social interactions. Together with smartphone usage data, metrics such as the number of incoming and outgoing text messages, phone call duration, number of phone calls, social media usage patterns, and the frequency of communication with friends or spouses can provide valuable insights into participants' social networks and interactions (Puura et al., 2022). Wearable devices combined with physiological sensors could be utilized to capture the physical and emotional context of social contacts. For example, heart rate variability and cortisol levels could be measured to understand the physiological impact of social contact, as studies have shown that physiological parameters, such as cortisol levels or blood pressure, can vary based on social interactions (Ditzen et al., 2008; Stoffel et al., 2021).

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Chapter IV

Paper 3: Momentary Within-Subject Associations of Affective States and Physical Behavior are Moderated by Weather Conditions in Real Life: An Ambulatory Assessment

Timm, I., Reichert, M., Ebner-Priemer, U. W., & Giurgiu, M. (2023). Momentary within-subject associations of affective states and physical behavior are moderated by weather conditions in real life: An ambulatory assessment study. *International Journal of Behavioral Nutrition and Physical Activity,* 20*(1),* 117. https://doi.org/10.1186/s12966-023-01507-0

Abstract

Background: Physical behavior (PB) is a key lifestyle factor in regulating and preventing diseases across the lifespan. Researchers identified affective, cognitive, and contextual factors like weather conditions, as significant contributors in determining if individuals are physically active. However, there is scarce empirical evidence about potential associations between PB and affective states influenced by weather conditions in daily life. Therefore, we explored if weather conditions moderated the within-subject association between momentary affective states and subsequent PB.

Methods: Utilizing ambulatory assessment, 79 participants completed electronic diaries about their affective states (i.e., valence, energetic arousal, and calmness) up to six times a day over five days, and their PB (i.e., physical activity and sedentariness) was simultaneously recorded via accelerometers. Weather conditions (i.e., temperature and precipitation) recorded near participants' locations served as moderators in the multilevel analyses.

Results: We confirmed earlier findings associating affective states with PB. Increased valence and energetic arousal were positively associated with physical activity

($\beta = 0.007$; $p < .001$), whereas calmness predicted lower levels of physical activity ($\beta = -0.006$; $p < .001$). Higher levels of calmness showed a positive association with sedentary behavior ($\beta = 0.054$; $p = .003$). In addition, we revealed a significant positive association between temperature, as a momentary weather condition, and physical activity ($\beta = 0.025$; $p = .015$). Furthermore, we showed that the association of affective states and physical activity was moderated by temperature. Higher temperatures enhanced the positive effects of valence on physical activity ($\beta = .001$, $p = .023$) and attenuated the negative effects of calmness on physical activity ($\beta = .001$, $p = .021$). Moreover, higher temperatures enhanced the positive effects of valence on reduced sedentary behavior ($\beta = -0.011$, $p = .043$).

Conclusions: Temperature alterations appeared to have an impact on subsequent physical activity. Furthermore, temperature alterations moderated the influence of affective states on conducted physical activity. This might offer the opportunity for just-in-time adaptive interventions to intervene in individually appropriate environmental conditions for promoting physical activity.

1 Background

There is compelling evidence that physical activity (PA) has beneficial consequences for both somatic and mental health [1, 2]. However, according to the WHO, 28% of the adult population is not active enough, i.e., does not comply with the activity guidelines of at least 150-300 minutes of moderate-intensity aerobic PA per week [3, 4]. Based on the definition by Bussmann and van den Berg-Emons, the construct of physical behavior (PB) includes both PA and sedentary behavior (SB) [5]. PA is defined by skeletal muscle effort [6] leading to an increase in energy expenditure and is usually unplanned and unstructured in daily life, e.g., going for a walk or working in the garden. SB is characterized by an energy expenditure lower than 1.5 metabolic equivalents, e.g., while in a sitting or reclined position (excluding sleep) [7]. Being physically inactive, e.g., in terms of prolonged SB, is associated with diabetes, hypertension, obesity, and depression [8], and is related to an increased risk of mortality [9].

The relevance of PB and affective well-being [10] associations for research on behavioral processes underlying entrance to or maintenance of a physically active lifestyle becomes obvious in this field progressing towards a comprehensive approach. Socio-ecological frameworks postulate that individuals are embedded within larger social systems [11], indicating that behavioral, psychosocial, as well as environmental factors contribute to different responses in maintaining or being physically active [12], and can significantly impact physical behavior choices. In this context, affective well-being is defined as an elementary simple primitive affective feeling corresponding to a neurophysiological state that is continuously retrievable by the conscious mind [13]. A commonly used conceptualization is a three-factor structure categorizing core affect into valence, energetic arousal, and calmness [14].

In recent years, an increasing number of studies have examined the associations between daily physical behaviors and affective states, but the findings have been inconsistent in some cases [15]. For example, several observational studies have revealed that individual momentary affective states influence subsequent PB to the extent that higher ratings of the affective dimension valence led to a subsequent increase in daily activities [16–18]. However, some studies did not find an association between valence and subsequent increases in PA [19, 20]. It was further observed that an increase in valence was associated with a reduction in SB [21]. In contrast, one study found no alterations in subsequent SB [20]. Concerning energetic arousal, it was shown that higher levels led to increased PA [16–18, 20]. Consistent with these findings, studies found that energetic arousal predicted lower amounts of SB [20, 21]. Furthermore, a higher level of calmness led to a subsequent reduction in time spent physically active [16–18], whereas preceding higher levels of calmness predicted an increase in PA levels in one study [19]. An increase in calmness was associated with higher SB after the e-diary assessment [21]. Dunton speculated that the ambiguity might be caused by context-specific effects [22] and that future studies should consider those contextual factors more closely, suggesting that PB influences should be considered in multi-layered frameworks. the difficulty in promoting a physically active lifestyle lies in determining the drivers of SB, which could be used to develop effective behavior intervention strategies.

While PB has been known to assume a significant role in health behaviors, researchers have attempted to identify potential determinants e.g., other environmental factors that might influence physical behavior choices. In this context, environmental factors, such as weather conditions, are increasingly being addressed in a very topical way; for example, weather exposures that affect people's daily activities and indoor versus outdoor locations, such as increased temperature might be related to changes in PB. Future projections indicate an eight to 50-fold increase in the number of days that will be unsafe for moderate physical activity by 2070 [23]. Based on data from over 1.9 million people, Obradovich and Fowler (2017) have shown that both cold and acutely hot temperatures, as well as precipitation days, reduce PA [24]. Thus, weather conditions can impact everyday PB and in line with global climate change, there is a need to quantify how weather conditions influence decisions and the capacity to perform PB in daily life [25, 26].

Weather conditions might not only influence individuals' immediate decisions regarding PA but also might act as a potential moderator in the overall affective states and PB relationship. Several contextual factors such as natural, built, or social environments that may influence the time-dynamic, within-subject affect–behavior relationship have been investigated [27–29]. Self-perceived weather, such as too rainy, was shown to have a negative effect on affect, or perceived too cold weather reduced positive affect [30]. Individual affective responses to weather conditions were recently shown to be linked to mental well-being [25]. In general, contextual environmental factors have the potential to generate an additive effect on the association between affective states and PB. For example, even if people are in a positive mood and ready for a walk, as expected in previous research, the current rainy weather conditions may hinder them from going outside. Otherwise, people might be not energetic enough for being active, but the bright weather triggers them to go for a walk.

So far, theoretical and model-like explanations are based on affective and cognitive approaches [31–33]. In particular, dual-process models assume that behavior, in general, is regulated by two different mental processes: first by an implicit, automatic process that requires minimal cognitive resources (Type-1) and second by a slower and reflective, conscious process (Type-2) [32]. Regarding PB, automatically activated momentary affect is assumed to be sufficient to influence PA at a preconscious level [34, 35], independent of motivational attitudes [36]. In other words, such implicit Type-1 (affective) processes influence whether an active lifestyle/behavior is initiated or maintained [37]. To determine those Type-1 drivers of PA, investigating microtemporal within-subject processes is necessary [22].

Since affective states are dynamic in nature [38], it is essential to capture multiple affective states within a person over time [39]. Therefore, in our study, we used the method of ambulatory assessment (AA) [40], which is defined as the use of field methods to assess the ongoing behavior, physiology, experience, and environmental aspects of people in naturalistic or unconstrained settings [41]. The key advantages of AA are as follows: a) real-time assessments to overcome retrospective biases [42]; b) real-life assessments to increase ecological validity (reflect real-life conditions); c) repeated assessments reveal fluctuations in the processes of interest [43], thereby providing a within-subject perspective; d) the inclusion of time-varying covariates, such as contextual weather conditions, environment, and social context; and e) adding sophisticated interactive assessment such as activity or sedentary triggered e-diaries [44–46].

We are not aware of any study that integrated objective weather conditions combined with device-based assessment of PB and momentary affective states in real-time. Our study tries to illustrate how individual affective states and environmental factors (i.e., weather conditions) interact as determinants of PB. Therefore, we hypothesized that higher valence, higher energetic arousal, and lower calmness would lead to higher PA (hypothesis Ia) and less time spent in SB (hypothesis Ib). Second, we hypothesized that higher temperatures would increase PA and decrease SB (hypothesis IIa), whereas higher precipitation would decrease PA and increase SB (hypothesis IIb). Third, based on previous findings [30, 47–50], we investigated the additive effect of weather on the association between affective states and PB (exploratory interaction analyses III), namely whether contextual weather conditions (i.e., temperature and precipitation) have an interaction effect on the relationship between affective states and subsequent PB.

2 Methods

2.1 Participants

We recruited a convenience sample of university students and employees from September 2019 to March 2020 in Germany. Participants were included if they were able to perform daily activities without physical restrictions, had no currently present injuries, and reported no current mental disorders. In total, we recruited 111 participants. We excluded participants i) if their e-diary compliance was less than 30%, or due to technical issues (N=4); ii) if they wore the accelerometers </= 10 hrs and if the accelerometer was worn for fewer than three days (N=12); iii) if their zip code did not match a particular weather station, that is, the residential distance had to be smaller than or equal to the distance of the weather station Rheinstetten, Germany to the furthest district of Karlsruhe (Grötzingen: 14.5 km) (N=16); iv) if participants spent single days outside the weather station area (N=33 days). The final sample consisted of 79 participants (60.8% females) between 17 and 49 years (22.7 ± 4.3 years) (for details, see Table 1). Written and oral information regarding the study procedures was presented to all eligible participants before written informed consent was obtained. All participants were free to withdraw from the study at any time. The ethics review board of the Karlsruhe Institute of Technology (KIT) approved this study.

Table 1: Participant and study characteristics (N=79).

Variable	N; Mean ± SD[1]	Minimum	Maximum
Female [%]	48, 60.8 %	---	---
Age [yrs.]	22.70 ± 4.26	17	49
BMI [kg/m^2]	22.07 ± 2.00	17.21	26.85
Answered e-diary assessments [per day][a]	4.76 ± 0.95	2.75	6.25
Answered e-diary assessments [%/5 days][a]	65.97 ± 16.65	31.43	96.77
Calmness [0-100][a]	67.51 ± 13.03	28.38	94.81
Valence [0-100][a]	70.37 ± 12.26	39.14	95.96
Energetic Arousal [0-100][a]	57.44 ± 11.91	22.46	85.83
Temperature [°C/day][b]	7.84 ± 4.72	-1.82	18.83
Precipitation [mm/day][c]	118.33 ± 202.60	0	1038
Wear time accelerometer [h/day][b]	23.26 ± 1.53	13.70	24
Sedentary time [h/day] [d]	9.60 ± 2.14	4.19	14.99
Movement acceleration [mg/day][d]	45.65 ± 12.79	21.79	91.06

[1] standard deviation; [a] assessed via e-diary, aggregated within participants; [b] average per day across study period; [c] sum per day across study period; [d] aggregated within participants and days.

2.2 Study procedures

The assessment took place over five consecutive days from Wednesday to Sunday to cover weekdays and weekends. The participants received individualized training to become familiarized with the accelerometers (move 4) and the loaned smartphone (Nokia 6, Nokia Corporation, Espoo, Finland, Android phones) [51]. The participants wore the accelerometers at three different positions (i.e., wrist, hip, and thigh) for 24 hrs per day and answered e-diary questions between 8.00 am and 9.30 pm on weekdays and between 9.30 am and 10 pm on weekends.

2.3 Study design

We used a mixed sampling strategy, combining activity-triggered assessments, sedentary-triggered assessments, and randomly triggered assessments. Technically, the thigh sensor analyzed and transmitted data on body position and movement acceleration to the smartphone in real-time via Bluetooth Low Energy.

Combined with random prompts, we used a sedentary-trigger algorithm that prompted the participants when they had spent ≥30 consecutive minutes in a sitting/lying body position (for details, see [46]), as well as an activity-triggered algorithm that prompted the participants if they spent ≥10 consecutive minutes of ≥ 220 mg (for details, see [45]). To reduce participant burden, time-out phases of 50 min were programmed, i.e., after an e-diary trigger, the participants would not receive another trigger in the following 50 min. If the prompt appeared at an inconvenient time, the participants had the option to postpone it by 5, 10, or 15 min. The three trigger conditions (sedentary, active, and random) were prompted until two of each were answered a day. This resulted in a maximum of six answered e-diary entries per day. The mixed sampling strategies and the e-diary assessments were implemented via movisensXS, version 0.7.47574 (movisens GmbH, Karlsruhe, Baden-Wuerttemberg, Germany).

2.4 E-diary assessments

To assess momentary affect, we used the 6-item e-diary scale of Wilhelm and Schoebi, which is the first scale designed and evaluated solely for e-diary research [14]. It is constructed on a three-dimensional concept of affect, including valence, energetic arousal, and calmness. The six bipolar item scale is divided into these three respective affect dimensions: valence (item 5: unwell to well; item 2: discontent to content), energetic arousal (item 4: without energy to full energy; item 1: tired to awake) and calmness (item 6: tense to relaxed; item 3: agitated to calm). The bipolar items were displayed to the participants in a mixed order and with reversed polarity. The participants were able to express the varying degrees of their current affective state using a visual analog scale (0-100). The scale showed satisfying psychometric properties, both in the original publication [14] and in our dataset, with reliability coefficients on the within-person level ranging between 0.74 and 0.81 in our sample.

2.5 Physical behavior measures

The Move 4 accelerometer is a validated device for measuring PB [52, 53]. The sensor measures triaxial acceleration with a range of ± 16 g, a sampling frequency of 64 Hz, and a resolution of 12 bits. The raw data from the sensor were saved to its internal memory card and bandpass filtered (0.25 to 11 Hz) to eliminate artifacts. PA and SB were calculated from the accelerometer's raw files in 1-min epochs using the software DataAnalyzer (version 1.13.7; movisens GmbH). PA was operationalized as the aggregated triaxial mean movement acceleration intensity in the gravitational constant g (9.81 m/s2) in 10 min segments after each e-diary entry, according to published procedures [16, 18]. The outcome variable mg indicates the intensity of physical behavior (e.g., jogging is about 1103 mg/min, walking is 367 mg/min and sitting 7 mg/min [53]).

SB was parameterized as the number of aggregated sedentary minutes within the 30 min time frame after each e-diary entry [21].

2.6 Meteorological measures

Meteorological data were retrieved from a publicly available dataset from the Climate Data Center of the German Weather Service (Deutscher Wetterdienst; DWD) [54, 55]. Specifically, we obtained hourly values for temperature [°C] and precipitation [mm] from a weather station in Rheinstetten [56], which is located approximately seven kilometers from the Karlsruhe Institute of Technology (station id: 4177; longitude: 48.5847; latitude: 8.1952, height: 116 m). We aligned temperature values to 60 min intervals before each e-diary assessment.

2.7 Data analysis

PA and SB data were merged with the ratings of the e-diary entries (using the software DataMerger, version 1.8.0, movisens GmbH) and the hourly weather parameters (via SPSS). The outcome parameter movement acceleration was log-transformed using a natural logarithm since the distribution was right-skewed. The skew statistic was 4.07, and after applying log-transformation to the PA data, skewness was reduced to 0.22.

Multilevel models were conducted to examine momentary within-person effects of affective states on subsequent PB outcomes [57]. In the calculated models, repeated measurements (on level-1) within participants (on level-2) were nested. First, we estimated the intraclass correlation coefficient (ICC), whereby the logarithmized values of movement acceleration [mg] and SB [min] served as dependent variables to indicate the amount of variance on the within- vs. between-person level by calculating unconditional (null-) models. Second, we added the time-variant and time-invariant predictors time [hour], time-squared [hours^2], age [years], sex [female vs. male], calmness [0-100], energetic arousal [0-100], valence [0-100] and BMI [m/kg^2] to our main model (see equation for hypothesis Ia below).

Model 1 (hypothesis Ia):

$$Y(movement\ acceleration)_{ij} = \gamma_{00} + \gamma_{01} * age_j + \gamma_{02} * BMI_j + \gamma_{03} * sex_j \quad + \gamma_{10} * \\ + \gamma_{40} * time\ of\ day_{ij} + \gamma_{50} * time\ of\ day_{ij}^2 + r_{ij}$$

On level 1, within-subject effects were estimated through participants' e-diary entries (subscript $_j$) at each measurement time point (subscript $_i$). Y_{ij} reflects the level of movement acceleration in person *j* at the time *i*. At level 1, beta coefficients represent the intercept (γ_{00}) and the effects of time, time-squared, within-subject valence, energetic arousal, and calmness (γ_{10}- γ_{50}). At level 2, beta coefficients represent time-invariant covariates (γ_{01}- γ_{03}). r_{ij} represents the residuals at level 1. Additionally, a multilevel random-intercept model was conducted to test whether the type of trigger (i.e., random vs. PB-triggered) might influence our main findings from hypotheses (Ia-IIb). Third, we added the weather parameters temperature [°C] and precipitation [mm] to our main model as time-variant predictors. Fourth, we conducted exploratory interaction analyses for PA and SB combining all possible interactions between affective states and weather parameters (i.e., resulting in twelve different interactions) (see equation in Additional file 1). We centered the affective states and weather predictors on a personal level. Significant random effects were included in our models. We specified our models by using restricted maximum likelihood (REML) as the model estimator and unstructured as covariance structure. To compare each predictor's effects, we calculated standardized beta coefficients (stand. β) following established procedures [54]. To compare the model fit, we used the -2ΔLL likelihood ratio test. To calculate the proportion of explained total outcome variance, we used the predicted outcome's squared correlation (R2) by using the fixed effects and actual values. Following established simulation studies towards multilevel power analysis [58], our data are suited for the detection of small within-subject effects and medium to large between-subject effects. To draw practical conclusions concerning the impact of alterations in contextual dimensions on PA, the percentage change rates were calculated using the following equation (see [16]). A 1-point increase in temperature (C°) would lead to a percentage change in PA by

$$\delta = ((e^{\beta(temperature)\times 1})\text{-}1) \times 100$$

For all analyses, the α-level was set to 0.05. All data analyses were conducted with SPSS software (IBM), version 26.0.0.0. We followed the strengthening the reporting of observational studies in epidemiology (STROBE) reporting guidelines (see Additional file 2) in reporting analyses and results.

3 Results

3.1 Descriptive statistics

In total, 2537 e-diary prompts were sent. On average, the 79 participants received 32 (range = 14-47; SD = 6.61) prompts during the study week, of which the participants responded to an average of 20.8 prompts over the five days (see Table 1). This resulted in an overall compliance of 66% (SD = 16.65). The average score reported by the participants for valence was 70.37 (SD = 12.26), for energetic arousal was 57.44 (SD = 11.91), and for calmness was 67.51 (SD = 13.03) on a scale of 0-100. The intraclass correlation coefficient (ICC) showed that 90.58% of SB (30 min timeframe) and 91.79% of PA (10 min timeframe) were due to within-subject fluctuations within the sample. The accelerometers were worn for an average of 23.26 (SD = 1.53) hrs per day per participant. Furthermore, the mean PA across participants was 45.65 mg (range = 21.79-91.06; SD = 12.79), and the mean time spent in SB was 9.6 hrs (range = 4.19-14.99; SD = 2.14) per day. The daily mean temperature ranged from -1.82 to 18.83 °C, with an average of 7.84 °C (SD = 4.72). The daily sum of precipitation ranged from 0 to 1038 mm (mean 118.33; SD= 202.60; 1000 mm equals 1 l/m^2). The 60 min timeframes of weather parameters prior to the e-diary prompts ranged from -3.42 to 25 °C (temperature) and from 0 to 3.93 mm (precipitation), respectively.

3.2 Association of affective states with physical behavior

Confirming hypothesis Ia, higher levels of valence and energetic arousal predicted higher levels of PA (stand. $\beta = 0.134$, $p < .001$; stand. $\beta = 0.156$, $p < .000$, respectively). That is, momentary ratings of valence and energetic arousal were positively associated with the subsequent movement acceleration within the 10 min after e-diary assessments. Translated to practice, on average, higher momentary ratings of valence (e.g., 80) compared to lower ratings (e.g., 20) were associated with subsequent higher levels of PA (12.23 mg). On average, higher ratings of energetic arousal (e.g., 80) compared to lower ratings (e.g., 20) were associated with subsequent higher amounts of PA of about 13.26 mg. As hypothesized, an increase in calmness negatively predicted movement acceleration (stand. $\beta = -0.130$, $p < .001$). This means, when participants felt more relaxed and calm (e.g., 80) compared to lower calmness ratings (e.g., 20), on average, their subsequent PA was 14.47 mg lower in the 10 min after each e-diary prompt. None of the other predictors (age, sex, BMI, time, time-squared) showed any significant influence on PB. We found no significant random effects for any predictors. A robust analysis showed that the main findings of our models (1-3b) were independent of the type of trigger (random vs. PB-triggered). In particular, adding the type of trigger as a covariate to the reported models did not change any significant values of our main findings. The results are presented in Table 2.

Table 2: Multilevel model analyses to predict physical behavior: fixed and random effects.

		PA models					SB models	
		Model 1 b /stand. b (SE)	Model 2 b /stand. b (SE)	Model 3 b /stand. b (SE)	Model 3 b /stand. b (SE)	Model 1b b /stand. b (SE)	Model 2b b /stand. b (SE)	Model 3b b /stand. b (SE)
Fixed effects	Intercept, β_{00}	3.393** (.570)	3.499** (.571)	3.519** (.575)	3.514** (.571)	22.167** (5.810)	21.450** (5.773)	21.438** (5.870)
	Sex[a], β_{03}	.076/.037 (.090)	.076/.036 (.090)	.073/.036 (.091)	.077/.038 (.090)	-.199/-.010 (.915)	-.202/-.009 (.908)	-.233/-.011 (.923)
	Age, β_{01}	-.009/-.025 (.010)	-.009/-.024 (.010)	-.009/-.026 (.010)	-.009/-.026 (.010)	-.175/-.048 (.099)	-.173/-.049 (.098)	-.173/-.047 (.100)
	BMI, β_{02}	-.017/-.033 (.022)	-.017/-.033 (.022)	-.016/-.032 (.022)	-.017/-.033 (.022)	-.029/-.006 (.226)	-.028/-.005 (.224)	-.029/-.006 (.228)
	Calmness, β_{30}	-.006**/-.130 (.002)	-.006**/-.128 (.002)	-.006**/-.126 (.002)	-.006**/-.127 (.002)	.054*/.109 (.018)	.051**/.109 (.018)	.054**/.108 (.018)
	Valence, β_{10}	.007**/.134 (.002)	.007**/.137 (.002)	.007**/.140 (.002)	.007**/.141 (.002)	-.026/-.049 (.021)	-.025/-.051 (.021)	-.028/-.054 (.021)
	Energetic Arousal, β_{20}	.007**/.156 (.001)	.007**/.157 (.001)	.007**/.156 (.001)	.007**/.161 (.001)	-.017/-.038 (.014)	-.019/-.039 (.014)	-.019/-.041 (.014)
	Temperature, β_{60}	---	.025/.139* (.010)	.026**/.138 (.009)	.025**/.136 (.009)	---	-.146/-.084 (.086)	-.150/-.081 (.086)
	Precipitation, β_{70}	---	.007/.003 (.081)	.008/.003 (.081)	.005/.002 (.081)	---	-.366/-.014 (.768)	-.365/-.014 (.767)
	Calmness*temperature, β_{80}	---	---	.001*/.072 (.001)	---	---	---	---
	Valence*temperature, β_{80}	---	---	---	.001*/.075 (.001)	---	---	-.011*/-.066 (.005)
	Time of day, β_{40}	.069**/.265 (.025)	.032/.120 (.028)	.027/.102 (.028)	.030/.114 (.028)	.034/.013 (.244)	.267/.101 (.277)	.276/.106 (.273)
	Time of day squared, β_{50}	-.005**/-.260 (.002)	-.002/-.124 (.002)	-.002/-.108 (.002)	-.002/-.116 (.002)	.009/.053 (.017)	-.006/-.029 (.019)	-.006/-.036 (.019)

			PA models				SB models	
		Model 1 b /stand. b (SE)	Model 2 b /stand. b (SE)	Model 3 b /stand. b (SE)	Model 3 b /stand. b (SE)	Model 1b b /stand. b (SE)	Model 2b b /stand. b (SE)	Model 3b b /stand. b (SE)
Ran-dom	Inter-cept, u_0	.087** (.022)	.087** (.022)	.089** (.023)	.087** (.022)	9.663** (2.428)	9.475** (2.409)	.089** (.023)
	Residual, r	.885** (.033)	.870** (.033)	.878** (.032)	.878** (.032)	90.753** (3.223)	89.106** (3.229)	.878** (.032)

Note[1]: Unstandardized / standardized estimates and standard errors [a] compared to males * P<.05 ** P<.01

The affective states valence and energetic arousal did not significantly predict sedentary time in the consecutive 30 min to the e-diary prompt (stand. $\beta = -0.050$, $p = .226$; stand. $\beta = -0.038$, $p = .209$, respectively); thus, hypothesis Ib regarding valence and energetic arousal was not verified. As it was assumed, higher levels of calmness significantly predicted more time spend sedentary in 30 min following the e-diary prompt (stand. $\beta = 0.109$, $p = .003$), thus verifying hypothesis Ib regarding calmness. In practice, a 1-point increase in calmness (scale: 0-100) led to an increase in SB of 0.05 min in the 30 min timeframe following the e-diary prompt.

3.3 Association of contextual weather conditions on physical behavior

In our second model, we tested whether contextual weather conditions predicted within-subject variations in PA intensity or time spent in SB. According to hypothesis IIa, we found a significant positive association between temperature and PA intensity. In detail, higher degrees of temperature positively influenced PA intensity (stand. $\beta = 0.139$, $p = 0.005$). There was no significant association between the amount of hourly precipitation on the subsequent PA intensity (stand. $\beta = 0.003$, $p = 0.967$) (hypothesis IIb). In addition, we found no significant within-subject associations between the predictors temperature (stand. $\beta = -0.084$, $p = 0.156$) and precipitation (stand. $\beta = -0.014$, $p = 0.633$) on time spent in SB (hypotheses IIa and IIb).

3.4 Exploratory interaction analyses

Three out of twelve exploratory multilevel models (3 affective states * 2 contextual weather conditions predicting 2 physical behaviors) revealed a significant interaction of affective states and contextual weather conditions on PB. In particular, temperature positively moderated the association between valence and PA (stand. $\beta = 0.075$, $p = .036$). This is depicted in Figure 1, showing all three effects, namely, the two main effects as well as the interaction. First, the main effect of temperature on PA is depicted in the orange area. A 5 °C temperature above the personal average would increase subsequent activity behavior by approximately 12.5% (light blue triangle), whereas a 5 °C temperature below the personal average would predict lower PA (dark blue rhombus). Second, the main effect of valence on PA is shown by the dashed blue line. If valence is rated higher by five points, the subsequent activity behavior in the 10 min after the e-diary prompt was increased by approximately 3.5%. Third, the interaction effect, which is the effect of valence on PA moderated by temperature, is depicted by the three different slopes (light blue triangle, dashed blue square, dark blue rhombus). A 5 °C temperature above the personal average was linked to a steeper association between valence and PA (light blue triangle) compared to the average context (dashed blue line with squares), whereas in the 5 °C temperature below the personal average condition, the slope is much lower (dark blue rhombus line). In other words, the temperature enhances the effect of valence on PA.

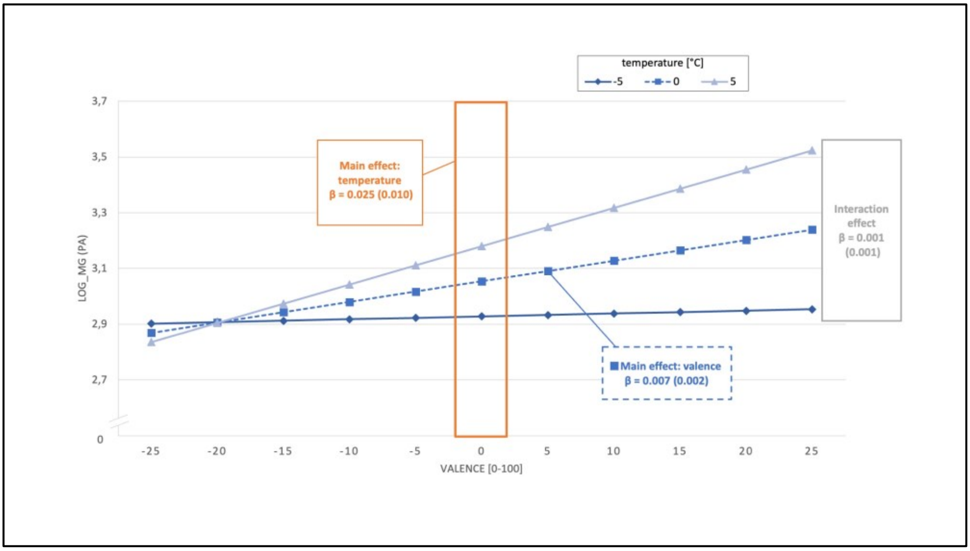

Figure 1: Beta coefficients of the ML model demonstrating the main effect of valence, the main effect of temperature and the interaction of valence*temperature on physical activity. Y-axis: log-transformed mg values; X-axis person-centered valence.

The second interaction model showed that temperature negatively moderated the association between valence and SB (stand. β = -0.066, p = 0.043), as demonstrated in Figure 2. The main effect of temperature on SB is depicted in the orange area, showing that 5 °C above the personal average was associated with a decrease in subsequent SB, whereas 5 °C below the personal average showed the opposite effect. The main effect of valence on SB was negative and shown by the dashed blue line. Increasing valence was related to less SB (non-significant). The interaction, which was the effect of valence on SB moderated by temperature, is depicted by the three different slopes. A 5 °C temperature above the personal average is linked to a steeper negative association between valence on SB (light blue triangle), whereas in the 5 °C temperature below the personal average condition, the slope is positive (dark blue rhombus). In other words, the effect of positive valence reducing SB was enhanced at higher temperatures.

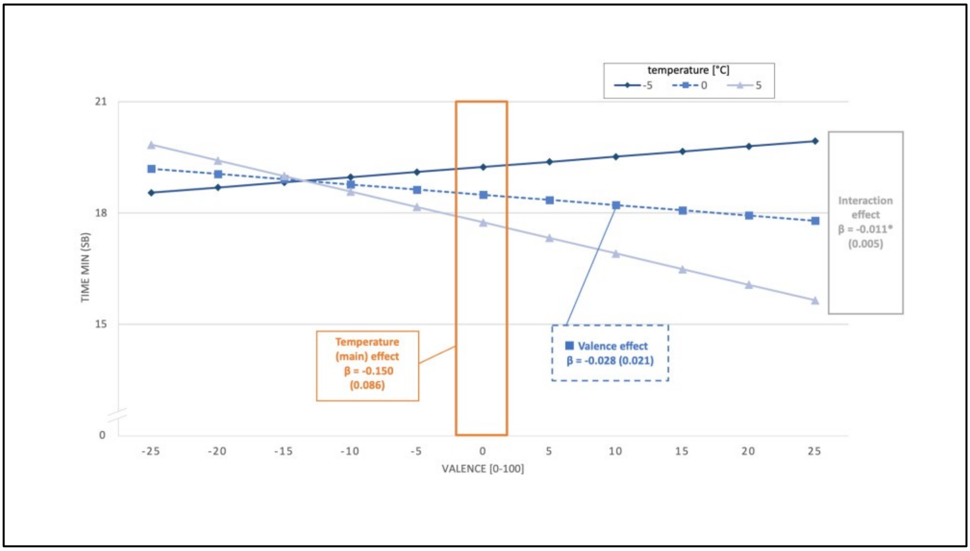

Figure 2: Beta coefficients of the ML model demonstrating the main effect of valence, the main effect of temperature and the interaction of valence*temperature on sedentary behavior. Y-axis: amount of time (min) spent in sedentary behavior; X-axis: person-centered valence.

Furthermore, the third significant interaction model showed that the effect of calmness on PA was moderated by temperature (stand. β = 0.072, p = 0.019), which is depicted in Figure 3. The main effect of temperature on PA is depicted in the orange area. A temperature 5 °C above the personal average increased subsequent PA by approximately 13% (light blue triangle), whereas a temperature 5 °C below the personal average predicted lower PA (dark blue rhombus). The negative association between calmness and PA is shown by the dashed blue line, with a 5-point increase in calmness resulting in 3% less PA. The interaction, which is the effect of calmness on PA moderated by temperature, is depicted by the three different slopes. A 5 °C temperature above the personal average was linked to a less pronounced association between calmness and PA (light blue triangle), whereas in the 5 °C temperature below the personal average condition, the slope is more negative (dark blue rhombus line). Oversimplified, the negative effect of calmness on PA dissolves with higher temperatures.

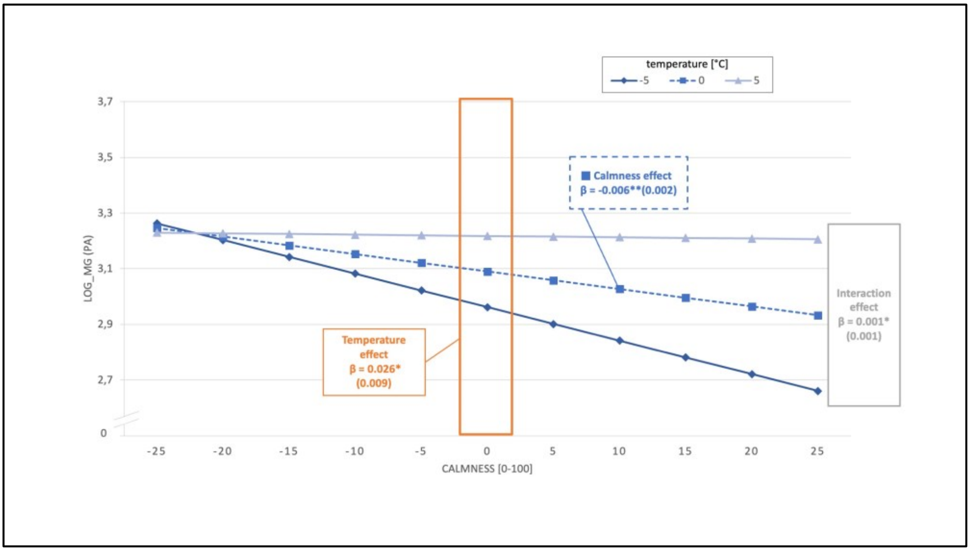

Figure 3: Beta coefficients of the ML model demonstrating the main effect of calmness, the main effect of temperature and the interaction of calmness*temperature on physical activity. Y-axis: log-transformed mg values; X-axis: person-centered calmness.

4 Discussion

To better understand how the interplay between affective states and contextual weather conditions drives our everyday life PB, we investigated momentary affective states (i.e., valence, energetic arousal, and calmness), contextual factors (i.e., precipitation and temperature), and PB in a sample of healthy adults. There was some evidence that the association between affective states and PA was moderated by temperature. In addition, we found associations between momentary contextual weather conditions and PA, and we confirmed earlier findings associating affective states with PB. Our exploratory interaction analyses have shown that contextual weather conditions slightly moderated the association between within-subject affective states and PB in three models. In detail, a higher temperature tentatively a) enhanced the positive effect of valence on PA, b) enhanced the effect of valence on reducing SB, and c) dissolves the negative effect of calmness on PA.

We confirmed that higher ratings of momentary energetic arousal and valence led to subsequent increases in PA intensity, whereas momentary calmness led to reductions in subsequent PA intensity (hypothesis Ia). These findings are in line with most previous studies that used similar methods [15]. In particular, several studies examined the short-term association with positive affect and the duration of accumulated subsequent PA levels (e.g., 10-30 min) provide evidence for positive affect predicting increased PA [59–61]. The same associations between affective states (i.e., valence, energetic arousal, calmness) and non-exercise activity were revealed by Reichert and colleagues [18], Kanning and Schoebi [17] in adults as well as by Koch and colleagues [16] in adolescents. These studies also applied short time frames for their analyses (i.e., 10-45 min). However, Kim and colleagues [20] used extended time intervals (PB up to 120 min after ratings of affect) and rarely found an association between affective states and PB, whereas Stavrakakis and colleagues [62] utilized 360 min revealing no associations in the affective dimension positive affect and another study found no associations of positive affect influencing subsequent PA after 1440 min [63]. Future studies might give greater consideration to the temporal resolution of associations between PB and affective states.

In contrast to our hypothesis Ib, momentary calmness but not valence and energetic arousal significantly predicted upcoming SB. In detail, higher momentary valence was not associated with subsequent device-measured SB, which was consistent with Kim and colleagues [20] in a sample of working adults but not consistent with several other studies showing that elevated valence was associated with decreased sedentariness [21, 64, 65]. We also revealed no association of energetic arousal with subsequent SB. This finding was supported by some other studies [65, 66], but contrary to Giurgiu and colleagues [21] and Kim and colleagues [20] that showed a relation between higher activation and reduced sedentary time. In line with our expectations, higher momentary calmness was associated with subsequently lower amounts of SB, thus confirming hypothesis Ib. Another study investigated the associations of calmness with SB and thus supported our findings [21].

The diverse findings might be due to a high degree of heterogeneity in the methodological assessments of PB and affect (e.g., accelerometer location, parametrization of SB, sample design, applied questionnaire, and item selection). We closely followed the methodological approach of previous studies [16, 18, 21] to enable comparability. Replication of methods and study designs is highly needed for establishing the reproducibility and generalizability of the findings and for future meta-analyses to integrate findings. Moreover, future research endeavors might be interested in researching a reciprocal nature between affective states and PB and their interactions with weather conditions, e.g., by applying dynamic structural equation modeling and through exploration of potentially more time-enduring (‘trait-like’) effects. Further analyses revealed that there was an association between temperature with PA, but not with SB (hypothesis IIa). In detail, temperature was independently positively associated with subsequent PA. This finding was supported by three studies that also objectively assessed temperature. In a sample of older adults, lower temperatures resulted in up to 10% less PA [67], and higher temperatures increased walking and cycling among adults [68, 69]. Studies with self-defined perceptions of weather conditions also support our findings [30, 63]. In contrast to our hypothesis, the amount of precipitation was not associated with PB (hypothesis IIb). Our results were in line with a study that examined daily precipitation and its influence on PA in over 200 adults and found no significant association [70]. Furthermore, in a sample of elderly individuals, Colom and colleagues [71] found no association between precipitation measured at the daily level and PA - either objectively measured via accelerometer or self-reported. However, in a study with COPD patients over 12 months, it was shown that the hours of rain per day were negatively associated with the number of steps taken [72].

In contrast to our hypothesis (IIb), we found no association between contextual weather conditions and SB, which is, at least partially, in contrast to the literature. In detail, Yildirim and colleagues [73] found a positive significant relationship between precipitation and SB in a sample of N=722 children. Sartini and colleagues [74] found a positive relation between SB and temperature in 1361 elderly individuals. One study revealed that SB was reduced when weather conditions change from rainy to sunny days [75], whereas another found an association between SB and temperature only on weekends [76]. However, in all those studies, meteorological data were analyzed on a daily basis, rather than an hourly basis as in our study.

How can our null findings be explained, given that our methods might be superior (hourly meteorological data; multisensor system to detect sedentariness). One possible explanation might be restricted variance. Our sample consisted of working adults who may exhibit a maximum of SB due to their work life. This might be less extreme in other studies with children and adolescents [48] and elderly individuals [74]. In addition, precipitation was quite low in our sample. However, having a higher timely resolution might mitigate this issue, thereby increasing variance over time. Additionally, it is theoretically possible that momentary weather conditions may influence a person's activity behavior more than average weather conditions throughout the day. Another explanation for the positive findings of the other studies might be their approach to detect SB. Using a wrist sensor might conflate true SB with PA and bias standing and sitting phases [52], thereby revealing associations between both constructs.

To the best of our knowledge, this is the first study that investigated moderation effects based on device-based data, whereas previous studies investigating the subjective appraisal of self-perceived weather conditions [30] in relation to PB on a daily level [63] revealed inconclusive results, which prevents us from discussing our findings against the background of the literature. However, our results may provide potential implications for future real-life interventions if replicated and verified to be of causal nature. It should be noted that the effects we found were small and thus should be interpreted with caution for further recommended actions. One may be tempted to speculate that intervention strategies on affective valence to increase PA and to decrease sedentary time should be especially applied at times and in settings with an above-average air temperature. According to our results, influencing affective valence in this context (e.g., via emotion regulation strategies such as mindfulness training) might be especially promising to counteract physical inactivity. Moreover, we are tempted to speculate that interventions on feelings of stress and calmness aiming to alter PA seem to be more promising when air temperature is below average since our findings showed calmness to scarcely be associated with PA in contexts of high air temperature. As a next step beyond replication and causality testing, differences between persons in these complex interactions should be researched. In summary, tailoring mobile interventions based not only on psychological determinants of PB but also on contextual influences such as weather conditions and especially on the interaction of psychological determinants with contextual influences may offer promising avenues for just-in-time adaptive interventions (JITAI) [77] to reduce physical inactivity. For example, future research endeavors might be interested in developing a "physical activity prediction" application or trigger based on the current mood and the upcoming weather forecast. With regard to changes in climatic conditions, awareness has to be raised that environmental factors might influence the promotion of PA. So far, the influences of seasonal conditions and weather factors have received little attention in the promotion of PA [78]. In our study, we demonstrated that temperature alterations might have the potential to influence subsequent PA. If this were to be the case, for example, community sports settings and outdoor summer sports may be most affected by climatic changes [23, 26]. This could be a pertinent indication for the development of health policy strategies to counteract this progress, as weather phenomena may be a deterrent for people to engage in PA.

Some limitations must be considered. First, our sample was recruited from university staff, which may hinder generalization to the general population. Also, larger sample sizes might be superior in terms of generalizability and between-subject effects. Second, our observed associations between affective states, PB, and weather conditions included data from September to March during the European fall and winter seasons, thus, limiting a generalization to other geographic areas with different weather conditions and physical behavior. Furthermore, the within-subject variability in precipitation was quite limited in our sample, which might have increased the difficulty of revealing meaningful associations. Future studies should consider potential seasonal effects, prolonged periods of time covering different seasons, and locations with higher precipitation. Third, we assessed contextual weather conditions objectively with a high temporal resolution. It is assumed that contextual weather conditions are linked to PA in an inverted u-shaped pattern, indicating that PA within individuals decreases under extreme weather conditions (e.g., ≥ 30 C°) [79–82]. Sound empirical evidence for those assumptions would require long-term monitoring across all seasons, and probably, the subjective perception of weather conditions. Assessing the individual subjective feeling of weather conditions (e.g., too cold, too hot) in addition to objective weather data from local stations might be a favorable add-on in future studies. Another limitation inherent in our study pertains to the exclusion of participants and single days in which participants did not reside within the proximity of the weather station. Future studies could address this issue by incorporating GPS data to track participants' location. Fourth, chronology only represents one aspect of causality [83]. Chronology suggests causality though does not prove it, as hidden third variables could have similar time-related characteristics. Additional studies are needed to support a causal hypothesis; one approach could be to employ ecological momentary interventions (EMI) to experimentally induce effects of PB in everyday life [84], potentially taking into account weather effects.

5 Conclusions

In this ambulatory assessment study, we investigated how within-subject affective states as well as weather conditions are associated with subsequent physical behavior, using recurring real-time and real-life assessments of affective states combined with device-based measured physical behavior in the everyday life of a community-based sample. We also explored the interaction of affective states, weather conditions, and physical behavior. We found that both momentary valence and energetic arousal were positively related to subsequent PA whereas calmness led to reductions in PA within the subsequent timeframe. In particular, the more participants felt content, energetic, and less calm in everyday life, the more they were physically active. Momentary calmness significantly predicted upcoming SB – in practice, if participants felt calmer and more relaxed, they engaged in more sedentary time. We also found temperature positively related to subsequent PA. Participants tended to be more physically active when temperatures were higher within the German fall and winter season, characterized by rather mild temperatures (10 C°/4.2 C° [85]). Furthermore, our exploratory interaction analyses showed small effects of weather conditions moderating the association between within-subject affective states and PB. In detail, higher temperatures enhanced the positive effect of valence on PA and on reducing SB and also dissolves the negative effect of calmness on PA. Long-term studies including vulnerable groups and covering additional climate zones are needed to observe the associations between weather variables and physical behavior. Future studies could identify at which environmental condition a decrease in physical activity occurs - for example, due to heat waves or air pollution [86]. Moreover, JITAIs could be assessed to encourage PA as they offer the possibility to incorporate momentary affect or contextual factors, such as weather conditions, in real-time and allow triggering individuals within their preferred conditions to promote PA. Such personalized real-time prompts should theoretically be superior and require an understanding of the influence of affect dimensions and weather conditions on an individual's behavior. JITAIs can incorporate opportunities for PA that have obscured the effectiveness of interventions in promoting PA. This may contribute to people adopting a physically active lifestyle, which can contribute to overall improved health outcomes.

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Additional files

Additional file 1.

Model 1:

$$Y(movement\ acceleration)_{ij}=\gamma_{00}+\gamma_{01}*age_j+\gamma_{02}*BMI_j+\gamma_{03}*sex_j++\gamma_{10}*valence_{ij}$$
$$+\gamma_{20}*energetic\ arousal_{ij}+\gamma_{30}*calmness_{ij}\gamma_{40}*time\ of\ day_{ij}+\gamma_{50}*time\ of\ day_{ij}^2+r_{ij}$$

$$Y(sedentary\ time)_{ij}=\gamma_{00}+\gamma_{01}*age_j+\gamma_{02}*BMI_j+\gamma_{03}*sex_j++\gamma_{10}*valence_{ij}$$
$$+\gamma_{20}*energetic\ arousal_{ij}+\gamma_{30}*calmness_{ij}\gamma_{40}*time\ of\ day_{ij}+\gamma_{50}*time\ of\ day_{ij}^2+r_{ij}$$

Model 2:

$Y(\textit{movement acceleration})_{ij}=\gamma_{00}+\gamma_{01}*\textit{age}_j+\gamma_{02}*\textit{BMI}_j+\gamma_{03}*\textit{sex}_j+\gamma_{10}*\textit{valence}_{ij}$
$+\gamma_{20}*\textit{energetic arousal}_{ij}+\gamma_{30}*\textit{calmness}_{ij}+\gamma_{40}*\textit{time of day}_{ij}+\gamma_{50}*\textit{time of day}_{ij}^2+$
$\gamma_{60}*\textit{temperature}_{ij}+\gamma_{70}*\textit{precipitation}_{ij}+r_{ij}$

$Y(\textit{sedentary time})_{ij}=\gamma_{00}+\gamma_{01}*\textit{age}_j+\gamma_{02}*\textit{BMI}_j+\gamma_{03}*\textit{sex}_j+\gamma_{10}*\textit{valence}_{ij}$
$+\gamma_{20}*\textit{energetic arousal}_{ij}+\gamma_{30}*\textit{calmness}_{ij}+\gamma_{40}*\textit{time of day}_{ij}+\gamma_{50}*\textit{time of day}_{ij}^2+$
$\gamma_{60}*\textit{temperature}_{ij}+\gamma_{70}*\textit{precipitation}_{ij}+r_{ij}$

Model 3:

$Y(\textit{movement acceleration})_{ij}=\gamma_{00}+\gamma_{01}*\textit{age}_j+\gamma_{02}*\textit{BMI}_j+\gamma_{03}*\textit{sex}_j+\gamma_{10}*\textit{valence}_{ij}$
$+\gamma_{20}*\textit{energetic arousal}_{ij}+\gamma_{30}*\textit{calmness}_{ij}+\gamma_{40}*\textit{time of day}_{ij}+\gamma_{50}*\textit{time of day}_{ij}^2+$
$\gamma_{60}*\textit{temperature}_{ij}+\gamma_{70}*\textit{precipitation}_{ij}+\gamma_{80}*\textit{valence}_{ij}*\textit{temperature}_{ij}+r_{ij}$

$Y(\textit{movement acceleration})_{ij}=\gamma_{00}+\gamma_{01}*\textit{age}_j+\gamma_{02}*\textit{BMI}_j+\gamma_{03}*\textit{sex}_j+\gamma_{10}*\textit{valence}_{ij}$
$+\gamma_{20}*\textit{energetic arousal}_{ij}+\gamma_{30}*\textit{calmness}_{ij}+\gamma_{40}*\textit{time of day}_{ij}+\gamma_{50}*\textit{time of day}_{ij}^2+$
$\gamma_{60}*\textit{temperature}_{ij}+\gamma_{70}*\textit{precipitation}_{ij}+\gamma_{80}*\textit{calmness}_{ij}*\textit{temperature}_{ij}+r_{ij}$

$Y(\textit{sedentary time})_{ij}=\gamma_{00}+\gamma_{01}*\textit{age}_j+\gamma_{02}*\textit{BMI}_j+\gamma_{03}*\textit{sex}_j+\gamma_{10}*\textit{valence}_{ij}$
$+\gamma_{20}*\textit{energetic arousal}_{ij}+\gamma_{30}*\textit{calmness}_{ij}+\gamma_{40}*\textit{time of day}_{ij}+\gamma_{50}*\textit{time of day}_{ij}^2+$
$\gamma_{60}*\textit{temperature}_{ij}+\gamma_{70}*\textit{precipitation}_{ij}+\gamma_{80}*\textit{valence}_{ij}*\textit{temperature}_{ij}+r_{ij}$

Additional file 2.

Additional Table 1: STROBE Statement—Checklist of items that should be included in reports of observational studies

	Item No	Recommendation	Page No.
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	p. 1; lines 1-3
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	p. 2; lines 30-57
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	p. 4; lines 67-153
Objectives	3	State specific objectives, including any prespecified hypotheses	p. 7; lines 153-161
Methods			
Study design	4	Present key elements of study design early in the paper	p. 9; lines 191-206
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	p. 7; lines 164-165
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants	p. 7; lines 165-178
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	p. 9; lines 208-237
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	p. 9; lines 208-237
Bias	9	Describe any efforts to address potential sources of bias	p. 9; lines 199-201
Study size	10	Explain how the study size was arrived at	-
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	p. 10; lines 239-285
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	p. 10; lines 239-285
		(*b*) Describe any methods used to examine subgroups and interactions	p. 10; lines 239-285
		(*c*) Explain how missing data were addressed	-

		(*d*) If applicable, describe analytical methods taking account of sampling strategy	Not applicable
		(*e*) Describe any sensitivity analyses	Not applicable
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	p. 7; lines 165-178
		(b) Give reasons for non-participation at each stage	-
		(c) Consider use of a flow diagram	-
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	Table 1; p. 8; lines 179-182
		(b) Indicate number of participants with missing data for each variable of interest	-
Outcome data	15*	Report numbers of outcome events or summary measures	Table 1; p. 8; lines 179-182
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	Table 2; p. 14; lines 322-324
		(*b*) Report category boundaries when continuous variables were categorized	-
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	-
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	p. 15; lines 346-363
Discussion			
Key results	18	Summarise key results with reference to study objectives	p. 17; lines 401-411
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	p. 21; line 511-535
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	p. 16; line 412-469
Generalisability	21	Discuss the generalisability (external validity) of the study results	p. 20; lines 470-510; 511-513
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	Not applicable

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

Chapter V

General Discussion

In our research, we have explored the intricate relationship between physical behavior and affective well-being using ambulatory assessment approaches. This work has contributed to a growing body of knowledge that seeks to unravel the complex dynamics between physical activity, sedentary behavior and affective well-being in real-life contexts. Our findings have also shed light on the crucial role of contextual factors in modulating these relationships. We could show that:

- The current state of research examining the association between physical behavior and affective well-being reveals considerable heterogeneity, both in methodological approaches and outcomes. Despite this variability, a consistent pattern has emerged: feelings of energy are positively related to higher levels of physical activity (Timm et al., 2024).
- Considering additional contextual factors provides insight into other dynamic processes that influence the relationship between affective well-being and physical behavior. Notably, we found that affective well-being partially mediates the relationship between social contact and both physical activity and sedentary behavior. The presence of others and positive feelings were observed to enhance subsequent activity levels (Timm et al., submitted).
- Furthermore, the integration of external environmental conditions revealed a moderation of the association between affective well-being on subsequent physical behavior. Specifically, higher temperatures were found to amplify the positive effects of valence on subsequent physical activity (Timm et al., 2023).

The significance of this research is underscored by the tremendous interest in understanding the underlying processes of affective well-being dynamics and in promoting physical activity. This interest is driven by the well-established links between physical activity and reduced risk of non-communicable diseases (Katzmarzyk et al., 2022), as well as the association between sedentary behavior and increased all-cause mortality (Owen et al., 2010). Previous research has indicated that the relationship between affective well-being and physical behavior is characterized by equivocal findings that resist simple summarization (Bourke et al., 2021a; Liao et al., 2015; Vries et al., 2020). This heterogeneity suggests the involvement of additional contextual factors at various levels, including intrapersonal, social, and environmental domains. While some Ecological Momentary Assessment (EMA) studies have begun to examine contextual factors such as weather (Bejarano et al., 2019) and social contact (Boyle et al., 2020), as proposed by the socio-ecological model, our work has contributed to further illuminating the influence of these factors. Specifically, we have corroborated that i) social contact may play a significant role in the relationship between affective well-being and physical activity, and ii) weather factors, particularly temperature, have a moderating influence on the relationship between affective well-being and physical activity. However, numerous factors remain unexplored, presenting opportunities for future research endeavors to gain more comprehensive insights into the complex interplay between physical behavior, affective well-being, and contextual variables.

Based on our findings and the identified gaps in current knowledge, we explore the influence of various moderators and mediators on the relationship between physical behavior and affective well-being, organized within the framework of the socio-ecological model. We discuss the following points, which could be of interest to future research and have the potential to significantly advance the field:

First, we are extending the socio-ecological model with the dual-process Affective-Reflective Theory to explain how affective and reflective processes interact across different levels within the socio-ecological model. At the intrapersonal level, moderators such as physical activity self-efficacy, circadian rhythm, and glucose levels are examined. Second, at the social environment level, the roles of social support, dyadic relationships, and social networks are explored. Third, at the natural environment level, factors such as air pollution, walkability, and planetary health concerns (e.g., climate anxiety) are considered. Furthermore, the discussion integrates implications at each level for developing just-in-time adaptive interventions (JITAIs). By integrating contextual and individual factors, just-in-time adaptive interventions are providing hyper-personalized and real-time interventions for sustainable behavior change.

Contextual Integration in Affective Well-Being and Physical Behavior Research: A Paradigm Shift

According to Stokols, an individual is embedded in various layers of the socio-ecological model, including intrapersonal, interpersonal, organizational, community, and public policy levels (Stokols, 1992). This perspective becomes particularly compelling when considering the daily routines of individuals. For instance, the choice of commuting by car or bicycle, working from home or in the office, engaging in personal interactions with colleagues, partners or family, participating in physical activity sessions indoors or outdoors, and sedentary activities like watching TV, all represent distinct contextual layers that shape both affective well-being and physical behavior.

The socio-ecological framework offers a comprehensive approach to understanding physical activity behavior by incorporating psychosocial models at various levels. From a theoretical perspective, social cognitive theories have traditionally dominated research, attempting to explain and predict sustained physical activity engagement. The theory of planned behavior (Ajzen, 1985), social cognitive theory (Bandura, 1986), transtheoretical model of behavior change (Prochaska & DiClemente, 1984), and self-determination theory (Deci & Ryan, 1996) have been frequently cited in studies on health-protective behaviors and physical activity research (Rhodes & Nigg, 2011). However, a meta-analysis found that social cognitive models account for only 33% of the variance in physical activity (Plotnikoff et al., 2013), suggesting that cognitive theories alone may be insufficient to explain why individuals persist in physical inactivity. Kahneman (2011) describes two systems of thought: the first is a fast, instinctive, and automatic system that includes affective responses (Type 1 process), while the second is a slower system responsible for logical, rational decision-making and reflective evaluation (Type 2 process) (Kahneman, 2011). While traditional cognitive theories primarily address the second system, more recent dual-process theories (Ekkekakis, 2013; Evans & Stanovich, 2013) seek to incorporate affective components, proposing a reciprocal relationship between affective states and physical activity (Brand & Schweizer, 2015).

Extension of the Socio-Ecological Model with the Affective-Reflective Theory

Dunton highlights limitations in traditional health behavior theories, noting that they often neglect time as a covariate, overlook context-specific differences, and fail to account for the dynamic fluctuations and stabilities in behavior across settings (Dunton, 2017). The Affective-Reflective Theory (ART) builds upon these insights, advancing beyond established cognitive theories by positing that human rationality is not solely responsible for behavioral change (Brand & Ekkekakis, 2018). The Affective-Reflective Theory explains physical activity behavior through a dual-process approach, hereby distinguishing between automatic affective reactions (Type-1 process, i.e., affective, automatic) and reflective processes (Type-2 process, i.e., reflective, deliberate) (Brand & Ekkekakis, 2018). While the Type-1 process involves immediate, automatic affective responses based on during or, previous physical activity experiences, feelings and bodily sensations, the Type-2 process encompasses rational deliberations, for example, about past experiences, health knowledge, values, and personal goals (Brand & Ekkekakis, 2018). A key proposition of the Affective-Reflective Theory is that it offers an explanation for the frequent discrepancy between individuals' intentions to engage in physical activity and their actual behavior. It does account for the persistence of physical inactivity despite an individual's awareness of the positive effects of physical activity.

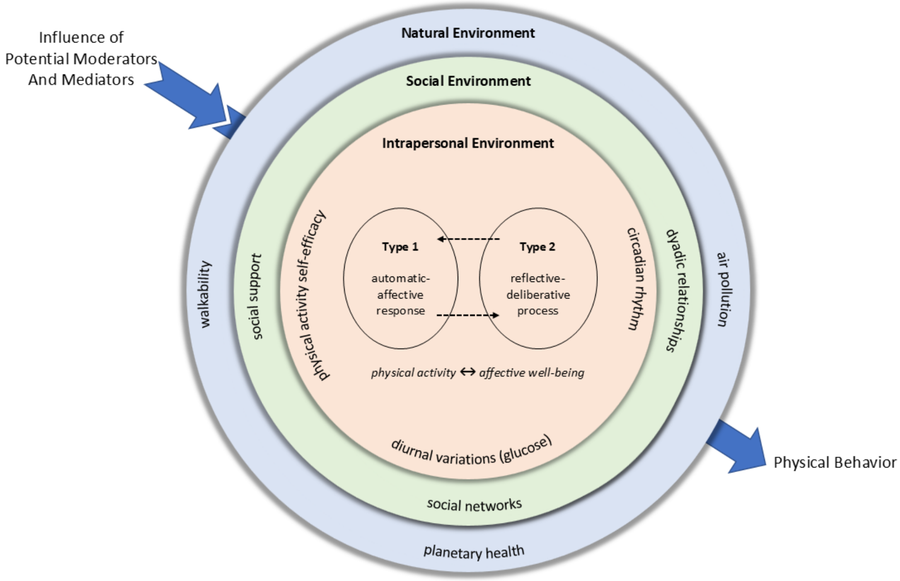

Figure 1: The newly developed model with the integration of the Affective-Reflective Theory into the socio-ecological framework and putative moderators and mediators influencing the affective well-being and physical behavior relationship (adapted from Sallis et al., 2006).

The integration of Affective-Reflective Theory within the socio-ecological framework allows for a more nuanced understanding of how environmental stimuli across different ecological levels influence physical activity behavior as moderators or mediators through both automatic and reflective pathways: In this now integrated scaffold, the socio-ecological framework provides the environmental and social contexts that act as stimuli for the affective and reflective processes described by the Affective-Reflective Theory (see Figure 1). These stimuli at each level - from intrapersonal to external environment - trigger both emotional reactions and thoughtful decision-making that influence physical activity behavior. This comprehensive approach acknowledges that health behaviors are not merely individual choices but emerge from complex interactions between individual and environmental factors across multiple levels.

In detail, at the intraindividual level, psychological and biological parameters can influence the affective well-being - physical behavior relationship. In particular, an individual's affective well-being and cognitive reflection can be influenced by bio-psychobehavioral factors like glucose, motivation, or self-efficacy, impacting the subsequent physical activity or sedentariness. Furthermore, at the second level, the social environment can act as stimuli, e.g., a supportive partner or friend might evoke positive emotions toward physical activity (affective response) or engage the individual in reflective thinking, like planning shared physical activity routines.

Additionally, concerning level three, external factors, such as temperature, air pollution, and access to safe, walkable parks, influence emotional and cognitive processes. For example, a pleasant environment may enhance mood, encouraging outdoor physical activity, while poor air quality might deter it. Thus, viewed holistically, the different layers of the socio-ecological framework can be approached as environmental-related stimuli that shape behavioral responses through both affective and cognitive pathways, determining whether an individual engages in physical activity or remains sedentary.

The methodological application of Intensive Longitudinal Data (ILD) is particularly suited to examining the processes outlined in this framework, as it allows disentangling dynamic individual processes through repeated assessments over time with a high density of real-life data (Trull & Ebner-Priemer, 2013). Ambulatory assessment emerges as an ideal method to collect data within the socio-ecological framework, capturing fluctuations in behavioral, biological, and psychological variables within-person processes in real-life environments (Ebner-Priemer & Trull, 2009). In addition to self-reported variables via triggered e-diaries (Ebner-Priemer et al., 2013; Intille, 2007) (e.g., mood, location, social context), ambulatory assessment enables the collection of various parameters, such as environmental conditions (e.g., noise, temperature, air quality), bio-markers (e.g., heart rate, blood pressure, glucose), social contact (e.g., via beacons), GPS tracking (Dorn et al., 2015; Reichert et al., 2017; Törnros et al., 2016), and physical activity data via accelerometers (Fahrenberg et al., 2007). This methodology allows for the examination of moderators and mediators, supporting a nuanced understanding of the socio-ecological model in everyday contexts in the relationship between affective well-being and physical behavior processes.

Existing ambulatory assessment studies have explored the impact of physical activity conducted across different socio-ecological layers on valenced affective responses

(Bourke et al., 2021b). In their systematic review, Bourke and colleagues found that outdoor activities (natural environment) were associated with greater pleasantness compared to indoor activities, while self-efficacy (intrapersonal level) explained inter-individual differences in the valenced response to physical activity. However, Bourke and colleagues' review primarily focused on studies capturing moderate-to-vigorous physical activity through accelerometers, which excludes everyday activities and represents a form of physical activity that is less frequently performed in daily life (Castro et al., 2020; Dyck et al., 2015; Giurgiu et al., 2019; Giurgiu, Koch, et al., 2020; Giurgiu, Plotnikoff, et al., 2020). Additionally, many of the included studies were conducted under controlled experimental conditions.

This shows a research gap for ambulatory assessment studies that include a comprehensive socio-ecological perspective, addressing factors across multiple layers without falling into the ecological fallacy (Zawadzki et al., 2016). To address these challenges, future research should adopt the above-outlined socio-ecological framework (see Figure 1) and the ambulatory assessment methodology, integrate diverse contextual variables to identify the interactions that influence physical activity and affective well-being with high ecological validity (Reichert, Giurgiu, et al., 2020). Recognizing that health behaviors are not solely individual choices but are shaped by complex interrelations between individual and environmental factors, this approach could lead to more effective strategies for promoting physical activity and enhancing overall well-being in the long run. The integration of just-in-time adaptive interventions offers additional potential by providing real-time, tailored behavioral support that responds to these multilayered interactions.

Layer 1. Integrating Intraindividual Factors: The Intrapersonal Environment

Affective Well-Being, Physical Behavior and Physical Activity Self-Efficacy

Self-efficacy can be conceptualized as the individual's belief in their own ability to accomplish tasks and achieve goals (Bandura, 1977, 1997). Regarding a domain-specific form of self-efficacy, physical activity self-efficacy refers to an individual's efficacious belief in their ability to overcome barriers for engaging in physical activity (Lewis et al., 2016; Marcus et al., 1992; S. Zhang et al., 2024).

Research has consistently demonstrated the influence of physical activity self-efficacy on physical activity engagement. For instance, a study examining college student groups found a positive correlation between physical activity and self-efficacy (Mercader-Rubio et al., 2023). Furthermore, evidence suggests that self-efficacy can serve as a mediating factor in the relationship between physical activity and affective well-being regulation (Mu et al., 2024; White et al., 2024). In particular, individuals lacking physical activity self-efficacy may experience decreased motivation to maintain physical activity, feel directionless, and potentially develop psychological disorders such as depression and anxiety, leading to diminished emotional management skills and awareness (Mu et al., 2024). This impact is particularly evident in vulnerable populations, where exercise behavior, exercise-induced mood, physical activity self-efficacy, and social support have been found to be negatively associated with depressive symptoms (Miller et al., 2019). In these above-mentioned studies, physical activity self-efficacy is not considered a psychological trait but rather depends on contextual influences. Furthermore, potential mechanisms through which physical activity can provoke beneficial affective responses may involve psychological processes such as the enhancement of self-efficacy, which can contribute to improved mood states (Dunton et al., 2014). In other words, the experience of successfully engaging in physical activity may boost an individual's beliefs about their capabilities, which can subsequently lead to more positive affective outcomes.

A key question for future research is whether physical activity self-efficacy, as a dynamic within-person construct, can help explain the variability between affective processes and physical activity engagement, and how physical activity self-efficacy interacts with affective states to influence physical activity behavior (Cushing et al., 2018). For example, an individual's affective and physical feeling states may be influenced by their cognitive processes, such as motivation, self-efficacy, and intentions, which can subsequently impact their level of physical activity engagement (Liao et al., 2017b; Rhodes & Nigg, 2011).

A recent study provided initial evidence for these processes, examining the role of physical activity self-efficacy in moderating the relationship between affect and moderate-to-vigorous physical activity among adolescents (Leslie-Miller & Cushing, 2024). The results revealed that negative affect was associated with decreased levels of moderate-to-vigorous physical activity, particularly among adolescents with low physical activity self-efficacy (Leslie-Miller & Cushing, 2024). In contrast, adolescents with higher levels of physical activity self-efficacy were less impacted by negative moods, suggesting self-efficacy may function as a protective factor. The differential influence of physical activity self-efficacy on the relationship between affect and moderate to vigorous physical activity underscores the potential for physical activity self-efficacy-enhancing strategies in interventions to mitigate the detrimental impact of negative mood states on physical activity engagement in this age group.

Given its modifiable nature, enhancing physical activity self-efficacy in interventions can be used to boost confidence and motivation for sustained activity levels. Consequently, future studies should consider integrating physical activity self-efficacy variables to gain further viable insight into the complex relationship between affective well-being and physical behavior. Examining how physical activity self-efficacy interacts with affective well-being to influence physical activity behavior could inform the development of more effective, tailored interventions.

Affective Well-Being, Physical Behavior and Circadian Rhythm

The circadian rhythm, or circadian clock, is a 24-hour cycle regulating physiological, molecular, and psychological processes - an inherent property of all living systems driven by an internal clock (Meyer et al., 2022; Vitaterna et al., 2001). In mammals, this clock is located in the hypothalamus’s suprachiasmatic nuclei (Fu & Kettner, 2013), which functions as a central pacemaker for rhythmic patterns in locomotor activity, sleep-wake cycles, body temperature, metabolism and physical activity (Dijk & Lockley, 2002; Hughes & Piggins, 2012; Kalsbeek et al., 2011; Waterhouse et al., 2005; Weinert & Gubin, 2022). Circadian rhythm is another crucial factor in the relationship between affective well-being and physical behavior. Modern lifestyles - marked by reduced natural light exposure and prolonged screen time - frequently disrupt these rhythms, impacting health adversely (Cho et al., 2015; Green et al., 2017; Gubin et al., 2017; Smolensky et al., 2015; Touitou et al., 2017). Given their essential role in health and metabolic regulation (Crnko et al., 2019), understanding the primary influences on circadian rhythms and developing treatment guidelines that align with these rhythms may enhance disease treatment success (Serin & Acar Tek, 2019).

Studies have shown that the timing of physical activity and sleep patterns significantly impact mortality risk (Zhang, Kivimäki, et al., 2024). In particular, engaging in physical activity early in the morning combined with irregular sleep patterns is associated with the highest risk for all-cause mortality (Zhang, Kivimäki, et al., 2024). This study also highlights considerable sociodemographic differences in these patterns, underscoring the need for health promotion strategies that are tailored to individual needs (Zhang, Kivimäki, et al., 2024). This suggests that interventions to address these differences should take into account a person's external contextual factors in order to respond individually to diurnal patterns. On the other hand, physical activity itself can positively influence sleep and circadian rhythms; a recent meta-analysis demonstrated a significant overall benefit of exercise on both sleep quality and circadian rhythm stability (Gururaj et al., 2024). However, prior research has largely relied on self-reported data. An ambulatory assessment study using device-based physical activity measurements found that particularly vulnerable groups with depression and anxiety, show disrupted circadian rhythms and lower physical activity levels (Difrancesco et al., 2019).

Recent technological developments in real-world monitoring systems have made it possible to capture human behavior and physiological functions as they occur naturally (Merikangas et al., 2019; Turek, 2016). When combined with the latest progress in chronobiology and molecular biology research (Shim et al., 2023, 2024; Takahashi, 2017), these advancements open up new possibilities for understanding how e.g., mood disorders are regulated and may enable potential intervention strategies (Merikangas et al., 2019). Further research indicates that disrupted patterns can impact affective well-being and cognition, with sleep-wake variability emerging as a predictor of mood fluctuations and cognitive deficits (Lau et al., 2024). This suggests that intra-individual factors such as diurnal patterns, glucose levels, and genetics may influence affective responses, which in turn are closely linked to physical activity engagement.

In line with the open science progress, multilevel datasets, for example, the Multilevel Monitoring of Activity and Sleep in Healthy people (MMASH) dataset, are already becoming publicly accessible (Rossi et al., 2020). This dataset provides comprehensive 24-hour continuous measurements including beat-to-beat heart data, triaxial accelerometer data, sleep quality assessments, and psychological characteristics such as stress events, and affective well-being. The inclusion of biological markers through saliva samples (cortisol and melatonin) alongside detailed activity logs makes it particularly valuable for investigating the complex relationships between biomarkers, sleep quality, psychological states, and physical activity. Such open-access resources enable researchers to accelerate scientific progress in understanding the interplay between circadian rhythms, mood regulation, and physical activity. In the future, consideration of intrinsic rhythms in the timing of interventions such as pharmacologic (e.g., melatonin-based interventions) and/or behavioral interventions designed to enhance circadian rhythmicity, may be more effective than interventions in one of these domains alone (Merikangas et al., 2019).

Affective Well-Being, Physical Behavior and Diurnal Variations in Biological Signals

As can be seen, circadian rhythms play an integral role in the intricate regulation of human physiological processes, this includes also diurnal variations in biological markers like blood glucose metabolism, with levels typically higher in the morning compared to the evening (Clavero-Jimeno et al., 2024). These fluctuations in physiological parameters are rigueur to consider, as they can directly shape the affective and reflective systems described in the Affective-Reflective Theory. An individual's emotional response to physical activity, as well as their cognitive reflection on it, can be influenced by real-time biological signals.

Previous laboratory studies have examined the relationship between glucose levels and mood states (Kohn et al., 2015; Owens et al., 1997). Owens and colleagues found a significant positive correlation between self-reported feelings of energy and blood glucose levels (Owens et al., 1997). Technological advances over the last decade have made it easier to monitor blood glucose in real time (Hermanns et al., 2022). For example, studies employing continuous glucose monitoring systems have been able to directly link glucose fluctuations to mood states (Polonsky & Fortmann, 2020). Furthermore, Wagner and colleagues found that both positive and negative affect could influence glucose regulation in a sample of individuals with type 2 diabetes (Wagner et al., 2017). Importantly, these relationships may be moderated by the time of day, as Zink and colleagues showed that adjusting for diurnal patterns can attenuate some of the associations between glucose and affective states (Zink et al., 2020).

To further understand the impact of intra-individual processes over time, ambulatory assessment studies have combined repeated real-life biological sampling (e.g., continuous glucose monitoring) with assessments of affective well-being (de Wit et al., 2023) and its antecedents/consequences in everyday life. For instance, Clavero-Jimeno and colleagues (2024) found that accumulating more than 50% of moderate-to-vigorous physical activity in the evening was linked to lower 24-hour glucose levels, a benefit that was particularly significant for individuals with impaired glucose regulation, suggesting that the timing of lifestyle physical activity may be a significant factor in glucose homeostasis (Clavero-Jimeno et al., 2024).

Likewise, studies in healthy adolescents showed that higher glucose levels were followed by increased positive affect and reduced fatigue, indicating that glucose variability may influence affective feelings (Zink et al., 2020). These findings suggest that glucose and other biological markers may play a role in moderating the relationship between affective well-being and physical activity, with intra-individual variability influencing both domains. With the rise of continuous glucose monitoring and wearable devices and applications, future studies could incorporate biomarkers like glucose in conjunction with circadian rhythms. Initial studies assessing the feasibility and validity of these devices have shown promise, paving the way for precision-based, adaptive interventions that leverage real-time data on biological rhythms and psychological states (Ehrmann et al., 2024; Hermanns et al., 2022; Rizvi et al., 2024).

Just-in-Time Adaptive Interventions in Health Behavior Change: Perspective for Physical Activity Promotion

Fluctuations in internal processes within individuals influenced by their interactions with people and their environment are observed - this shows the need of capturing behavioral, physiological, and biological processes in daily life (Fahrenberg et al., 2007; Trull & Ebner-Priemer, 2013). Passive data collected through smartphones over time can create a digital phenotype that predicts an individual's psychopathological status (Ebner-Priemer & Santangelo, 2020). It allows for unobtrusive, continuous, and objective monitoring of mental states and psychopathological symptoms in patients' daily environments, using data from personal digital devices (Ebner-Priemer et al., 2020). This method is particularly relevant for identifying individuals with mental disorders at moments of high symptom intensity or at specific risk moments enabling targeted interventions to prevent negative outcomes (Akdeniz et al., 2014; Myin-Germeys et al., 2016; Reichert et al., 2021).

To support individuals precisely when they need it most, the next step involves integrating just-in-time adaptive interventions with Ecological Momentary Assessment in the context of affective states and physical behavior. While Ecological Momentary Interventions (EMIs) (Myin-Germeys, 2020) and just-in-time adaptive interventions share many overlapping features, just-in-time adaptive interventions are distinguished by their adaptive nature, providing interventions and improving their delivery over time based on an individual’s context (Balaskas et al., 2021). Hardeman and colleagues define three key just-in-time adaptive intervention components such as combining real-time data collection, adaptive tailoring, and system-initiated support (Hardeman et al., 2019). Just-in-time adaptive interventions are designed to adapt the type, timing, and intensity of support based on an individual’s dynamic status and context, ensuring that intervention delivery occurs "at the moment and in the context that the person needs it most and is most likely to be receptive" (Spruijt-Metz et al., 2015) p.511). Just-in-time adaptive interventions have been applied in various health domains, including alcohol use (Gustafson et al., 2014), mental illness (Ben-Zeev et al., 2013), smoking cessation (Riley et al., 2008), stress management (Loo Gee et al., 2016), and weight loss (Patrick et al., 2009).

As an example for just-in-time adaptive intervention concerning affective well-being, the planned Feel.Well study will investigate the potential of a digital just-in-time adaptive intervention to help participants better manage emotions and thoughts in daily life (Zentralinstitut für Seelische Gesundheit (ZI), n.d.). In particular, the developed application uses Ecological Momentary Assessment to monitor participants' mood throughout the day and identifies patterns or triggers associated with negative affect. Based on this data, the intervention dynamically adapts its content, offering tailored mindfulness exercises or thought-restructuring prompts during challenging moments. This approach exemplifies the potential of just-in-time adaptive interventions to integrate mood tracking with timely, personalized support, and thereby enhancing emotional well-being.

Furthermore, in the development and implementation of just-in-time adaptive interventions in the health behavior sector, there are some open-source solutions like the Beiwe platform (Onnela et al., 2021) focusing on digital phenotyping and the AwarNS framework (Kumar et al., 2021). The AwarNS framework (González-Pérez et al., 2023) follows the sense-analyze-act paradigm; it leverages smartphone sensors and processing capabilities to collect passive data such as geolocation, Wi-Fi signals, Bluetooth proximity, and physical activity tracking (i.e., sense). This data is then analyzed using tools like geofencing or machine learning models to recognize patterns and predict user behavior (i.e., analyze). The framework enables real-time interventions, such as sending notifications or reminders, based on user-specific and environmental contexts (i.e., act).

In physical activity research, just-in-time adaptive interventions aim to address situations where individuals are likely to engage in sedentary behaviors or miss opportunities for physical activity. For example, just-in-time adaptive interventions could prompt individuals to choose walking over taking the bus during their commute (Nahum-Shani et al., 2014). In the context of physical activity, just-in-time adaptive interventions are not only designed to promote immediate behavioral changes but also to support prevention and self-management (Merikangas et al., 2019). For example, Van Dantzig and colleagues (2018) developed a context-aware coaching system, where participants' step counts and locations were continuously monitored. Personalized daily step targets were set, and coaching was delivered via a smartphone app, demonstrating the potential of just-in-time adaptive interventions to adaptively support physical activity (van Dantzig et al., 2018).

Research into just-in-time adaptive interventions for increasing physical activity and reducing sedentary behavior is still in its early stages (Hardeman et al., 2019). Hardeman and colleagues (2019) conducted a comprehensive review of just-in-time adaptive interventions in physical activity and sedentary behavior, revealing mixed evidence regarding effectiveness. Future challenges in developing optimal just-in-time adaptive interventions require multidisciplinary research approaches (Schneider et al., 2023), integrating robust theoretical frameworks (Nahum-Shani et al., 2018), advanced intervention techniques (Nahum-Shani et al., 2015), and measurement methods that accurately capture momentary behavior linked to outcomes (Collins et al., 2004). One of the significant challenges in developing effective just-in-time adaptive interventions is the lack of empirical evidence about which constructs reliably identify moments of risk or opportunities for behavior change and how these constructs predict specific proximal outcomes (Schneider et al., 2023).

Another approach using machine learning is described in the proposed physical activity intervention platform by Vandelanotte and colleagues (2023). This system presents a just-in-time adaptive intervention designed to promote physical activity through hyper-personalized, real-time support (Vandelanotte et al., 2023). It integrates real-time data collection, machine learning, and a conversational digital assistant to adapt interventions to individual user contexts and behaviors. The platform uses machine learning techniques, such as contextual bandits, which are decision-making systems to optimize decisions based on contextual information (e.g., GPS location, weather conditions, or physical activity data) and past outcomes to dynamically select actions and optimize rewards, making it particularly useful for adaptive health interventions in real-time settings (Tewari & Murphy, 2017). A Natural Language Processing-based assistant further engages users by initiating conversations on activity-related topics, answering questions using generative AI tools, and enhancing motivation and knowledge. This conversational agent is always available, and capable of providing real-time, highly personalized advice and nudges. These approaches may lead the path to the next generation of automated personalized physical activity interventions (Vandelanotte et al., 2023).

Our studies have demonstrated that affective well-being is strongly connected to physical behavior, with moderators like weather and mediators like social contact influencing this association. In the discussion section, we will highlight interventions designed to account for these and other potential moderators and mediators. For example, just-in-time adaptive interventions could prompt users to engage in physical activity when favorable conditions are detected (e.g., sunny weather or proximity to a workout partner), and ecological momentary assessment self-reports could trigger tailored messages, such as motivational prompts during periods of low affect or notifications about nearby friends to encourage social physical activity. By incorporating these variables into adaptive interventions, the precision and effectiveness of behavior change strategies in real-world contexts could be enhanced.

Layer 2. Interpersonal Influences: Social Support, Social Networks, and Dyads: The Social Environment

Affective Well-Being, Physical Behavior and Social Support

At the interpersonal level, social relationships can act as stimuli that trigger affective and reflective responses. For example, a supportive partner or friend might evoke positive feelings toward physical activity (affective response) or engage the individual in reflective thinking, like planning shared exercise routines, which enhances commitment to physical activity. Our research demonstrates that social contact positively influenced physical activity (Timm et al, submitted). We could even show, that affective processes mediated the relationship between social contact and physical behavior (Timm et al, submitted).

This research was a continuation of a study published by Benedyk and colleagues (2024), which found that physical activity can compensate for the loss of affective well-being caused by social isolation. The findings indicated that about one hour of walking at moderate intensity compensates for the social-affective deficit, even at lower doses or when performed at home(Benedyk et al., 2024)(Benedyk et al., 2024). The effect is especially pronounced in individuals at higher neural risk for affective disorders, such as those with smaller social networks or loneliness. This highlights physical activity as a practical strategy to mitigate social isolation's negative effects (Benedyk et al., 2024).

We were particularly interested in investigating how an individual's activity levels are contingent upon specific social relationships. To address this, we conceptualized a "supporting people" group encompassing friends, family, and romantic partners. Prior research substantiates that individuals demonstrate more positive affective states when surrounded by social connections compared to solitary contexts (Larson, 1990). Complementing behavioral observations, biochemical processes provide additional perspective. An ambulatory assessment study involving over 200 participants additionally assessed saliva samples for the evaluation of cortisol and oxytocin (Schneider et al., 2023). The results indicated that affectionate touch correlated with decreased self-reported anxiety, improved mood, and elevated oxytocin levels. These findings suggest that social contact, including affectionate touch, can have an impact on psychological well-being (Schneider et al., 2023).

Subsequent studies have consistently highlighted the critical role of social interactions in physical activity engagement. For instance, Cabrita and colleagues (2017) documented that being active with a partner, pleasure increased, and engaging in activities with someone else predicted higher pleasure than doing the same activities alone. The authors noted that the strength of predictors of pleasure varied greatly among participants, but social contact was consistently important (Cabrita et al., 2017). Boyle and colleagues further substantiated these findings, demonstrating that walking with a partner, compared to walking alone, was associated with decreased latency and greater duration of subsequent physical activity (Boyle et al., 2020).

Research examining partnered relationships has yielded prevailing evidence. A study focusing on older adults in long-term, cohabitating relationships revealed that partner support significantly influences the interaction between sedentary behavior and positive affect (Zhaoyang & Martire, 2019). Similarly, Arigo and colleagues observed that women in midlife with elevated cardiovascular disease risk reported increased motivational levels when experiencing higher frequencies of positive social interactions (Arigo, Brown, et al., 2022). Dunton and colleagues' (2015) comprehensive study of 116 adults, utilizing actigraphy to assess physical activity, further emphasized the significance of social context. The findings indicated that the affective benefits of physical activity were substantially more pronounced when surrounded by other people compared to being alone (Dunton et al., 2015). The review of White and colleagues showed, that social support was both a strong mediator and moderator in the relationship between mental health and physical activity (White et al., 2024).

These findings emphasize the pivotal role of supportive social environments in promoting physical activity. However, while our initial exploration revealed the broader impacts of social contact, to further refine our understanding, there is the need for more in-depth examinations of interpersonal dynamics within close, sustained relationships, specifically, dyadic relationships. As Dunton (2017) suggests, dyadic and social network analytic approaches provide advanced methodologies for exploring interpersonal dynamics over time on physical activity in ambulatory assessment studies (Dunton, 2017). These methods are particularly relevant for investigating relationships within dyads, such as romantic partners or parent-child pairs, and their effects on physical activity engagement (Dunton, 2017; Laurenceau & Bolger, 2005).

Dyadics and the Actor-Partner Interdependence Model

For example, parents, i.e., mothers, benefit from participating in activities with their children with higher positive affective states (Kanning et al., 2020). Moreover, children's positive affective states also influence the mother's level of physical activity (Yang, Huh, et al., 2020). These dyadic relationships between mothers and children showed that their affective states might be influenced by each other and, therefore, the amount of physical activity (Yang, Huh, et al., 2020). These dyadic relationships highlight the importance of close bonds, such as those between mothers and children, as contextual factors within the interpersonal layer that can influence subsequent physical behavior. This underscores the need for future physical activity promotion interventions to leverage these unique relationships to enhance effectiveness.

A promising approach to analyzing the dynamics within dyads, such as mother-child pairs, is the Actor-Partner Interdependence Model (APIM) (Kenny et al., 2006). The Actor-Partner Interdependence Model is a statistical framework designed to analyze bidirectional effects within dyads, such as mother-child or partner relationships, when both members' behaviors or affective states are measured.

This method enables the examination of how each individual's affective experiences independently influence their own and their partner's physical activity and sedentary behavior. APIM separates actor effects (how an individual's state or behavior influences their own outcomes) from partner effects (how one member's state influences the other's outcomes), addressing the interdependence between dyad members (Dunton, 2017). For example, Yang and colleagues utilized APIM with multilevel dyadic data (occasions nested within individuals) to explore how mothers' and children's affective states independently affected their own and each other's physical activity and sedentary behavior (Yang, Huh, et al., 2020). This model avoids overestimating intrapersonal or interpersonal effects and enables direct comparison of actor and partner influences across within- and between-subject levels (Cook & Kenny, 2005).

A randomized controlled trial demonstrated that dyadic activity planning benefits individuals with insufficient physical activity, cardiovascular conditions, or type 2 diabetes (Kulis et al., 2022). Participants who created shared physical activity plans with their partners experienced increased moderate-to-vigorous physical activity minutes at a 36-week follow-up compared to the control condition (Kulis et al., 2022). The shared goal likely contributed to mutual motivation, as both partners were encouraged to achieve their physical activity targets (Helgeson et al., 2018).

Using partner effects to enhance physical activity can be effectively integrated into adaptive interventions, particularly in managing non-communicable diseases (Carr et al., 2019). For example, Dyadic Management of chronic diseases (DyMand) is an open-source system designed for ambulatory assessment, focusing on assessing and intervening in dyadic coping and support processes among couples managing chronic diseases like type 2 diabetes (Boateng et al., 2019). This system can be further used to be integrated into just-in-time adaptive interventions, as it combines smartphone and smartwatch technology to monitor partner proximity and interaction. DyMand functions with a smartphone, a smartwatch app, and a cloud server system. The system uses Bluetooth Low Energy signal strength between smartwatches to track partner proximity and interaction patterns. The smartwatch collects sensor data (i.e., audio, heart rate, accelerometer, gyroscope, ambient light) in 5-minute intervals once per hour, and the smartphone collects video, audio and ambient light data during the subscription of the self-reports. In addition, the self-report is only triggered every hour when the participants are physically close; this closeness is identified via a certain threshold of the Bluetooth Low Energy signal, as well as with a voice activity detection algorithm. The self-report on the smartphone gathers information on social support, coping behaviors, emotions, and health activities. This combined system offers promising opportunities for real-time, tailored interventions in coping and support processes among couples facing chronic illnesses and may be further used to enhance dyadic health behavior (Boateng et al., 2019). Future ambulatory assessment research should incorporate dyadic relationships to better understand social contact and how they are intertwined with physical behavior and affective well-being, and derive implications for interventions, for example, in close relationships or the family setting.

Affective Well-Being, Physical Behavior and Social Network Analysis

Another promising approach is the integration of social network analyses in combination with ambulatory assessment. As we could observe mediation effects of affective well-being in the relationship between social contact and physical behavior (Timm et al., submitted), future methodological approaches may unravel dynamic momentary social processes that shape pathways between affective well-being and physical behavior by adding the social networks of individuals. Drawing inspiration from Granovetter's (1973) work on the strength of weak ties, incorporating social network perspectives into ambulatory assessment offers an opportunity to explore how individuals within social groups mutually shape each other's behaviors over time (Dunton, 2017).

Through the momentary assessment of social contact and data from the accelerometer, a map of how specific social contacts within an individual's network potentially cause increased activity levels can be drawn. This combination may offer a more nuanced understanding of how different social ties - ranging from close relationships to peripheral connections - may differentially motivate and foster physical activity. The examination of social network dynamics may reveal how specific interpersonal connections of an individual can serve as catalysts for increased physical activity. For instance, Fingerman and colleagues demonstrated the beneficial effects of various, peripheral social ties: diverse and frequent social interactions of participants in late adulthood were associated with both higher physical activity levels and improved mood (2020). The findings revealed that having a reliable social network in late adulthood has an impact on overall physical and mental well-being. Other studies' findings revealed that the combination of ecological momentary assessment and network analysis is also helpful in uncovering social isolation dynamics (Shi et al., 2024). In particular, being involved in activities outside the home reduced perceived social isolation and negative emotions in participants with mild to moderate stroke severity. In addition, the smartphone provides the ability to actively prompt self-reporting, but also passively collects social and behavioral data continuously (Keusch & Conrad, 2022). This data from the operating system and built-in sensors offers to chance for granular information about participants' communication patterns, digital social interactions, communication frequencies and social media engagement, which are especially interesting when researching social networks and activity patterns.

In a study by Sano and colleagues (2018), daily behaviors and social networks via wearable devices and participants' smartphones were used to monitor physiological, behavioral, and social factors to predict sleep, stress, and mental health outcomes. Conducted over a month with 201 college students, the study design incorporated twice-daily electronic diaries (i.e., questions about sleep, mood, social interactions, stress), continuous wearable sensor data (i.e., physical activity, skin conductance, heart rate), and smartphone-tracked behaviors (i.e., phone usage, screen time, timings of calls, text messages, app usage, location data). These data enable the analysis of how health-related behaviors could spread within a social network (Sano et al., 2018). By integrating device-based physical behavior tracking, subjective well-being assessments, social contact, and quantitative data on social interactions e.g., via calls, SMS, and emails, patterns of social influence can be uncovered, thus leading the way in developing targeted interventions to leverage these networks effectively to support everyday active lifestyles.

Initial implementations, such as those by Bruening and colleagues, involve a study tracking 1,450 university freshmen to explore the influence of social networks on health behaviors over an academic year. Participants' social networks are assessed beforehand via electronic questionnaires. During the ambulatory assessment phase, participants answer real-time prompts, reporting on their activities (i.e., sedentary behavior, physical activity, eating habits) and the individuals they are currently with, using an ego-centric approach to map interactions and analyze how friendship networks influence health behaviors and weight gain. In addition, the student card of the participants also assesses information about location including geographical information system (GIS), amount of expenditure, check-ins at campus exercise facilities, and time stamp; this will be linked to the friendship network data (Bruening et al., 2016). Analyzing longitudinal data allows for observing the evolution of friendship networks and assessing their influence on health behaviors. Tracking social connections across multiple points helps determine whether activities are performed simultaneously, which friends impact subsequent behaviors, and how the strength of relational ties influences long-term health patterns (Bruening et al., 2016). This study analyzes factors across the socio-ecological model, examining intrapersonal, interpersonal, and environmental layers. By linking multidimensional data, this allows for a nuanced understanding of how contextual factors function as potential moderators or mediators in health behavior processes. However, this study lacks device-based measurement of physical activity, relying instead on self-reported data, which may introduce bias or inaccuracies.

In the future, the findings may lead to the development of interventions that account for the complex social network mechanisms underlying health behaviors. These study design examples point out the importance of social networks as dynamic contributors to physical activity behaviors, emphasizing the value of social network analytic strategies in examining how relationships influence physical activity and may serve as potential moderators influencing physical activity levels over time.

Leveraging Social Networking and BLE Beacons through Smartphone Applications for Real-Time Social Interaction Triggers in Just-In-Time Adaptive Interventions

Integrating interpersonal factors, such as social support, dyadic relationships, and social networking, offers promising directions for interventions enhancing physical activity. Studies indicate that social contact, such as being active with a partner or in group settings, can positively influence physical activity engagement and enjoyment. For instance, in a recent randomized controlled trial, Coringrato and colleagues (2024) implemented a community gardening intervention spanning nine months. The study recruited a diverse sample encompassing varied age groups, ethnicities, and socioeconomic backgrounds. Employing accelerometers for device-based physical activity measurement, the researchers found compelling evidence of the intervention's potential to enhance health behaviors (Litt et al., 2023). In particular, the findings revealed a significant intervention effect for moderate-to-vigorous physical activity. Participants in the intervention group demonstrated approximately 5.8 minutes more daily moderate-to-vigorous physical activity compared to the control group. Beyond physical activity, participants in the community gardening intervention experienced notable reductions in perceived stress and anxiety levels.

This multicomponent intervention was grounded in the socio-ecological model, illustrating how different contextual layers, by activating emotional processes (i.e., intrapersonal level), social contact through shared social activities (i.e., interpersonal level), and through nature-based activities (i.e., environmental level) can improved health behaviors (Litt et al., 2023). However, a notable limitation is the absence of assessing affective well-being multiple times per day. Nevertheless, the approach shows promising future possibilities for health-promoting interventions, which may be easily transferred in urban settings via community gardens in cities, and thereby offering broad accessibility.

Furthermore, just-in-time adaptive intervention through mobile technologies could be a complement to the community gardening intervention to provide personalized, real-time support. By leveraging smartphone sensors, individual context could be continuously monitored, e.g., encompassing critical dimensions such as location proximity to community gardens, momentary affective well-being, social contact, and time of the day. Based on the collected data, personalized intervention trigger via a mobile application could strategically suggest garden-based activities when an individual is near a garden, dispatch motivational notifications when activity levels are low, and provide real-time social connection opportunities within the community garden network e.g., via the proximity of other garden members. An example is the system UbiFit Garden which uses activity sensing to provide real-time feedback and visual reinforcement through a smartphone app, encouraging users to meet their physical activity goals (Consolvo et al., 2008). By combining just-in-time adaptive interventions with social network analysis, the data could track how social interactions influence the intervention's effectiveness. In addition, more nuanced, context-aware intervention strategies could be generated. Participants would receive adaptive feedback through the application based on individual response patterns on physical activity and affective well-being, and the perceived value of shared social activities within the collaborative gardening context.

In a study by Morrissey and colleagues (2015), it was shown that family and friend support influences physical activity patterns among adolescents over five years. Data from 13-, 15-, and 17-year-old participants showed that increased support from family and friends was associated with higher device-based measured moderate-to-vigorous physical activity. The findings also showed that low support at age 13 from family and friends persisted into later adolescence, highlighting the need for interventions targeting families and peers to create supportive environments. These could include family-based activities and peer relationship-building strategies, fostering a sustained culture of physical activity and helping adolescents overcome barriers to being active (Morrissey et al., 2015).

Therefore, leveraging social networking through smartphone applications offers a promising avenue for interventions, as social connections can serve as valuable sources of support for adopting and maintaining an active lifestyle (Lewis et al., 2017). A study involving adults with elevated cardiovascular risk demonstrated that digital, social micro-interventions effectively increased physical activity motivation and behavior compared to baseline (Arigo et al., 2024). In this study, ambulatory assessment was combined with momentary randomized micro-interventions. Participants received either social support prompts, offering encouragement and informational support, or social comparison prompts. Results indicated a preference for social support messages (Arigo et al., 2024).

In a physical activity promotion program for women aged 40-65 with cardiovascular conditions (e.g., hypertension, type 2 diabetes, high cholesterol, metabolic syndrome, or recent smoking cessation), both individual and social factors are integrated into the intervention ("Women's Health Study," 2019). This intervention program was developed based on a foundation of existing research (Arigo et al., 2020; Arigo, Hevel, et al., 2022; Arigo, Mogle, Brown, et al., 2021; Arigo, Mogle, & Smyth, 2021). The planned 8-week program supports previously inactive women through six coaching sessions aimed at setting personal activity goals ("Women's Health Study," 2019). The social dimension is emphasized by pairing participants into mutual support teams. Using an app, each participant creates a peer profile detailing their typical weekly step count and active minutes. Based on shared activity goals or interests (e.g., highly active or moderately active), women are matched to partners with similar objectives. In addition to three joint coaching sessions, participants are encouraged to communicate with their partner throughout the study. Each participant receives an activity tracker and completes daily questionnaires, assessing positive and negative affect, as well as comparisons and connections with others in the program. This approach fosters a supportive environment to motivate and sustain physical activity.

The proposed intervention could be enhanced through adaptive triggering mechanisms that leverage both contextual and individual data. For instance, proximity-based triggers could be activated when a partner or supportive network member is nearby, creating opportunities for collaborative physical activity. Additionally, by integrating accelerometer data, the intervention system could dynamically recognize when an individual's predetermined daily activity goals remain unachieved, generating personalized motivational prompts. The just-in-time adaptive intervention would incorporate individual mood assessment items, enabling a feedback loop that allows for continuous, adaptive modification of concomitant personal goal-setting and partner support strategies, ensuring that the intervention remains responsive to both emotional states and physical progress, fostering sustained health behavior engagement and motivation to be physically active.

How can social contact triggers be technically implemented in real-time for just-in-time adaptive intervention to promote physical activity? One possibility is utilizing participants' personal or study-provided smartphones, which are equipped with sensors, such as Bluetooth, accelerometers, GPS, light sensor, proximity sensor, and microphones (Harari et al., 2016). Bluetooth scans also allow for measuring the size of in-person social groups (Chen et al., 2014). For context capture in combination with physical activity and mood dimensions, the combination of accelerometer and Bluetooth offers a method to assess the amount of time spent alone or with groups of people in different locations, as well as the degree of physical activity in contact with others. Bluetooth technology enables apps to identify nearby Bluetooth low-energy beacons, assessing the duration and frequency of interpersonal interactions (Barnett et al., 2024). The approach provides an unobtrusive and ecologically valid method for real-time analysis of social dynamics, over long time periods (Harari et al., 2015).

Study protocols by Barnett and colleagues (2024) and Jackson and colleagues (2024) demonstrated the feasibility and functionality of using Bluetooth low energy beacons in interventions. Participants identified in advance three peers likely to influence their behaviors, such as alcohol consumption. These peers carried Bluetooth low energy beacons with a unique ID, which were linked to the participant's smartphone app. When a beacon was detected within 4.6 meters for 15 minutes, it triggered a signal-contingent self-report. This approach aims to use Bluetooth low energy beacons within just-in-time adaptive interventions to help individuals or others avoid risky behaviors by identifying high-risk contexts in their current situation, providing alerts, and offering adaptive strategies or encouragement to mitigate the risk (Barnett et al., 2024; Jackson et al., 2024).

Building on this concept, Bluetooth low energy beacons can also promote physical activity through proximity-triggered interventions. For instance, in Girolami and colleagues' SocializeME framework, Bluetooth low energy signals were used to detect face-to-face interactions and model social dynamics (Girolami et al., 2020). The study encompassed a data collection process involving over 820,000 Bluetooth low energy signals across various configurations to model typical social interaction scenarios, including participants standing or sitting and holding devices in their hands or pockets. The researchers developed the SocializeME Detector (SME-D) algorithm to process Bluetooth low energy signal strength for detecting social interactions. The algorithm focuses on accurately identifying the start and end times of interactions, achieving an accuracy of 81.56% and an F-score of 84.7%. Key parameters include beacon loss rate and received signal strength (RSS) between paired users during interactions. This approach enables real-time monitoring of social behaviors without relying on intrusive audio or video recording methods and highlights the potential for fostering physical activity by creating situational prompts e.g., notifying a participant when a supporting contact is nearby to encourage shared activity.

Social proximity, shared time, and interaction frequency are essential interpersonal contextual factors in relationships that can be effectively captured using Bluetooth low energy beacons (Mehl et al., 2024) and may serve as moderators in the affective well-being – physical behavior association and can be implemented into just-in-time adaptive interventions. The integration of beacon-sensor data and accelerometer measurements could identify joint physical activities and discover mobility patterns. For example, beacon-triggered notifications can serve as situational cues (Timmons et al., 2015) to initiate physical activity, such as notifying a participant that a friend is nearby to encourage shared activities like going for a walk. These systems underscore the potential of Bluetooth low energy-based systems for scalable and non-invasive social sensing and provide valuable insights for the implementation of just-in-time adaptive interventions in public health research, creating environments where physical activity is more accessible and engaging through collaborative activities.

Layer 3. Interactions of Affective Well-Being, Physical Behavior and Environmental Conditions: The Natural Environment

Affective Well-Being, Physical Behavior and Air Pollution

Additional external factors include air quality, or pollution, which has been designated as the second leading risk factor globally for noncommunicable diseases (World Health Organization, 2024). In 2019, 99% of the global population was exposed to levels of air pollution exceeding WHO guidelines, highlighting the need for ongoing research on this "invisible" hazard (World Health Organization, 2024). Pollutants in the air, such as particulate matter ($PM_{2.5}$ and PM_{10}), carbon monoxide (CO), lead (Pb), ozone (O_3), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2), and exposure to these, can have detrimental health effects on both respiratory and cardiovascular systems (Brunekreef & Holgate, 2002). For example, higher concentrations of air pollutants have been associated with increased blood pressure and decreased ventilatory function, while exposure to elevated ozone levels has been linked to reduced exercise capacity and performance (Cakmak et al., 2011; Marr & Ely, 2010; Perera, 2017). Studies have shown that air pollution can be monitored effectively using wearable sensors. For instance, Hu and colleagues (2014) combined participatory air pollution sensing with wearable devices to monitor individual activity levels, which allowed for a more accurate estimation of personal exposure based on activity types and intensity, such as jogging, cycling, or driving (Hu et al., 2014).

Thus far, no gold standard has been established for the measurement of physical behavior and air pollution (Dons et al., 2017). The WHO has highlighted the need to integrate air pollution monitoring into physical activity research (World Health Organization, 2021). In a review conducted by Tainio and colleagues (2021), it was demonstrated that elevated air pollution levels can contribute to the avoidance of physical activity. A meta-analysis revealed that a one-unit (µg/m³) increase in ambient $PM_{2.5}$ concentration raised the likelihood of physical inactivity by 1.1% among U.S. adults (An et al., 2018). Additionally, a study by Cheng and colleagues (2024) revealed that increased $PM_{2.5}$ levels corresponded to a decline in daily step count (by approximately 362 steps) and time spent in various physical activity intensities (Cheng et al., 2024).

However, physical activity also has the potential to mitigate the health consequences of harmful air pollution exposures (D'Oliveira et al., 2023). Therefore, air pollution represents another critical environmental stimulus influencing physical activity engagement.

Additionally, the interaction between air pollution and sedentary behavior has been largely unexplored. Initial findings indicate that high air pollution levels combined with inactivity exacerbate health risks (Molina-Sotomayor et al., 2019; Yu et al., 2017; Zhan et al., 2023). Furthermore, the relationship between affective well-being and other variables such as anxiety, sleep, and stress (D'Oliveira et al., 2023) in relation to physical activity and air pollution has yet to be sufficiently investigated in future long-term studies using ambulatory assessment methodologies.

Towards Personalized Air Pollution Monitoring: Integrating Mobile Technologies and Environmental Models

In Karlsruhe, Germany, there are only two official measuring stations of the Baden-Wuerttemberg State Institute for Environmental and Measurement Technology (Landesanstalt für Umwelt Baden-Wuerttemberg (LUBW), 2024). As they provide precise static data on emission data (air quality index, nitrogen dioxide (NO_2), particulate matter ($PM_{2.5}$ and PM_{10}), ozone (O_3)), they fail to capture spatial dynamic processes occurring within the city and detailed information about urban pollution. Therefore, future research approaches for air pollution monitoring in urban environments need to develop innovative methodologies through more dynamic sensing networks with a higher spatial resolution of measurement points. Participatory sensing and citizen science initiatives, such as sensor.community, have already been initiated with the objective of constructing a global, collaborative monitoring network using low-cost air quality sensors (*Sensor.Community, 2020*). These developed networks enable fine-grained pollution mapping that becomes increasingly accurate with broader public participation, e.g., for detecting in-situ pollution hotspots. This network has the potential to serve as a recurrent data source for the analysis of microscale models (*Project Smart Air Quality Network*, n.d.). A further technological development is to include hardware add-ons for the smartphone. These approaches integrate clip-on sensor modules and process algorithms for real-time personal exposure monitoring (Budde et al., 2019; Hinterreiter et al., 2018).

The use of individualistic, realistic concentrations of smartphone-based measured air stressors may allow for a more detailed analysis of the relationship between particulate matter exposure and further related health topics, e.g., consequences to the cerebral vascular systems (Babadjouni et al., 2017; Hamanaka & Mutlu, 2018). These analyses can be conducted with the help of microscale models and agent-based modeling systems that integrate real environmental conditions and mobility patterns to assess individual exposure. For example, dispersion models like the Graz Lagrangian model (GRAL model), can be utilized for wind fields or allergen tracking. In particular, pollen dispersion from sources such as the birch tree can be simulated to individual exposure in an urban environment (Bakhshizadeh et al., 2021; Berchet et al., 2017; Romanov et al., 2020). In the future, interdisciplinary approaches, combining participatory sensing, mobile technologies, and computational modeling, represent important steps in developing comprehensive, dynamic, and real-time urban air quality monitoring systems, allowing for fine-grained analysis of mental and physical health consequences.

Affective Well-Being, Physical Behavior and Walkability

Features like walkability, access to parks, and safety in neighborhoods serve as external stimuli that influence both emotional and reflective processes, e.g., a walkable environment may trigger a positive affective response to walking. Walkability refers to built environment characteristics (Forsyth et al., 2008; Sugiyama et al., 2012) or walkability indices (Frank et al., 2010), that differ in composition and data sources, but often encompass street connectivity, land use mix, proximity to destinations, population density, and safety features (Glazier et al., 2014). Moreover, walkability is increasingly recognized as a critical element of public health strategies. For example, the U.S. Call to Action 2015 emphasized the importance of walkable communities to promote physical activity (Bartshe et al., 2018). Recent advances in mobile technology, such as smartphones equipped with GPS, Bluetooth, and magnetometers, now allow researchers to assess walkability dynamically. These tools can track geolocation and proximity, enabling real-time data collection on how the built environment impacts physical behavior (Reichert, Braun, et al., 2020).

The level of walkability in a neighborhood influences physical activity behaviors, such as walking for recreation, transportation, or commuting. Perceived neighborhood walkability has been consistently associated with higher levels of physical activity (Bartshe et al., 2018). For instance, individuals living in more walkable areas are more than twice as likely to walk, bicycle, or use public transit and significantly less likely to rely on private vehicles compared to those in less walkable areas (Glazier et al., 2014). Built environment features, such as proximity to destinations, street connectivity, and mixed land use, encourage walking and cycling. Frank and colleagues (2010) demonstrated that people living in neighborhoods designed to support active transportation (e.g., walking and biking) were less likely to be overweight or obese than those in suburban areas reliant on motorized transportation (Frank et al., 2010). Similarly, Gao and colleagues (2018) found that both the built and natural environments significantly influence cycling duration in the Netherlands, supporting the broader idea that environmental infrastructure can shape active behaviors (Gao et al., 2018).

A further study examined how neighborhood walkability influences perceived health-related fitness in 592 adults in Canada using both self-reported and objective measures of walkability (McCormack et al., 2020). Findings revealed that higher perceived walkability, measured using the Physical Activity Neighborhood Environment Scale (PANES), was positively associated with all components of health-related fitness, including cardiorespiratory fitness, muscular strength, and flexibility. Furthermore, positive perceptions of neighborhood parks were linked to improved fitness levels, emphasizing the importance of accessible and supportive green spaces in promoting active lifestyles (McCormack et al., 2020). This research shows that environmental features of the natural environment have a unique and independent influence on individuals' physical activity levels, even after accounting for the effects of psychosocial and sociodemographic factors.

Integrating Geographic Ecological Momentary Assessment (GEMA) into the Affective-Well-Being and Physical Behavior Relationship

Dunton and colleagues (2012) conducted an ecological momentary assessment study to investigate the contextual factors influencing physical activity, relying on self-reported data to capture immediate environments and behavioral contexts (Dunton et al., 2012). While this approach provided sophisticated insights into subjective perceptions of physical activity contexts, integrating GPS monitoring and Geographic Information Systems (GIS) mapping represents an inevitable next step. With advancements in technology, combining ambulatory assessment with geolocation tracking has become increasingly feasible (Schipperijn et al., 2014), allowing researchers to capture data from participants in real-time and their natural environments (DeVille et al., 2021; Kirchner & Shiffman, 2016). These geographic ecological momentary assessment (GEMA) methods are central to evaluating contexts (Kestens & Kingsbury, 2024). Contextual factors assessed through geolocation tracking to trigger e-diaries have been applied in several studies (Dorn et al., 2015; Törnros et al., 2016). For instance, Tost and colleagues utilized a combination of ecological momentary assessment, GPS tracking, and neuroimaging to explore real-time environmental influences (Tost et al., 2019). In their study, GPS tracking was employed to capture geolocation data, repeated mood assessments were collected via e-diaries, and physical activity was measured using accelerometers. The findings demonstrated that exposure to inner-city greenspaces significantly enhanced momentary well-being (i.e., affective valence). This interdisciplinary approach underscores the potential of greenspaces in fostering mental health, particularly for vulnerable populations.

In addition, the ECO-MIND study is a multi-country research project aimed at examining how exposure to nature influences pro-environmental behaviors and mental health in urban youth (Bubalo et al., 2024). The study uses Geographic Ecological Momentary Assessment and mental models to understand these dynamics in urban contexts, focusing on participants aged 18–24 from three countries (Bangladesh, Uganda, and the Netherlands) with a sample size of 660 participants. By including both Global South and Global North locations, the research explores cultural and contextual variations in youth interactions with nature. The project investigates whether youth exposed to more greenspace (i.e., availability, accessibility, and visibility) report better mood, lower stress, and improved well-being and whether nature connectedness and mental models serve as mediators in these associations. For data collection, the researcher utilize ecological momentary assessment to capture real-time interactions with greenspaces, thereby also incorporating satellite and street-view imagery to measure greenspace exposure. A semi-random sampling design over two weeks with 6 prompts per day will be conducted with geocoded prompts. In addition, the mobility of the participants will be tracked via smartphone-based GPS with a sampling of 20 seconds. The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the relationships between greenspace exposure, nature connectedness, mental models, mental health, and pro-environmental behaviors. This statistical approach is particularly suited for handling complex models with multiple pathways and temporal data (Hair et al., 2022). This project exemplifies how advanced technology and interdisciplinary approaches can broaden our understanding of environmental determinants, that could serve as mediators in shaping mental well-being processes.

It would be of interest to include physical activity in the relationships explored in the ECO-MIND study. Specifically, increased exposure to greenspaces might not only enhance mood and reduce stress but also encourage more frequent physical activity (Mennis et al., 2018). For example, accessible and appealing greenspaces could facilitate walking, jogging, or other outdoor activities. Existing research already demonstrated the beneficial effects of engaging in physical activity outdoors compared to indoors. For instance, engaging in outdoor physical activity has been associated with decreased latency to initiate subsequent physical activity sessions and longer activity durations (Boyle et al., 2020). Moreover, being outdoors during physical activity appears to buffer negative affective responses while enhancing positive ones (Dunton et al., 2015). Research also suggests that outdoor physical activity leads to more significant reductions in symptoms of depression and anxiety than indoor activity (Teychenne et al., 2020; Thompson Coon et al., 2011). Furthermore, individuals who engage in moderate-to-vigorous physical activity outdoors at baseline are more likely to sustain higher daily moderate-to-vigorous physical activity levels at follow-up (Yang, Maher, et al., 2020). These results underline the role of the natural environment in shaping both immediate and sustained health outcomes associated with physical activity.

Keeping this in mind, pro-environmental behaviors could act as a mediating factor in the relationship between greenspace exposure and subsequent physical activity. Youth engaging in physical activity within greenspaces might experience enhanced benefits to mood and stress reduction, emphasizing the dual impact of nature exposure and physical behavior. By including physical activity in the framework, the study could emanate how greenspaces and nature connectedness contribute to healthier, more active lifestyles, and how this could be used in translating to just-in-time adaptive intervention.

Integrating Mobility-Based Environmental Insights into Just-in-Time Adaptive Interventions for Physical Activity Promotion

Zhang and colleagues emphasize in their systematic review the potential of integrating geographic methods like GPS and Geographic Information Systems (GIS) tracking with real-time self-reports to capture dynamic interactions between individuals and their environments (Zhang, Li, et al., 2024). The study identifies the efficacy and feasibility of Geographical Ecological Momentary Assessment in public health research, prognosing the growing trend of using these methodologies to better understand the role of environmental contexts, such as urban green spaces, walkability, and pollution, on physical health behaviors.

Building on the integration of ecological momentary assessment with GPS monitoring, the next logical step is to connect Geographical Ecological Momentary Assessment with just-in-time adaptive interventions. While Geographical Ecological Momentary Assessment offers high-resolution data on the dynamic interactions between individuals and their environments, just-in-time adaptive interventions can utilize this data in real-time to deliver tailored, context-sensitive interventions (Nahum-Shani et al., 2018). For instance, Geographical Ecological Momentary Assessment could identify moments when individuals are near greenspaces or walkable areas, triggering just-in-time adaptive interventions to encourage physical activity or provide motivational nudges.

This approach will be implemented primarily in vulnerable groups, for example, a study by Skeen and colleagues (2023) outlines the development and pilot testing of an application, designed to support individuals living with HIV through a trauma-informed and geospatially aware approach (Skeen et al., 2023). This just-in-time adaptive mobile health (mHealth) intervention integrates twice-daily Geographical Ecological Momentary Assessment prompts to assess users' geographic contexts and delivers tailored coping strategies and mental health support in real-time. The intervention aims to improve engagement in care, medication adherence, and overall mental well-being. This approach reflects the potential of just-in-time adaptive interventions dovetail with geospatial technology to address complex mental health challenges and improve the quality of life for vulnerable populations.

Integrating not only temporal mobility patterns such as mobility-based exposure to environmental factors such as air pollution, noise, and green spaces that affect key health behaviors, but also assessing risk factors for chronic diseases such as physical inactivity, poor dietary habits, inadequate sleep, and mental well-being and understanding their interaction with environmental exposures could decisively enhance public health strategies (Yi et al., 2024). Future concepts would also benefit from more refined frameworks and interdisciplinary collaboration to harness the amalgamation of Geographical Ecological Momentary Assessment and just-in-time adaptive interventions effectively in public health promotion strategies.

Affective Well-Being, Physical Behavior, and Planetary Health

Planetary health is an interdisciplinary field focused on understanding and addressing the interconnections between human health, the health of natural systems, and the broader challenges posed by environmental changes (Whitmee et al., 2015). It emphasizes that the health and well-being of humans are inextricably linked to the health of the planet (Myers, 2017). Environmental factors such as air pollution and green space exposure are already known to influence physical activity behaviors. Furthermore, our own findings demonstrated that temperature significantly affects subsequent physical activity levels and serves as a moderator in the relationship between affective well-being and physical behavior (Timm et al., 2023). Due to global warming caused by increased greenhouse gas emissions, climate change has increasingly become a major area of research in various sciences (natural, medical, social, and political) (Marx et al., 2021). Global warming has many impacts, including extreme weather events such as heat waves, droughts, floods, hurricanes, rising sea levels and disruptions to food and water security, and wildfires, all of which have significant public health implications. For example, heat waves are defined as a period of excessively hot weather that may be accompanied by high humidity (i.e., wet bulb global temperature) (International Organization for Standardization, 2017; Marx et al., 2021). Recent research suggests that heat waves are becoming more frequent and severe due to global warming, even in regions with traditionally temperate climates. For example, studies from Switzerland have already documented significant health impacts of rising temperatures, including increases in hospitalizations and suicides (Bär et al., 2022; Bundo et al., 2023). Furthermore, experts anticipate that certain extreme weather events, particularly heat waves and precipitation extremes, will intensify as global temperatures continue to rise (Coumou & Rahmstorf, 2012).

Research indicates that global climate change, particularly extreme weather events such as heat waves, floods, droughts, tornadoes, hurricanes, and wildfires, significantly impacts not only physical but also mental health: a descriptive review highlights the immediate psychological effects of such events, linking them to conditions like PTSD, depression, anxiety, increased suicide rates, substance use, and aggressive behavior (Cianconi et al., 2020). However, the review also underscores the complexity of studying these effects, emphasizing the heterogeneity in measuring climate change variables and their psychological impacts. This methodological variability limits the current body of research on climate-related mental health outcomes. Moreover, emerging terms such as eco-anxiety, eco-guilt, ecopsychology, ecological grief, solastalgia, and biospheric concern reflect growing recognition of the psychological dimensions of climate change, but these concepts still require clearer definitions and broader adoption in the literature (Cianconi et al., 2020). This underscores the need for more standardized methodologies, and longitudinal data in real-time to fully understand the multifaceted impacts.

For example, the results of an ecological momentary assessment study involving 906 participants in Switzerland demonstrated that daily temperature has an impact on subsequent mood. In the healthy sample, there was a positive association between self-reported mood and higher temperature. However, it was also demonstrated that subjects with a psychiatric disorder exhibited a negative response to elevated temperatures (Bundo et al., 2023). This is corroborated by further study results, which showed a significant correlation between panic attacks and anxiety disorders in the context of elevated temperatures (Oh et al., 2020). Additionally, individuals with schizophrenia, dementia, and substance misuse were particularly vulnerable to an increased mortality risk in the context of rising temperatures (Page et al., 2012). Climate change disproportionately affects vulnerable groups, who are at heightened risk of both physical and mental health challenges, but despite their susceptibility, these groups are often underrepresented in research. These populations include the elderly, children, individuals with pre-existing psychiatric or medical conditions, women, low-income communities, and indigenous populations, all of whom face amplified risks such as exacerbated mental health conditions, respiratory illnesses (e.g., asthma, COPD), and adverse outcomes during extreme weather events like heat waves (Boutou et al., 2019; Bundo et al., 2023; Cianconi et al., 2020; Poole et al., 2019; Salvo et al., 2023; Stamatakis et al., 2013).

As one of the first reviews, Zisis and colleagues summarized the findings of the association between climate change, 24-hour movement behaviors (physical activity, sedentary behavior, and sleep), and health outcomes (Zisis et al., 2021). The mini umbrella review synthesizes findings from eight systematic reviews published between 2010 and 2020, revealing multi-directional links between climate change and various health outcomes, such as sleep disturbances and impacts on physical activity. However, the review highlights a significant gap in understanding the specific mechanisms by which climate change influences 24-hour movement behaviors and how these behaviors, in turn, affect health. While some studies suggest a negative impact of climate change on sleep and physical activity, the evidence on sedentary behavior is still very limited. The review calls for further research to explore these mechanisms and to develop effective strategies for mitigating climate change while promoting healthier movement behaviors.

A further systematic review by Lee and colleagues synthesized evidence on the interplay between climate change, 24-hour movement behaviors, and health among 6.6 million individuals across 25 countries (Lee et al., 2024). The findings emphasize that physical activity can serve as both a mediator and moderator in the relationship between climate change indicators and health outcomes. Specifically, physical activity, when combined with low air pollution or increased greenspace, amplifies its mediating effects on health. However, of the 79 included studies, only 6 provided device-based measured physical behavior. Moreover, no study to date has incorporated compositional data (Chastin et al., 2015; Dumuid et al., 2019), including all 24-hour movement behaviors (physical activity, sleep, and sedentary behavior), in conjunction with climate change-related predictors. Although initial evidence suggests that 24-hour movement behaviors are associated with mood (Giurgiu et al., 2022), the interaction between these behaviors and environmental factors like air pollution, extreme weather, or rising temperatures remains unexplored.

The review by Bernard and colleagues researched the effects of climate change on physical activity and sports, highlighting how environmental factors such as air pollution, extreme weather conditions, and natural disasters directly influence physical activity (Bernard et al., 2021). The review reveals a consistent negative impact of these climate-related factors on physical activity, particularly for individuals with chronic diseases, higher body mass index, and older people. The authors emphasize the need for further research on the interplay between climate change and physical activity to develop effective strategies for promoting physical activity while mitigating the adverse effects of climate change. The study also suggests that environmental factors such as air quality, temperature, and greenspace availability can moderate these effects, emphasizing the importance of considering these variables in future physical activity-related interventions.

Already in 2013, Stamatakis and colleagues emphasized the urgent need for research on the interplay between the influence of ambient temperature, climate parameters, and leisure-time physical activity at a population level (Stamatakis et al., 2013). This includes also understanding the mechanisms linking climate factors to sedentary behavior. Despite this call to action, existing studies remain limited in scope and design. Current research predominantly relies on cross-sectional studies, often lacking methodological rigor and device-based measures of physical activity. These studies also fail to integrate ambulatory assessment principles, which could augment real-time physical activity behaviors and mental health states. Moreover, the current state of research clearly shows that global warming significantly affects both mental health and physical behavior. However, the above-mentioned systematic reviews reveal critical gaps in the literature: there are no standardized methodologies, and a dearth of longitudinal data, for linking climate change indicators (e.g., air pollution, weather conditions) with both physical activity and mental health outcomes. Additionally, the potential of ambulatory assessment to capture these dynamic interactions in real-time remains underexplored. Gearing ambulatory assessment methods by integrating device-based measures of physical activity with subjectively assessed mental health states, could provide more comprehensive details into how global warming deleteriously influences physical behavior and mental well-being. Integrating these elements into the proposed model (see Figure 3) would allow for the identification of key moderators and mediators that influence subsequent physical activity behavior and could be the basis of a theoretical model.

Emerging technologies offer promising solutions. For example, assessing climate or eco-anxiety as a moderator in the relationship between affective well-being and physical behavior in future research could harvest information on how psychological and emotional responses to environmental challenges mediate or modify health behaviors and outcomes. The awareness of and worry about climate change consequences, such as heat waves, loss of biodiversity, or reduced access to nature, could negatively affect affective well-being by increasing stress, anxiety, and a sense of helplessness, thereby indirectly reducing physical activity levels (Brosch, 2021; Hickman et al., 2021). Or climate anxiety might motivate pro-environmental behaviors like walking or cycling instead of driving, potentially leading to increased physical activity levels (Stanley et al., 2021).

Incorporating Climate Factors into Just-In-Time Adaptive Interventions

In future approaches, climate factors could be systematically integrated into research exploring the relationship between affective well-being and physical activity. Future studies should scrutinize how long-term climate patterns, seasonal changes, and extreme weather events modify the affective well-being and physical activity relationship. Advanced machine learning predictive models could leverage comprehensive climate data (Schröter et al., 2018) to dynamically modulate intervention recommendations, accounting for nuanced environmental conditions that impact individual behavior and well-being. By employing geospatial technologies and environmental sensor networks, researchers can develop more refined person-place interactions that dynamically respond to specific environmental thresholds. For example, advanced geolocation and environmental sensors can identify unfavorable conditions, like heat waves or poor air quality, and adapt recommendations - for instance, suggesting indoor activities or safer routes to maintain physical activity levels. On the other hand, walking triggers (Kanning et al., 2022) could be programmed to encourage users to walk during optimal conditions, such as when temperatures are comfortable or air pollution is low. As for now, the potential for incorporating climate and environmental factors into just-in-time adaptive interventions remains substantially uncharted.

In doing so, just-in-time adaptive interventions present an opportunity in creating adaptive, context-sensitive recommendations based on microclimate variations that optimize individual physical engagement while ensuring participant safety and behavioral sustainability. Besides, incorporating feedback on environmentally sustainable behaviors, such as active transport (e.g., walking or cycling instead of driving), can simultaneously promote individual health and alleviate carbon emissions. By integrating these elements, just-in-time adaptive interventions not only enhance physical activity engagement but also align with broader goals of climate action and urban resilience.

Perspective

We have observed an exponential increase in the number of ambulatory assessment studies over the past 20 years, alongside advancements in technology that allow for the inclusion of additional contextual factors. In our research, we demonstrated that contextual factors as moderators and mediators influence the relationship between affective well-being and physical behavior. From a public health perspective, it can be concluded, that these contextual factors will gain increasing importance in designing interventions in promoting sustainable physical activity. We showed in our work that both the contextual factors weather and social contact, substantively contribute to subsequent physical behavior and can be regarded as further potentially health-shaping moderators and mediators.

Aligned with advancements in technology, we proclaimed a new framework that integrates affective and cognitive processes within the socio-ecological model. This model highlights additional moderators and mediators influencing physical activity behavior across intrapersonal, social, and environmental levels. As conceptualized by Olvera Alvarez and colleagues, these factors can function as either resources or susceptibilities in generating positive behavioral responses (Olvera Alvarez et al., 2018). Furthermore, there is an increasing trend toward leveraging interventions to promote a sustainable active lifestyle, emphasizing the importance of targeting these interconnected layers to maximize the impact of health promotion strategies. The development of effective just-in-time adaptive interventions necessitates a comprehensive approach addressing three critical domains: 1) theoretical grounding, 2) advanced intervention techniques, and 3) sophisticated measurement methodologies (Collins et al., 2004; Nahum-Shani et al., 2015, 2018).

First, concerning the haphazard lack of theoretical grounding, Lewis and colleagues (2017) emphasize the necessity for studies to be more theory-driven, and Nahum-Shani and colleagues (2018) similarly note that many just-in-time adaptive interventions have been developed with little empirical or theoretical support. Both self-regulatory processes and environmental support play critical roles in shaping health behaviors (Best et al., 2014). By integrating theories such as the Affective-Reflective Theory into the ecological framework, which explores the interplay between affective and reflective processes, we can assiduously understand how internal motivations interact with external environmental factors. This additional theoretical perspective helps explain the frequent disconnect between physical activity intentions and actual behavior, particularly the persistence of sedentary behavior despite awareness of physical activity's benefits. This new framework ensures that externally initiated prompts resonate with personal volition and agency (Schueller et al., 2017), and can provide a theoretical basis for understanding how external cues interact with internal decision-making processes to drive behavior. In addition, it suggests that effective interventions require a comprehensive approach addressing both cognitive and affective processes while considering the environmental context in which affective mechanisms operate (Brand & Ekkekakis, 2018).

Secondly, we demonstrated that opportunities for adaptive and intelligent interventions have expanded and can be integrated into the new framework. Building on the need for context-sensitive and adaptive support, recent advancements in artificial intelligence and machine learning offer promising opportunities to enhance just-in-time adaptive intervention designs. For example, Vandelanotte and colleagues (2023) proposed a just-in-time adaptive intervention platform that promotes physical activity using hyper-personalized, real-time support. The system combines machine learning techniques (i.e., contextual bandits), with a Natural Language Processing-based conversational assistant to analyze contextual data (e.g., GPS, weather, activity levels) and deliver tailored advice, motivation, and nudges to enhance physical activity engagement. These technologies can dynamically adapt interventions based on user-specific data, such as physical activity patterns, environmental conditions, and personal preferences. For example, barriers to physical activity, such as overly intense exercise, an uncomfortable environment, or being indoors and alone could be detected by the adaptive system, which could provide strategies to overcome these challenges (e.g., taking a partner for a walk in a park) (Dunton et al., 2015; Liao et al., 2017a).

Thirdly, we have shown that it is already feasible to capture contextual data through a variety of methodologies, such as geolocation, beacons, and air sensors, and effectively integrate this information into interventions. Future just-in-time adaptive interventions for physical activity promotion should incorporate advanced methods for capturing and analyzing relevant data for example, continuous physiological monitoring tools (e.g., heart rate monitors, accelerometers, and glucose sensors) enable real-time assessment of individual health metrics, while passive sensing technologies (e.g., noise, temperature, and air pollution) provide critical environmental context. These data streams can be further enriched by integrating affective well-being assessments through ecological momentary assessments. Advancements in global positioning system-based tracking and geographic ecological momentary assessment, offer further opportunities for capturing dynamic person-place interactions (Bubalo et al., 2024). Combining these tools with machine learning techniques could enable the detection of patterns, such as family or dyadic behavior dynamics, and the personalization of interventions to specific contexts or individual needs. The complexity of these integrated methods calls for interdisciplinary collaboration among scientists in the fields of health (i.e., psychology, epidemiology, medicine, public health, sports science), machine learning experts, and software developers to improve research methodologies and the impact of interventions for promoting physical activity (Vandelanotte et al., 2023). The new framework not only offers a comprehensive view of moderators and mediators influencing physical behavior but also, to maximize their effectiveness, interventions must account for moderators and mediators influencing behavior across multiple levels. Therefore, this model aligns with the principle that interventions targeting various socio-ecological levels - individual, interpersonal, and environmental - are most impactful (Sallis et al., 2006). By leveraging adaptive algorithms and sophisticated methodologies, it becomes possible to create personalized, context-sensitive interventions that promote physical activity, even in uncontrolled real-world environments (Ben-Zeev et al., 2014, 2015).

While we developed a holistic framework integrating potential moderators and mediators influencing physical activity, the proposed model still requires empirical validation. We anticipate that future endeavors will combine this theoretical framework with novel intervention designs and methodologies, enabling a nuanced identification of the moderators and mediators shaping the relationship between affective well-being and physical behavior. This approach holds the potential to advance health promotion strategies and foster long-term engagement in a physically active lifestyle.

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