Protocol

# Lion Tracks: Protocol for a Microlongitudinal Feasibility Study of Health Behaviors and Emotional Dynamics in Mother-Child Dyads

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## Abstract

**Background:** Adolescence is a critical developmental period during which physical activity, sleep, digital-media engagement, cognition, and emotional health become increasingly interconnected. However, reliance on retrospective self-report and low-frequency longitudinal designs limits understanding of how these domains relate within individuals and families in daily life. Few studies have integrated ecological momentary assessment (EMA), passive sensing, and wearable monitoring within mother-child dyads.

**Objective:** Lion Tracks aims to evaluate the feasibility and acceptability of an integrated ambulatory monitoring protocol. Secondary exploratory aims are to characterize within-person, between-person, and dyadic temporal associations among health behaviors, physiological measures, cognition, and momentary anxiety.

**Methods:** Lion Tracks is a prospective, observational, microlongitudinal feasibility study targeting 25 mother-child dyads (50 participants), with children aged 11-14 years. Participants complete baseline assessments, 4 weeks of ambulatory monitoring, and poststudy assessments. Garmin wearables monitor physical activity, sleep, heart rate, and heart rate variability. MetricWire (MetricWire, Inc) collects passive smartphone screen-on duration and timing and delivers repeated EMA of momentary affect, anxiety, context, and behaviors. Digital-media engagement characteristics are self-reported through EMA. Brief mobile cognitive testing assesses cognitive performance. A hybrid EMA design combines fixed, pseudorandom, and behavior-contingent assessments to capture daily experiences while limiting participant burden. Primary outcomes include recruitment, retention, acceptability, participant burden, wearable compliance, EMA completion, and data completeness. Descriptive statistics and CIs will summarize feasibility outcomes. Exploratory multilevel mixed-effects models will examine within-person and between-person associations, while time-lagged and cross-lagged analyses will explore temporal relationships and behavioral synchrony within dyads.

**Results:** The study received approval from The Pennsylvania State University Institutional Review Board (STUDY00027664). Recruitment is ongoing, with 7 mother-child dyads enrolled as of October 2026. Data collection is anticipated to conclude by June 1, 2027. Analyses will follow completion of data collection.

**Conclusions:** Lion Tracks represents Phase 1 of a larger research program designed to progressively optimize ambulatory monitoring and subsequently incorporate mobile electroencephalography to examine neural correlates of daily behaviors, cognition, and emotional functioning. Findings will inform protocol refinement and assess the feasibility of a scalable, multimodal platform for future family-centered behavioral health research.



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**KEYWORDS**

EMA; passive sensing; wearable technology; emotional regulation; mental health; ecological momentary assessment

# Introduction

## Background

Adolescence is a critical developmental period characterized by increased susceptibility to mental health problems, including anxiety and depressive symptoms, alongside rapid changes in behavior, autonomy, and social context [1-3]. Health behaviors such as lower levels of regular physical activity, lack of sleep, and excessive sedentary behavior, with the latter often associated with use of digital devices (eg, smartphones), are strongly linked to lower emotional well-being [4-6]. The link is particularly acute for symptoms of anxiety, which represent one of the most prevalent and developmentally salient mental health challenges during adolescence [7,8]. However, much of the existing scientific literature relies on retrospective self-report and cross-sectional designs, limiting the ability to capture within-person dynamics and real-time behavioral processes with high precision [9-11]. Capturing the in-the-moment temporal dynamics would allow for more targeted interventions that speak to the proximal mechanisms shaping behavior. This study proposes to address this gap by integrating ecological momentary assessment (EMA), passive sensing, and wearable monitoring to characterize real-world temporal relationships among physical activity, sleep, digital behavior, cognition, and anxiety within mother-child dyads.

A robust body of evidence demonstrates that both higher levels of single bouts and regular physical activity are associated with improved mood and reduced symptoms of anxiety in youth [4,12,13]. Sleep also plays a critical role in emotional regulation, with insufficient or irregular sleep consistently linked to heightened anxiety, poorer stress regulation, and impaired cognitive functioning during adolescence [14,15]. Importantly, physical activity, sleep, and sedentary behavior, including screen time and digital-media use, are highly interrelated behaviors that dynamically influence one another across daily life [16]. Similarly, screen time (particularly smartphone use) has been associated with poorer mental health outcomes, though findings remain inconsistent, potentially due to heterogeneity in measurement approaches and reliance on retrospective self-report, which can blur temporal ordering (recall bias) [5,17]. Notably, physical activity may serve as a central upstream health behavior during adolescence by not only directly supporting emotional well-being through physiological and psychosocial mechanisms, but also indirectly promoting mental health benefits by reducing sedentary screen time and improving sleep duration and quality [18-21]. Collectively, these interrelated effects position physical activity as a particularly promising behavioral target for supporting emotional regulation and reducing anxiety risk during adolescence. However, these findings are largely derived from between-person analyses and do not capture how fluctuations in physical activity, sleep, and digital-media exposure, as a distinct type of sedentary behavior, relate to momentary emotional states within individuals. For example, emerging passive sensing research indicates that adolescents frequently underestimate their smartphone use relative to objective measures, suggesting that traditional assessments may obscure meaningful behavioral patterns and their real-time relationships with sleep, stress, and anxiety [17,22].

A growing body of research supports the dynamic and reciprocal relationships among physical activity, sedentary behavior, mood, and cognition in daily life. Studies consistently show that affective states fluctuate within individuals and are closely tied to contextual and behavioral factors [17,23]. Wearable-based studies indicate that higher levels of physical activity are associated with improved cognitive performance and psychological well-being [24,25], while excessive sedentary behavior and screen engagement are linked to poorer mental health and attentional outcomes [5,26]. Advances in passive sensing and digital phenotyping further suggest that device-based measures of behavior provide more accurate and nuanced insights into behavioral patterns than self-reports alone [27,28]. Additionally, mobile cognitive testing has demonstrated feasibility for capturing intraindividual variability in cognitive performance in real-world settings, particularly in adult populations [29,30], with emerging support in youth [31]. Together, these findings highlight the importance of high-resolution, real-world measurement approaches for examining the complex temporal dynamics between health-related behaviors and specific behavioral outcomes, including approaches such as microlongitudinal studies with ambulatory assessment [17,32-36].

EMA complements passive sensing by capturing real-time self-reports of affect, context, and behavior in naturalistic settings, reducing recall bias and enhancing ecological validity [34,35]. Combining EMA with wearable monitoring has demonstrated feasibility and acceptability in adolescent populations while capturing meaningful within-person variability in affect and behavior [17,36]. Importantly, these behavioral and emotional processes occur within the broader family context, where parent-child interactions, shared routines, and environmental influences shape youths' daily experiences [37,38]. Mothers often play a central role in establishing family routines related to physical activity, sleep, and digital-media use, while also modeling health behaviors that may influence children's emotional and behavioral development [39-41]. Consistent with this perspective, device-based studies demonstrate associations between parent and child physical activity and sedentary behavior patterns, suggesting potential coregulation within dyads [42,43]. However, these approaches have rarely been applied within family-based, dyadic designs. Although dyadic EMA studies have demonstrated feasibility in



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assessing family functioning, few studies have simultaneously captured real-time behavioral and emotional processes in both members of a parent-child dyad across multiple domains [44]. This represents a critical research gap in the literature, which, when addressed, would allow for better informing relevant stakeholders (eg, policymakers and clinicians) on appropriate health actions.

Importantly, momentary anxiety—defined here as the current subjective feeling of anxiety rather than an anxiety disorder or diagnostic risk—is well-suited for microlongitudinal investigation. Its relevance to adolescent emotional well-being and potential relationships with daily health behaviors motivate its inclusion in this study [45]. EMA studies consistently demonstrate that anxiety and related affective states vary substantially within individuals across hours and contexts, even when reflecting fairly stable underlying traits [35,46]. Research also supports carefully selected single-item measures as a low-burden approach to assessing momentary affect. These fluctuations are closely linked to real-time environmental exposures, social interactions, and health behaviors, including physical activity, sleep, and digital engagement [23]. Momentary anxiety may involve dynamic regulatory processes involving interactions among physiological arousal (eg, autonomic activity), attentional control, and environmental demands, which unfold continuously in daily life [47]. These short-timescale processes may not be adequately captured by retrospective or low-frequency assessments. High-resolution, real-time measurement approaches can help characterize their temporal dynamics and context-dependent variability [17,35]. Emerging dynamic behavioral frameworks further suggest that physical activity, sedentary behavior, sleep, and affective states should be conceptualized as temporally interrelated processes that continuously interact across the day rather than as isolated health behaviors [48]. This perspective underscores the need for integrated, real-world approaches capable of capturing these dynamic interactions across multiple behavioral and psychological domains.

Despite these advances, several key research gaps remain. First, most studies examine physical activity, sleep, digital behavior, mental states (eg, mood and anxiety), and cognition (the ability to efficiently process information, maintain attention, and support self-regulation) [49] independently rather than integrating these domains within a unified framework [22,23]. Second, much of the literature relies on cross-sectional or low-frequency longitudinal designs, limiting the ability to capture within-person variability, context, and temporal dynamics, which may aid our understanding of causality and time course [6]. Third, research in pediatric populations, particularly using mobile cognitive assessment, is still limited, and only a few studies have extended these methods into family or dyadic contexts [17,50]. Notably, mother-child dyads represent a critical but understudied unit for understanding coregulation of health behaviors [30,34]. Fourth, there is limited evidence on how these processes interact in real time within natural environments over extended periods [6,51].

To address these research gaps, Lion Tracks is structured as a phased program of research, with Phase 1 serving as a microlongitudinal feasibility study integrating EMA with passive smartphone sensing and wearable monitoring in mother-child dyads. By continuously capturing real-world patterns of physical activity, sleep, smartphone-based digital behavior, affect, anxiety, and cognition, this initial phase is designed to establish the feasibility of a multimodal ambulatory monitoring platform for studying interrelated 24-hour behavioral and emotional processes in naturalistic family settings.

The primary aim of Phase 1 is to evaluate the feasibility, acceptability, participant adherence, and data completeness of the protocol while informing optimization of the monitoring platform for subsequent phases of the Lion Tracks program. As a secondary, exploratory aim, Phase 1 will generate preliminary evidence regarding within-person and mother-child dyadic relationships among daily health behaviors, cognition, and momentary anxiety. Specifically, exploratory analyses will examine whether lower physical activity, poorer sleep, and greater smartphone-based digital-media exposure are associated with elevated real-time anxiety and poorer momentary cognitive performance, while also evaluating preliminary evidence of dyadic synchrony and reciprocal influence, whereby changes in one partner's behavior, emotional state, or physiological context correspond with changes in the other partner across the day. Findings from this phase will inform the refinement of study procedures, hypotheses, and analytic approaches for future fully powered investigations.

## Theoretical Framework

The Lion Tracks conceptual framework integrates constructs from social cognitive theory (SCT) [52] and family systems theory (FST) [53] to explain how maternal health behaviors and dyadic family processes may shape momentary anxiety and emotional regulation across adolescence. Within SCT, key constructs include observational learning, behavioral capability, self-efficacy, outcome expectations, and reciprocal determinism. Lion Tracks focuses primarily on observational learning and reciprocal determinism, proposing that mothers influence children's health behaviors by modeling daily physical activity, sleep routines, stress-management strategies, and smartphone-based digital-media habits. Over time, repeated exposure to these behaviors may shape children's behavioral expectations, confidence, and engagement in similar health behaviors. For example, mothers who consistently engage in regular physical activity and demonstrate confidence in overcoming barriers to exercise may foster greater self-efficacy and more favorable physical activity behaviors in their children through observation and shared experiences.

FST complements this perspective by emphasizing interconnectedness, reciprocal influence, coregulation, family routines, and system organization. Rather than viewing health behaviors and anxiety as characteristics of isolated individuals, FST conceptualizes mothers and children as members of a dynamic relational system in which each person's behaviors and emotional states continuously influence the other. Shared daily routines, emotional climate, communication patterns, and reciprocal behavioral exchanges are therefore expected to shape both individual and dyadic patterns of physical activity, sleep, digital-media use, and emotional functioning.

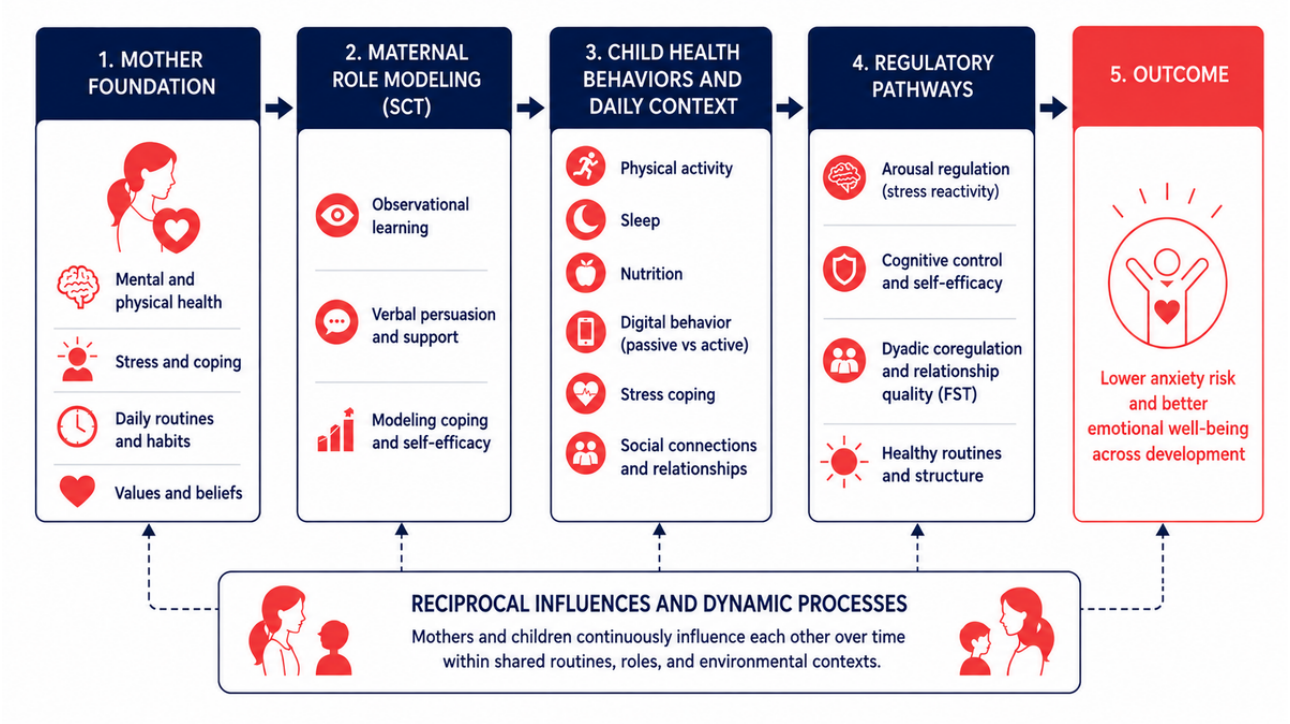


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These theoretical perspectives directly informed the conceptual framework and selection of study measures. Constructs related to maternal modeling are reflected in assessments of physical activity, sleep, digital-media behavior, and stress, while family systems constructs are operationalized through repeated assessment of both members of the dyad, allowing examination of within-person fluctuations, dyadic synchrony, and reciprocal influences over time. By integrating SCT and FST, Lion Tracks conceptualizes health behaviors and emotional functioning as dynamic, interconnected processes that unfold within families in real-world settings, providing a theoretical foundation for examining how daily behavioral patterns may contribute to anxiety risk and resilience across development.

The focus on middle school-aged youth is developmentally strategic, as early adolescence represents a period in which anxiety symptoms rise sharply while physical activity declines, sleep becomes increasingly dysregulated, screen exposure intensifies, and lifelong behavioral patterns begin consolidating [54-56]. Importantly, this developmental window provides a unique opportunity to examine how maternal and child health behaviors coexist and dynamically interact within daily life while maternal influence on routines and emotional support remains highly salient. Rather than viewing health behaviors as isolated individual factors, Lion Tracks seeks to characterize how physical activity, sleep, smartphone-based digital-media use, stress, and emotional states are shared, synchronized, or disrupted within mother-child dyads in real-world settings. By focusing on this age group, the study aims to identify which dyadic health behaviors and family routines may be most strongly associated with anxiety vulnerability versus resilience, ultimately informing future family-centered intervention targets designed to better support mental health during adolescence (Figure 1).

**Figure 1.** Conceptual framework. FST: family systems theory; SCT: social cognitive theory.




Importantly, these levels are not static but dynamically linked across time. Daily behavioral contexts influence physiological and cognitive regulatory processes, which in turn shape momentary emotional states within individuals and propagate across dyads through processes such as emotional contagion, behavioral synchrony, and coregulation. Within this framework, maternal health behaviors are hypothesized to shape child anxiety risk both directly through coregulated emotional environments and indirectly through modeling of physical activity, sleep, and digital-media routines that support emotional regulation. By situating real-time physiological, affective, behavioral, and digital processes within this multilevel relational system, the Lion Tracks framework advances beyond traditional individual-level models and emphasizes temporally evolving, family-centered mechanisms of anxiety risk and resilience.

## Methods

### Study Design and Phased Program Overview

Lion Tracks is designed as a prospective, observational, microlongitudinal feasibility study using repeated ambulatory assessments within mother-child dyads. The study spans approximately 4 weeks and consists of three sequential components: (1) baseline assessment, (2) a 4-week intensive monitoring phase, and (3) a final closing session. The protocol integrates wearable sensing, smartphone-based EMA, passive digital-use monitoring, and brief mobile cognitive testing to achieve high temporal resolution while maintaining low participant burden. A 4-week monitoring period was selected to balance capture of meaningful within-person variability across daily routines with participant burden and long-term adherence to ambulatory assessment. This study has received approval



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from The Pennsylvania State University Institutional Review Board (STUDY00027664).

Lion Tracks is a multiphase study comprising sequential phases that evaluate the feasibility and optimization of a multimodal ambulatory monitoring protocol for mother-child dyads (Figure 1). This phased approach is intended to balance scientific rigor with feasibility, emphasize ecological validity, and ensure that each stage of the protocol is acceptable, scalable, and developmentally appropriate for families. Rather than implementing all assessment modalities simultaneously, the Lion Tracks program begins with a core ambulatory monitoring protocol centered on passive sensing and EMA. Subsequent phases build on this foundation by optimizing the protocol and incorporating mobile electroencephalogram (EEG) assessments as feasibility is established.

In the first phase, mother-child dyads complete a microlongitudinal protocol integrating Garmin-based monitoring of physical activity and sleep, smartphone-based EMA, passive phone-use sensing through MetricWire (MetricWire Inc), and brief mobile cognitive tasks embedded within daily assessments. This initial phase is designed to establish whether families can successfully engage in repeated, real-world monitoring across days and weeks, while generating temporally rich data on daily routines, momentary affect, and cognitive functioning. The central purpose of this phase is not only to assess adherence and participant burden, but also to refine the cadence, timing, and integration of the data streams that form the foundation of the broader Lion Tracks platform.

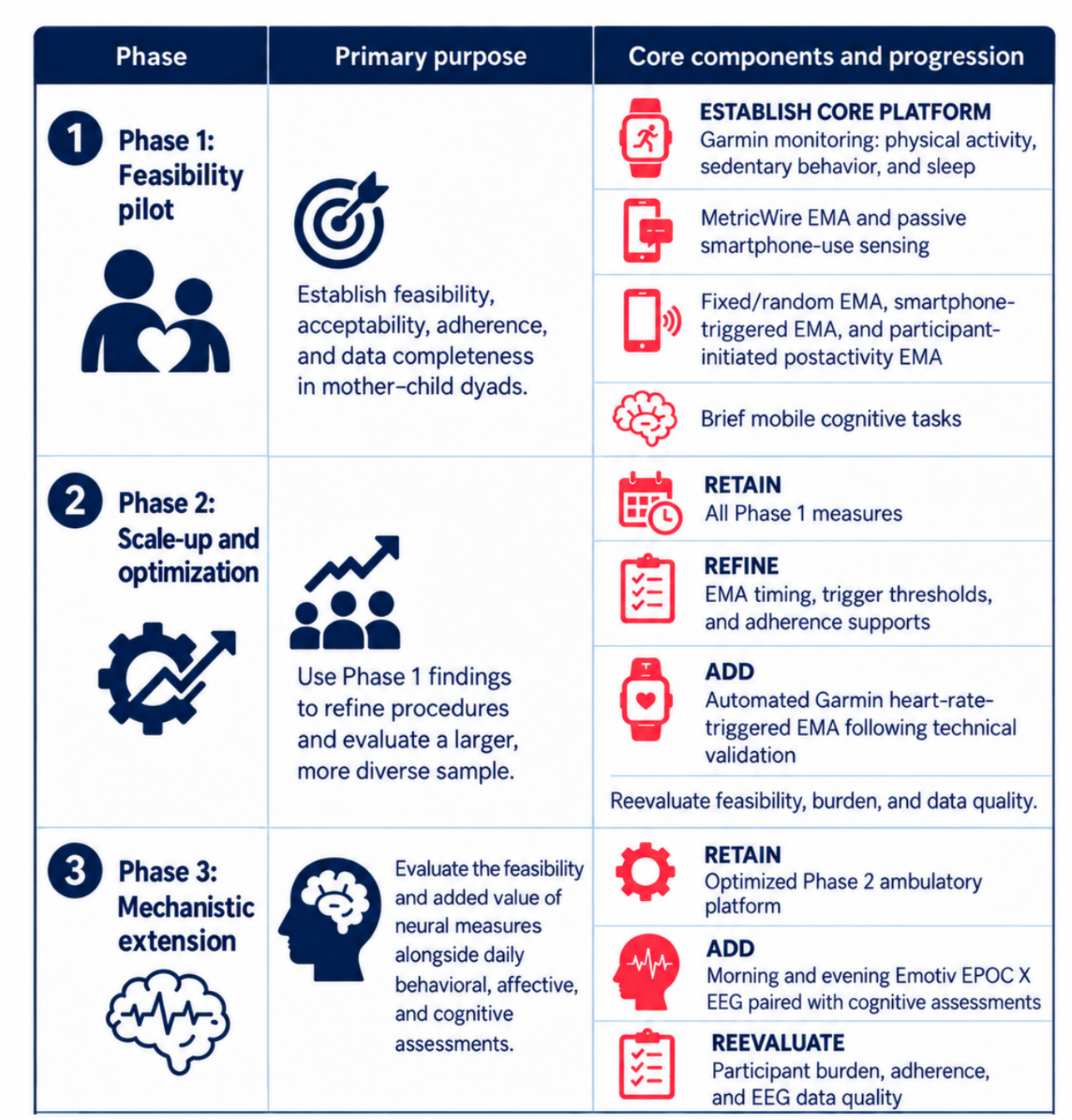
The second phase is designed to build directly on findings from the feasibility pilot by scaling and optimizing the ambulatory protocol. Once the Garmin- and EMA-based platform has been demonstrated to be workable in daily life, this phase will focus on refining the prompting strategy, strengthening adherence supports, and improving trigger logic, including the introduction of Garmin-based, heart rate–triggered EMA. The protocol will then be evaluated in a broader sample and, potentially, across more diverse settings. This phase is critical for allowing the core platform to mature before more complex mechanistic measures are introduced. By prioritizing optimization and reliability at this stage, the study design remains grounded in pragmatism: the protocol must first function consistently and with low burden in real-world contexts before advancing to more intensive forms of neurobehavioral monitoring.

The third phase of Lion Tracks will extend the optimized ambulatory platform by incorporating brief morning and evening mobile EEG assessments using the Emotiv EPOC X system [57]. This future phase is intended to test whether neural markers of cognitive readiness, particularly frontal midline theta signals, can be feasibly captured in daily life and integrated with concurrent behavioral, cognitive, and emotional data [58]. The addition of EEG is grounded in the broader conceptual model of Lion Tracks, in which daily health behaviors and contexts not only shape affective states but also regulatory and cognitive processes that may alter vulnerability to anxiety across the day. By introducing EEG only after the feasibility and scalability of the core protocol are established, Lion Tracks preserves a staged and methodologically disciplined trajectory, allowing each phase to inform the next (Figure 2).



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**Figure 2.** Lion Tracks phases and goals. EEG: electroencephalogram; EMA: ecological momentary assessment.




Taken together, these phases reflect a deliberate progression from feasibility to scale-up and neural assessment. This structure strengthens the overall program of research by ensuring that Lion Tracks develops from a realistic, family-centered ambulatory protocol into a more comprehensive platform for understanding how daily movement, sleep, smartphone-based digital exposure, cognition, and emotional functioning interact within and across mother-child dyads in real-world settings.

This protocol describes Phase 1 only. Phase 1 findings on adherence, acceptability, participant burden, and data completeness will inform Phase 2 refinements to prompting and adherence procedures. Phase 3 retains the optimized platform and adds mobile EEG to evaluate the feasibility and added value of neural assessments alongside behavioral, affective, and cognitive measures.

## Recruitment Setting and Procedures

Mother-child dyads will be recruited from communities surrounding The Pennsylvania State University in central Pennsylvania using convenience sampling. Recruitment will occur through community advertisements, school and community partner outreach, social media postings, and existing university and community networks. Study participation will be primarily remote, with online questionnaires, virtual onboarding, mailed wearable devices, and ambulatory monitoring conducted during participants' usual daily activities at home, school, work, and other community settings.

Recruitment materials will provide a brief study description, basic eligibility criteria, participation requirements, and instructions for contacting the research team or accessing the



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online screening questionnaire. Interested mothers will complete an initial screening questionnaire to assess eligibility for themselves and their child, including age, shared household residence, access to compatible smartphones, and ability to complete the monitoring procedures. Study staff will review screening responses, clarify eligibility information as needed, and contact potentially eligible families to explain study requirements and answer questions. Enrollment will occur at the dyad level, with both members required to meet eligibility criteria. Maternal informed consent, parental permission, and child assent will be obtained before baseline assessments and device onboarding. Recruitment and screening records will be used to summarize the numbers of families expressing interest, screened, eligible, and enrolled, along with reasons for ineligibility or declining participation when available.

## Participants and Eligibility Criteria

Participants will include approximately 50 mother-child dyads (n=100). Consistent with the primary objective of this Phase 1 feasibility study, the sample size was selected to provide adequate precision for estimating key feasibility outcomes, including participant recruitment, protocol adherence, EMA completion, wearable-device compliance, retention, and data completeness, rather than to detect intervention effects or test efficacy hypotheses. With approximately 50 dyads, feasibility proportions can be estimated with acceptable precision (approximately ±10%-14%, depending on the observed proportion), providing sufficient information to determine whether progression to a larger study is warranted and to inform protocol refinement and sample size calculations for future confirmatory studies [59,60].

Mothers must be at least 18 years of age and reside with the participating child. Children will be between the ages of 11 and 14 years, reflecting a developmental period characterized by increasing autonomy in daily routines and high rates of smartphone access. Additionally, from a pilot feasibility perspective, this age group is more likely to have access to a smartphone to complete phone-based data collection (allowing coupling with maternal smartphone data), and the Garmin actigraphy has been validated in middle schoolers and adults [61,62]. Both members of the dyad must have access to a compatible smartphone capable of running the MetricWire app and supporting background data collection.

Consistent with the feasibility aims of Phase 1, recruitment will use a convenience sampling approach. Participants will be recruited through community advertisements, school and community partner outreach, social media postings, and existing university and community networks within the surrounding region. Interested participants will complete an initial screening questionnaire to determine eligibility. Participants will be eligible if they are cleared for physical activity using the Physical Activity Readiness Questionnaire for Everyone (PAR-Q+) [63], report anxiety and depressive symptoms below severe clinical thresholds, and are able to comply with smartphone- and wearable-based monitoring. Participants may be excluded or referred for additional evaluation prior to enrollment if they are not cleared by the PAR-Q+, score in the severe range on the [64] (Generalized Anxiety Disorder-7) or Patient Health Questionnaire-9 (PHQ-9)/Patient Health Questionnaire-8 (PHQ-8) [65], endorse acute safety concerns, or are unable to complete ambulatory monitoring procedures. Enrollment occurs at the dyad level, and both members must meet eligibility criteria.

## Ethical Considerations

The study was approved by The Pennsylvania State University Institutional Review Board (STUDY00027664). Mothers will provide electronic informed consent for their own participation and parental permission for their child's participation, and children will provide electronic assent before study activities begin. Consent and assent materials will describe study procedures, potential risks, confidentiality protections, compensation, and the requirement to accept MetricWire's Privacy Policy. Mothers and children will each review and accept this policy separately within the app before data collection. Participation is voluntary, and either member may withdraw at any time without penalty; withdrawal of either member will result in withdrawal of the dyad.

Research data will be coded using unique study identifiers. The master list linking names and contact information to study identifiers will be stored separately from research data and consent documents on secure, encrypted, password-protected Penn State–approved servers, accessible only to authorized study personnel. Analyses will use datasets labeled with study identifiers rather than direct identifiers. Garmin data will be synchronized to a secure server under the participant's study identifier. MetricWire will record EMA responses, timestamps, and basic technical diagnostics but will not collect GPS location, contacts, audio, keystrokes, or screen content.

Each participant may receive up to US $150 in electronic Visa or Amazon gift cards for their time and effort: US $15 for completing baseline surveys and onboarding, US $25 for each of the two 2-week monitoring periods, and US $85 for completing poststudy activities and returning the Garmin device. Compensation will be distributed electronically at study milestones, with partial compensation provided for completed activities if participants do not finish the study.

## Study Procedures

Following informed consent and assent, participants complete a baseline online survey assessing demographics, mental health, factors related to sleep and physical activity, and family context. Both mothers and children complete a brief online survey (~20 minutes) administered via a secure, mobile-compatible platform. Parallel assessments across dyad members allow for examination of individual and interdependent psychological and behavioral processes. Validated instruments include the Patient-Reported Outcomes Measurement Information System (PROMIS) measures [66] for anxiety and depression [67], and perceived sleep quality and sleep-related problems [68]. PROMIS instruments demonstrate strong internal consistency across pediatric and adult samples (Cronbach $\alpha$ typically ≥0.90) and robust construct validity [66-68]. Physical activity self-efficacy is assessed using a brief physical activity confidence scale adapted from established measures, which have demonstrated acceptable to strong reliability in youth and adult populations



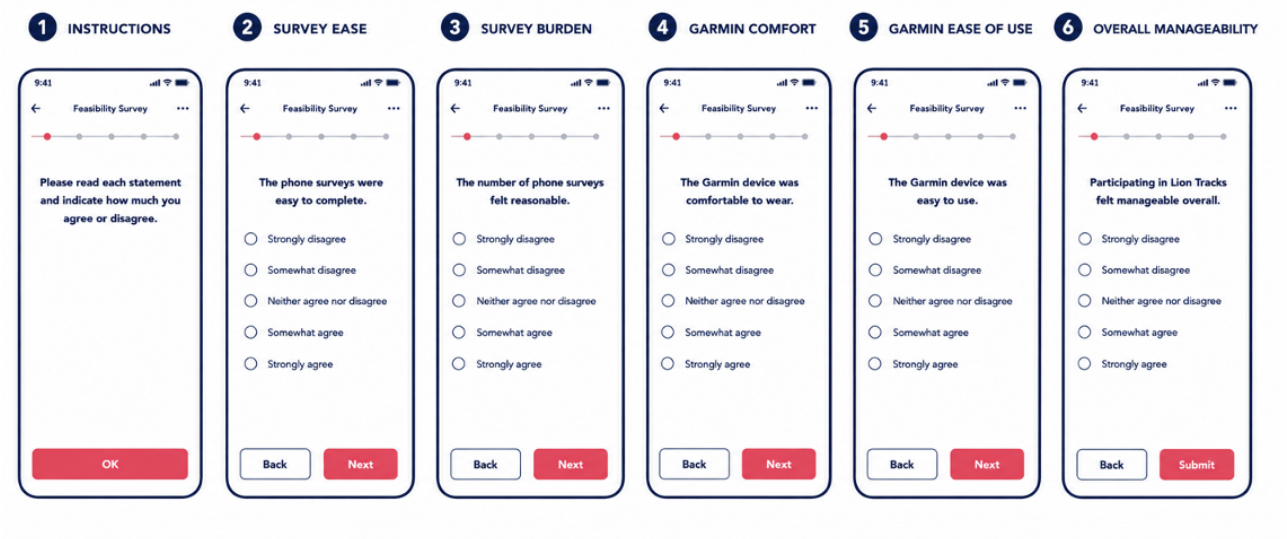
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(Cronbach $\alpha \approx 0.80$-$0.90$) [69]. Family relational processes are assessed using the Child-Parent Relationship Scale (CPRS), which captures dimensions such as closeness and conflict and has demonstrated good internal consistency (Cronbach $\alpha \approx 0.72$-$0.86$) [70].

Participants receive their Garmin device in the mail with a handout with common questions and guidance on wear (eg, wear on nondominant hand, charge the device when you are showering each day, sync your data to MetricWire nightly, and so on), then attend a virtual onboarding session (~30 minutes) conducted via videoconference. During this session, study staff guides participants through device setup, including pairing and activation of the Garmin wearable device and installation and configuration of the MetricWire mobile app. Participants are instructed on how to wear the Garmin device continuously (24 h/d, except during charging) and how to respond to EMA prompts. Notifications, permissions (eg, screen time tracking and background activity), and app settings are verified to ensure proper data collection.

After onboarding, participants enter a 4-week intensive monitoring phase. During this phase, continuous passive sensing is maintained, and EMA prompts are delivered according to a hybrid schedule. At the end of the monitoring period, participants complete a closing session (~30 minutes) to return devices and complete a feasibility and acceptability survey (Figure 3). Figure 4 provides an overview of all procedures. Mothers and children complete the survey independently, with children reporting their own perceptions rather than mothers responding on their behalf. Child-facing items use concrete, age-appropriate language, and study staff are available to clarify instructions without directing responses.

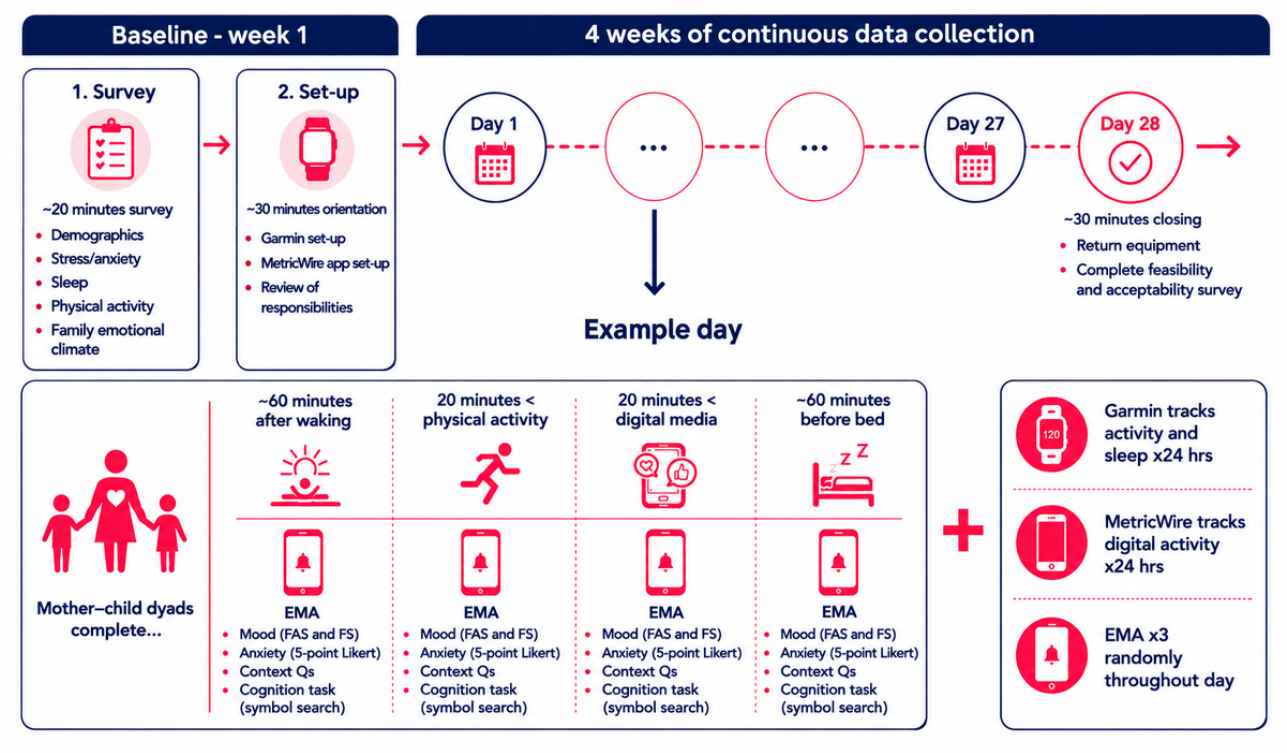
**Figure 3.** Feasibility and acceptability survey.






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**Figure 4.** Flow of project. EMA: ecological momentary assessment; FAS: Felt Arousal Scale; FS: Feeling Scale.



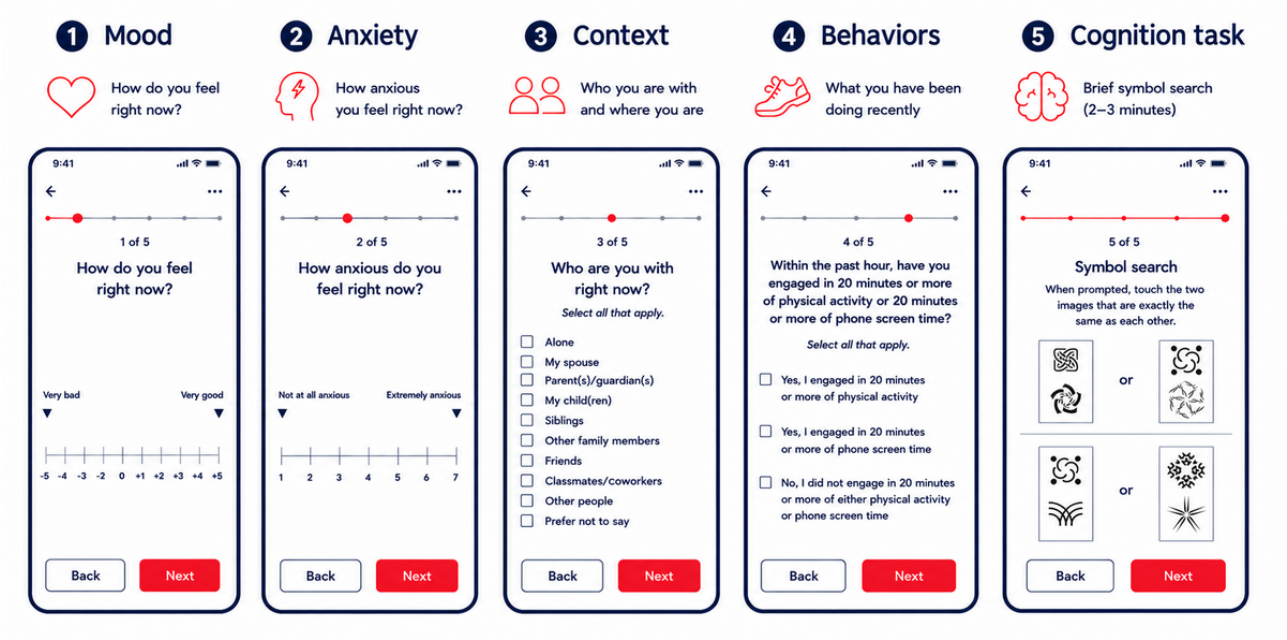

## EMA

EMA is delivered via the MetricWire platform using a hybrid prompting schedule that integrates fixed, random, and behavior-contingent triggers (Figure 5). Data collection will occur continuously over the 4-week monitoring period and include both weekdays and weekends to capture variability across school, home, and leisure contexts. Two fixed prompts are delivered daily: one approximately 60 minutes after waking and one approximately 60 minutes before average bedtime. Initial onboarding surveys assess participants' typical sleep and wake schedules to guide prompt timing, and Garmin-derived sleep/wake detection data are additionally used to refine and verify individualized prompt delivery windows throughout the monitoring period. These prompts anchor daily assessment and include brief cognitive tasks (ie, symbol search). In addition, up to 3 pseudorandom prompts are delivered each day within predefined windows (9:00 AM to noon, noon to 3:00 PM, and 3:00 PM to 6:00 PM). Prompt timing is randomized within each window to maximize temporal coverage while reducing participant anticipation. Each prompt remains active for 90 minutes, with reminder notifications delivered every 30 minutes (up to 3 notifications) if no response is recorded. The prompting schedule was intentionally designed to accommodate typical school-day routines by allowing a 90-minute response window, enabling participants to complete assessments during natural breaks (eg, between classes, lunch, or after school) when immediate responses are not feasible. Missed prompts are retained as indicators of real-world unavailability rather than treated as protocol deviations.



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**Figure 5.** Ecological momentary assessment probes.




Event-contingent EMA prompts are triggered based on real-time behavioral data streams. A 20-minute threshold was selected pragmatically to standardize event-contingent EMA triggering across sustained physical activity and smartphone engagement episodes while minimizing excessive prompting from brief or fragmented behaviors. Specifically, prompts are initiated when MetricWire detects at least 20 minutes of continuous smartphone screen engagement. Smartphone engagement was selected as the primary screen-based trigger because MetricWire supports continuous passive sensing of smartphone activity, enabling high-resolution real-time behavioral monitoring within a scalable ambulatory framework. Although smartphone engagement does not comprehensively capture all sedentary behaviors, smartphone-based screen use represents one of the most prevalent and behaviorally salient forms of digital sedentary behavior among adolescents [54,55,71].

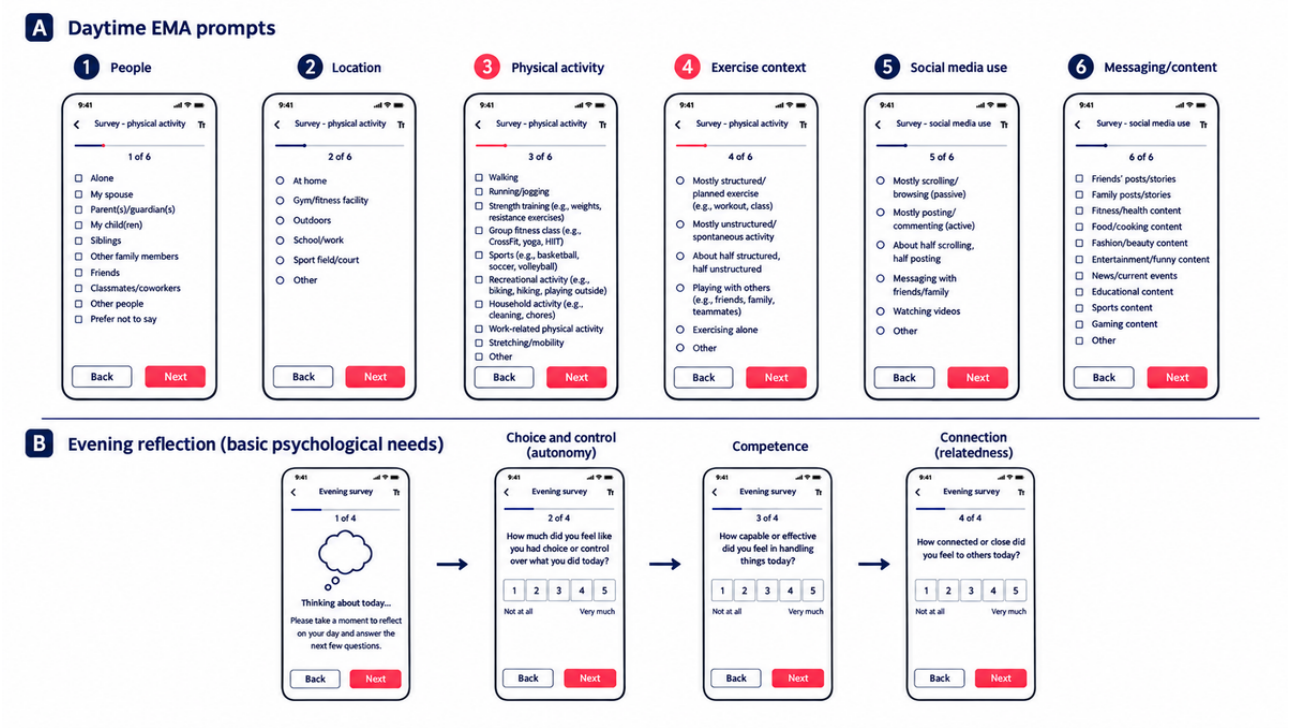
Due to current technical limitations, Garmin data cannot trigger EMA prompts in real time; therefore, following a bout of at least 20 consecutive minutes of moderate-to-vigorous-intensity physical activity, participants will be instructed to open the MetricWire app and complete a brief survey. To reduce participant burden, a minimum interval (lockout period) of at least 60-180 minutes is enforced between prompts, and prompts are suppressed during predefined do-not-disturb windows. Therefore, in Phase 1, event-contingent EMA for physical activity is participant-initiated, whereas screen-based EMA is automatically triggered. Full automation of activity-based triggering will be tested in Phase 2 following proof-of-concept work, with real-time Garmin heart rate data triggering EMAs.

Each EMA prompt requires less than 1 minute to complete and includes brief, mobile-optimized items assessing momentary affect using the Feeling Scale (FS) [72] and Felt Arousal Scale (FAS) [73] as well as a 7-point Likert-scale measure of current anxiety [74]. We use affect as an umbrella term encompassing feeling states, including emotions and moods. Emotions are relatively brief responses to salient events or situations, whereas moods are more diffuse and sustained states that need not have an identifiable trigger. In this protocol, momentary affect is operationalized through affective valence (FS) and perceived activation (FAS), while the anxiety item assesses a specific momentary emotional state. These assessments capture current feelings rather than sustained mood. Brief affect assessments have been used in smartphone-based EMA with children aged 8-12 years [10], and the FS and FAS have been used in exercise research with children and adolescents [75]. These studies provide precedent for brief affect assessment in youth, although they do not establish the developmental suitability of every item and response format used in this protocol. Item comprehension and usability will therefore be evaluated during Phase 1. Prompts also assess social context (eg, alone, peers, and parents), location, and recent behaviors, including smartphone and social media engagement characteristics (eg, content type, passive vs active engagement, messaging, and video viewing) [76] as well as physical activity type, context, and perceived intensity (Figure 6A). These smartphone and social media variables are self-reported through EMA. In addition, participants complete a brief mobile-based symbol search task (~2-3 minutes) assessing processing speed and attentional control. The evening assessment also includes a brief end-of-day reflection assessing satisfaction of the 3 basic psychological needs—autonomy (choice and control), competence (feeling capable and effective), and relatedness (feeling connected to others)—using single-item ratings adapted from basic psychological needs theory (Figure 6B) [77]. This multimodal EMA approach enables high-resolution, within-person assessment of dynamic relationships among affect, anxiety, behavior, context, and cognition in naturalistic settings.



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**Figure 6.** Supplemental ecological momentary assessment (EMA) questions.




Prior work using similar platforms [78,79], and define "usable" participants a priori as those completing at least 65% of scheduled EMAs and 21 or more days of valid Garmin wear (≥16 h/d) [80,81]. If adherence falls below these thresholds, the study team will implement contingency strategies, including tailored reminders, adaptive reduction of random EMA prompts while preserving fixed and event-triggered prompts, incremental incentives tied to adherence milestones, and real-time adherence monitoring dashboards to facilitate proactive troubleshooting. This protocol yields approximately 200 EMA observations per participant and more than 18,000 total dyadic observations, providing sufficient temporal density to estimate within-person and dyadic temporal associations.

## Wearable Monitoring and Passive Smartphone Sensing

Behavioral patterns, such as time spent on physical activity, sleep, and sedentary behaviors (defined as any waking behavior characterized by low energy expenditure while in a sitting, reclining, or lying posture) [48] and specific physiologic parameters (ie, heart rate) are continuously measured using Garmin wearable devices (eg, Garmin vívoactive series). Heart rate and heart rate variability (HRV) are assessed as physiological measures and are not interpreted as direct measures of psychological stress. Phase 1 does not directly assess stressor exposure or perceived stress. Garmin devices were selected for their ability to provide continuous, high-resolution physiological and activity data, as well as their growing compatibility with mobile platforms that enable near real-time data access. Additionally, Garmin wearables demonstrate particularly strong validity for step-count estimation (eg, mean absolute percentage error [MAPE] ≈ 4.6%), moderate validity for heart rate monitoring, and acceptable sleep/wake detection (~89% agreement), although energy expenditure and sleep-stage classifications are more variable across studies [82,83]. These data are used for descriptive and analytic purposes; however, at this stage, Garmin data do not directly trigger EMA prompts. Instead, participants are instructed to self-initiate a brief survey within the MetricWire app following at least 20 minutes of sustained physical activity. Participants are asked to wear the device continuously throughout the study period, removing it only for charging or activities incompatible with device use (eg, situations where wearable devices are prohibited, or prolonged water exposure beyond device recommendations). Data are synced via the participant's smartphone to ensure continuous upload.

In Phase 2, a personalized EMA triggering algorithm will be implemented using wearable-derived physiological and movement data. During week 1 (days 1-7), continuous Garmin data will be used to estimate each participant's resting heart rate and characterize habitual movement patterns to calibrate individualized moderate-intensity activity thresholds. The primary trigger will be based on heart rate reserve (HRR), and consistent with established exercise-intensity guidelines, moderate-intensity physical activity corresponds to approximately 40%-59% HRR [84,85]. Age-predicted maximum heart rate will be estimated using established equations (eg, 208 − [0.7 × age]) to calculate individualized HRR thresholds. Although HRR will serve as the primary trigger, accelerometer- and activity-derived metrics will also be explored to determine whether combining physiological and movement data improves classification of sustained moderate-intensity physical activity in free-living settings. Because evidence regarding multisensor approaches remains heterogeneous, the final algorithm will be selected based on its classification performance, stability, and feasibility for real-time implementation.

A graded exercise test to establish physical activity intensity zones will not be conducted because the ambulatory, remotely monitored design prioritizes ecological validity, scalability, and participant feasibility in real-world settings, where



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laboratory-based maximal exercise testing would substantially increase participant burden and reduce protocol accessibility. During weeks 2-4 (days 8-28), EMAs will be triggered following detection of a qualifying moderate-intensity activity bout using the individualized wearable-based algorithm. Initially, qualifying bouts will be defined as sustained moderate-intensity activity for at least 20 consecutive minutes, with brief interruptions (≤60 seconds) permitted to accommodate expected variability in wearable-derived physiological signals. EMAs will not be delivered during activity; instead, prompts will occur following recovery, operationalized as a return toward baseline heart rate maintained for at least 2 minutes, with an optional delay of 1-3 minutes to reduce participant burden during postexercise transitions. Because Phase 2 is intended to optimize the triggering algorithm, the 20-minute threshold and trigger logic will be evaluated using observed activity patterns, EMA trigger frequency, classification performance, and participant burden. If qualifying bouts are infrequent or trigger performance is suboptimal, these parameters will be refined in subsequent phases while preserving the objective of capturing meaningful postactivity affective and cognitive states.

Additional constraints include configurable lockout periods (eg, 90-180 minutes) to prevent repeated prompts and predefined do-not-disturb windows to minimize interruptions during inflexible school or work periods. Importantly, passive sensing and wearable-derived objective data collection will continue during these windows; only random EMA prompting will be temporarily suppressed to reduce participant burden and improve feasibility in real-world contexts. In addition to traditional physical activity metrics (eg, duration, intensity, frequency, and steps) [86], exploratory analyses may examine temporal behavioral characteristics derived from wearable data, including activity bout duration, timing, fragmentation, and density (ie, temporal spacing and clustering of physical activity across the day) [87].

MetricWire is a secure, cloud-based mobile data collection platform designed for EMA and passive sensing in real-world settings. The platform enables (1) delivery of scheduled and event-contingent EMA prompts; (2) collection of self-report responses in real time; (3) passive capture of smartphone usage data, including screen-on duration and timing; and (4) integration with external data streams for trigger-based prompting.

MetricWire operates in the background of the participant's smartphone, allowing continuous monitoring of digital behavior without requiring active engagement. The platform also supports configurable logic for EMA delivery, enabling prompts to be triggered by behavioral thresholds (eg, sustained screen use) and scheduled according to study-specific parameters. In this study, MetricWire serves as the central hub for EMA delivery and digital behavior monitoring, while also coordinating with Garmin-derived data to support event-contingent triggering.

### Mobile Cognitive Assessment

Brief cognitive tasks are administered via the M2C2 (Mobile Monitoring of Cognitive Change) platform (eg, symbol search task) and delivered through integration with the MetricWire app during selected EMA prompts, specifically within morning and evening assessment windows. These tasks are designed to assess cognitive processes including attentional control, visual processing speed, and perceptual discrimination, and are optimized for repeated, low-burden administration in naturalistic settings. The M2C2 toolkit enables precise, scalable mobile cognitive assessment with high temporal resolution, making it well suited for ambulatory, microlongitudinal study designs.

The primary task is a mobile-adapted symbol search task (Figure 3, screen 1), modeled after established neuropsychological paradigms. On each trial, participants are presented with one or more target symbols alongside a set of search symbols and are asked to indicate, as quickly and accurately as possible, whether any of the target symbols appear in the search set. Responses are recorded via touchscreen input. The task consists of a series of rapid trials (eg, ~60-80 trials), with performance indexed by reaction time, accuracy, and composite efficiency scores (eg, correct responses per unit time).

To minimize burden and maximize compliance, each assessment requires approximately 2-3 minutes to complete and is designed for repeated administration across days. Task parameters (eg, symbol complexity and number of distractors) are standardized across participants, and brief instructions are provided at each administration. This approach enables the capture of within-person variability in cognitive performance across real-world contexts while maintaining feasibility in a microlongitudinal design. To minimize potential ceiling effects and practice-related gains, task difficulty will be calibrated during pilot testing and adjusted as needed to ensure sufficient variability in performance. Where possible, parallel/alternate task versions will be used across administrations to reduce item memorization and repeated-exposure effects. Task parameters may include variation in symbol arrays, distractor sets, and trial order while maintaining consistent underlying task demands across participants and time points. Early administrations may also be treated as practice or acclimation trials in sensitivity analyses to evaluate whether rapid learning effects influence observed cognitive performance patterns.

This design balances brevity with sufficient trial numbers to estimate behavioral interference and associated frontal-midline theta activity, while minimizing fatigue and movement artifacts during at-home EEG recording [30,88]. To reduce variability associated with repeated self-placement of the EEG headband across days, participants will receive standardized onboarding procedures, including visual placement guides, supervised fitting practice, and brief written instructions provided at each assessment. To address noise and artifacts inherent to home-based EEG, data will undergo standardized preprocessing, including band-pass filtering, automated artifact detection, and rejection of segments with excessive movement or signal loss; sessions will be considered usable if they yield at least 2 minutes of artifact-free resting data and 60% or more of task segments [89,90]. When a session fails these quality-control thresholds, participants will be prompted to repeat the recording at the next fixed sampling window, with brief staff troubleshooting (phone or video) provided as needed. Because ambulatory EEG introduces greater positioning variability than laboratory-based systems, analyses will primarily emphasize within-person fluctuations across repeated assessments rather than absolute



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between-person neural values**.** We anticipate that at least 75% of scheduled EEG sessions will meet usability criteria across the monitoring period.

MetricWire-based EMA instruments demonstrate strong reliability for affective and contextual constructs (Cronbach $\alpha$=0.80-0.94) and high compliance rates (>85%) across youth and adult populations [46,91]. Participants also wear Garmin Vívoactive 5 devices to collect physical activity, sleep, heart rate, and HRV data. Garmin-derived activity, sleep, and HRV metrics demonstrate acceptable agreement with research-grade accelerometry and actigraphy systems (intraclass correlation coefficient [ICC] ≈ 0.85-0.96) [81,92-94]. EMA cognitive test composites exhibit acceptable internal consistency within youth and adult samples (Cronbach $\alpha \approx 0.77$-0.86) [30,95]. Together, this Garmin-MetricWire ecosystem yields a multimodal dataset capable of capturing real-time fluctuations in physical activity, sleep, affect, arousal, cognition, and smartphone-based digital engagement while maintaining an acceptable burden through ultra-brief assessments (<1 minute per EMA) and brief neural sampling epochs.

This study represents Phase 1 of the Lion Tracks program and focuses on establishing the feasibility, acceptability, and operational performance of the multimodal ambulatory monitoring platform. Consistent with the iterative phased design, findings from Phase 1 will directly inform refinement of the protocol before broader implementation. Specifically, feasibility outcomes—including participant adherence, EMA completion, wearable compliance, participant burden, and data completeness—will be used to optimize EMA timing, event-triggering algorithms, adherence strategies, and data integration procedures.

Phase 2 will evaluate the refined protocol in a larger and more diverse sample while implementing optimized prompting schedules and wearable-based triggering algorithms. Building on these findings, Phase 3 will incorporate additional neural assessments, including mobile EEG, to examine neural correlates of cognitive and emotional regulation within the established ambulatory monitoring framework. This iterative progression from feasibility testing to protocol optimization and mechanistic investigation is intended to ensure that each phase is informed by empirical findings from the preceding phase while maintaining a scalable and participant-centered research platform.

EEG assessments in Phase 3 will use the Emotiv EPOC X system during morning and evening assessment windows. EEG recordings will be paired with the existing mobile cognitive tasks to capture neural markers of cognitive readiness, including frontal midline theta activity, while preserving the ambulatory monitoring framework developed in the earlier phases. EEG adds a neural measure that complements self-reported affect, wearable-derived physiology, and cognitive task performance. Morning and evening EEG assessments will allow exploratory examination of temporal relationships between daily health behaviors and neural activity. Specifically, we will examine whether the previous day's physical activity, sleep during the intervening night, and digital-media engagement are associated with next-morning EEG indices and cognitive performance. We will also explore whether evening EEG indices predict next-day behavioral, cognitive, and affective outcomes beyond prior-day measures. This approach may help characterize how daily experiences relate to the brain's functional state at the start of each day and identify candidate markers for future intervention research. The EPOC X system device provides stable 4-channel EEG indices during brief resting and task periods, including individual alpha frequency, frontal alpha asymmetry, and frontal-midline theta—markers relevant to attentional readiness, inhibitory control, and prefrontal engagement. These measures demonstrate acceptable reliability when aggregated across epochs, with reported internal consistency or test-retest reliability in children and adults [96,97] (ICC ≈ 0.82-0.95) [98,99]. If feasible and informative, these measures could help identify periods when behavioral support may be most useful, informing hypotheses for future intervention studies.

## Outcomes, Measures, and Data Sources

Consistent with the primary objective of this Phase 1 feasibility study (Table 1), the primary outcomes include protocol feasibility, participant recruitment and retention, EMA adherence, wearable-device compliance, participant burden, acceptability, and data completeness. These outcomes will be used to evaluate the operational performance of the multimodal ambulatory monitoring platform and identify areas requiring refinement before implementation in subsequent phases of the Lion Tracks program. Secondary exploratory outcomes include physical activity, sleep, digital-media engagement, physiological arousal (eg, heart rate and HRV), momentary anxiety, affective states, and cognitive performance. Physical activity, sleep, heart rate, HRV, and related physiological measures will be derived from Garmin wearable devices. Smartphone screen engagement and passive digital-media metrics will be collected through the MetricWire platform. Momentary affective, contextual, and anxiety-related variables will be assessed using EMA, and cognitive performance (eg, reaction time, accuracy, and efficiency) will be obtained using the mobile symbol search task administered through the M2C2 platform. All data streams will be synchronized using timestamp alignment and securely stored on university servers for integrated analysis.



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**Table 1.** Measures and key metrics for Phase 1.

| Domain | Source/instrument | Key metrics |
|---|---|---|
| Feasibility | Study records | Recruitment, retention, EMA[a] adherence, wearable compliance, participant burden, acceptability, and data completeness |
| Physical activity and physiology | Garmin wearable | Physical activity intensity and timing, steps, heart rate, heart rate variability (lnRMSSD[b] and HF[c]), and sedentary time |
| Sleep | Garmin wearable | Sleep duration, sleep efficiency, and sleep timing |
| Digital behavior | MetricWire passive sensing and EMA surveys | Smartphone screen time, app use, digital-media engagement (passive vs active) |
| Context and momentary affect | EMA surveys | Anxiety, valence, arousal, stress, activity context, and social context |
| Cognition | M2C2[d] symbol search | Accuracy, reaction time, and processing efficiency |

[a]EMA: ecological momentary assessment.

[b]lnRMSSD: natural log root mean square of successive differences.

[c]HF: high-frequency power.

[d]M2C2: Mobile Monitoring of Cognitive Change.

## Statistical Analyses

Analyses will be conducted according to the primary and secondary aims of Phase 1. For the primary feasibility aim, recruitment, retention, EMA completion, wearable-device compliance, participant burden, acceptability, and data completeness will be summarized using descriptive statistics, including proportions, means, SDs, and 95% CIs. All statistical analyses will be conducted using RStudio (Posit Software, PBC) with R (R Foundation for Statistical Computing) [100]. We will evaluate protocol feasibility and acceptability using participant retention, EMA completion, wearable-device compliance, participant-reported burden and acceptability, and overall data completeness to inform protocol refinement and progression to subsequent study phases.

For the secondary exploratory aim, multilevel mixed-effects models will be used to estimate within- and between-person associations among physical activity, sleep, digital-media engagement, physiological arousal, cognition, and momentary anxiety while accounting for repeated observations nested within individuals and mother-child dyads. We further hypothesize that higher levels of physical activity and better sleep will be associated with lower momentary anxiety, more positive affect, and improved cognitive performance, whereas greater sedentary behavior and smartphone-based digital-media engagement will be associated with poorer psychological and cognitive outcomes. Additionally, we hypothesize that mothers' and children's behavioral, physiological, cognitive, and emotional states will exhibit temporal concordance, such that changes within one member of the dyad will predict subsequent changes in the other. Time-lagged and cross-lagged models will be used to examine temporal relationships within and across dyads, including whether fluctuations in one member's behavior, emotional state, cognitive performance, or physiological context correspond with subsequent changes in the other member. Child age (centered), baseline anxiety severity, and dyadic role (mother vs child) will be evaluated as between-person moderators of both average levels and temporal coupling parameters to explore developmental and individual differences in daily behavioral and emotional dynamics.

## Sample Size Justification

Approximately 50 mother-child dyads (n=100 participants) will be enrolled. Consistent with the objectives of a Phase 1 feasibility study, the sample size was selected to provide adequate precision for estimating key feasibility outcomes, including recruitment, retention, EMA adherence, wearable compliance, participant burden, and data completeness, rather than to formally test behavioral hypotheses. With approximately 50 dyads, feasibility estimates can be obtained with acceptable precision while providing sufficient information to refine study procedures and inform the design and sample size calculations of future adequately powered studies [59,60]. Exploratory analyses are intended to generate preliminary effect-size estimates and characterize within-person and dyadic variability to guide subsequent phases of the Lion Tracks program.

## Missing Data

Missing EMA observations, intermittent device nonwear, and incomplete passive sensing data are anticipated in ambulatory monitoring studies and will be addressed using established intensive longitudinal data procedures [6,35,46]. EMA prompts not completed within the allowable response window will be classified as missed observations. Garmin data will be considered valid when wear-time criteria are met (≥16 h/d), and usable participants will be defined a priori based on completion of at least 65% of scheduled EMAs and 21 or more valid wear days. Patterns of missingness will be evaluated descriptively and analytically, and missing data will be addressed using multiple imputation and maximum likelihood estimation approaches where appropriate. Real-time adherence monitoring will be used to facilitate proactive troubleshooting and minimize avoidable data loss.



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## Results

Recruitment is ongoing, with 7 mother-child dyads (14 participants) enrolled as of October 2026. Data collection is anticipated to be completed by June 1, 2027. Feasibility, acceptability, adherence, and exploratory behavioral and dyadic outcomes will be analyzed following completion of data collection.

## Discussion

### Principal Findings

This protocol outlines Lion Tracks, a novel microlongitudinal study designed to capture real-time interactions among physical activity, sleep, smartphone-based digital behavior, cognition, and affect within mother-child dyads. By integrating passive sensing with EMA, this study addresses several critical limitations in the current literature, including reliance on retrospective self-report, low temporal resolution, and a lack of dyadic, family-centered designs.

### Expected Contributions

A primary contribution of this work is its emphasis on within-person and dyadic dynamics. Rather than treating health behaviors and emotional outcomes as static or independent constructs, Lion Tracks is positioned to examine how fluctuations in daily routines relate to momentary anxiety and how these processes propagate across family members. This aligns with FST and extends prior research by operationalizing coregulation in real-world contexts using high-frequency, multimodal data. If feasible, this approach may provide one of the most temporally precise examinations of behavioral-emotional coupling in youth and caregivers to date.

The study also advances the broader research field of precision behavioral health methodologically by demonstrating the feasibility of a low-burden, ambulatory sensing ecosystem. The integration of Garmin-based physiological monitoring with MetricWire-delivered EMA and passive smartphone sensing represents a scalable framework for capturing real-world behavior. Importantly, the hybrid prompting design—combining fixed, random, and event-contingent triggers—balances ecological validity with participant burden, a persistent challenge in intensive longitudinal research. Findings from this phase will be critical for optimizing adherence thresholds, trigger logic, and data completeness in future scale-up efforts.

Another key innovation is the inclusion of mobile cognitive assessment, with planned expansion to neural measures (eg, mobile EEG) in later phases. This positions Lion Tracks to examine neural correlates alongside behavioral, cognitive, and affective measures, particularly regarding cognitive readiness and its role in moderating daily emotional vulnerability. If successful, this staged approach—from feasibility to mechanistic extension—provides a strong model for building translational, real-world neuroscience into behavioral health research.

### Limitations

Despite these strengths, several limitations should be acknowledged. First, as a feasibility pilot, the sample size is modest and may limit generalizability. Second, although passive sensing reduces reporting bias, it introduces potential challenges related to data completeness, device adherence, and technical variability across platforms. Additionally, passive sensing in this protocol focuses specifically on smartphone-based screen engagement and does not comprehensively capture all sedentary behaviors or screen-based contexts (eg, television viewing, tablet use, and seated academic work). Third, while the dyadic design is a strength, focusing exclusively on mother-child pairs may not capture broader family dynamics or diverse caregiving structures. Fourth, this study focuses on middle-school-aged youth (11-14 years), in part because existing smartphone- and wearable-based multimodal assessment technologies are most feasible and validated in this developmental period. Future research should extend these approaches to younger children and investigate how real-time, multimodal physiological and behavioral data collection can be implemented validly and feasibly in earlier developmental stages. Fifth, the reliance on smartphone-based participation may introduce selection bias toward families with access to compatible technology. Finally, Garmin-derived heart rate has moderate validity and may introduce measurement error into estimates of physiological-affective associations. These data will therefore be interpreted as wearable-derived estimates rather than clinical measures. In Phase 2, measurement error may also lead to missed or incorrectly timed activity-triggered EMA prompts. Wearable-based triggering will require validation and refinement before implementation, including evaluation of whether combining heart rate with movement data improves trigger performance.

### Future Directions

Future directions will involve scaling the protocol to larger and more diverse populations, refining EMA and sensing algorithms, and incorporating neural measures to test hypothesized mechanisms of regulation and resilience. Ultimately, Lion Tracks is designed not only as an observational platform but as a foundation for developing just-in-time adaptive interventions (JITAIs) that target real-world behavioral and emotional processes as they unfold [101].

By establishing a scalable, low-burden platform for capturing real-time dyadic health dynamics, Lion Tracks provides a critical foundation for future precision health interventions targeting family systems in naturalistic settings.

### Acknowledgments

The authors thank the participating mothers and children for their time and contributions to the Lion Tracks study, as well as the research staff and community partners supporting recruitment and study implementation.



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## Data Availability

Data collection is ongoing. Because the study includes intensive longitudinal behavioral and mental health data from mothers and minor children, individual-level data will not be made publicly available to protect participant privacy. Following study completion, requests for deidentified data may be directed to the corresponding author and will be considered subject to participant consent, institutional requirements, and an appropriate data use agreement.

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## Generative AI Use

The authors used Canvas AI to assist with editing figures of the manuscript ([1]adjust this figure to fit the tagged color scheme, [2] pull text from screenshots of phone screen and insert in draft on slide X, and [3] edit tagged figure to match the image on slide X). All AI-assisted figures were reviewed and revised by the authors, who take full responsibility for the accuracy, integrity, and originality of the final figures.

## Authors' Contributions

Conceptualization: JW, FH
Funding acquisition: JW
Investigation: JW, JG
Methodology: JW, MG, JG, FH
Project administration: JW, JG
Writing – original draft: JW
Writing – review & editing: MG, JG, KP-E, DSD, FH

## Conflicts of Interest

None declared.

## References

1. Steinberg L. Cognitive and affective development in adolescence. Trends Cogn Sci. 2005;9(2):69-74. [doi: 10.1016/j.tics.2004.12.005] [Medline: 15668099]
2. Merikangas KR, He J, Burstein M, Swanson SA, Avenevoli S, Cui L, et al. Lifetime prevalence of mental disorders in U.S. adolescents: results from the National Comorbidity Survey Replication--Adolescent Supplement (NCS-A). J Am Acad Child Adolesc Psychiatry. 2010;49(10):980-989. [FREE Full text] [doi: 10.1016/j.jaac.2010.05.017] [Medline: 20855043]
3. Dahl RE. Adolescent brain development: a period of vulnerabilities and opportunities. Keynote address. Ann N Y Acad Sci. 2004;1021:1-22. [doi: 10.1196/annals.1308.001] [Medline: 15251869]
4. Biddle SJH, Ciaccioni S, Thomas G, Vergeer I. Physical activity and mental health in children and adolescents: an updated review of reviews and an analysis of causality. Psychol Sport Exerc. May 2019;42:146-155. [doi: 10.1016/j.psychsport.2018.08.011]
5. Twenge JM, Campbell W. Associations between screen time and lower psychological well-being among children and adolescents: evidence from a population-based study. Prev Med Rep. Dec 2018;12:271-283. [FREE Full text] [doi: 10.1016/j.pmedr.2018.10.003] [Medline: 30406005]
6. Bolger N, Laurenceau JP. Intensive Longitudinal Methods An Introduction to Diary and Experience Sampling Research. New York City. The Guilford Press; 2013.
7. Farmakopoulou I, Lekka M, Gkintoni E. Clinical symptomatology of anxiety and family function in adolescents-the self-esteem mediator. Children (Basel). 2024;11(3):338. [FREE Full text] [doi: 10.3390/children11030338] [Medline: 38539373]
8. Tng GYQ, Law E, Chen H, Nadarajan R, Eriksson JG, Chong YS, et al. Developmental trajectories of anxiety subtypes from childhood to early adolescence: the role of parenting practices and maternal distress. Res Child Adolesc Psychopathol. 2025;53(11):1699-1712. [doi: 10.1007/s10802-025-01364-4] [Medline: 40883624]
9. Prochnow T, Wang W, Wang S, Li J, Rothman AJ, Intille SS, et al. Understanding longitudinal ecological momentary assessment completion: results from 12 months of burst sampling in the TIME study. JMIR Mhealth Uhealth. 2025;13:e67117. [FREE Full text] [doi: 10.2196/67117] [Medline: 41124691]
10. Wang S, Yang C, Brown D, Cheng A, Kwan MYW. Participant compliance with ecological momentary assessment in movement behavior research among adolescents and emerging adults: systematic review. JMIR Mhealth Uhealth. 2025;13:e52887. [FREE Full text] [doi: 10.2196/52887] [Medline: 39933165]



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11. Rodman AM, Burns JA, Cotter GK, Ohashi YB, Rich RK, McLaughlin KA. Within-person fluctuations in objective smartphone use and emotional processes during adolescence: an intensive longitudinal study. Affect Sci. 2024;5(4):332-345. [doi: 10.1007/s42761-024-00247-z] [Medline: 39649461]
12. Rognmo K, Opdal IM, Handegård BH, Horsch A, Lillevoll K, Furberg AS, et al. The relationship between self-reported and device-based measurements of physical activity and mental distress among adolescents: results from the fit futures study. BMC Public Health. 2025;25(1):2617. [FREE Full text] [doi: 10.1186/s12889-025-23902-x] [Medline: 40753245]
13. Liu C, Liang X, Sit C. Physical activity and mental health in children and adolescents with neurodevelopmental disorders: a systematic review and meta-analysis. JAMA Pediatr. 2024;178(3):247-257. [doi: 10.1001/jamapediatrics.2023.6251] [Medline: 38285440]
14. Wang W, Zhu Y, Yu H, Wu C, Li T, Ji C, et al. The impact of sleep quality on emotion regulation difficulties in adolescents: a chained mediation model involving daytime dysfunction, social exclusion, and self-control. BMC Public Health. 2024;24(1):1862. [FREE Full text] [doi: 10.1186/s12889-024-19400-1] [Medline: 38992632]
15. Hyndych A, El-Abassi R, Mader EC. The role of sleep and the effects of sleep loss on cognitive, affective, and behavioral processes. Cureus. 2025;17(5):e84232. [doi: 10.7759/cureus.84232] [Medline: 40525051]
16. Oliveira AP, Nobre J, Monteiro F, Rodrigues C, Louro O, Valente N, et al. Sleep habits, physical exercise, and social media use and their influence on perceptions of physical and mental health-case study at a higher education institution in Portugal. Healthcare (Basel). 2026;14(3):343. [FREE Full text] [doi: 10.3390/healthcare14030343] [Medline: 41682193]
17. Odgers CL, Jensen M. Annual research review: adolescent mental health in the digital age: facts, fears, and future directions. J Child Psychol Psychiatry. 2020;61(3):336-348. [FREE Full text] [doi: 10.1111/jcpp.13190] [Medline: 31951670]
18. Wanjau MN, Möller H, Haigh F, Milat A, Hayek R, Lucas P, et al. Physical activity and depression and anxiety disorders: a systematic review of reviews and assessment of causality. AJPM Focus. 2023;2(2):100074. [FREE Full text] [doi: 10.1016/j.focus.2023.100074] [Medline: 37790636]
19. Anderson E, Shivakumar G. Effects of exercise and physical activity on anxiety. Front Psychiatry. 2013;4:27. [FREE Full text] [doi: 10.3389/fpsyt.2013.00027] [Medline: 23630504]
20. Kredlow MA, Capozzoli MC, Hearon BA, Calkins AW, Otto MW. The effects of physical activity on sleep: a meta-analytic review. J Behav Med. 2015;38(3):427-449. [doi: 10.1007/s10865-015-9617-6] [Medline: 25596964]
21. Friel CP, Duran AT, Shechter A, Diaz KM. U.S. children meeting physical activity, screen time, and sleep guidelines. Am J Prev Med. 2020;59(4):513-521. [FREE Full text] [doi: 10.1016/j.amepre.2020.05.007] [Medline: 32863080]
22. Orben A, Przybylski AK. The association between adolescent well-being and digital technology use. Nat Hum Behav. 2019;3(2):173-182. [doi: 10.1038/s41562-018-0506-1] [Medline: 30944443]
23. Dunton GF. Ecological momentary assessment in physical activity research. Exerc Sport Sci Rev. 2017;45(1):48-54. [FREE Full text] [doi: 10.1249/JES.0000000000000092] [Medline: 27741022]
24. Hillman CH, McDonald K, Logan N. A review of the effects of physical activity on cognition and brain health across children and adolescence. Nestle Nutr Inst Workshop Ser. 2020;95:116-126. [doi: 10.1159/000511508] [Medline: 33161407]
25. Murphy D, Henderson A, Bradley J, Connolly B, Wilson JJ, O'Neill B. Device-based measurement of physical activity and sedentary behaviour after critical illness: a scoping review. PLoS One. 2025;20(6):e0322339. [FREE Full text] [doi: 10.1371/journal.pone.0322339] [Medline: 40460111]
26. Tremblay S, LeBlanc A, Kho M, Saunders TJ, Larouche R, Colley RC, et al. Systematic review of sedentary behaviour and health indicators in school-aged children and youth. Int J Behav Nutr Phys Act. 2011;8:98. [FREE Full text] [doi: 10.1186/1479-5868-8-98] [Medline: 21936895]
27. Przybylski AK, Weinstein N. Digital screen time limits and young children's psychological well-being: evidence from a population-based study. Child Dev. 2019;90(1):e56-e65. [doi: 10.1111/cdev.13007] [Medline: 29235663]
28. Ellis DA, Davidson BI, Shaw H, Geyer K. Do smartphone usage scales predict behavior? Int J Hum-Comput Stud. 2019;130:86-92. [doi: 10.1016/j.ijhcs.2019.05.004]
29. Ghadimi S, Ereso J, Kaula A, Taptiklis N, Cormack F, Alessi C, et al. Feasibility of cognitive testing and ecological momentary assessments using smartphones in middle aged and older adults with insomnia. BMC Digit Health. 2025;3(1):21. [doi: 10.1186/s44247-025-00158-4] [Medline: 40606001]
30. Sliwinski MJ, Mogle JA, Hyun J, Munoz E, Smyth JM, Lipton RB. Reliability and validity of ambulatory cognitive assessments. Assessment. 2018;25(1):14-30. [FREE Full text] [doi: 10.1177/1073191116643164] [Medline: 27084835]
31. Young SR, Novack M, Dworak E, Kaat AJ, Hosseinian Z, Gershon RC. Using the mobile toolbox in child and adolescent samples: a feasibility study. Child Dev. 2024;95(4):1416-1424. [FREE Full text] [doi: 10.1111/cdev.14066] [Medline: 38217474]
32. Reichert M, Giurgiu M, Koch E, Wieland LM, Lautenbach S, Neubauer AB, et al. Ambulatory assessment for physical activity research: state of the science, best practices and future directions. Psychol Sport Exerc. 2020;101742:50. [FREE Full text] [doi: 10.1016/j.psychsport.2020.101742] [Medline: 32831643]
33. Herold F, Giurgiu M, Ebner-Priemer U, Brakenridge CJ, Hallgren M, Owen N, et al. Physical activity and cognition: examining temporal dynamics via micro-longitudinal studies with ambulatory assessment. Exerc Sport Sci Rev. 2026;54(1):26-41. [doi: 10.1249/JES.0000000000000377] [Medline: 41128524]




XSL•FO
RenderX

34. Fosco GM, Chen L, DeFelice J. Intraindividual variability in adolescent impulsivity: the predictive role of family and peer relationships. Res Child Adolesc Psychopathol. 2025;53(9):1367-1380. [doi: 10.1007/s10802-025-01340-y] [Medline: 40540045]
35. Burke LE, Shiffman S, Music E, Styn MA, Kriska A, Smailagic A, et al. Ecological momentary assessment in behavioral research: addressing technological and human participant challenges. J Med Internet Res. 2017;19(3):e77. [FREE Full text] [doi: 10.2196/jmir.7138] [Medline: 28298264]
36. Romanzini CLP, Romanzini M, Batista M, Barbosa CCL, Shigaki GB, Dunton G, et al. Methodology used in ecological momentary assessment studies about sedentary behavior in children, adolescents, and adults: systematic review using the checklist for reporting ecological momentary assessment studies. J Med Internet Res. 2019;21(5):e11967. [FREE Full text] [doi: 10.2196/11967] [Medline: 31094349]
37. Lobo FM, Lunkenheimer E. Understanding the parent-child coregulation patterns shaping child self-regulation. Dev Psychol. 2020;56(6):1121-1134. [FREE Full text] [doi: 10.1037/dev0000926] [Medline: 32309982]
38. Perlman SB, Lunkenheimer E, Panlilio C, Pérez-Edgar K. Parent-to-child anxiety transmission through dyadic social dynamics: a dynamic developmental model. Clin Child Fam Psychol Rev. Mar 2022;25(1):110-129. [FREE Full text] [doi: 10.1007/s10567-022-00391-7] [Medline: 35195833]
39. Yang CH, Huh J, Mason TB, Belcher BR, Kanning M, Dunton GF. Mother-child dyadic influences of affect on everyday movement behaviors: evidence from an ecological momentary assessment study. Int J Behav Nutr Phys Act. 2020;17(1):56. [FREE Full text] [doi: 10.1186/s12966-020-00951-6] [Medline: 32393359]
40. Ho YCL, Mahirah D, Ho CZH, Thumboo J. The role of the family in health promotion: a scoping review of models and mechanisms. Health Promot Int. 2022;37(6):daac119. [FREE Full text] [doi: 10.1093/heapro/daac119] [Medline: 36398941]
41. Hesketh KR, Brage S, Cooper C, Godfrey KM, Harvey NC, Inskip HM, et al. The association between maternal-child physical activity levels at the transition to formal schooling: cross-sectional and prospective data from the Southampton women's survey. Int J Behav Nutr Phys Act. 2019;16(1):23. [FREE Full text] [doi: 10.1186/s12966-019-0782-9] [Medline: 30786904]
42. Petersen TL, Møller LB, Brønd JC, Jepsen R, Grøntved A. Association between parent and child physical activity: a systematic review. Int J Behav Nutr Phys Act. 2020;17(1):67. [FREE Full text] [doi: 10.1186/s12966-020-00966-z] [Medline: 32423407]
43. Hesketh KR, Goodfellow L, Ekelund U, McMinn AM, Godfrey KM, Inskip HM, et al. Activity levels in mothers and their preschool children. Pediatrics. 2014;133(4):e973-e980. [doi: 10.1542/peds.2013-3153] [Medline: 24664097]
44. Bülow A, van Roekel E, Boele S, Denissen JJA, Keijsers L. Parent-adolescent interaction quality and adolescent affect-an experience sampling study on effect heterogeneity. Child Dev. 2022;93(3):e315-e331. [FREE Full text] [doi: 10.1111/cdev.13733] [Medline: 35099070]
45. Hovenkamp-Hermelink JHM, van der Veen DC, Oude Voshaar RC, Batelaan NM, Penninx BW, Jeronimus BF, et al. Anxiety sensitivity, its stability and longitudinal association with severity of anxiety symptoms. Sci Rep. 2019;9(1):4314. [FREE Full text] [doi: 10.1038/s41598-019-39931-7] [Medline: 30867472]
46. Shiffman S, Stone AA, Hufford M. Ecological momentary assessment. Annu Rev Clin Psychol. 2008;4:1-32. [doi: 10.1146/annurev.clinpsy.3.022806.091415] [Medline: 18509902]
47. Davidson RJ. Affective style, psychopathology, and resilience: brain mechanisms and plasticity. Am Psychol. 2000;55(11):1196-1214. [doi: 10.1037/0003-066x.55.11.1196]
48. Giurgiu M, Ebner-Priemer UW. The 24-hour cognitive-affective physical behavior model: a theoretical framework for studying determinants and health consequences of physical activity, sedentary behavior, and sleep. J Act Sedentary Sleep Behav. Apr 08, 2025;4(1):6. [doi: 10.1186/s44167-025-00077-9]
49. Heatherton TF. Neuroscience of self and self-regulation. Annu Rev Psychol. 2011;62:363-390. [FREE Full text] [doi: 10.1146/annurev.psych.121208.131616] [Medline: 21126181]
50. Torous J, Onnela J, Keshavan M. New dimensions and new tools to realize the potential of RDoC: digital phenotyping via smartphones and connected devices. Transl Psychiatry. 2017;7(3):e1053. [FREE Full text] [doi: 10.1038/tp.2017.25] [Medline: 28267146]
51. Hamaker EL, Kuiper RM, Grasman RPPP. A critique of the cross-lagged panel model. Psychol Methods. 2015;20(1):102-116. [doi: 10.1037/a0038889] [Medline: 25822208]
52. Bandura A. Social cognitive theory: an agentic perspective. Annu Rev Psychol. 2001;52:1-26. [doi: 10.1146/annurev.psych.52.1.1] [Medline: 11148297]
53. Watson WH. Family systems. In: Encyclopedia of Human Behavior. Amsterdam. Elsevier; 2012:184-193.
54. Kruzan KP, Williams KDA, Meyerhoff J, Yoo DW, O'Dwyer LC, De Choudhury M, et al. Social media-based interventions for adolescent and young adult mental health: a scoping review. Internet Interv. 2022;30:100578. [FREE Full text] [doi: 10.1016/j.invent.2022.100578] [Medline: 36204674]
55. Woods HC, Scott H. #Sleepyteens: social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem. J Adolesc. 2016;51:41-49. [FREE Full text] [doi: 10.1016/j.adolescence.2016.05.008] [Medline: 27294324]




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56. Hoge E, Bickham D, Cantor J. Digital media, anxiety, and depression in children. Pediatrics. 2017;140(Suppl 2):S76-S80. [doi: 10.1542/peds.2016-1758G] [Medline: 29093037]
57. Duvinage M, Castermans T, Petieau M, Hoellinger T, Cheron G, Dutoit T. Performance of the Emotiv Epoc headset for P300-based applications. Biomed Eng Online. 2013;12:56. [FREE Full text] [doi: 10.1186/1475-925X-12-56] [Medline: 23800158]
58. Hallgren M, Dunstan D, Owen N. Passive versus mentally active sedentary behaviors and depression. Exerc Sport Sci Rev. 2020;48(1):20-27. [doi: 10.1249/JES.0000000000000211] [Medline: 31663866]
59. Whitehead AL, Julious S, Cooper C, Campbell MJ. Estimating the sample size for a pilot randomised trial to minimise the overall trial sample size for the external pilot and main trial for a continuous outcome variable. Stat Methods Med Res. 2016;25(3):1057-1073. [FREE Full text] [doi: 10.1177/0962280215588241] [Medline: 26092476]
60. Kunselman AR. A brief overview of pilot studies and their sample size justification. Fertil Steril. 2024;121(6):899-901. [FREE Full text] [doi: 10.1016/j.fertnstert.2024.01.040] [Medline: 38331310]
61. Mayorga-Vega D, Casado-Robles C, Guijarro-Romero S, Viciana J. Validity of activity wristbands for estimating daily physical activity in primary schoolchildren under free-living conditions: school-fit study. Front Public Health. 2023;11:1211237. [FREE Full text] [doi: 10.3389/fpubh.2023.1211237] [Medline: 37554735]
62. Briggs BC, Hall KS, Jain C, Macrea M, Morey MC, Oursler KK. Assessing moderate to vigorous physical activity in older adults: validity of a commercial activity tracker. Front Sports Act Living. 2021;3:766317. [FREE Full text] [doi: 10.3389/fspor.2021.766317] [Medline: 35047769]
63. Warburton DER, Jamnik VK, Bredin SSD. The Physical Activity Readiness Questionnaire for Everyone (PAR-Q+) and Electronic Physical Activity Readiness Medical Examination (ePARmed-X+). The Health & Fitness Journal of Canada. 2011:1. [FREE Full text] [doi: 10.14288/hfjc.v4i2.103]
64. Spitzer RL, Kroenke K, Williams JBW, Löwe B. A brief measure for assessing generalized anxiety disorder: the GAD-7. Arch Intern Med. 2006;166(10):1092-1097. [doi: 10.1001/archinte.166.10.1092] [Medline: 16717171]
65. Wu Y, Levis B, Riehm KE, Saadat N, Levis AW, Azar M, et al. Equivalency of the diagnostic accuracy of the PHQ-8 and PHQ-9: a systematic review and individual participant data meta-analysis. Psychol Med. Jun 2020;50(8):1368-1380. [FREE Full text] [doi: 10.1017/S0033291719001314] [Medline: 31298180]
66. Cella D, Riley W, Stone A, Rothrock N, Reeve B, Yount S, et al. PROMIS Cooperative Group. The Patient-Reported Outcomes Measurement Information System (PROMIS) developed and tested its first wave of adult self-reported health outcome item banks: 2005-2008. J Clin Epidemiol. 2010;63(11):1179-1194. [FREE Full text] [doi: 10.1016/j.jclinepi.2010.04.011] [Medline: 20685078]
67. Pilkonis PA, Choi SW, Reise SP, Stover AM, Riley WT, Cella D, et al. PROMIS Cooperative Group. Item banks for measuring emotional distress from the patient-reported outcomes measurement information system (PROMIS®): depression, anxiety, and anger. Assessment. 2011;18(3):263-283. [FREE Full text] [doi: 10.1177/1073191111411667] [Medline: 21697139]
68. Buysse DJ, Yu L, Moul D, Germain A, Stover A, Dodds NE, et al. Development and validation of patient-reported outcome measures for sleep disturbance and sleep-related impairments. Sleep. 2010;33(6):781-792. [FREE Full text] [doi: 10.1093/sleep/33.6.781] [Medline: 20550019]
69. Sallis JF, Pinski RB, Grossman RM, Patterson TL, Nader PR. The development of self-efficacy scales for healthrelated diet and exercise behaviors. Health Educ Res. 1988;3(3):283-292. [doi: 10.1093/her/3.3.283]
70. Pianta RC. Adult–child relationship processes and early schooling. Early Educ Dev. 1997;8(1):11-26. [doi: 10.1207/s15566935eed0801_2]
71. Haegele JA, Aigner C, Healy S. Prevalence of meeting physical activity, screen-time, and sleep guidelines among children and adolescents with and without visual impairments in the United States. Adapt Phys Activ Q. 2019;36(3):399-405. [doi: 10.1123/apaq.2018-0130] [Medline: 31155913]
72. Hardy CJ, Rejeski WJ. Not what, but how one feels: the measurement of affect during exercise. J Sport Exerc Psychol. 1989;11(3):304-317. [doi: 10.1123/jsep.11.3.304]
73. Thorenz K, Berwinkel A, Weigelt M. A validation study for the German versions of the feeling scale and the felt arousal scale for a progressive muscle relaxation exercise. Behav Sci (Basel). 2023;13(7):523. [FREE Full text] [doi: 10.3390/bs13070523] [Medline: 37503971]
74. Davey HM, Barratt A, Butow P, Deeks JJ. A one-item question with a likert or Visual Analog Scale adequately measured current anxiety. J Clin Epidemiol. 2007;60(4):356-360. [doi: 10.1016/j.jclinepi.2006.07.015] [Medline: 17346609]
75. Benjamin CC, Rowlands A, Parfitt G. Patterning of affective responses during a graded exercise test in children and adolescents. Pediatr Exerc Sci. 2012;24(2):275-288. [doi: 10.1123/pes.24.2.275] [Medline: 22728418]
76. Zhang Z, Chen Y, Yu Q, Li J, Zou L, Mavilidi MF, et al. A neurobiological taxonomy of sedentary behavior for brain health. Trends Neurosci. 2025;48(11):853-864. [doi: 10.1016/j.tins.2025.09.002] [Medline: 41038753]
77. Vansteenkiste M, Ryan RM, Soenens B. Basic psychological need theory: advancements, critical themes, and future directions. Motiv Emot. Jan 21, 2020;44(1):1-31. [doi: 10.1007/s11031-019-09818-1]




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RenderX

78. Myin-Germeys I, Kasanova Z, Vaessen T, Vachon H, Kirtley O, Viechtbauer W, et al. Experience sampling methodology in mental health research: new insights and technical developments. World Psychiatry. 2018;17(2):123-132. [FREE Full text] [doi: 10.1002/wps.20513] [Medline: 29856567]
79. Wen CKF, Schneider S, Stone AA, Spruijt-Metz D. Compliance with mobile ecological momentary assessment protocols in children and adolescents: a systematic review and meta-analysis. J Med Internet Res. 2017;19(4):e132. [FREE Full text] [doi: 10.2196/jmir.6641] [Medline: 28446418]
80. Migueles JH, Cadenas-Sanchez C, Ekelund U, Delisle Nyström C, Mora-Gonzalez J, Löf M, et al. Accelerometer data collection and processing criteria to assess physical activity and other outcomes: a systematic review and practical considerations. Sports Med. 2017;47(9):1821-1845. [FREE Full text] [doi: 10.1007/s40279-017-0716-0] [Medline: 28303543]
81. Chinoy ED, Cuellar J, Huwa K, Jameson JT, Watson CH, Bessman SC, et al. Performance of seven consumer sleep-tracking devices compared with polysomnography. Sleep. 2021;44(5):zsaa291. [FREE Full text] [doi: 10.1093/sleep/zsaa291] [Medline: 33378539]
82. de Leon MF, Camic CL, Kowal RA, Aldape B, Lochbaum B, Stefan R, et al. Accuracy of the garmin vivoactive 4 for estimating heart rate, energy expenditure, and step count during treadmill exercise. Appl Sci. 2026;16(3):1286. [doi: 10.3390/app16031286]
83. Sicbaldi M, Bartoli L, Albites-Sanabria J, D'Ascanio I, Silvani A, Chiari L, et al. Is my smartwatch a valid witness? A systematic review and meta-analysis. Forensic Sci Int. 2026;384:112901. [FREE Full text] [doi: 10.1016/j.forsciint.2026.112901] [Medline: 41819643]
84. Garber CE, Blissmer B, Deschenes M. Quantity and quality of exercise for developing and maintaining cardiorespiratory, musculoskeletal, and neuromotor fitness in apparently healthy adults. Med Sci Sports Exerc. 2011;43(7):1334-1359.
85. Bishop DJ, Beck B, Biddle SJH, Denay KL, Ferri A, Gibala MJ, et al. Physical activity and exercise intensity terminology: a joint American College of Sports Medicine (ACSM) expert statement and Exercise and Sport Science Australia (ESSA) consensus statement. Med Sci Sports Exerc. 2025;57(11):2599-2613. [doi: 10.1249/MSS.0000000000003795] [Medline: 41085254]
86. Herold F, Zou L, Theobald P, Manser P, Falck RS, Yu Q, et al. Beyond FITT: addressing density in understanding the dose-response relationships of physical activity with health-an example based on brain health. Eur J Appl Physiol. 2025;125(10):2679-2707. [doi: 10.1007/s00421-025-05858-3] [Medline: 40569418]
87. Kobeissi E, Dempsey P, Alshallal A. A systematic review and taxonomy of metrics and methods used to describe temporal movement behavior patterns measured using wearable devices. J Meas Phys Behav. 2026;9(1). [doi: 10.1123/jmpb.2024-0035]
88. Scarpina F, Tagini S. The stroop color and word test. Front Psychol. 2017;8. [doi: 10.3389/fpsyg.2017.00557]
89. Fraschini M, Demuru M, Hillebrand A, Cuccu L, Porcu S, Di Stefano F, et al. EEG functional network topology is associated with disability in patients with amyotrophic lateral sclerosis. Sci Rep. 2016;6:38653. [FREE Full text] [doi: 10.1038/srep38653] [Medline: 27924954]
90. Gudmundsson S, Runarsson TP, Sigurdsson S, Eiriksdottir G, Johnsen K. Reliability of quantitative EEG features. Clin Neurophysiol. 2007;118(10):2162-2171. [doi: 10.1016/j.clinph.2007.06.018] [Medline: 17765604]
91. Trull TJ, Ebner-Priemer U. Ambulatory assessment. Annu Rev Clin Psychol. 2013;9:151-176. [FREE Full text] [doi: 10.1146/annurev-clinpsy-050212-185510] [Medline: 23157450]
92. Martinko A, Karuc J, Jurić P, Podnar H, Sorić M. Accuracy and precision of consumer-grade wearable activity monitors for assessing time spent in sedentary behavior in children and adolescents: systematic review. JMIR Mhealth Uhealth. 2022;10(8):e37547. [FREE Full text] [doi: 10.2196/37547] [Medline: 35943763]
93. Evenson KR, Goto M, Furberg RD. Systematic review of the validity and reliability of consumer-wearable activity trackers. Int J Behav Nutr Phys Act. 2015;12:159. [FREE Full text] [doi: 10.1186/s12966-015-0314-1] [Medline: 26684758]
94. Schäfer A, Vagedes J. How accurate is pulse rate variability as an estimate of heart rate variability? A review on studies comparing photoplethysmographic technology with an electrocardiogram. Int J Cardiol. 2013;166(1):15-29. [doi: 10.1016/j.ijcard.2012.03.119] [Medline: 22809539]
95. John SE, Evans S, Kim B, Ozgul P, Loring DW, Parker M, et al. Examination of the reliability and feasibility of two smartphone applications to assess executive functioning in racially diverse older adults. Neuropsychol Dev Cogn B Aging Neuropsychol Cogn. 2022;29(6):1068-1086. [FREE Full text] [doi: 10.1080/13825585.2021.1962790] [Medline: 34382482]
96. Williams NS, McArthur GM, de Wit B, Ibrahim G, Badcock NA. A validation of Emotiv EPOC Flex saline for EEG and ERP research. Peer J. 2020;8:e9713. [FREE Full text] [doi: 10.7717/peerj.9713] [Medline: 32864218]
97. Badcock NA, Preece K, de Wit B, Glenn K, Fieder N, Thie J, et al. Validation of the emotiv EPOC EEG system for research quality auditory event-related potentials in children. PeerJ. 2015;3:e907. [FREE Full text] [doi: 10.7717/peerj.907] [Medline: 25922794]
98. Krigolson OE, Williams CC, Norton A, Hassall CD, Colino FL. Choosing MUSE: validation of a low-cost, portable EEG system for ERP research. Front Neurosci. 2017;11:109. [FREE Full text] [doi: 10.3389/fnins.2017.00109] [Medline: 28344546]
99. Ratti E, Waninger S, Berka C, Ruffini G, Verma A. Comparison of medical and consumer wireless EEG systems for use in clinical trials. Front Hum Neurosci. 2017;11:398. [FREE Full text] [doi: 10.3389/fnhum.2017.00398] [Medline: 28824402]




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100. RStudio: integrated development for R. RStudio. 2024. URL: https://www.r-project.org/conferences/useR-2011/abstracts/180111-allairejj.pdf [accessed 2026-11-03]
101. Nahum-Shani I, Smith S, Spring B, Collins LM, Witkiewitz K, Tewari A, et al. Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support. Ann Behav Med. 2018;52(6):446-462. [FREE Full text] [doi: 10.1007/s12160-016-9830-8] [Medline: 27663578]

## Abbreviations

**CPRS:** Child-Parent Relationship Scale
**EEG:** electroencephalogram
**EMA:** ecological momentary assessment
**FAS:** Felt Arousal Scale
**FS:** Feeling Scale
**FST:** family systems theory
**GAD-7:** Generalized Anxiety Disorder-7
**HRR:** heart rate reserve
**HRV:** heart rate variability
**ICC:** intraclass correlation coefficient
**JITAI:** just-in-time adaptive intervention
**lnRMSSD:** natural logarithm of the root mean square of successive differences
**M2C2:** Mobile Monitoring of Cognitive Change
**MAPE:** mean absolute percentage error
**PAR-Q+:** Physical Activity Readiness Questionnaire for Everyone
**PHQ-8:** Patient Health Questionnaire-8
**PHQ-9:** Patient Health Questionnaire-9
**PROMIS:** Patient-Reported Outcomes Measurement Information System
**SCT:** social cognitive theory

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