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Abstract

Background: Ecological momentary assessments (EMAs) are a widely used method in health and psychological research to assess people's thoughts, emotions, and behaviours in daily life. However, EMAs are affected by several response biases including compliance, carelessness, and delayed responses, which can compromise data quality and threaten validity. Although some design and contextual factors influencing these biases have been identified, the role of momentary cognitive states (e.g., stress, fatigue, affect) remains underexplored.

Objective: This study examined how cognitive states at the moment of responding influenced participants' compliance, carelessness, delayed responding to EMAs.

Methods: We conducted a secondary analysis using data from the COBRA study, a prospective observational cohort study on health behaviours in Singapore. The dataset included 29'797 EMA responses from 617 Singaporean adults who were prompted to complete six smartphone-based surveys daily for nine days. Using mixed-effects regression models, we examined how five cognitive states (stress, fatigue, hunger, positive affect, and sleep quality) predicted compliance, carelessness, and response delay, while adjusting for demographic and temporal covariates.

Results: Overall compliance at the next prompt was high (92%), and no cognitive states were significantly associated with compliance. Careless responding was more likely at higher levels of stress and hunger, and less likely at higher levels of sleep quality, fatigue, and positive affect. Several demographic and temporal factors such as age, time of day, and number of missed prior prompts also significantly influenced response behaviors.

Conclusions: This study demonstrates that cognitive states significantly influence careless and delayed responding in EMA studies, but they do not impact compliance. Our findings highlight the need to consider participants' cognitive states as potential sources of systematic bias, particularly in studies investigating stress, hunger, and affective states. Future EMA research should therefore incorporate strategies to detect and mitigate response biases, such as tracking those variables and using just-in-time delivered warnings, rewards, and educational messages.

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4. Effects of Cognitive States on Momentary Response Biases in an Ecological Momentary Assessment Study

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6. Keywords

Ecological Momentary Assessment, Careless Responding, Compliance, Response Delay, Experience Sampling Method, Insufficient Effort Responding, Data quality, mHealth.

7. Abstract

Background: Ecological momentary assessments (EMAs) are a widely used method in health and psychological research to assess people's thoughts, emotions, and behaviours in daily life. However, EMAs are affected by several response biases including compliance, , careless, and delayed responses, which can compromise data quality and threaten validity. Although some design and contextual factors influencing these biases have been identified, the role of momentary cognitive states (e.g., stress, fatigue, affect) remains underexplored.

Objectives: This study examined how cognitive states at the moment of responding influenced participants' compliance, careless responding, delayed responding to EMAs.

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Results: Overall compliance at the next prompt was high (92%), and no cognitive states were significantly associated with compliance. Careless responding was more likely at higher levels of stress and hunger, and less likely at higher levels of sleep quality, fatigue, and positive affect. Several demographic and temporal factors such as age, time of day, and number of missed prior prompts also significantly influenced response behaviors.

Conclusions: This study demonstrates that cognitive states significantly influence careless and delayed responding in EMA studies, but they do not impact compliance. Our findings highlight the need to consider participants' cognitive states as potential sources of systematic bias, particularly in studies investigating stress, hunger, and affective states. Future EMA research should therefore incorporate strategies to detect and mitigate response biases, such as tracking those variables and using just-in-time delivered warnings, rewards, and educational messages.

1. Introduction

Ecological momentary assessments (EMA) are a widely used structured survey method designed to capture participants' experiences in everyday life. These experiences can cover events, social interactions, cognitions, emotions, and behaviors [1–3]. In an EMA study, participants are typically asked to respond to consecutive short surveys randomly throughout the day over several days.

The use of EMAs has become increasingly prevalent in psychology, health, and social science research [4–8] due to advantages over traditional retrospective questionnaires, which are prone to recall bias and poor ecological validity [2,4,9]. However, EMAs are also affected by response biases, such as compliance, careless, and delayed responding, which pose psychometric challenges [10]. These issues reduce the number of valid observations and introduce systematic biases, diminishing statistical power and the precision of statistical estimates.

Non-compliance has an estimated prevalence of about 15-30% in EMA studies [10], and refers to instances where participants either miss or consciously dismiss survey prompts. Meanwhile, careless responding occurs when participants respond without fully engaging with the prompt, which is considered a form of “satisficing” – a cognitive shortcut where individuals provide “good enough” answers rather than exerting effort to provide accurate responses [10–12]. While careless responding is a well-known issue in cross-sectional survey research, it has received little attention in EMA research [10,13]. Two common indicators of careless responding in EMA are fast responses (those that are submitted too quickly to be thoughtful) and straight-lining (consecutively selecting the same response options) [14]. By contrast, delayed responding refers to instances where participants postpone their responses due to situational factors (e.g., during a conflict or while exercising) [10]. Although the response is eventually submitted, it may no longer reflect a participant's actual momentary state and lead to an overrepresentation of “calm” moments in the final dataset [15].

Psychometric issues in EMA are a particular problem if they are related to the phenomenon being examined. For example, in mental health studies, if participants are more likely to respond when in a positive mood or stressed but less likely when feeling neutral or fatigued, the ecological validity of the study could be compromised [16–18]. Understanding these biases is critical for improving the validity of EMA research and ensuring that findings accurately reflect real-world experiences.

Despite the widespread use of EMAs in psychological and behavioral research, there is a lack of understanding regarding the factors that influence compliance, careless responding, and delayed responding. Existing research has focused mainly on stable individual characteristics (e.g., gender,

smoking status, personality traits) [18,19], EMA design factors (e.g., financial incentives, inter-prompt intervals, survey length) [13,20–22], or contextual factors (e.g., location, social setting) [21,22]. However, much less attention has been given to the role of momentary cognitive and affective states—despite their potential to bias EMAs systematically. Cognitive states can be defined as “states of a person’s cognitive processes” involving mental actions such as memory, attention, reasoning, and problem-solving [23]. Preliminary evidence suggests that cognitive states such as stress, hunger, and affect may influence compliance and delayed responses to EMAs [15,21,22,24–26]. However, these findings are inconsistent, and their underlying mechanisms remain unclear [15,21,22,24–26]. As predicting response biases is challenging in the absence of valid information at the current prompt, these studies typically employed cognitive states reported at one prompt to predict response behaviours at the next prompt [15,21,22,24–26]. For instance, some studies suggest that hunger increases compliance at the next prompt, while stress is associated with a higher likelihood of missed prompts [24,26]. The effects of positive and negative affect on compliance are mixed, with some studies suggesting that positive affect increases compliance, while others indicate the opposite [24,25]. Additionally, delayed responding has been linked to decreases in positive affect and increases in negative affect [15]. However, the effect of other cognitive states, such as fatigue or hunger, is still unknown [15]. Finally, to our knowledge, there is no evidence of the effects of momentary cognitive states on careless responding, which remains a largely unexamined issue compared to compliance and delayed responding.

This study seeks to address this research gap by primarily examining how cognitive states influence compliance, careless responding, and response time in EMA research using data from 617 adult participants of a prospective cohort study in Singapore. As a secondary aim, we explore the degree to which additional covariates such as stable participant characteristics (e.g., age, gender), and temporal factors (e.g., time of the day, day of the week) are associated with these outcomes.

2. Methods

This manuscript was prepared following the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines [27]. The STROBE checklist is provided in the Multimedia Appendix 1.

2.1 Ethical considerations

The study involves secondary data analysis of EMA data from the 'Continuous Observations of Behavioural Risk Factors in Asia' (COBRA) study [28], an observational prospective cohort study examining health behaviours in Singaporean adults using high-frequency EMA. All participants in the COBRA study provided written informed consent before enrolling. Participant data were anonymized before analysis to ensure privacy and confidentiality. Participants received monetary compensation for their participation. During the course of the study, the reimbursement amount was modified and reduced from \$30 to \$20 per participant. This analysis was approved by the local ethics committee of the National University of Singapore (IRB Number: NUS-IRB-2023-369).

2.2 Study procedure

A detailed protocol of the COBRA study can be found elsewhere [28]. Briefly, EMA data were collected via a smartphone-based research app (Avicenna Research, avicennaresearch.com, Canada) designed specifically for EMA studies. The EMA comprised questions about physical activity and diet-related health behaviours, contextual factors (i.e., location, social context), and cognitive states (i.e., stress, fatigue, hunger, positive affect, and sleep quality). Participants received six surveys daily for nine days, delivered via push notifications at random times within predefined time windows: (1) 8:00 a.m. to 9:30 a.m., (2) 10:30 a.m. to 12:00 p.m., (3) 1:00 p.m. to 2:30 p.m., (4) 3:30 p.m. to 5:00 p.m., (5) 6:00 p.m. to 7:30 p.m., and (6) 8:00 p.m. to 9:30 p.m. To encourage timely responses, the app sent up to four reminders (spaced 10 minutes apart) for the first five surveys and two reminders for the final survey of the day. Participants had a 60-minute response window before the survey expired.

Each survey included between five and 40 questions, depending on how the participant responded. The first question was a retrospective assessment asking: "What have you been doing since the last prompt?" Answer options determined subsequent follow-up questions. All surveys ended with four questions assessing momentary cognitive states relating to stress, fatigue, hunger, and positive affect. Additionally, the first survey of each day included a question on sleep quality.

2.3 Outcomes

2.3.1 Next-prompt compliance

Next-prompt compliance was defined as completing the EMA at the subsequent prompt and was measured dichotomously with '1' for completed surveys and '0' for incomplete surveys. The last EMA of the day was excluded from the analysis to avoid associations spanning the night.

2.3.2 Careless responding

2.3.2.1 Next-prompt straight-lining

Straight-lining was identified using the longstring index, which measures the maximum number of consecutive identical responses [14]. Survey responses were labelled as straight-lined if the participant selected the same answer option (e.g., 6,6,6,6) for all four cognitive state questions (i.e., stress, fatigue, hunger, and positive affect) at the subsequent prompt. To establish the reliability of the longstring index in detecting careless responding in our dataset, we conducted correlation analyses (Multimedia Appendix 2 Table S1). Next-prompt straight-lining was measured dichotomously with '1' for careless and '0' for careful responses. We also excluded the last survey of the day from this analysis to prevent associations spanning overnight, and excluded any prompts where the next survey was not completed.

2.3.2.2 Fast responding

Fast response times, typically measured as time per item (TPI) per assessment, can indicate careless responses in EMA studies [14,29,30]. TPI was calculated as the time to complete the survey divided by the number of survey items. While responses with TPI < 1 second are generally considered random or "by chance," Jaso et al. (2021) found that TPI between 1-1.5 seconds may also reflect careless responses. Due to the very low number of responses with TPI < 1s (164 out of 29,797; <0.6%), modeling TPI as a binary outcome led to convergence issues due to the severe class imbalance and would have likely resulted in unreliable parameter estimates. Therefore, TPI was treated as a continuous outcome, but we excluded TPI < 1 second in our main analysis to remove overly fast, likely random responses. Since TPI for all EMAs was positively skewed (skew: 16.38) with extreme outliers ($z > 4$), we applied the upper fence of the interquartile rule (Upper fence = $Q3 + 1.5 \times IQR$) to remove any EMAs with excessively long TPI [30,31]. Additionally, we performed a sensitivity analysis excluding TPI between 1 and 1.5 seconds to assess the impact of a stricter threshold for careless responding [30].

2.3.3 Response delay

In the absence of established cut-off values for delayed EMA responses in the literature [10], response delay was treated as a continuous outcome (in seconds), measured as the time elapsed between the app issuing a survey and the participant responding to the first survey item [32]. To prevent confounding effects from engagement reminders, we excluded responses with delays > 10 minutes, as the study app began sending reminders at this point.

2.4 Cognitive States

Stress, fatigue, hunger, positive affect, and sleep quality were measured on a seven-point Likert Scale ranging from 'not at all' (0) to 'very much' (6) (adapted from [33–38]). Sleep quality was assessed only in the first survey of each day, as it reflects the previous night's sleep and is not expected to vary across the day. Therefore, this morning-reported value was carried forward and used as the sleep quality value for subsequent surveys on the same day. To address occasional missing values in this first survey, we applied median substitution based on each participant's reported sleep quality across days. Participants with fewer than three completed sleep quality ratings were excluded from this imputation step. This procedure resulted in 3,400 substituted values in the sleep quality predictor, which corresponds to 9.1% of total observations. Given the relatively low proportion and the within-subject imputation strategy, we considered this an acceptable approach to minimize data loss while preserving individual response patterns.

2.5 Participants

This analysis used data from the first 692 participants enrolled in the COBRA study, recruited between January 16, 2022, and July 9, 2023, which represented the dataset available at the time of this project. The corresponding dataset comprised a total of 37,368 EMAs. Of these, 52 participants were excluded because they did not receive all surveys during the 54 predefined time windows. Eleven participants were excluded because they left the study prematurely, and seven were excluded because they had fewer than three valid entries in the sleep quality predictor to conduct median imputation. Five were removed due to missing values in at least one of the predictor variables (specifically, stress, hunger, and positive affect). After removing incomplete prompts, the final sample included 29,797 observations (with 3,521 non-responses) from 617 (89.2%) participants. The final dataset contained 12'034 observations for response delay and up to 27'694 for TPI for each of the four outcomes to conduct regression analyses with a maximum of eleven independent variables. Since this sample size is substantially larger than what is typically recommended [39], we concluded that the study is sufficiently powered to conduct the intended analyses. Details of the data processing flow can be found in Figure 1.

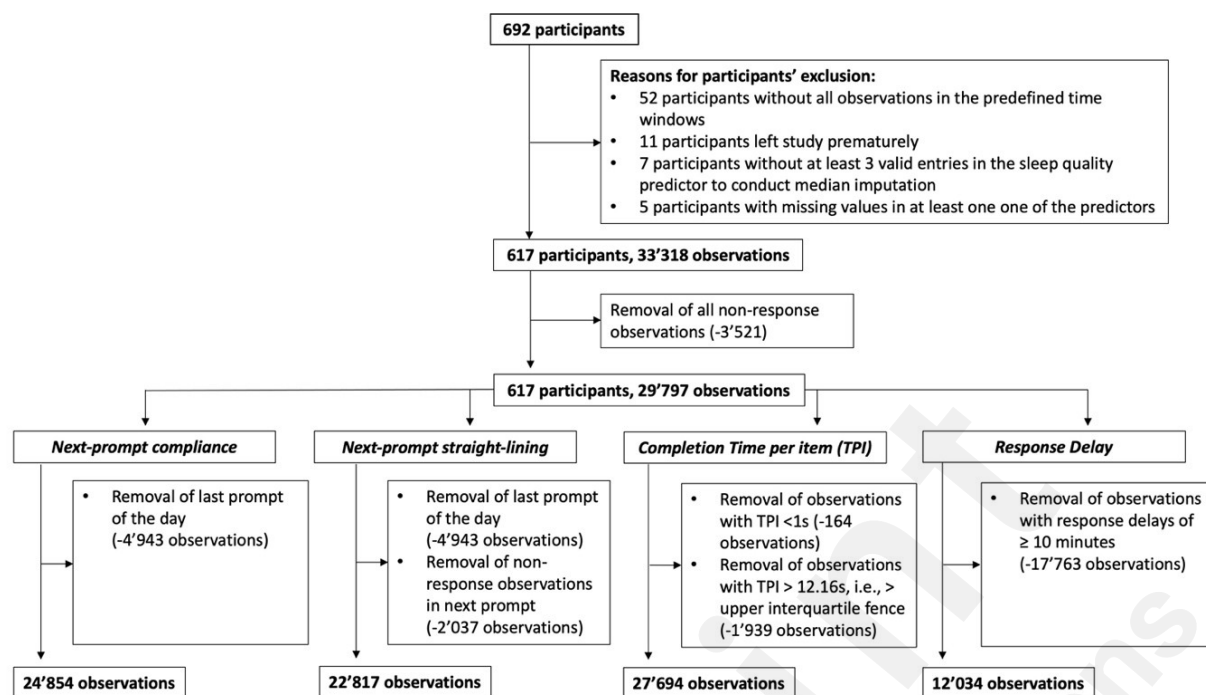


Figure 1. Data processing flow of the COBRA dataset.

2.6 Statistical analyses

Analyses were performed using mixed-effects logistic regression models for the binary outcomes (next-prompt compliance and next-prompt straight-lining) and mixed-effects linear regression models for the continuous outcomes (fast responding (TPI) and response delay). We added several demographic and temporal covariates to the models based on previous literature [20,21,40], specifically age, gender, incentive category, chronological study days, time of the day, day of the week, and the inter-prompt interval (IPI) (Multimedia Appendix 3). To account for autocorrelation, we included a pseudo-autocorrelation variable that counts the number of missed prompts on the same day before the current prompt [21]. For response delay, we adapted this variable to count the number of completed prompts within 10 minutes before the current prompt. Illustrations of the coding for these two predictors are provided in Multimedia Appendix 4.

All models included random intercepts for participants within the study, day number within participants, and prompt number within participants, with day number and prompt number added as crossed random effects. Due to convergence issues, we standardized all continuous predictors (stress, fatigue, hunger, positive affect, sleep quality, age, number of missed prior prompts, number of not responded prompts in 10 minutes, and IPI) to a mean of 0 and a standard deviation of 1,

allowing for a direct comparison of effect sizes. Finally, the response delay outcome was log-transformed to ensure uniformly distributed residuals. We conducted the analyses using R 4.2.1 with packages lme4 [41], lmerTest [42], and car [43].

3 Results

Figure 1 shows the flowchart of the data collected within COBRA. Among 617 individuals, overall next-prompt compliance was 92%. In the careless responding outcomes, overall next-prompt

straight-lining was 5.0% and the average time per item (TPI) of the included surveys was 5.0s (SD: 2.3s). For the delayed responding outcome, the average response delay was 198s (SD: 182s). Table 1 presents a descriptive summary of the participant characteristics and describes the cognitive state variables.

Table 1. Study participant characteristics and descriptive information on the cognitive states variables (n = 617, N = 29,797 EMA observations).

Participant characteristic		Total n = 617
Age, year, mean $\pm$ SD (median)		41 $\pm$ 14.2 (37)
Gender, female, n (%)		406 (65.8%)
Ethnicity, n (%)		
	Chinese	528 (86)
	Malay	54 (9)
	Indian	20 (3)
	Others	15 (2)
Education, n (%)		
	Secondary or lower	65 (11)
	Pre-tertiary	192 (31)
	University degree and above	360 (58)
Employment status, n (%) [#]		
	Employed	495 (80)
	Student or trainee	35 (6)
	Homemaker	34 (6)
	Retired	33 (6)
	Voluntary work	4 (1)
	Unemployed	16 (3)
Monthly household income, n (%) [#]		
	Less than \$2,000	45 (7)
	\$2,000-3,999	93 (15)
	\$4,000-5,999	121 (20)
	\$6,000-9,999	158 (26)
	\$10,000 or more	153 (25)
	Not reported	47 (8)
Cognitive state		Mean $\pm$ SD, range
Sleep quality		3.78 $\pm$ 1.30, 0-6
Stress		1.61 $\pm$ 1.40, 0-6
Positive Affect		3.61 $\pm$ 1.34, 0-6
Hunger		1.58 $\pm$ 1.41, 0-6
Fatigue		2.31 $\pm$ 1.53, 0-6

n = Number of participants; N = Number of EMA observations; SD = Standard deviation;

[#]Percentages do not add up to 100% due to rounding.

In the following sections, we present the results of the multivariable analyses examining associations between cognitive states and response behaviors, including next-prompt compliance, straight-lining, time per item (TPI), and response delay. We first report the compliance and careless responding results, followed by the

results on TPI and response delay. Full model outputs are described in the Multimedia Appendix 5.—

3. 1. Associations of Cognitive States with Next-Prompt Compliance

We found no significant associations of the five cognitive states on next-prompt compliance (Multimedia Appendix 5). Among covariates, we found that older age (OR = 0.79, 95% CI: 0.72–0.87, $p < .001$), a higher monetary incentive (\$30 vs. \$20; OR = 0.81, 95% CI: 0.67–0.98, $p = .026$), a greater number of missed prior prompts (OR = 0.94, 95% CI: 0.91–0.98, $p = .003$), shorter inter-prompt intervals (OR = 1.05, 95% CI: 1.00–1.11, $p = .038$), and weekends (OR = 0.76, 95% CI: 0.69–0.85, $p < .001$) were significant predictors of lower compliance at the next-prompt. Participants were also less likely to respond on the sixth day of the study compared to the first day (OR = 0.80, 95% CI: 0.65–0.98, $p = .032$), as well as during 6:00 pm – 7:30 pm (OR = 0.77, 95% CI: 0.66–0.91, $p = .002$) compared to the first survey of the day (8:00 am – 9:30 am).

3.2. Associations of Cognitive States with Next-Prompt Straight-lining

Several cognitive states were significantly associated with next-prompt straight-lining (Multimedia Appendix 5). Notably, higher stress levels (OR = 1.26, 95% CI: 1.09–1.45, $p = .001$) and greater hunger (OR = 1.20, 95% CI: 1.07–1.34, $p = .002$) increased the likelihood of next-prompt straight-lining, whereas higher sleep quality (OR = 0.85, 95% CI: 0.74–0.98, $p = .023$) and higher positive affect (OR = 0.77, 95% CI: 0.67–0.88, $p < .001$) reduced the likelihood.

Among covariates, older age (OR = 0.70, 95% CI: 0.54–0.91, $p = .007$) was associated with less straight-lining. Straight-lining was less likely during 10:30 am – 12:00 pm (OR = 0.64, 95% CI: 0.49–0.83, $p = .001$), 3:30 pm – 5:00 pm (OR = 0.72, 95% CI: 0.56–0.94, $p = .015$), and 6:00 pm – 7:30 pm (OR = 0.54, 95% CI: 0.41–0.71, $p < .001$) compared to the first survey of the day (8:00 am – 9:30 am). Straight-lining also increased as the study progressed, with significant increases observed on days 7 (OR = 1.71, 95% CI: 1.11–2.63, $p = .016$), 8 (OR = 1.77, 95% CI: 1.15–2.73, $p = .009$), and 9 (OR = 1.92, 95% CI: 1.25–2.95, $p = .003$) compared to the first day of study.

3.3 Associations of Cognitive States with Time Per Item (TPI)

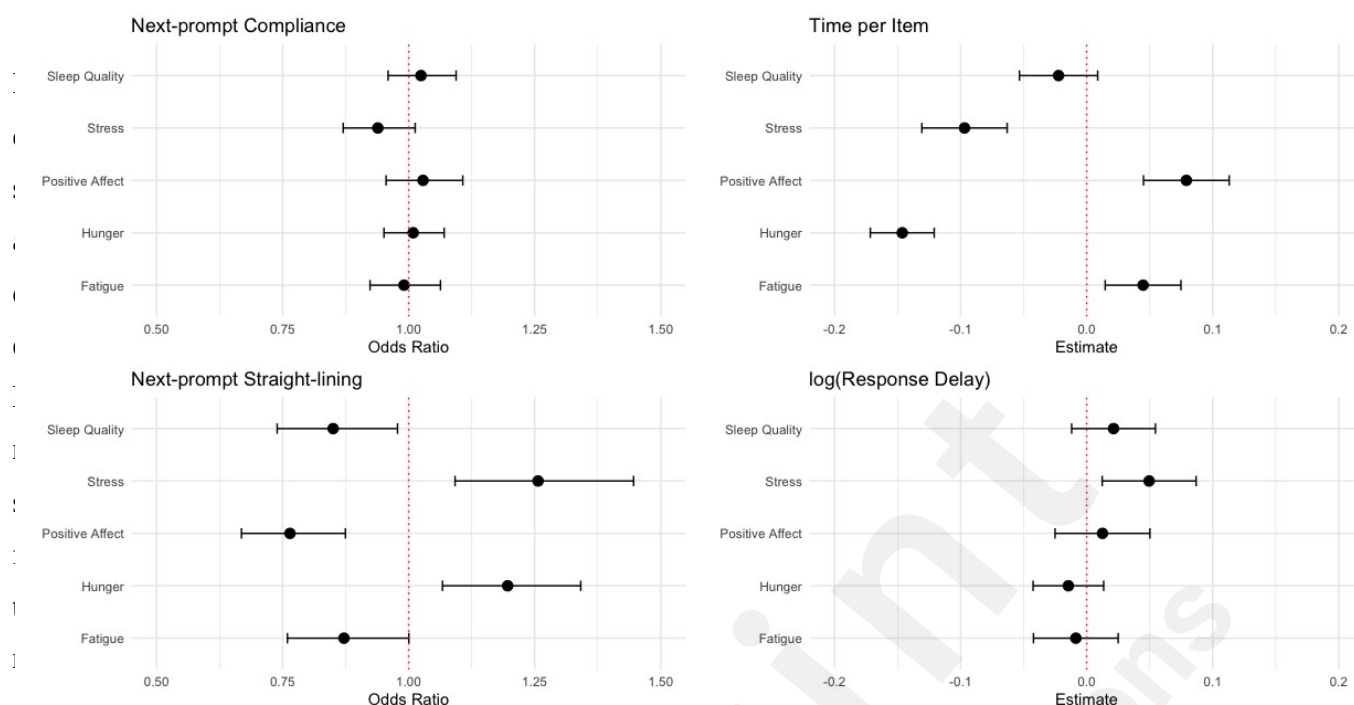
Cognitive states were also associated with TPI (Multimedia Appendix 5). Specifically, higher stress ($b = -0.10$, 95% CI -0.13 to -0.06 , $p < .001$) and hunger ($b = -0.15$, 95% CI -0.17 to -0.12 , $p < .001$) were negatively associated with time per item (TPI), indicating faster responses when stress or hunger was higher. In contrast, higher positive affect ($b = 0.08$, 95% CI 0.05 to 0.11 , $p < .001$),

fatigue ($b = 0.05$, 95% CI 0.02 to 0.08, $p = .004$), were positively associated with TPI, reflecting longer response times. These associations remained consistent in the sensitivity analysis, which excluded TPI between 1.0 and 1.5 seconds (see Multimedia Appendix 5).

Among covariates, older age ($b = 1.09$, 95% CI: 1.00 to 1.18, $p < .001$) and female gender ($b = 0.31$, 95% CI: 0.13 to 0.49, $p = .001$) were significantly associated with longer TPI. In contrast, TPI was shorter during all periods compared to the first survey of the day (8:00 am – 9:30 am). TPI also decreased over time, with all study days showing shorter TPI compared to the first day of the study. Finally, TPI was longer on weekends compared to weekdays ($b = 0.15$, 95% CI: 0.11 to 0.20, $p < .001$) and when more prior prompts were missed ($b = 0.08$, 95% CI: 0.05 to 0.10, $p < .001$).

3.4. Associations of Cognitive States with Response Delay

Of the five cognitive states investigated, only higher stress ($b = 0.05$, 95% CI 0.01 to 0.09, $p = .009$) was associated with a significant increase in response delay (Multimedia Appendix 5). Among the covariates, age ($b = 0.13$, 95% CI 0.08 to 0.19, $p < .001$) female gender ($b = 0.12$, 95% CI 0.01 to 0.23, $p = .040$), higher incentive (\$30 vs. \$20; $b = 0.19$, 95% CI 0.08 to 0.30, $p = .001$) and a greater number of prior prompts not responded to within 10 minutes ($b = 0.06$, 95% CI 0.03 to 0.09, $p < .001$) were significantly associated with longer response delay. Response delay tended to decrease as the day progressed, with significant reductions observed at 1:00 pm – 2:30 pm ($b = -0.10$, 95% CI -0.18 to -0.01 , $p = .026$), 3:30 pm – 5:00 pm ($b = -0.13$, 95% CI -0.22 to -0.05 , $p = .003$), 6:00 pm – 7:30 pm ($b = -0.15$, 95% CI -0.23 to -0.06 , $p < .001$), and 8:00 pm – 9:30 pm ($b = -0.21$, 95% CI -0.30 to -0.12 , $p < .001$) compared to the first survey of the day (8:00 am – 9:30 am) (see Multimedia Appendix 5).



Notes: The following covariates were added to the models: Age, gender, incentive category, chronological study days, time of the day, day of the week, inter-prompt interval, number of missed prior prompts (in next-prompt compliance, next-prompt straight-lining, and TPI model), number of not within 10 minutes responded prior prompts (only in response delay model). All predictor variables were standardized before analysis; thus, odds ratios represent the change in odds associated with a one standard deviation increase in the predictor. Full model results, including covariates, are reported in the Multimedia Appendix 5.

Definitions:

Next-prompt compliance: Whether participants responded to the next EMA prompt following the current one.

Straight-lining: A common indicator of careless responding, where a participant repeatedly selects the same response option (e.g., consistently choosing “5 = Very much”) across four or more consecutive items on a 5-point Likert scale ranging from 1 = “Not at all” to 5 = “Very much”.

TPI (Time Per Item): Refers to the average response time per question within a prompt.

4. Discussion

This is the first study to investigate the associations of cognitive states with compliance, careless responding, and delayed responding (as reflected by response delays) to EMAs. Our results suggest that while cognitive states do not significantly affect next-prompt compliance, they influence careless responding and response delays. Specifically, stress, hunger, lower positive affect, and poor sleep quality were associated with an increased risk of careless responding, while fatigue was associated with longer response times (higher TPI), and psychological stress was associated with longer response delays. These findings highlight careless and delayed responses as potential sources of systematic bias, which can distort relationships between variables in EMA studies measuring, stress, fatigue, hunger, positive affect, and sleep quality. These findings underscore the importance of designing EMA protocols that minimise data quality issues: for example, by optimally timing prompts to opportune moments, incorporating passive sensing modalities to detect non-compliance or careless responding in real time, or using motivational prompts and reminders to encourage careful responding.

The associations between stress, hunger, and positive affect with careless responding may be a particular issue for studies investigating these cognitive states as outcomes, such as studies examining daily life experiences and processes underlying stress, hunger, or positive affect (e.g., [44–46]). Typically, identified careless responses, detected as fast responses or straight-lining, are removed from the dataset and treated as missing values [14]. Therefore, careless responding is considered a hidden form of non-compliance [10,14,30], often assumed to be ‘missing at random’. Our findings suggest that this assumption may not hold, as careless responses may be ‘missing not at random’ concerning key study variables. This could lead to biased parameter estimates, potentially inflating or attenuating observed associations.

Contrary to previous research [21,22,24,26], we found no significant effects of cognitive states on next-prompt compliance. This discrepancy may be attributed to our high compliance rate (89%), which was facilitated by a rigorous EMA protocols including up to four reminder messages, which were not consistently implemented in prior studies [21,22,24,26]. Regarding demographic covariates, we found age and gender-related differences in response behaviours. Older participants were more likely to be non-compliant or delayed in responding, but were less prone to careless responding. Female participants had longer response delays and were less likely to engage in fast responding than male participants. These findings contribute to the limited literature on person-specific predictors of careless responding in EMA studies. In addition to previously identified personality traits associated with careless responding, such as lower conscientiousness, extraversion, agreeableness, and emotional stability [29,47,48], we provide the first empirical evidence linking younger age and male gender to increased careless responding. For temporal covariates, we observed that non-compliance and careless responding increased over the number of days in our study, highlighting data quality deterioration throughout the study. While the observed increase in non-compliance is consistent with previous research [21,25,49], our study is the first to report a progressive increase in careless responding over time, with a significant reduction in TPI from day 2 onwards and a significant increase in straight-lining from day 7 onwards. The effects of time of day on data quality were, however, inconclusive. Participants were less likely to give straight-line responses later in the day, but also less likely to respond quickly in the morning. Additionally, participants were more likely to be non-compliant during weekends compared to weekdays. Other studies have reported minor weekday-weekend variations, but they did not establish a consistent pattern favoring either [21,49]. Finally, we found that longer inter-prompt intervals increased the likelihood of responding to the next prompt, suggesting that lower frequency EMA protocols are less burdensome [50]. However, this finding contrasts with prior research suggesting that EMA prompts that are too infrequent may lead to disengagement [21,22]. This discrepancy may be due to the use of reminder notifications in our study, which were not consistently implemented in previous studies [13,21]. While these reminders may have improved the overall compliance rate in our study, they

may have also increased the perceived burden of each EMA prompt, particularly when prompts occurred in close succession. This could explain why longer inter-prompt intervals were more effective in our study. Future research should experimentally evaluate the effect of the presence and frequency of reminder notifications on participant burden and compliance.

While careless responding is less prevalent than non-compliance in EMA studies [10], it remains an underappreciated issue. Studies that fail to account for careless responses risk inflated effect sizes and spurious findings [51]. To mitigate the impact of careless and delayed responding, researchers could consider leveraging passive sensor data from wearables or smartphones to infer cognitive states when responses are missing. For example, prior research has suggested that information on phone usage (e.g., screen unlock events) and accelerometer-derived activity information can serve as digital markers for heightened stress, hunger, and affective states [52–54]. Additionally, recent studies suggest that it is possible to predict participant disengagement or dropout, often framed as non-adherence, using phone usage data [55–57]. Another possible avenue is to use multiple imputation models incorporating data on stress, affect, and hunger from preceding or subsequent prompts [58], or to apply inverse probability weighting to account for systematic response biases [59]. One could also implement a system to deter careless responses, such as prompts encouraging careful answering, including warnings, rewards, or educational messages or to delay EMA prompts until a more valid response is likely [24,60]. However, sending additional messages needs to be considered with caution as it may exacerbate non-compliance or cause resentment among participants, especially when warning messages are perceived as harsh [61].

Our findings also have implications for ecological momentary interventions (EMIs) or just-in-time adaptive interventions (JITAIs) that are commonly used in mHealth apps [62–67]. Delayed responses may cause participants to miss time-sensitive intervention content, reducing the effectiveness of support. Similarly, careless responses or engagement with app content, may compromise intervention outcomes for example in participants with lower levels of intrinsic motivation, which may lead to more superficial interactions with the app [68,69]. Understanding the predictors of delayed and careless responding can inform intervention timing to maximise receptivity (e.g., during low levels of stress, hunger, and high levels of positive affect) [32,64,70].

4. 1. Strengths and Limitations

This study had two main strengths. First, our study involved a large sample from a multi-ethnic population and a broad age range [28], allowing generalisability of our findings to other populations. Second, our study was conducted using an electronic assessment via a smartphone app that

yielded accurate timestamps of when participants received, started, and finished their survey responses. In contrast, previous research often used paper-and-pencil assessments [15,21], which are prone to mismatches in the reported and actual timestamps that can potentially result in erroneous negative completion time or response delay values. Paper-and-pencil assessments have also been associated with backfilling of experiences in the past, which can be a source of error [71].

It is also important to acknowledge the limitations of our study. First, our protocol only included six prompts per day with an average inter-prompt interval of 145 minutes, which limited the temporal granularity of the data compared to previous studies with more frequent assessments [21]. It is, therefore, possible that the cognitive states reported at one prompt may have already changed at the following prompt. Second, our analysis offers only indirect evidence of the momentary predictors' associations and compliance, because we could only investigate associations between cognitive states observed at prompts where participants responded and the subsequent prompt. Third, the results in the response delay outcome should be interpreted with caution, as the delay may have masked actual differences in cognitive states at the time of the prompt (e.g., if a participant experienced low mood when prompted but waited until the mood improved before responding), which could potentially attenuate the observed association (i.e., beta coefficients) between cognitive states and response delay.

4.2 Conclusions

This study provides novel insights into the influence of momentary cognitive factors on careless responding, delayed responding, and non-compliance in EMA studies. Our findings suggest that higher levels of stress, hunger, poor sleep quality, and lower levels of fatigue and positive affect are associated with at least one of two metrics of careless responding. In addition, greater psychological stress is also associated with response delays. These results highlight the importance of considering participant states as potential sources of systematic bias in EMA studies, particularly in studies investigating stress, hunger, and positive affect. Future studies should track those variables to mitigate the effects of careless and delayed responding post hoc and utilise just-in-time delivered warnings, rewards, and educational messages to pre-empt problematic response behaviours.

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9. Conflict of Interests

FVW, TK, and JLM are affiliated with the Centre for Digital Health Interventions (CDHI), a joint initiative of the Institute for Implementation Science in Health Care at the University of Zurich, the Department of Management, Technology, and Economics at ETH Zurich and the School of Medicine and Institute of Technology Management at the University of St Gallen, and the Singapore-ETH Centre. CDHI is funded in part by CSS, a Swiss health insurer, MTIP, a Swiss digital health investor company, and Mavie Next, an Austrian health provider. TK co-founded Pathmate Technologies in 2017, a University spin-off company that creates and delivers digital clinical pathways. Since 2023, TK has had no shares or any other formal roles with Pathmate Technologies. Moreover, Pathmate Technologies, CSS, MTIP, and Mavie Next were not involved in this research. The remaining authors declare that the research was conducted without any commercial or financial relationships that could be regarded as a potential conflict of interest.

10. Data availability

The dataset supporting the study findings includes detailed information on participants' cognitive states (i.e., sleep quality, stress, positive affect, hunger, and fatigue), health behaviours (diet and

physical activity), and contextual factors (e.g., location, social setting). The datasets analysed during the current study are not publicly available for privacy and confidentiality reasons, but are available from the corresponding author on reasonable request (with an appropriate ethical and data protection policy in place).

11. Code availability

The underlying modeling code for this study is available in Multimedia Appendix 5. The preprocessing code is available upon request to the corresponding author.

12. Author contributions

Conceptualization: RK, SME, JLM. Supervision: FVW, TK, SME, JLM. Writing: RK. conceptualisation of the COBRA study, funding and data acquisition: XHC, XS, RVD, FMR, SME. Data analysis: RK, SN. Critical Review: RK, SN, TK, FVW, XHC, XS, RVD, FMR, SME, JLM. All authors read and approved the final manuscript.

13. Abbreviations

EMA: Ecological momentary assessment

COBRA: Continuous Observations of Behavioural Risk Factors in Asia

IPI: Inter-Prompt Interval

IRB: Institutional Review Board

IQR: Interquartile Range

STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

TPI: Time Per Item

14. Multimedia Appendix

Multimedia Appendix for this article is available online.

15. References

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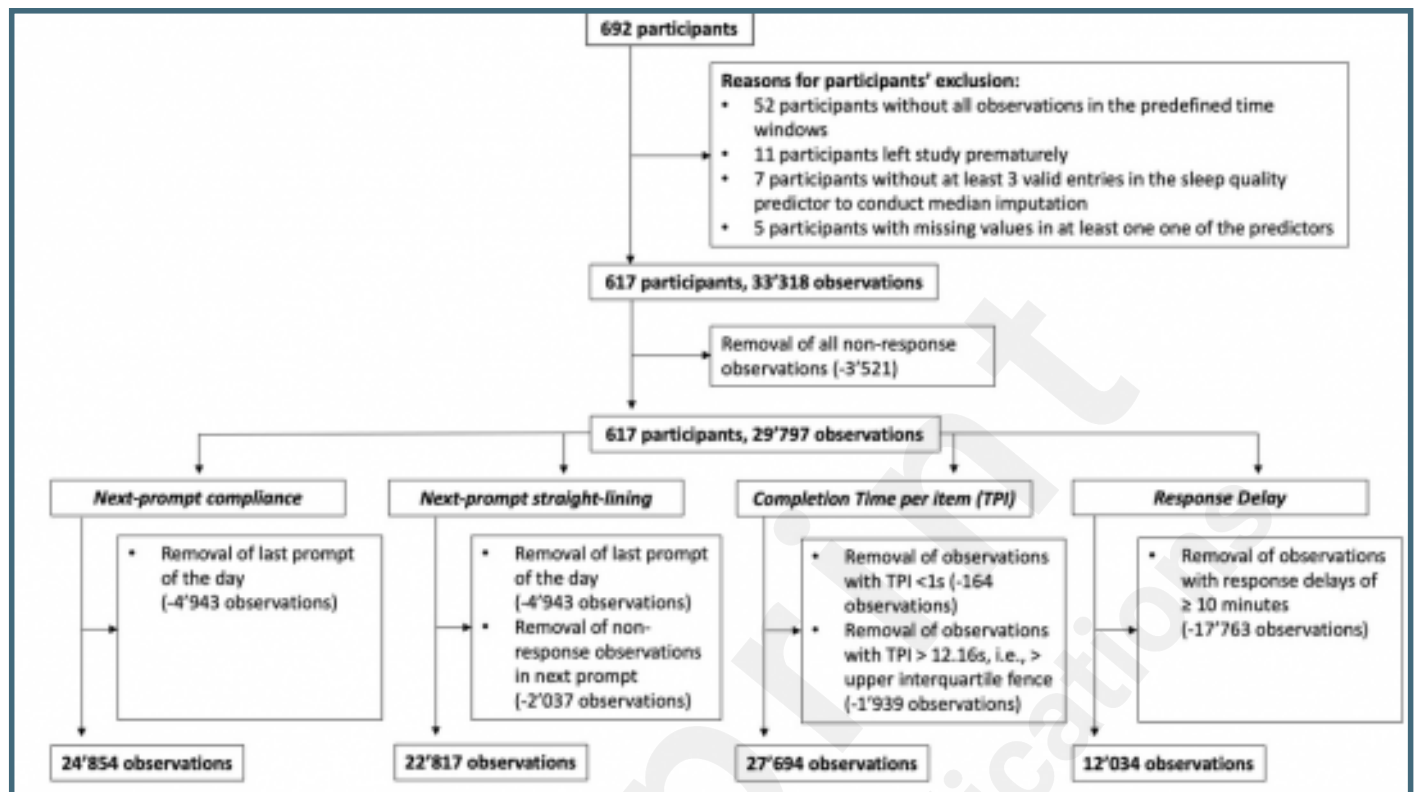
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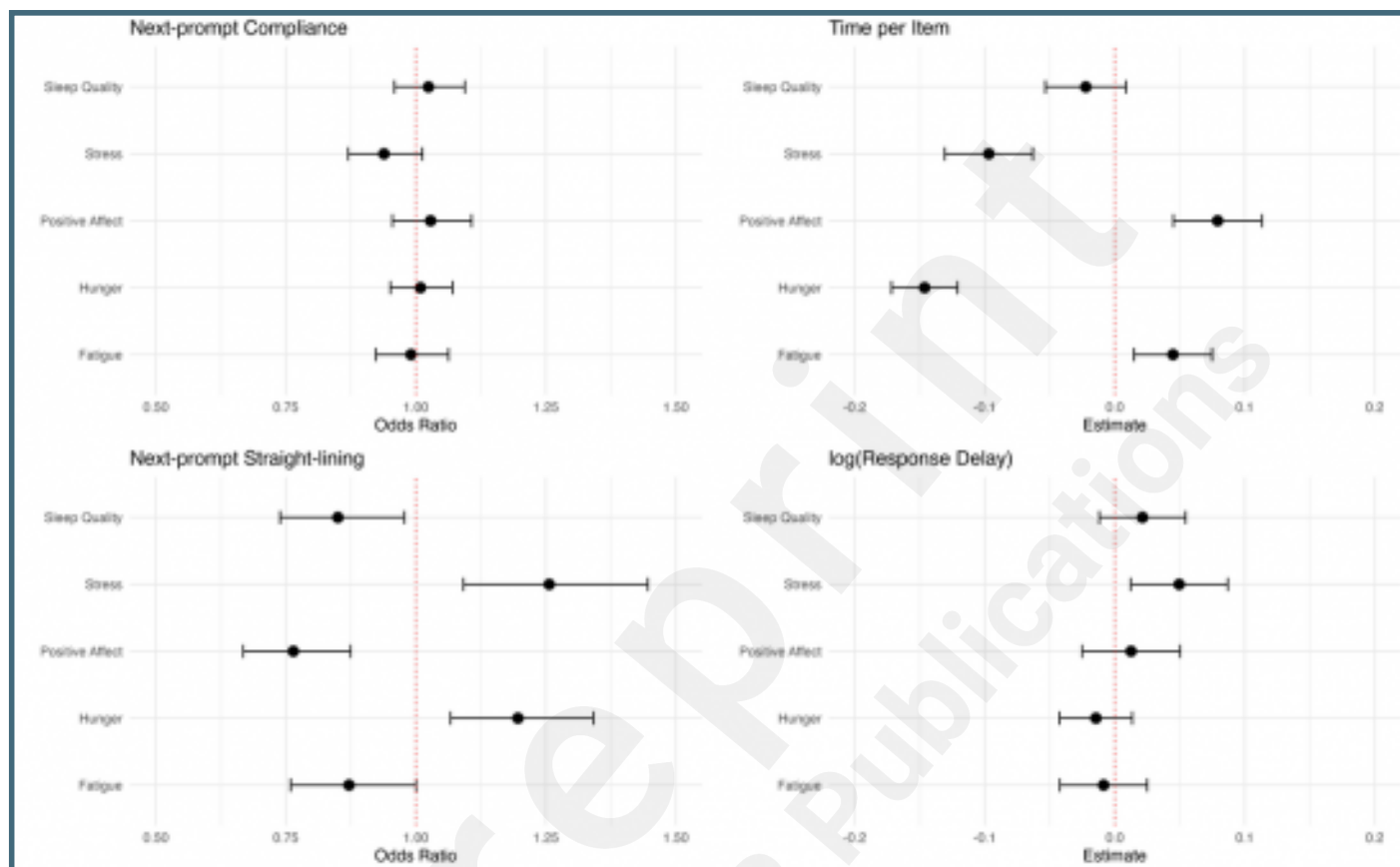
Supplementary Files

Figures

Data processing flow of the COBRA dataset.



Panel of forest plots displaying the results of mixed-effect regression models for five cognitive states: sleep quality, stress, positive affect, hunger, and fatigue. The two plots on the left side show the odds ratios and confidence intervals from mixed-effect logistic regression models for compliance (top left) and straight-lining behavior (bottom left) at the next prompt, respectively. The two plots on the right side present the estimates and confidence intervals from mixed-effect linear regression models for the time per item (TPI) (top right) and the logarithmized response delay (bottom right), respectively.



Multimedia Appendixes

Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Checklist.

URL: <http://asset.jmir.pub/assets/6fd65cb95b4940855d2caebd780e6651.docx>

Correlation coefficients between psychometric items (positive affect, stress, fatigue, hunger) used to validate the next-prompt straight-lining outcome.

URL: <http://asset.jmir.pub/assets/bbf17b727fcd9071fbf5217d7c381ce7.docx>

Coding of covariates used in statistical analyses.

URL: <http://asset.jmir.pub/assets/61d2f1a39baa4d85739db01a397ea306.docx>

Coding and descriptive statistics of pseudo-autocorrelation variables.

URL: <http://asset.jmir.pub/assets/cfdff490d2a9385fa33c5d4ac118fe09.docx>

Full mixed-effects model results for next-prompt compliance, next-prompt straight-lining, time per item, and response delay, including sensitivity analyses.

URL: <http://asset.jmir.pub/assets/6759bf8e63cc7fff3cddd383ae4d8c26.docx>

TOC/Feature image for homepages

Hands interacting with a smartphone to select a survey response.

