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Enrollment and Compliance in an Ecological Momentary Assessment Study of Later Life

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Abstract
This study addresses enrollment and compliance in ecological momentary assessment (EMA) research by focusing on a sample of older adults with varying levels of technological familiarity. This is noteworthy because contemporary EMA studies predominantly require participants to use smartphones to record data in real time. We employ a two-stage analysis where we estimate the probability of enrollment based on sociodemographic and research design attributes and next use the output from this model to address potential selection bias in a subsequent model estimating compliance rates. We find that smartphone ownership is a major predictor of enrollment and that offering participants a loaner smartphone is insufficient to overcome this barrier. Ultimately, our findings suggest that while there are some potential design strategies that prospective researchers could

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implement to improve enrollment and compliance, there will likely always be some people whose attributes decrease their probability of enrollment and compliance regardless of intervention.

Introduction

Ecological momentary assessments (EMAs) constitute a data collection method that allows participants to record their behaviors and perceptions as they are experienced in their natural environments using smartphone technology (Browning et al. 2024; Roth 2024; Shiffman et al. 2008). Participants typically commit to a study for multiple days or weeks, during which time they are repeatedly prompted to respond to a series of EMAs via smartphone apps, text messages, or paper diaries. At the end of the study period, each participant will have ideally recorded a predetermined number of EMAs that can be used to analyze within-participant and between-participant variation. This increasingly popular method has provided unique insights into numerous areas of social science such as health, aging, and crime (Browning et al. 2021; Goldman and Compernolle 2023; Harcey et al. 2022; Tyler et al. 2018).

Although EMAs offer an effective method of documenting everyday life, they are accompanied by considerable participant burden that causes noteworthy methodological issues. First, researchers often have trouble convincing individuals to enroll in their study. This task presents a growing concern that exists in nearly all survey-based research (Leeper 2019). This is especially heightened in EMA research where the prospect of having one's daily routine repeatedly interrupted by notifications asking them to complete a series of EMAs may cause participants to hesitate before agreeing to enroll (Stone et al. 2023, 2024). Second, there is a realistic possibility that enrolled participants will not complete all their EMAs during the study period. For instance, a study that prompts participants with four EMAs per day for seven days should produce a dataset that contains 28 EMAs per participant. Yet participants often fail to respond to all their EMA notifications, especially because researchers typically implement a limited response window for participants to record each EMA (Browning et al. 2024; Stone et al. 2023). Indeed, a recent meta-analysis found that compliance rates ranged from as low as 10% to as high as 100% (mean = 79%, SD = 14%) across 347 studies, with the number of prompts and days influencing results only after one week (Wrzus and Neubauer 2023). Imperfect compliance rates result in a loss of statistical power, an increased likelihood of failing to capture target activities, and potential bias in reporting certain activities.

In the present study, we address enrollment and compliance in a smartphone-based EMA study by analyzing data from a population-based sample of 510 older adults living in Indiana. Older adults are particularly noteworthy in this context as they provide high compliance rates for EMAs (Burke and Naylor 2022; Fritz et al. 2017; Maher et al. 2018; Yao et al. 2023). However, these compliance rates only reflect those who successfully enrolled in EMA studies. This ignores whether barriers to enrollment systematically exclude people who would have been less compliant had they enrolled in the study. Many EMA studies choose to prompt participants at random times throughout the day to complete an EMA session. This design increases the chances of capturing select moments that, on aggregate, represent a typical day. But it can also make responding stressful or challenging (Compernolle et al. 2024). These challenges are likely exacerbated given that older adults have traditionally faced less access to smartphone technology than younger populations (Faverio 2022; Mobile Fact Sheet 2024). This selection bias into EMA studies is important because challenges affecting enrollment can create systematic patterns among participants who would typically refuse to enroll, as well as among enrolled participants who do not complete all the requested EMAs (Dutwin et al. 2015; Groves 2006).

We build on this burgeoning literature by employing a two-stage analysis that accounts for potential selection bias in an EMA study. In the first stage, we estimate the probability of participant enrollment based on a combination of sociodemographic attributes and research design attributes. In the second stage, we use these same attributes to estimate variation in compliance rates across participants while adjusting for any selection effects that emerge from the first stage. This approach offers an important methodological contribution because a study that only analyzes enrollment says nothing about how well prospective participants comply with the daily EMAs, whereas a study that only analyzes compliance of enrolled participants ignores the possibility that non-enrolled participants would have been more likely to have exhibited lower compliance rates had they have enrolled in the study.

Methods

We use data from the Social Environment and Cognitive Health in Urban and Rural Areas (SECHURA) study. This is a probability sample of 510 Indiana residents that was designed to examine variation in cognitive function in later life. Participants were drawn from a subsample the Person-to-Person Health Interview Study (P2P), which was a state representative health and wellness study conducted from 2018 to 2021 (Green and Pescosolido 2024;

Railey and Greene 2024). The following three inclusion criteria were used to select SECHURA participants: (1) they were 55 years or older; (2) they were still living in Indiana; (3) they had agreed to be contacted for follow-up studies after their participation in the P2P. There was one P2P participant whose age was incorrectly recorded prior to SECHURA recruitment. It was discovered after they had been onboarded to the SECHURA study that they were 53 years old. We retained this participant because (a) they had already completed the CAPI survey and EMA module; (b) excluding a single participant who was two years below the cutoff would have negligible impact on our results and does not meaningfully alter the age composition of our sample; (c) we prioritize transparency of data collection by documenting this deviation rather than excluding otherwise valid data in post hoc fashion.

The baseline wave of SECHURA data collection, which ran from November 2023 to March 2024, was comprised of two distinct modules. First, all participants completed a computer-assisted personal interview (CAPI) survey that was delivered by a team of trained field interviewers. This CAPI survey provided baseline data on their sociodemographic attributes, social lives, and health. Upon completing the CAPI survey, participants were invited to enroll in a follow-up module that required them to complete a week of EMAs using a smartphone app called LifeData. Although Internet access was required during the installation phase, the app worked offline for the remainder of the study period. All responses were stored in the phone's memory and uploaded to LifeData's online platform as soon as the phone returned to a Wi-Fi zone. The 80 participants who did not own a smartphone were offered a loaner device that was to be returned at the end of the study period. Only nine of these participants (11%) accepted a loaner phone.

A total of 273 of the 510 participants (54%) enrolled in the EMA module. For the next seven days, these participants were randomly prompted four times per day between 8:00 am and 8:00 pm to respond to an EMA that asked them where they were, what they were doing, and who they were with. Participants had 20 minutes after the notification to initiate a response. A first, second, and third reminder notification came in five-minute increments. All EMAs that went unanswered after 20 minutes were recorded as missing. It took participants one minute and 18 seconds, on average, to complete each EMA after they initiated a response. Participants completed an average of 20.48 EMAs (i.e., 73% compliance rate). Participants received a $75 Visa© card for completing the CAPI survey and earned up to $20 extra if they enrolled in the EMA module ($5 for completing 1–10 EMAs, $10 for completing 11–20 EMAs, $15 for completing 21–27 EMAs, and $20 for completing all 28 EMAs). Further details on the SECHURA research design are documented elsewhere (Roth et al. 2024).

Dependent Variables

There are two dependent variables accompanying the two-stage analysis. In the first stage, we model EMA enrollment as a dichotomous variable documenting whether participants enrolled in the EMA module (n=273) or did not enroll (n=237). In the second stage, we model the compliance rate for the 273 who enrolled in the EMA module. Compliance is measured as a count variable indicating the number of missing EMAs out of 28 possible opportunities. We operationalize the variable in this fashion because the majority of participants missed a small number of EMAs. Measuring the compliance variable as the number of missing EMAs therefore produces the positive skew that is required for a modeling count variable (see distribution in Figure S1).

Sociodemographic Variables

We include age (years), gender (woman/man), race (White, Black, other), educational attainment (high school or less, technical certificate, some college, college), employment status (retired, employed, other), personal network size, depression, functional limitations, cognitive function, and county of residence as sociodemographic variables. Personal networks were enumerated using five name generating prompts (people with whom participants discussed important matters, people with whom they discussed their health, people who tried to get them to do something about their health, people with whom they spent their free time, and people who caused them problems). There was no limit on the number of network members that participants could name.

Depression is measured using the 15-item Geriatric Depression Scale, which asks participants to respond to statements such as “do you prefer to stay at home, rather than going out and doing new things?” (Yesavage and Sheikh 1986). Functional limitations is measured using the activities of daily living (ADL) index, which asks respondents to report the level of difficulty experienced in nine regular activities, such as walking, getting dressed, getting out of bed (Katz et al. 1963). Cognitive function is measured using the Montreal Cognitive Assessment, which is a clinical screener used to detect signs of cognitive impairment (Nasreddine et al. 2005). County of residence is measured using the Indiana County Classification, where counties are either “urban,” “mixed,” or “rural,” based on a combination of population density, county’s largest municipality, and a subjective account of how residents view their home counties (Ayres et al. 2012). Finally, we include a dummy variable indicating whether participants own a smartphone and an ordinal variable asking participants how frequently they have used a computer, tablet, or smartphone in the past year (daily, weekly, or less than weekly) as proxies of their technological proficiency.

Research Design Variables

We also assessed whether certain research design attributes were associated with enrollment and compliance. This included the number of times the participants were contacted to be recruited to the SECHURA study (as a proxy for reluctancy), the month they enrolled (November, December, January, February, March), and the time it took them to complete the CAPI survey (minutes). This last variable was used to assess participant fatigue leading up to the EMA module.

Analytic Strategy

We start by presenting summary statistics to provide a sense of the composition of our sample. Next, we employ a two-stage analysis to account for potential selection bias. In the first stage, we estimate a probit model to assess the probability of enrollment in the EMA module across all 510 participants. This model not only provides estimations of the associations between the independent variables and enrollment, but is also used to obtain an inverse mills ratio (IMR). The IMR—which is the expected value of the error term from the probit model for each participant given their probability of enrollment—is subsequently used in the second stage to address potential selection bias (Heckman 1976). In this latter stage, we estimate a negative binomial model to assess the number of EMA notifications that participants missed during their study period. This model only includes the participants who enrolled in the EMA module (n=273) because the non-enrollees would present structural zeros on this metric (i.e., they did not miss any notifications because they never received any).

The independent variables stay the same as the previous model with two exceptions: (1) smartphone ownership is withheld because it serves as the exclusion restriction; (2) the IMR is added to adjust for a potential selection effect. Including the IMR variable accounts for unobserved factors—captured via the error term in the probit model—that may have influenced participant enrollment in the EMA module (and hence their presence in the second-stage model). The negative binomial model is appropriate in this circumstance because the outcome is a count variable with evidence of overdispersion. We present average marginal effects (AMEs) for the probit model and negative binomial model. These AMEs are interpreted as the change in predicted probability of enrollment for a one-unit increase in the independent variable in the probit model and as the change in the expected count of missing EMAs for a one-unit increase in the independent variables in the negative binomial model. All models apply survey weights that account for sampling design and baseline response rates. Model diagnostics and robustness checks are presented in the supplementary materials (Tables S2–S5).

Results

Table 1 presents the summary statistics for the sample. The average age was 69.9 years (SD= 9.32), and the majority were women (65%) and White (90%). Educational attainment showed a relatively even distribution across the four categories, with 30% holding a high school diploma or less, 16% holding a technical certificate, 22% having attended some college, and 32% holding a college degree. Over half the participants (55%) were retired. Participants reported an average of 2.94 depressive symptoms out of a possible 15 (SD = 2.80) and an average MoCA score of 23.7 (SD = 4.44)—which is above the suggested clinical cut-point of 22 for mild cognitive impairment (Freitas et al. 2013). Most participants (84%) owned a smartphone and used a computer or similar device everyday within the past year (84%). Participants were contacted an average of 5.81 times (SD = 2.19) before they officially enrolled in the study. The CAPI survey took an average of 79.2 minutes (SD = 30.7) to complete.

Enrollment

Table 2 presents the average marginal effects from the probit model that predicts EMA enrollment. Age was negatively associated with the outcome, indicating that older participants had a lower probability of enrolling in the EMA module compared to younger participants (AME = −0.11, SE = 0.04, $p < 0.01$). Using the probit model in Table 2 to calculate the predicted probabilities for participants at different ages, we found that a 55-year-old participant was predicted to have a 0.61 probability of enrollment (SE = 0.06), compared to a 70-year-old participant who was predicted to have 0.44 probability (SE = 0.03), and an 85-year-old participant who was predicted to have a 0.28 probability of participation (SE = 0.03), adjusting for all covariates. Cognitive function, meanwhile, was positively associated with the outcome such that a one-point increase in the MoCA score corresponded to a two-percentage point increase in EMA enrollment (SE = 0.01, $p < 0.05$). Smartphone ownership was also positively associated with enrollment (AME = 0.27, SE = 0.09, $p < 0.01$). Participants who owned a smartphone had a 0.49 probability of enrolling in the EMA module (SE = 0.03), whereas participants who did not own a smartphone had a 0.22 probability (SE = 0.08). Finally, the number of attempts made to recruit participants to the SECHURA study was negatively associated with EMA enrollment such that every additional recruitment attempt corresponded to a 0.03 decrease in the probability of enrollment (SE = 0.01, $p < 0.05$). Additional results documenting the qualitative comments for non-enrollment (n=19) support technology-driven and health-related reasons for not enrolling (see supplementary material for detail).

Table 1. Descriptive statistics.

	All (n=510)			EMA enrollment (n=273)			EMA non-enrollment (n=237)			
	Mean/Prop.	SD	Min-Max	Mean/Prop.	SD	Min-Max	Mean/Prop.	SD	Min-Max	t-stat / $\chi2$
EMAs completed[a]	20.48	(6.59)	1 – 28	20.48	(6.59)	1 – 28	--	--	--	
Age	69.90	(9.32)	53-102	67.16	(7.73)	53-88	73.06	(9.98)	55-102	7.51***
Gender										
Women	0.65			0.70			0.59			6.64*
Men	0.35			0.30			0.31			
Race										
White	0.90			0.92			0.89			1.66
Black	0.07			0.07			0.08			
Other	0.03			0.02			0.03			
Education										32.18***
< HS	0.30			0.24			0.37			
Technical certificate	0.16			0.13			0.20			
Some college	0.22			0.21			0.22			
College	0.32			0.42			0.20			
Employment status										15.18***
Retired	0.55			0.48			0.62			
Employed	0.28			0.36			0.20			
Other	0.17			0.17			0.17			
Computer use										57.76***
Daily	0.84			0.94			0.73			
Weekly	0.05			0.04			0.06			
< Weekly	0.11			0.02			0.21			

(continued)

Table 1. (continued)

	All (n=510)			EMA enrollment (n=273)			EMA non-enrollment (n=237)			
	Mean/Prop.	SD	Min-Max	Mean/Prop.	SD	Min-Max	Mean/Prop.	SD	Min-Max	t-stat / $\chi 2$
Smartphone	0.84			0.97			0.70			74.62***
MoCA	23.65	(4.44)	1-30	24.84	(3.48)	14 – 30	22.27	(5.00)	1-30	6.79***
ADL	0.26	(0.33)	0-2	0.22	(0.29)	0 – 1.67	0.31	(0.37)	0-2	3.21***
Network size	5.38	(2.93)	0-20	5.65	(3.07)	1-20	5.07	(2.73)	0-15	2.24*
Depression	2.94	(2.80)	0-14	2.79	(2.75)	0-14	3.12	(2.86)	0-14	1.33
County										4.81
Urban	0.51			0.56			0.46			
Mixed	0.08			0.07			0.10			
Rural	0.40			0.37			0.43			
Recruitment attempts	5.81	(2.19)	3-14	5.89	(2.21)	3-14	5.72	(2.17)	3-13	0.91
Survey duration (minutes)	79.23	(30.73)	30-443	79.04	(32.50)	30-443	79.45	(28.63)	31-349	0.15
Survey month										12.96*
November	0.25			0.30			0.20			
December	0.28			0.29			0.26			
January	0.22			0.19			0.24			
February	0.19			0.18			0.20			
March	0.06			0.04			0.09			

Note: [a]This statistic only applies to participants who enrolled in the EMA module (n=273). MoCA = Montreal Cognitive Assessment; ADL = Activities of daily living * $p < 0.05$ *** $p < 0.001$.

Table 2. Average marginal effects on EMA enrollment (probit) and compliance (negative binomial).

	Enrollment			Compliance		
	AME	(SE)	*p*-value	AME	(SE)	*p*-value
Age (Decades)	-0.11**	(0.04)	0.005	0.20	(0.95)	0.828
Gender (ref: Man)						
Woman	0.07	(0.06)	0.226	1.25	(1.06)	0.240
Race (ref: White)						
Black	-0.03	(0.09)	0.800	0.81	(1.81)	0.641
Other	-0.19	(0.14)	0.214	9.01*	(6.24)	0.035
Education (ref: ≤ HS)						
Technical certificate	-0.15	(0.09)	0.094	-0.09	(1.47)	0.948
Some college	-0.01	(0.08)	0.861	1.59	(1.81)	0.377
College	0.12	(0.08)	0.104	0.09	(1.74)	0.957
Occupation (ref: Retired)						
Employed	0.01	(0.07)	0.852	2.38*	(1.18)	0.039
Other	-0.06	(0.09)	0.493	2.74	(1.74)	0.080
MoCA	0.02*	(0.01)	0.026	-0.40*	(0.17)	0.018
ADL	0.02	(0.11)	0.897	1.09	(2.02)	0.588
Network size	-0.01	(0.01)	0.220	-0.12	(0.17)	0.495
Depression	-0.01	(0.01)	0.348	-0.44*	(0.20)	0.028
County (ref: Urban)						
Rural/Mixed	-0.15	(0.08)	0.085	-0.71	(1.48)	0.646
Rural	-0.05	(0.07)	0.453	2.58	(1.78)	0.116
Computer use (ref: Daily)						
Weekly	0.10	(0.09)	0.310	5.35*	(2.10)	0.002
< Weekly	-0.11	(0.14)	0.392	12.59*	(7.61)	0.007
Smartphone ownership	0.27**	(0.09)	0.009			
Recruitment attempts	-0.03*	(0.01)	0.031	0.56*	(0.29)	0.047
Survey duration (hours)	0.01	(0.05)	0.814	-0.68	(1.24)	0.583
Survey month (ref: November)						
December	-0.04	(0.08)	0.594	0.29	(1.32)	0.825
January	0.03	(0.09)	0.750	-1.75	(1.37)	0.201
February	-0.03	(0.09)	0.741	-2.03	(1.46)	0.176
March	-0.16	(0.11)	0.150	0.65	(2.76)	0.809
Inverse mills ratio (IMR)				-1.36	(2.99)	0.647
Pseudo R^2	0.27			0.04		
χ^2	97.98***			78.47***		
N	510			273		

Note: The first model includes all participants who were invited to enroll in the EMA module (*n*=510). The second model assesses compliance rates conditional on EMA enrollment (*n*=273). Age is converted to decades (e.g., 55 years = 5.5 decades). AME = average marginal effect; SE = Standard error; ADL = activities of daily living; MoCA = Montreal Cognitive Assessment; * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Compliance

The negative binomial model included the inverse mills ratio (IMR) that was derived from the probit model to account for potential selection bias into the EMA module. As seen in Table 2, the IMR variable was not statistically significant in this model ($p = 0.65$), thus providing no evidence of selection bias affecting compliance rates. There were, however, several significant independent variables elsewhere in the model. Employed participants were predicted to miss 2.38 (SE = 1.18, $p < 0.05$) more EMA sessions than retired participants. Participants who reported using a computer several times per week were predicted to miss 5.35 (SE = 2.10) more EMAs than participants who reported using a computer every day. Cognitive function (AME = −0.40, SE = 1.17, $p < 0.05$) and depression (AME = −0.44, SE = 0.20, $p < 0.05$) were both negatively associated with EMA compliance. In other words, participants who scored better on the cognitive assessment and participants who reported more depressive symptoms were expected to miss fewer EMA sessions than participants who scored lower on the assessment and participants who were reported fewer depressive symptoms, respectively. Similar to the probit model that predicted enrollment, recruitment attempts were significantly associated with compliance. Specifically, each recruitment attempt was associated with an additional 0.56 missed EMA notifications ($p < 0.05$, SE = 0.29).

Discussion

The present study addressed enrollment and compliance issues in EMA research using data on 510 older adults from the Social Environment and Cognitive Health in Urban and Rural Areas study. Focusing specifically on older adults draws attention to a population who has traditionally had less access to smartphones but is increasingly adopting such technology and has shown high responsiveness to EMA research (Yao et al. 2023). Relying on a probability-based sample helped reduce selection bias, yet several key findings emerged that point toward areas that can create bias in compliance.

First, we found that smartphone ownership—which we used as a proxy for technological familiarity—was a significant correlate of enrollment in the EMA module. Indeed, smartphone owners were 27% more likely to enroll than non-smartphone owners. Although offering a loaner smartphone shows promise in addressing potential digital divides in internet-based studies (Bell et al. 2024; Stone et al. 2023), only nine of the 80 participants who did not own a smartphone agreed to borrow one for the duration of our study. Higher frequency of computer use, meanwhile, decreased the number of missed EMAs among enrolled participants. The low acceptance rate and subsequent compliance—alongside the qualitative responses highlighting the challenge

of using a smartphone app—indicates that it may not be worth the cost of purchasing loaner phones with the hopes of increasing enrollment rates, especially since smartphone ownership is already strongly associated with the decision to enroll in the EMA module. Alternatively, EMA designs that do not require adoption of new technology (e.g., text messaging instead of app-based responses) are likely to elicit higher compliance (Mindlis et al. 2024). Other studies also note that more extensive training should accompany the introduction of smartphones (Bell et al. 2024; Compernolle et al. 2024).

Second, we found that older participants and participants with signs of cognitive impairment were systematically less likely to enroll in the EMA module compared to their younger and more cognitively intact counterparts. These findings resonate with existing discussions surrounding EMAs and older adults (Cain et al. 2009; Dowell-Esquivel et al. 2024; Yao et al. 2023). Indeed, evidence from recent studies suggests that providing training on various technological skills can improve compliance in EMA studies (Dowell-Esquivel et al. 2024; Jung et al. 2025). These insights highlight opportunities to improve EMA compliance by targeting enrollment of older participants, potentially through digital literacy with emerging technologies (Jung et al. 2025).

On a similar note, we found that participants who required many recruitment attempts simultaneously exhibited a lower probability of enrollment in the EMA module and were slower to enroll missed more EMAs than participants who were quicker to agree to participate in the SECHURA study. The assumption here is that participants who scheduled an in-home visit after only a few attempts from our research team were probably more agreeable overall than participants who required many attempts before scheduling their in-home visit. Mitigating enrollment and compliance issues in circumstances where motivation to participate is low may be addressed by increasing monetary incentives or other positive feedback based on participation. Indeed, existing research suggests that although contingent reinforcement shows limited results in groups that are already motivated to participate, addressing the value of the study or appealing to individual motivations with incentives at the onset may help (Wrzus and Neubauer 2023).

Finally, employed participants missed slightly more EMAs than retired participants. Existing EMA studies would point to a variety of factors that contribute to this finding, such as flexibility of daily schedule and the presence of job-related stress (Compernolle et al. 2024; Wrzus and Neubauer 2023). While we cannot pinpoint the specific reasons, extending the response window for each EMA can accommodate people with less flexible daily schedules. This may be an appropriate approach for any age group with daily commitments and extend to others within our sample who are older but not working as well as those with cognitive impairment. At the same time, extending the response window runs the risk of misrepresenting the true nature of the sampled experiences.

Limitations

This study has several limitations. Although we leveraged data on 273 participants who enrolled in the EMA module and 237 participants who did not enroll, there was nevertheless an imperfect enrollment into the SECHURA study (66% response rate). We therefore applied survey weights that accounted for the sampling design and selection into the SECHURA study. This helps mitigate but does not completely eliminate potential selection basis. We also compared the sociodemographic characteristics from the SECHURA sample with the Indiana population that it was drawn from and found some differences (see Table S1). In other words, we could not completely address all issues of potential selection bias in this study. Second, we used smartphone ownership and frequency of computer use as proxies for technological familiarity. We maintain that this is a safe assumption, but it is possible that some people who neither own a smartphone nor frequently use a computer are capable of operating a smartphone but simply chose not to enroll in the study for other reasons. Third, the SECHURA study prompted participants with four EMAs per day for seven days. This frequency and duration is within the range that is often applied in EMA studies (Wrzus and Neubauer 2023), but our findings may not necessarily extend to studies that employ a greater number of EMA prompts per day or those that span a longer timeframe. Finally, the compliance portion of our analysis focused on the number of missing EMAs but did not investigate the reasons for missingness. This represents another methodological problem that is beyond the scope of our study, but nevertheless is worth investigation in its own right (Markowski et al. 2021; McLean et al. 2017; Peng et al. 2026; Stone et al. 2023).

Conclusion

This study contributed to the EMA literature by simultaneously evaluating enrollment and compliance among a probability sample of older adults. The findings offer a mix of insights for prospective researchers. On the one hand, some of our findings hint at strategies that researchers could take to ensure that they get the highest possible enrollment rates in their study (e.g., providing participants with sufficient time to address technological problems). On the other hand, some of our other findings highlight the simple fact that certain people have attributes that will decrease their likelihood of enrollment and compliance, regardless of researcher intervention (e.g., older age, cognitive impairment).

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ARR designed the study. ARR and JNJ conducted the analysis and wrote the first draft of the article. AFR, SP, MF, and TQ provided comments and approved the manuscript. AFR and ARR revised the manuscript. ARR and SP secured funding.

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Supplemental Material

Supplemental material for this article is available online.

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