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Smartphone screen time and suicide risk in daily life captured through high-resolution screenshot data

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Ross Jacobucci[1] ✉, Miguel Blacutt[2], Nilàm Ram[3] & Brooke A. Ammerman[4]

Suicide rates are rising in the U.S., prompting interest in contributing factors like smartphone use. While screen time has been linked to mental health, its role in suicide risk is unclear. This study examined bidirectional associations between smartphone screen time and suicide risk in 79 adults with recent suicidal thoughts or behaviors. Over 28 days, participants provided ecological momentary assessments (EMA) of suicide risk six times daily and contributed ~7.5 million screenshots, collected every 5 seconds during phone use. Within-person increases in screen time were linked to elevated suicide risk in the following three hours, while screen time more than three hours prior predicted reduced planning and desire. Suicide risk also predicted subsequent screen time, and screen time was associated with greater EMA response rates. Findings suggest screen time may indicate both distress and coping, depending on context. These insights could inform real-time monitoring tools for suicide prevention and adaptive intervention strategies.

Despite increased attention and prevention efforts, suicide rates in the U.S. continue to rise, with an approximate 2.6% increase from 2021 to 2022, resulting in over 49,000 deaths[1]. Such increases have been met with concern regarding cultural or societal phenomena that may be contributing. Across popular press[2,3] and scientific literature[4], smartphones have become a prominent focus of interest. Smartphones have become pervasive in our daily lives, with over 310 million smartphone users in the U.S., representing approximately 96% of the population[5]. While smartphones may be viewed as a near necessity, with many adults relying on them for internet access[5], their impact on mental and social health is complex and not well understood. However, a key feature of smartphone use – screen time – has shown promise in understanding the potential link with suicidality.

Many individuals report feeling like they spend too much time on their smartphones and that screen time harms their mental health and social relationships[6]; notably, over one-third of individuals report using their smartphones "almost constantly"[7]. This lived experience perspective parallels a rise in scientific literature outlining the concerns of too much screen time. Research has linked the amount of screen time to mental health difficulties, including suicidal thoughts and behaviors. For example, researchers have consistently found a positive association between the amount of screen time and suicidal thoughts and behaviors in both cross-sectional[8] and longitudinal[9] study designs.

Yet, the limitations of this prior research leave many questions unanswered, including the specific impact of *smartphone* screen time on suicide risk[8,9]. Indeed, prior research has often examined the cumulative effect of screen time across types of screen exposure (i.e., smartphone, video games, television). However, given the increasing presence of smartphones in individuals' daily lives, combined with the fact that smartphones were the most used device in prior screen time research[10], there is a need to study the unique impact of smartphone screen time on suicide risk. It is also notable that research to date has heavily relied on self-reported screen time. While a product of technological limitations, this approach likely underestimated actual screen time[11], potentially attenuating the strength of known relationships. Thus, an objective assessment of smartphone screen time would provide a more accurate portrayal of the potential impact of smartphone screen time in relation to suicide risk.

Finally, while researchers have considered the longitudinal relationship between screen time and suicide risk, follow-up periods have ranged from 6 months to a decade[9]. In contrast, it has been strongly supported that key elements of suicide risk – suicidal ideation and suicidal desire – fluctuate at an hourly level[12] and that many suicide risk relationships follow a comparable pattern[13]. Similarly, smartphone use varies throughout a given day, dependent on contextual and emotional factors[14]. Thus, while prior research has provided foundational knowledge regarding the impacts of screen time

[1]Center for Healthy Minds, University of Wisconsin Madison, Madison, WI, USA. [2]Department of Psychology, University of Notre Dame, Notre Dame, IN, USA. [3]Department of Psychology, Department of Communication, Stanford University, Stanford, CA, USA. [4]Department of Psychology, University of Wisconsin Madison, Madison, WI, USA. ✉e-mail: jacobucci@wisc.edu

on suicide risk, there is a need to capture the associations with smartphone screen time as they occur in daily life.

There is also an aspect of the screen time – suicide risk relationship that has been understudied – the potential bi-directionality of the relationship. Early theoretical models of problematic phone use highlight that it may be a form of emotional regulation[15,16]. There has also been empirical support for this postulation, such that the link between smartphone use and mental health outcomes (i.e., depression, anxiety) can be explained by distress tolerance, emotion regulation, rumination, and/or self-control[14,17–19]. Thus, it is possible that there may be a reciprocal relationship between smartphone screen time and suicide risk. Suicide-related outcomes might predict increased screen time at the momentary level, suggesting that smartphone use could serve as a coping mechanism for distress related to suicidality. Despite having important implications for intervention efforts, including those aimed at reducing screen time, which may ultimately improve other health indicators[20], this bidirectional relationship has yet to be examined at the momentary level.

To our knowledge, this is the first study to examine the bidirectional relations between smartphone screen time and suicide risk, defined as suicidal thinking, planning, and desire, via an intensive time sampling design that leverages an objective measure of screen time. We employed a specific form of digital phenotyping, screenomics[21–23], where smartphone screens were automatically captured every five seconds during active phone use. These data provide an unbiased estimate of dynamic smartphone screen time that, when combined with ecological momentary assessment (EMA) of suicidal experiences, can be utilized to predict near-term suicide risk. The first aim of the study was to investigate whether smartphone screen time was proximally predictive of suicide risk. We hypothesized, based on findings from cross-sectional and traditional longitudinal studies[8,9], that elevations in smartphone screen time would be predictive of near-term increases in suicidal thinking, planning, and desire. The second aim of the study was to investigate the bidirectional nature of this association, examining if suicide risk indicators were predictive of smartphone screen time. Given the literature suggesting that smartphone use may be a potential coping mechanism for emotional distress[14], we hypothesized that there would be an elevation in smartphone screen time following reports of suicidal thinking, planning, and desire. Finally, given the implications of missing data in intensive longitudinal designs, which has been a focus in recent research[13,24], we also examined whether smartphone screen time was predictive of non-response to prompts for self-reported suicide risk.

Results

The study captured 7,501,670 screenshots in total, with participants averaging 92,613 screenshots each (median = 85,795) across the study period. Suicide attempt history ($n = 48$) ($p = 0.09$), presence of comorbid psychopathology ($p = 0.49$), and employment status ($p = 0.98$) did not significantly distinguish in the total screenshots collected. Individual screenshot image counts ranged substantially, from 2185 to 431,623 per participant. 75.3% of 10-minute windows had no images (range across participants = 23.3–99.7%), and of the 10-minute windows with images, the mean was 72.8 (range across participants = 23.6–108.1). The sample had an EMA compliance rate of 68.8% and an average of 3.4 hours elapsed between EMA surveys. Prior to model fitting, we visualized the relationships between suicide risk variables and smartphone screen time in two ways. Figure 1 illustrates the average suicide risk responses in relation to the presence or absence of smartphone screen time within 10-minute windows. In Fig. 2, we depicted the average discrepancy in image counts per 10-minute window for when individuals reported a non-zero versus zero response in each of the suicide risk outcomes.

In this, we see higher smartphone image counts leading up to the EMA assessment, and immediately after, when individuals report non-zero active SI, passive SI, and suicidal desire, with less clear results for suicidal planning. However, note that this only depicts responses of zero versus non-zero for the suicide risk variables, while the models below differentiate these relationships. Among the four suicide risk variables, zero values were observed for 65.0% of passive suicidal ideation, 67.3% of active suicidal ideation, 79.2% of suicidal desire, and 86.9% of suicidal planning responses. Below, we separate results by aim, only highlighting the significant results. The full set of parameter estimates for each model is contained in Tables 1–9.

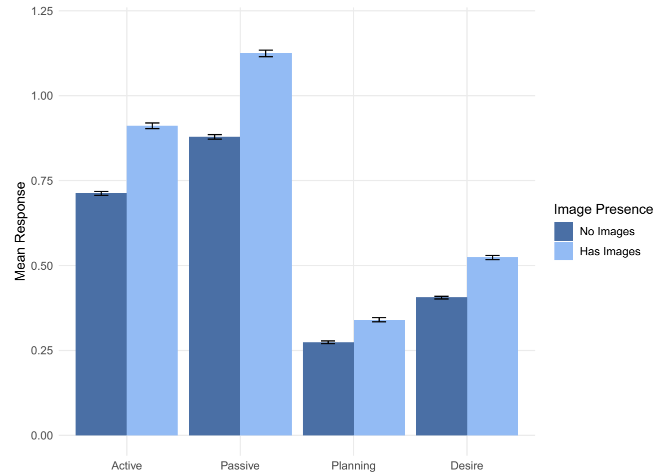

Fig. 1 | Average response to each of the four suicide variables for 10-minute windows that do/do not have images. In this figure, we see that across all four suicide variables, participants had higher responses when they had used their phone during a 10-minute window leading up to an EMA assessment.

Aim 1

For Aim 1, we used smartphone screen time to predict each of the suicide risk variables.

Passive suicidal ideation

The only significant interaction effect was in the count part of the model. In the count portion, the effect of within-person any smartphone screen time was not significant when time until assessment was >3 hours, but there was a significant, positive effect when <3 hours ($b = 0.04$, CI = 0.02, 0.06). In the excess zero part of the model, there was no significant effect for either between- or within-person any smartphone screen time.

Active suicidal ideation

The only interaction effect that was significant was for the count part of the model, with within-person any smartphone screen time ($b = 0.08$, CI: 0.03, 0.13). While the effect of within-person any smartphone screen time was not significant when >3 hours ($b = -0.04$, CI: −0.08, 0.01), there was a significant positive effect at <3 hours ($b = 0.04$, CI: 0.02, 0.07). Also in the count part, there was a significant, positive effect of within-person proportion of smartphone screen time ($b = 0.06$, CI: 0.01, 0.11). In the excess zero part of the model, there was a significant, positive effect of within-person proportion of smartphone screen time ($b = 0.23$, CI: 0.02, 0.43).

Suicidal planning

The interaction effect was only significant for within-person any smartphone screen time in the count portion of the model ($b = 0.11$, CI = 0.03, 0.1). When the time until EMA assessment was <3 hours, there was a significant, positive association ($b = 0.15$, CI = 0.02, 0.26), whereas this relationship was significant and negative when >3 hours (b = -0.09, CI = −0.16, −0.02). For excess zeros, there was a positive association with within-person any smartphone screen time ($b = 0.23$, CI = 0.04, 0.43).

Suicidal desire

In the count part of the model, the interaction effect was significant for within-person any smartphone screen time ($b = 0.07$, CI: 0.001, 0.13). When

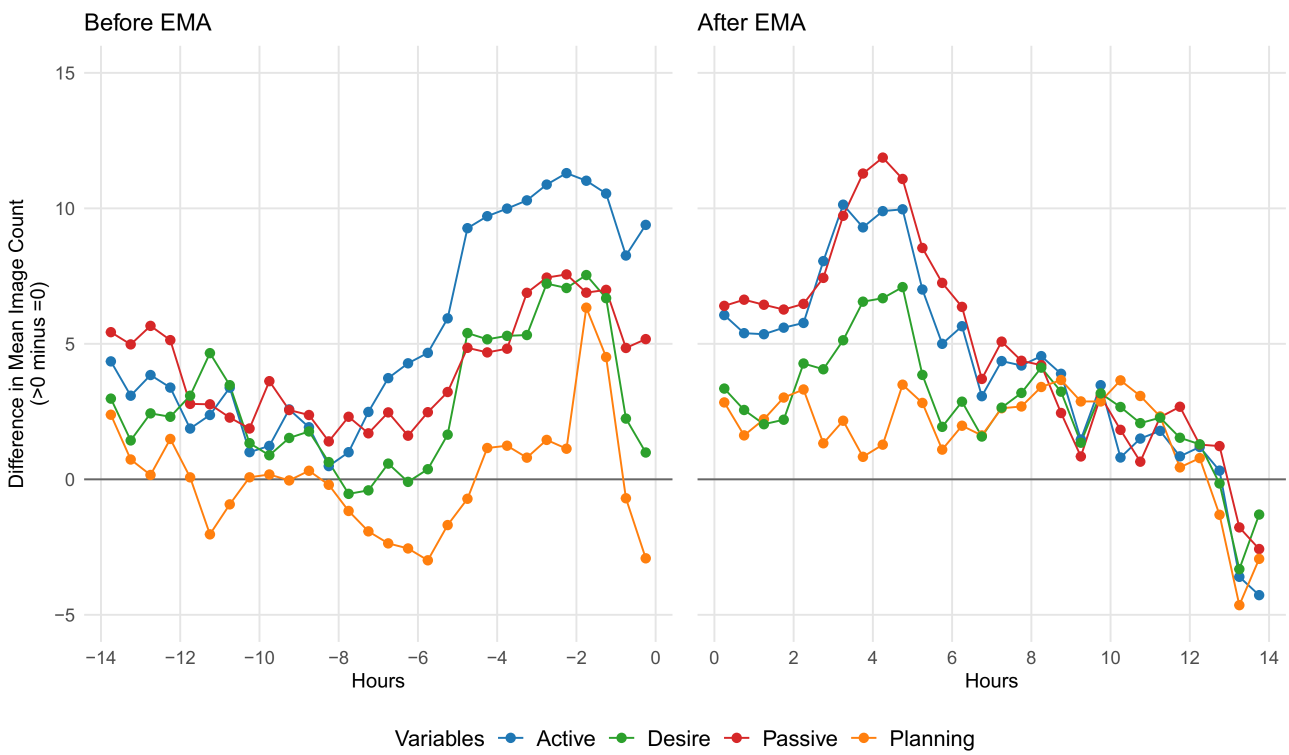

Fig. 2 | The difference in mean image counts across each 10-minute window for each of the four suicide variables. The difference is calculated between EMA prompts where participants responded with non-zero responses versus responses of zero for each suicide variable. The left panel depicts the hours leading up to an EMA assessment, while the right panel depicts the hours following an EMA assessment. Across all four variables, we see that when an individual had a response of >0 on each of the four suicide variables, they tended to have used their phone for 20–100 seconds more in the 10-minute blocks both preceding and following the EMA assessment.

Table 1 | Screenshot image count, time from an EMA response, and their interaction predicting passive suicidal ideation

	Count Portion				Zero-Inflated Portion			
Predictor	Est.	SE	95% CI	ESS	Est.	SE	95% CI	ESS
Intercept	−0.211	0.256	[−0.738, 0.306]	420	0.230	0.728	[−1.150, 1.706]	79
bp_prop_use	1.670	1.178	[−0.650, 4.038]	300	−3.258	3.163	[−9.648, 3.021]	43
wp_any_use	−0.026	0.019	[−0.062, 0.010]	1720	−0.085	0.069	[−0.217, 0.054]	1483
wp_anyproportion_use	0.022	0.024	[−0.024, 0.068]	1715	0.090	0.091	[−0.094, 0.266]	1616
time	0.045	0.005	[0.034, 0.055]	1395	−0.096	0.020	[−0.137, −0.058]	1717
wp_any_use:time	0.065	0.022	[0.023, 0.109]	1756	0.071	0.082	[−0.089, 0.237]	1466
wp_anyproportion_use:time	−0.030	0.028	[−0.084, 0.024]	1730	−0.144	0.108	[−0.356, 0.067]	1558
sd_sd(Intercept)	1.316	0.131	[1.082, 1.591]	715				
sd_sd(zi_Intercept)	4.262	0.457	[3.471, 5.287]	559				
shape	1236.856	264.211	[807.808, 1825.804]	1685				

Est. Estimate, *SE* Standard Error, *CI* Credible Interval, *ESS* Effective Sample Size, *Time* = < or > 3 hours, *bp_prop_use* Between-person proportion of phone use, *wp_any_use* Within-person any phone use, *wp_anyproportion_use* Within-person proportion of phone use.

hours > 3, there was not a significant effect; however, when hours <3, it was positive, but non-significant ($b = 0.03$, CI: −0.003, 0.07). In the excess-zero part of the model, both interaction effects were significant. For within-person any smartphone screen time, when hours >3, there was a positive effect ($b = 0.26$, CI: 0.10, 0.42), and when hours <3, the significant effect was negative ($b = -0.21$, CI: −0.30, −-0.11). For the within-person proportion of smartphone screen time, there was a significant, negative association when hours >3 ($b = -0.63$, CI: −0.84, −0.43); however, it was non-significant when <3 hours ($b = -0.01$, CI: −0.14, 0.13).

Aim 2

For Aim 2, each of the EMA-assessed suicide risk variables was used to predict subsequent smartphone screen time.

Passive suicidal ideation

In the count portion of the model, there were no significant effects. In the excess zero part of the model, there was a significant interaction with within-person, relative intensity of passive SI ($b = -0.05$; CI = −0.09, −0.01). The effect was less positive at <3 hours ($b = 0.03$, CI: 0.01, 0.05) than at >3 hours ($b = 0.08$, CI: 0.05, 0.12). There was a significant, negative effect for within-person, relative presence of passive SI ($b = -0.26$, CI: −-0.34, −0.17), but the interaction was not significant.

Active suicidal ideation

There were no significant effects in the count part of the model. In the excess zero part of the model, there was a significant interaction for within-person, relative intensity of active SI, with a non-significant effect when <3 hours

Table 2 | Screenshot image count time from an EMA response, and their interaction predicting active suicidal ideation

	Count Portion				Zero-Inflated Portion			
Predictor	Est.	SE	95% CI	ESS	Est.	SE	95% CI	ESS
Intercept	−0.186	0.193	[−0.578, 0.208]	522	0.475	0.914	[−1.314, 2.230]	38
bp_prop_use	0.850	0.879	[−0.967, 2.609]	444	−6.883	5.065	[−16.905, 2.988]	27
wp_any_use	−0.037	0.022	[−0.079, 0.006]	1686	−0.028	0.076	[−0.174, 0.115]	1439
wp_anyproportion_use	0.056	0.027	[0.002, 0.111]	1666	0.229	0.102	[0.020, 0.427]	1460
time	0.095	0.007	[0.083, 0.108]	1468	0.013	0.022	[−0.030, 0.056]	1690
wp_any_use:time	0.078	0.026	[0.026, 0.128]	1639	−0.026	0.089	[−0.201, 0.148]	1455
wp_anyproportion_use:time	−0.021	0.033	[−0.085, 0.044]	1590	−0.013	0.119	[−0.239, 0.228]	1464
sd_sd(Intercept)	1.011	0.103	[0.837, 1.237]	805				
sd_sd(zi_Intercept)	4.653	0.516	[3.790, 5.773]	793				
shape	490.515	153.372	[256.964, 834.205]	2006				

Est. Estimate, SE Standard Error, *CI* Credible Interval, ESS Effective Sample Size, *Time* = < or > 3 hours, *bp_prop_use* Between-person proportion of phone use, *wp_any_use* Within-person any phone use, *wp_anyproportion_use* Within-person proportion of phone use.

Table 3 | Screenshot image count, time from an EMA response, and their interaction predicting suicidal planning

	Count Portion				Zero-Inflated Portion			
Predictor	Est.	SE	95% CI	ESS	Est.	SE	95% CI	ESS
Intercept	−1.501	0.418	[−2.412, −0.728]	237	0.895	0.762	[−0.723, 2.299]	68
bp_prop_use	2.124	1.798	[−1.312, 5.683]	179	−2.574	3.739	[−9.040, 5.140]	44
wp_any_use	−0.089	0.035	[−0.158, −0.024]	1557	0.231	0.099	[0.036, 0.427]	1476
wp_anyproportion_use	0.040	0.046	[−0.047, 0.130]	1658	0.036	0.130	[−0.219, 0.296]	1523
time	0.095	0.012	[0.071, 0.118]	1619	0.276	0.030	[0.217, 0.335]	1533
wp_any_use:time	0.108	0.043	[0.027, 0.189]	1602	−0.085	0.113	[−0.315, 0.129]	1605
wp_anyproportion_use:time	−0.060	0.057	[−0.170, 0.053]	1540	0.021	0.158	[−0.287, 0.336]	1650
sd_sd(Intercept)	2.053	0.219	[1.668, 2.569]	760				
sd_sd(zi_Intercept)	4.431	0.586	[3.398, 5.663]	703				
shape	7.927	0.397	[7.211, 8.723]	1542				

Est. Estimate, *SE* Standard Error, *CI* Credible Interval, *ESS* Effective Sample Size, Time = < or > 3 hours, *bp_prop_use* Between-person proportion of phone use, *wp_any_use* Within-person any phone use, *wp_anyproportion_use* Within-person proportion of phone use.

Table 4 | Screenshot image count, time from an EMA response, and their interaction predicting suicidal desire

	Count Portion				Zero-Inflated Portion			
Predictor	Est.	SE	95% CI	ESS	Est.	SE	95% CI	ESS
Intercept	−0.611	0.237	[−1.076, −0.157]	677	1.354	0.786	[−0.123, 2.927]	133
bp_prop_use	1.597	1.058	[−0.444, 3.670]	592	−2.531	3.666	[−9.836, 4.336]	67
wp_any_use	−0.035	0.029	[−0.092, 0.021]	1645	0.261	0.082	[0.102, 0.423]	1537
wp_anyproportion_use	−0.036	0.037	[−0.110, 0.036]	1655	−0.632	0.104	[−0.838, −0.434]	1615
time	0.063	0.009	[0.046, 0.079]	1542	−0.040	0.025	[−0.090, 0.009]	1630
wp_any_use:time	0.066	0.034	[0.000, 0.132]	1646	−0.468	0.097	[−0.659, −0.282]	1433
wp_anyproportion_use:time	0.005	0.045	[−0.080, 0.091]	1592	0.625	0.126	[0.383, 0.873]	1568
sd_sd(Intercept)	1.166	0.133	[0.942, 1.474]	639				
sd_sd(zi_Intercept)	4.305	0.489	[3.494, 5.384]	737				
shape	573.597	172.476	[312.898, 992.847]	1684				

Est. Estimate, SE Standard Error, *CI* Credible Interval, *ESS* Effective Sample Size, Time = < or > 3 hours, *bp_prop_use* Between-person propotion of phone use, *wp_any_use* Within-person any phone use, *wp_anyproportion_use* Within-person proportion of phone use.

Table 5 | Active suicidal ideation, time since EMA response, and their interaction predicting image count

	Count Portion				Zero-Inflated Portion			
Predictor	Est.	SE	95% CI	ESS	Est.	SE	95% CI	ESS
sd(Intercept)	0.328	0.032	[0.271, 0.399]	2682				
sd(zi_Intercept)					2.271	0.238	[1.863, 2.779]	2259
Intercept	4.212	0.041	[4.130, 4.293]	4660	2.272	0.260	[1.768, 2.784]	3873
BP	0.037	0.042	[−0.045, 0.121]	4778	−0.282	0.261	[−0.797, 0.207]	4507
RP	−0.002	0.030	[−0.060, 0.056]	6041	−0.111	0.044	[−0.196, −0.026]	6501
time	−0.046	0.008	[−0.061, −0.030]	6100	−1.305	0.013	[−1.330, −1.280]	6137
RI	−0.015	0.012	[−0.038, 0.008]	6001	0.098	0.018	[0.064, 0.133]	6134
RP:time	0.026	0.035	[−0.042, 0.096]	6023	0.062	0.055	[−0.048, 0.170]	6286
time:RI	0.014	0.014	[−0.013, 0.041]	5669	−0.095	0.021	[−0.137, −0.053]	5909
shape	1.652	0.011	[1.632, 1.673]	6024				

Est. Estimate, *SE* Standard Error, *CI* Credible Interval, *ESS* Effective Sample Size, Time = < or > 3 hours, *RI* Relative Intensity, *RP* Relative Presence, *BP* Between-person.

Table 6 | Passive suicidal ideation, time since EMA response, and their interaction predicting image count

	Count Portion				Zero-Inflated Portion			
Predictor	Est.	SE	95% CI	ESS	Est.	SE	95% CI	ESS
sd(Intercept)	0.328	0.032	[0.271, 0.399]	2682				
sd(zi_Intercept)					2.271	0.238	[1.863, 2.779]	2259
Intercept	4.222	0.041	[4.140, 4.303]	4791	2.400	0.279	[1.864, 2.955]	4181
BP	0.052	0.042	[−0.032, 0.134]	4561	−0.433	0.302	[−1.042, 0.151]	3906
RP	−0.011	0.030	[−0.070, 0.049]	6089	−0.255	0.044	[−0.343, −0.167]	6030
time	−0.044	0.008	[−0.060, −0.028]	6253	−1.302	0.013	[−1.328, −1.278]	5708
RI	−0.002	0.012	[−0.025, 0.021]	5941	0.082	0.017	[0.049, 0.115]	6205
RP:time	0.051	0.035	[−0.017, 0.120]	6021	0.035	0.055	[−0.075, 0.144]	6042
time:RI	0.000	0.013	[−0.025, 0.026]	5677	−0.049	0.020	[−0.090, −0.011]	6234
shape	1.699	0.011	[1.677, 1.721]	6025				

Est. Estimate, *SE* Standard Error, *CI* Credible Interval, *ESS* Effective Sample Size, Time = < or > 3 hours, *RI* Relative Intensity, *RP* Relative Presence, *BP* Between-person.

Table 7 | Suicidal desire, time since EMA response, and their interaction predicting image count

	Count Portion				Zero-Inflated Portion			
Predictor	Est.	SE	95% CI	ESS	Est.	SE	95% CI	ESS
sd(Intercept)	0.328	0.032	[0.271, 0.399]	2682				
sd(zi_Intercept)					2.271	0.238	[1.863, 2.779]	2259
Intercept	4.223	0.043	[4.139, 4.308]	4535	2.181	0.259	[1.667, 2.692]	4368
SD BP	0.010	0.043	[−0.073, 0.096]	4356	−0.038	0.254	[−0.530, 0.449]	4349
SD RP	0.075	0.037	[0.002, 0.148]	6124	−0.448	0.056	[−0.557, −0.338]	5996
time3	−0.045	0.008	[−0.061, −0.029]	5728	−1.312	0.013	[−1.338, −1.286]	5620
SD RI	−0.032	0.015	[−0.062, −0.003]	6023	0.170	0.021	[0.128, 0.212]	6150
SD RP:time3	−0.025	0.043	[−0.111, 0.059]	5997	0.295	0.068	[0.164, 0.429]	5893
time3:SD RI	0.019	0.017	[−0.015, 0.052]	6004	−0.141	0.024	[−0.189, −0.092]	5996
shape	1.683	0.011	[1.661, 1.705]	5988				

Est. Estimate, *SE* Standard Error, *CI* Credible Interval, *ESS* Effective Sample Size, Time = < or > 3 hours, *RI* Relative Intensity, *RP* Relative Presence, *BP* Between-person, *SD* Suicidal Desire.

($b = 0.00$, CI: −0.02, 0.02) and a significant positive effect when >3 hours ($b = 0.10$, CI: 0.06, 0.13). Further, there was a significant, negative effect of within-person, relative presence passive SI ($b = -0.11$, CI: −0.20, −0.03). The interaction was not significant.

Suicidal planning

In the count part of the model, there were no significant effects. In the excess zero part of the model, there was a significant interaction with within-person, relative intensity of suicidal planning ($b = -0.07$, CI:−0.12, −0.02).

Table 8 | Suicidal planning, time since EMA response, and their interaction predicting image count

	Count Portion				Zero-Inflated Portion			
Predictor	Est.	SE	95% CI	ESS	Est.	SE	95% CI	ESS
sd(Intercept)	0.328	0.032	[0.271, 0.399]	2682				
sd(zi_Intercept)					2.271	0.238	[1.863, 2.779]	2259
Intercept	4.233	0.043	[4.147, 4.319]	3930	2.339	0.283	[1.790, 2.905]	3070
BP	0.003	0.039	[−0.072, 0.080]	3713	−0.304	0.267	[−0.824, 0.228]	3211
RP	0.007	0.041	[−0.074, 0.087]	6072	−0.256	0.062	[−0.381, −0.137]	5502
time3	−0.048	0.008	[−0.063, −0.032]	6278	−1.280	0.013	[−1.306, −1.254]	6283
RI	−0.015	0.015	[−0.045, 0.015]	6287	0.099	0.023	[0.055, 0.145]	5453
RP:time	0.039	0.047	[−0.051, 0.130]	6026	0.138	0.074	[−0.008, 0.286]	5974
time:RI	0.008	0.017	[−0.025, 0.039]	6269	−0.071	0.025	[−0.123, −0.022]	6007
shape	1.652	0.011	[1.632, 1.673]	6024				

Est. Estimate, *SE* Standard Error, *CI* Credible Interval, *ESS* Effective Sample Size, Time = < or > 3 hours, *RI* Relative Intensity, *RP* Relative Presence, *BP* Between-person.

Table 9 | Screenshot image count, time from an EMA response, and their interaction predicting EMA response

Predictor	Est.	SE	95% CI	ESS
sd(Intercept)	1.723	0.152	[1.458, 2.049]	121
Intercept	0.316	0.299	[−0.203, 0.969]	70
bp_prop_use	2.335	1.556	[−0.785, 5.094]	72
wp_any_use	−0.038	0.033	[−0.104, 0.027]	1119
time	0.003	0.009	[−0.014, 0.021]	3233
wp_anyproportion_use	0.132	0.043	[0.047, 0.217]	1083
wp_any_use:time	0.436	0.041	[0.358, 0.516]	1088
time: wp_anyproportion_use	−0.008	0.054	[−0.114, 0.097]	1063

Est. Estimate, SE Standard Error, *CI* Credible Interval, *ESS* Effective Sample Size, Time = < or > 3 hours, *bp_prop_use* Between-person proportion of phone use, *wp_any_use* Within-person any phone use; *wp_anyproportion_use* Within-person proportion of phone use.

The effect was less positive at <3 hours ($b = 0.03$, CI: 0.01, 0.05) than at > 3 hours ($b = 0.10$, CI: 0.06, 0.15). Further, there was a negative effect of within-person, relative presence of suicidal planning ($b = -0.26$, CI: −0.38, −0.14), however, the interaction was not significant.

Suicidal desire

In the count part of the model, the interactions were not significant; however, there was a significant negative effect of within-person, relative intensity of suicidal desire ($b = -0.03$, CI: −0.06, −0.002), and a significant, positive effect of within-person, relative presence of suicidal desire ($b = 0.08$, CI: 0.002, 0.15). In the excess zero part of the model, both interactions were significant. For within-person, relative intensity of suicidal desire, the effect was less positive at <3 hours ($b = 0.03$, CI: 0.01, 0.05) than at >3 hours ($b = 0.17$, CI: 0.13, 0.21). For within-person, relative presence of suicidal desire, the effect was less negative at <3 hours ($b = -0.15$, CI: −0.23, −0.08) than at >3 hours ($b = -0.45$, CI: −0.56, −0.34).

Aim 3

To address Aim 3, similar to Fig. 2, in Fig. 3, we depict the distinction in smartphone screen time relative to whether someone responds to an EMA prompt or not. There was a significant interaction effect with within-person any smartphone screen time ($b = 0.44$, CI: 0.36, 0.52), with the effect more positive and significant at <3 hours ($b = 0.40$, CI: 0.35, 0.44). Further, there was a significant, positive effect of within-person proportion of smartphone screen time ($b = 0.13$, CI: 0.05, 0.22).

Discussion

This was the first study to examine the bidirectional impact of smartphone screen time on suicidal thinking, planning, and desire via an intensive time sampling design with an objective assessment of smartphone screen time. Study hypotheses were partially supported in that smartphone screen time was found to predict several indicators of suicide risk, and there was evidence of bidirectional associations. It is also notable that some of these effects were strongest within the three hours prior to an EMA prompt, highlighting the dynamic nature of the risk relationship. These findings shed light on the salience and complexity of the smartphone screen time – suicide risk relationship.

Results indicate that within-person screen time (i.e., image count) predicts self-reported suicide risk indicators when examining near-term associations. These findings build on prior cross-sectional and longitudinal research[8,9] by extending them to momentary, real-world contexts. Specifically, they reveal that relative increases in smartphone screen time are associated with an elevated near-term risk of experiencing suicidal thoughts, planning, and desire, underscoring the proximal nature of the relationship. While the mechanisms underlying this relationship remain unclear, existing research points to potential contributors, such as distress tolerance, emotion regulation, rumination, and self-control difficulties[14,17–19]. Increased smartphone screen time may amplify psychological vulnerability by fostering maladaptive coping strategies or reinforcing negative cognitive patterns. For instance, excessive use could reflect or exacerbate difficulties in disengaging from distressing thoughts or emotions. Moreover, prior studies have linked high screen time to poorer indicators of psychological well-being, such as challenges in forming meaningful social connections and reduced emotional stability[25], which may compound risk. These findings highlight the need for further investigation into the proximal mechanisms driving this relationship. Identifying whether specific types of smartphone screen time—such as passive consumption versus active engagement—or contextual factors (e.g., type of

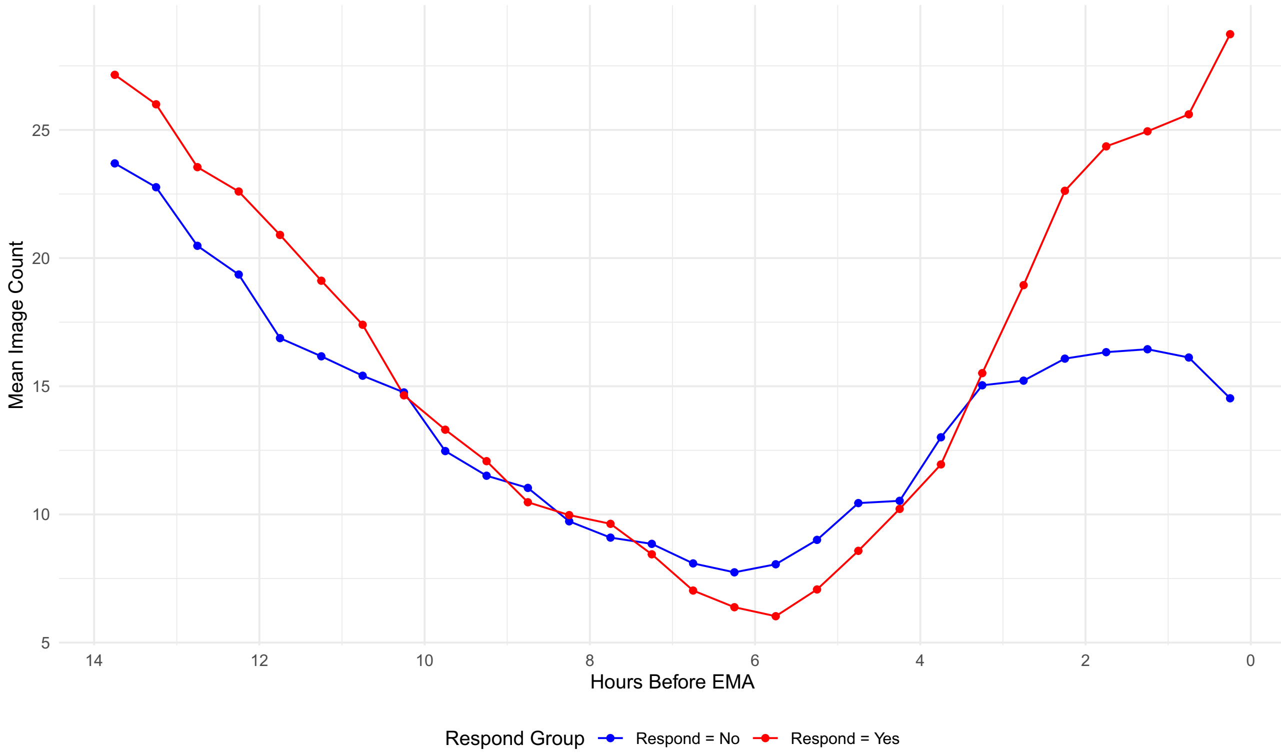

Fig. 3 | Image count, differentiated by whether an EMA prompt was responded to or not, in the hours leading up to that EMA prompt.

content, time of day, social interaction) play a moderating role could provide critical insights for intervention efforts.

There were also unexpected findings regarding smartphone screen time predicting suicide risk outcomes. Specifically, for both suicidal planning and suicidal desire, when examining relations with greater distance from self-reported experiences (i.e., more than three hours before the EMA prompt), there was a possible protective effect of smartphone screen time. While speculative, the conflicting findings may suggest distinct roles for proactive versus reactive smartphone use. Smartphone use occurring well before reports of suicidal planning or desire may reflect proactive engagement in behaviors such as distraction, social connection, or emotional regulation, providing individuals the opportunity to process emotions and prevent escalation toward suicidal planning and desire. Conversely, near-term smartphone use may indicate reactive responses to acute distress, where the smartphone is used impulsively or maladaptively, potentially exacerbating emotional dysregulation. This reactive use could signal an immediate risk state, marked by ineffective attempts to cope with heightened emotional arousal. To further clarify these dynamics, future research should focus on operationalizing reactive smartphone use, potentially through real-time monitoring of usage patterns (e.g., frequency, duration, and type of engagement during periods of distress). For example, identifying patterns of passive scrolling, compulsive app switching, or engagement with triggering content could help distinguish between proactive and reactive use. Additionally, examining contextual factors, such as the type of smartphone activity, time of day, or environmental stressors, may illuminate how these interactions vary across individuals and situations. Understanding these nuanced relationships could pave the way for targeted interventions, such as promoting proactive smartphone behaviors (e.g., connecting with supportive networks or using mindfulness apps) while discouraging maladaptive patterns of use during moments of acute distress.

Our results revealed a complex relationship between smartphone screen time and active suicidal ideation. Higher within-person smartphone screen time predicted both an increased likelihood of having no active SI (excess zero part) and greater severity of active SI when it was present (count part). This pattern suggests that smartphone use may serve different functions depending on an individual's current psychological state. When individuals are using their phones more than usual, they might be successfully engaging in protective behaviors (e.g., social connection, distraction) that prevent SI altogether. However, when SI does occur during periods of increased smartphone screen time, it tends to be more severe, possibly indicating unsuccessful attempts at coping with acute distress. This dual pattern highlights how the same behavior (increased phone use) might reflect both adaptive and maladaptive processes, depending on whether active SI has already emerged.

Regarding potential bidirectional effects, findings demonstrated consistent patterns across the relative presence of suicide outcomes in predicting the presence of screenshots in the zero-inflated models. Specifically, the relative presence of suicidal thinking, planning, and desire were negatively associated with the absence of screenshots, suggesting that when individuals experienced *any* level of suicidality, they were more likely to have some screen time captured. This consistency highlights a potential link between the presence of suicide risk and increased engagement with devices, which may reflect the use of digital tools for coping, distraction, or seeking support during distressing periods[14]. In contrast, greater relative intensity of passive ideation, active ideation, suicidal planning, and suicidal desire were associated with a reduced likelihood of the presence of detecting any screenshots (or having a non-zero screenshot image count), suggesting that individuals with more persistent or elevated suicide risk might experience greater withdrawal or disengagement from digital activities. While divergent from the literature finding that social isolation is predictive of suicidal ideation[26], results highlight the potential for a more dynamic process than previously captured. The divergence between relative presence and relative intensity could reflect distinct behavioral patterns: transient or episodic experiences of suicidal thoughts may prompt brief bursts of smartphone screen engagement, while sustained or chronic elevations in these thoughts may be linked to broader patterns of avoidance or reduced interaction with technology. Notably, prior research has highlighted that different forms of coping may differentially impact distress levels, such that active coping may be more effective in reducing subjective distress than evasive (i.e., emotional venting) coping[27], which may have parallels to smartphone use.

Alternatively, many prominent therapy modalities promote active coping (i.e., self-soothing[28]) or behavior activation (i.e., taking a walk[29]) for high-stress or crisis states, skills that may divert individuals from smartphone engagement. These findings require further replication but underscore the importance of considering both within-person variability and average levels of suicidal risk when interpreting screen time behaviors and their implications for mental health.

The findings that both within-person metrics of smartphone screen time predicted greater likelihood of self-reported responses to EMA prompts have important implications for understanding and managing missing data in intensive longitudinal studies of suicide risk. The positive interaction effect for near-term associations (<3 hours) suggests that periods of recent smartphone engagement are associated with an increased likelihood of responding to prompts, which could indicate that individuals are more engaged or accessible when they are actively using their devices. These results highlight the potential utility of leveraging smartphone screen time patterns to predict and mitigate missing data in such studies. For example, researchers could design adaptive sampling methods that allow time prompts to coincide with periods of higher phone activity, thereby increasing response rates. Additionally, these findings underscore the importance of considering technological engagement as a contextual factor in analyzing longitudinal data, as smartphone screen time patterns may influence not only response patterns but also the interpretation of EMA data regarding suicide risk.

The limitations of this study should be noted. First, we did not find any significant between-person effects. This may have been due to the small sample size; while the study design provided sufficient power for within-person analyses, it may have been underpowered to detect between-person effects. Additionally, participants were allowed to toggle the screenshot capture application on and off, potentially leading to an underestimation of actual smartphone use. However, the observed average of 4.5 hours of daily phone use aligns with large-scale studies on smartphone use in the United States[30], suggesting this limitation may not have substantially biased our findings. A further limitation is the reliance on smartphone screen time as a proxy for engagement in daily life, which leaves questions about what individuals are doing or experiencing during times when they are not using their phones. The observed positive association between smartphone screen time and EMA responsiveness highlights this gap and suggests the need for additional data sources to capture offline behaviors. Similarly, an analysis of the specific phone use activity was beyond the scope of the current study aims, but will be fruitful for future work to provide greater insights into the potential drivers of the smartphone screen time - suicide risk relationship. For example, active social media use (i.e., posting, one-on-one exchanges) has been hypothesized to yield positive outcomes, while passive use (i.e., scrolling) may increase the risk for social and mental health difficulties[31,32]. These effects may also be amplified by specific social media platforms (i.e., applications, e.g., Snapchat, Instagram), which can encourage particular patterns of use or contribute to risks that extend across multiple platforms[33]. It is also possible that the observed relationships are motivated by psychological variables not examined in the current study, such as emotional distress. Emotional distress may be directly influenced by phone use behaviors[34,35], and this effect may be exacerbated among individuals at heightened suicide risk[36]. Further, emotional distress is one of the most significant short-term predictors of suicide risk[37], highlighting its potential role in the demonstrated associations.

While the study included adults with recent suicidality, the sample mean age was 35, participants were predominantly white, and reported high levels of comorbid psychopathology. As such, the findings may not generalize to other populations, such as children or adolescents, individuals of differing race or ethnic backgrounds, or individuals experiencing either recent onset of suicide risk or more acute suicidality, whose smartphone use patterns and behaviors may differ[6,38]. Similarly, it is unclear if findings will generalize to individuals who use iOS smartphones, given work suggesting potential differences in socioeconomic status[39]. Finally, the self-selected nature of the sample and the use of EMA methods may have introduced bias, as participants with a greater willingness or capacity to engage with technology may differ from those who are less inclined or unable to participate, potentially limiting the broader applicability of the findings. Future studies should explore these questions in larger, more diverse samples and incorporate complementary methods, such as wearable sensors or ecological momentary assessments independent of smartphones, to provide a fuller picture of daily life and risk factors.

There are additional limitations to how the data was structured and modeled, owing to the complex nature of linking two data streams at very different timescales. Firstly, while our analyses ultimately utilized a binary time representation (>3 hours) due to convergence issues with continuous time models, this approach may have limited our ability to detect nuanced temporal relationships between phone use and subsequent experiences, particularly given that phone use was binned in 10-minute increments. Secondly, our analytical approach employed listwise deletion for missing EMA responses rather than multiple imputation, which, although justified by the pattern of missingness occurring primarily at the prompt rather than item level, meant that smartphone screen time preceding missed assessments was not linked to subsequent responses, potentially introducing bias in the temporal associations we observed. Finally, to our knowledge, this is the first study to model EMA suicide risk outcomes with a multilevel zero-inflated distribution. While we believe this better accounts for the complex structure of responding to suicide risk items, it further complicates the interpretation of each model.

In conclusion, this study provides novel insights into the complex and bidirectional relationship between smartphone screen time and suicide risk indicators, emphasizing the dynamic and context-dependent nature of these associations. The findings suggest that increased smartphone screen time may serve as both a marker of heightened acute distress and a potential tool for coping, depending on the timing and context of use. These results have important implications for suicide prevention efforts, particularly in leveraging smartphone usage patterns to identify periods of elevated risk and develop targeted interventions. For example, real-time monitoring and adaptive intervention strategies could capitalize on screen time behaviors to provide timely support or promote healthier coping strategies during moments of acute distress. However, this requires the complex interplay of data upload, storage, processing, and transmission of an intervention. The study also highlights the need for further research into the proximal mechanisms linking smartphone use and suicide risk, as well as the contextual factors that may moderate these associations. By addressing these gaps and exploring broader populations, future work can build on these findings to enhance both the precision of suicide risk assessments and the efficacy of interventions tailored to individual needs and contexts.

Methods

Participants

The sample consisted of 79 adults who reported past-month suicidal thoughts (i.e., active suicidal ideation) or behaviors, owned an Android-based smartphone (required for screenshot capture), and demonstrated variability on the variables of interest (e.g., suicidal ideation, image count) during 28 days of data collection. Participants were recruited from a mid-sized city in the Midwest, U.S. Participants ranged in age from 20–63 years (M = 35.15, SD = 11.07); 68.3% were female, 84.8% identified as white, and 92.4% identified as non-Hispanic/Latino. The majority of participants identified as straight (48.1%), followed by bisexual (24.1%) and pansexual (12.7%). Of the 79 participants, 18.9% had completed some high school or a high school degree, 27.9% had completed some college, 36.7% had completed college graduation, and 16.5% had completed some advanced education; 44.3% were employed full-time, and 40.5% were unemployed or unable to work.

Most participants (93.7%) had engaged in individual therapy or counseling in their lifetime. Regarding current diagnostic presentation: 43.0% met diagnostic criteria for major depressive disorder, 34.2% for generalized anxiety disorder, 40.5% for panic disorder, 25.3% for social anxiety disorder, 32.9% for post-traumatic stress disorder, 22.8% for alcohol use disorder, and 25.3% for substance use disorder. Of the overall sample, 83.8% met diagnostic criteria for at least one psychiatric disorder, and 64.9% met current diagnostic criteria for two or more disorders. Considering suicide risk history, 39.2% reported past week suicidal ideation; 72.2% had a lifetime history of a suicide plan (38% in the past year, 15.1% in the past month); and 64.5% had a lifetime history of a suicide attempt (12.7% in the past year, 2.5% in the past month).

Procedures

After receiving detailed information about the study procedures and consenting to participate, participants completed an in-laboratory assessment, including a diagnostic interview, an interview of their suicide risk history, and an orientation to all out-of-lab procedures. Then, participants completed 28 days of an out-of-lab protocol. During this period, participants received six signal-contingent EMA prompts per day (i.e., randomized within 2-hour windows across a 12-hour block) to complete a survey that took approximately 3–4 minutes. In parallel, smartphone screenshots were collected unobtrusively at 5-second intervals when their smartphone was in use via the *Screenlife Capture* application, where screenshots were initially stored on the local device and then encrypted and transmitted in bundles to secure research servers. During the informed consent process, participants were fully informed of all data collection procedures (i.e., screenshot capture every 5 second their phone was in use), including the possibility of capture of sensitive data throughout the study period, data storage procedures, and steps taken to help protect participant confidentiality (i.e., limited viewing of raw screenshot files). Limits of confidentiality were also discussed, including circumstances during which the research staff was concerned for their immediate safety. All participants received resources at study enrollment. If non-zero active suicidal ideation was reported via EMA, an automated pop-up of crisis resources was provided. If high levels of active suicidal ideation (i.e., ≥4 out of 5) were reported, the study team reached out to conduct a comprehensive risk assessment. All procedures were approved by the Institutional Review Board (University of Notre Dame: #21-12-6965; UW-Madison: #2024-1031).

Ecological momentary assessment

Suicide risk was conceptualized as having three components – ideation, planning, and desire – that might fluctuate in different ways over time and in relation to fluctuations in smartphone screen time. Due to the low base rate occurrence of suicide attempts, particularly over a 28-day window, suicide attempts were not included in the current operationalization of suicide risk.

In each EMA survey, four questions that have been validated for use in high-risk populations[40] assessed momentary (i.e., "At this moment…") passive suicidal ideation (i.e., "Life is not worth living for me"; "There are more reasons to die than to live for me") and active suicidal ideation (i.e., "I think about taking my life"; "I want to die"). Responses provided on a 5-point Likert scale were summed for each pair of items to create passive suicidal ideation and active suicidal ideation composite scores for each assessment.

The extent of suicidal planning since the last prompt was measured at each EMA using three items adapted from the Beck Suicide Scale[41] (i.e., "Considered a specific suicide method"; "Identified how to acquire your suicide method"; "Made other preparation for your death [e.g., wrote a suicide note, made arrangements]"). Responses provided on a 5-point Likert scale were summed to create a suicidal planning composite score for each assessment.

Momentary suicidal desire (i.e., "At this moment…") was measured at each EMA using two items (i.e., "How strong is your urge to make a suicide attempt?"; "How intense is your desire to kill yourself?"). Responses provided on a 5-point Likert scale were summed to create a suicidal desire composite score for each assessment.

Derived variables

For each EMA prompt delivered, we noted whether the participant did not (=0) or did (=1) complete the associated survey and used this binary variable to examine whether and how changes in screen time were related to compliance/completion.

Throughout the 28-day study period, screenshots of participant's smartphones were obtained every 5 seconds when they were using the phone. For this study, smartphone screen time was operationalized as screenshot image count. The sequence of timestamps that accompanied the screenshots was used to derive variables indicating when and for how long participants used their smartphones each day. Preliminary examination of the data indicated that the average smartphone use session – defined here as contiguous use with no break longer than 30 seconds – lasted about 11 minutes ($M = 696.73$ seconds, 95% CI: 518.49, 874.96). Using this information, we quantified and examined changes in participants' screen time (i.e., image count) across ten-minute windows. Specifically, we calculated the amount of time the screen was in use for every ten-minute window prior to a given EMA assessment (specifically prompt time, thus calculated the same regardless of prompt completion; back to the prior EMA), and for every ten-minute window following a given EMA assessment (forward to the next EMA). The same procedure was used when the screenshot image count was the outcome, but using a lead version of the screenshot image count, which ensured that the suicide risk responses only predicted future screenshot image counts.

Modeling was done using listwise deletion for missing EMA responses (there was no missing for phone use, given the contiguous 10-minute bins). We opted for this over multiple imputation given that missingness was almost exclusively at the prompt level and not the item (e.g., not responding to one or two items). This was repeated for Aim 2, where modeling was only done when participants responded to the prompt. Importantly, phone use bins leading up to a missed prompt were not linked to the following assessment. For instance, if someone used their phone 1 hour before a missed EMA response, that phone use was not linked to their next EMA response (likely 3–4 hours later).

To disaggregate between- and within-person effects for smartphone screen time, and to account for the zero-inflated nature of the data, the smartphone screen time variable (i.e., screenshot image count) was operationalized two ways: as a binary indicator of any use (0/1) and as a continuous measure of use intensity (proportion of the 10-minute interval spent using the device). For each measure, we disaggregated between (termed between-person) and within-person (termed within-person) effects by calculating: (1) each participant's average probability of any use and their interval-specific deviations from this average, and (2) each participant's average proportion (relative to 120 images) of use within intervals and their corresponding interval-specific deviations from this average proportion. We originally specified separate models for each way of coding smartphone screen time; however, we found a model that combined the coded predictors to fit better and have improved convergence. This model included a between-person effect for the proportion of use, as well as both within-person probability of any use and within-person proportion of use.

For suicide variables predicting smartphone screen time, we included three variables: (1) a between-person variable (person-specific mean), and two within-person variables: (2) relative presence (binary deviations indicating whether the indicator was present vs. absent compared to personal typical patterns), and (3) relative intensity (standardized deviations from person-specific means).

To accommodate the possibility that the strength of the relations between smartphone screen time and suicide risk may manifest differently at different time intervals, we created two lag time variables. *Hours until EMA assessment* for each of the repeated measures of screen time (10-minute windows) was calculated as the number of hours between the start time of the 10-minute window and the time that the following EMA assessment was prompted. A binary *proximal to EMA assessment* version of the lag time variable indicating whether a 10-minute screen time window occurred within the 3 hours prior to the EMA assessment. See Table 10 for an illustration of the resulting data structure.

Data analysis

Given our interest in the bidirectional associations between suicide risk and smartphone screen time, we considered using a bivariate multilevel model.

Table 10 | Example snippet of the dataset structure

ID	Passive SI	time_diff_hours	image_count	EMA #	Notification.Time	Earliest.Time.10 min
14	1	0.54	118	92	2023-02-24 13:42:16	2023-02-24 13:10:00
14	1	0.37	115	92	2023-02-24 13:42:16	2023-02-24 13:20:00
14	1	0.2	73	92	2023-02-24 13:42:16	2023-02-24 13:30:00
14	1	0.04	6	92	2023-02-24 13:42:16	2023-02-24 13:40:00
14	1	0.42	96	93	2023-02-24 14:15:10	2023-02-24 13:50:00
14	1	0.25	22	93	2023-02-24 14:15:10	2023-02-24 14:00:00
14	1	0.09	41	93	2023-02-24 14:15:10	2023-02-24 14:10:00
14	NA	2.16	104	94	2023-02-24 16:29:29	2023-02-24 14:20:00
14	NA	1.99	2	94	2023-02-24 16:29:29	2023-02-24 14:30:00
14	NA	1.82	26	94	2023-02-24 16:29:29	2023-02-24 14:40:00
14	NA	1.66	114	94	2023-02-24 16:29:29	2023-02-24 14:50:00

In this, Notification. Time refers to the time that participants were prompted to fill out an EMA assessment. Earliest.Time. 10 min is the 10-minute window used to bin the screenshot count (image_count), prior to each EMA assessment (EMA #). To include hours until assessment into the models, time_diff_hours was used directly, and dichotomized based on whether it was <3 hours.

However, the computational complexity of the non-normal outcomes precluded this approach. Instead, we used separate sets of generalized multilevel models (univariate) for each aim.

The relations in the data were examined using generalized multilevel models that accommodated the nested nature of the data (repeated assessments nested within persons) and the non-normal distributions of the suicide risk and smartphone screen time variables, all of which were characterized by excess zero values (see Fig. 4 for the distribution of image count[42,43]). Given this, we specified both zero-inflated negative binomial (ZINB; note that zero-inflated Poisson had a high rate of convergence problems) and cumulative logit distributions (for suicide risk outcomes). We gave preference to the ZINB models as: they demonstrated superior fit (using the leave-one-out cross-validation information criteria[44]); there were convergence problems for the thresholds in ordinal models; and they allowed us to model the outcome as consisting of two parts (0/non-zero part and the count part; referred to as excess zero and count in-text, respectively).

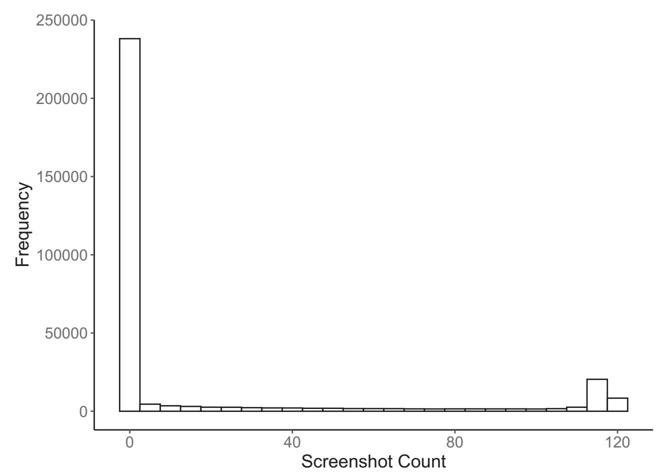

Fig. 4 | The distribution of screenshot count across all 10-minute windows. As seen in the figure, there is a bimodal distribution, notably with a secondary peak close to 120, meaning that an individual used their phone continuously for the entire 10-minute block.

Aim 1: Smartphone screen time predicting suicide risk. This model took the general form:

$$active_{ti} \sim \beta_{0i} + \beta_1 \cdot bp\_prop\_use_i + \beta_2 \cdot wp\_any\_use_{ti} + \beta_3 \cdot wp\_proportion\_use_{ti} + \varepsilon_{ti}$$

$$zi_{ti} \sim \gamma_{0i} + \gamma_1 \cdot bp\_prop\_use + \gamma_2 \cdot wp\_any\_use_{ti} + \gamma_3 \cdot wp\_anyproportion\_use_{ti}$$

This zero-inflated negative binomial mixed-effects model analyzes the active status variable, $active_{ti}$, for each observation i. The model includes a random effect for the intercept for β_{0i}, along with fixed effects for $\beta_1 \cdot bp\_prop\_use_i$ (between-person differences in proportion use), $\beta_2 \cdot wp\_any\_use_{ti}$ (within-person deviations from average use [0/1]), and $\beta_3 \cdot wp\_prop\_use_{ti}$ (within-person deviations from average proportion of use). Additionally, a zero-inflation component, zi_{ti}, adjusts for excess zeros, with γ_{0i} as its random intercept along with the same fixed effects for the count portion of the model, representing the influences of average use and deviations on the likelihood of zero responses on $active_{ti}$. This model structure captures both counts and the probability of responses of zero, providing a comprehensive view of the factors affecting each outcome. Finally, this model includes a shape parameter (θ) controlling over-dispersion in the negative binomial distribution.

Aim 2: Suicide risk predicting smartphone screen time. We used the same model specification, with slightly different predictor coding (detailed above), for using suicide risk variables to predict smartphone screen time.

Aim 3: Smartphone screen time predicting EMA completion. For predicting the EMA completion (i.e., responded = 1/missing = 0) variable, we used a logistic multilevel model of the same form, but with a Bernoulli link function that accommodated the binary nature of the outcome variable.

Our interest in using time as a variable was two-fold: (1) we hypothesized relations would be stronger when less time had elapsed between the two assessments, and (2) we wanted to remove the influence of the first and last assessments of the day, as this involves examining relationships across days. As a result, we tested multilevel models that included interaction effects between each within-person variable (two for Aims 1 and 2) and each time variable (detailed above). Finally, we incorporated models that included hours until EMA assessment as a random effect; however, these sets of models experienced consistent convergence issues. Below, we only report results for models that included a binary representation of time (>3 hours), as these models demonstrated improved fit via the LOOIC[44] across outcomes.

The full set of 9 generalized (ZINB or logistic) multilevel models was estimated in a Bayesian framework using the brms package[45] in R[46].

Posterior samples for each parameter were obtained using 15 chains, with at least 200 samples per chain (100 of which were burn in). Model convergence and mixing were assessed using the $\hat{R}$ metric and effective sample size (ESS[44]). Additionally, we checked the viability of estimating continuous-time versions of the models using Mplus. However, those models did not converge and were deemed non-viable for these data, likely because of the size of the data (>300k rows) and limitations on how the distributions could be specified in that program (only normal distributions available). Given the interaction parameters in each model, simple effects were assessed with the *hypothesis* function from brms.

Raw images were counted within each 10-minute timeframe, with an expected maximum of 120 images. In 0.58% (=1842/313121) of time windows the Screenlife Capture app obtained more than 120 images (i.e., a clock-time processing scenario where the operating system pre-executes a pending task and obtains screenshots at <5 second interval); in these instances, we did not include any screenshots that occurred at <5 seconds intervals in our calculation of image count, thus the maximum value is 120.

Data availability
The de-identified dataset with 10-minute windows of phone use and self-report is publicly available at DOI 10.17605/OSF.IO/CJAST.

Code availability
Each of the R scripts to run the multilevel models is available at the same OSF repository as the data.

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Author contributions
R.J., B.A. and N.R. conceptualized the study, B.A. oversaw data collection, R.J. and B.A. wrote the main manuscript text, R.J. ran primary analyses, with consultation from N.R. and M.B.

Competing interests
The authors declare no competing interests.

Additional information
Correspondence and requests for materials should be addressed to Ross Jacobucci.