Smartphone Against Smartphone: An IT-Enabled Social Network Activation for Reducing Smartphone Overuse

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1. Introduction

Nowadays, smartphones have become ubiquitous, with their overuse prevalent around the world. As of 2024, 91 % Americans own a smartphone. [1]. In 2024, Americans spent 279 minutes on smartphones per day on average [2]. This is equivalent to 14 years of an individual's lifetime, accounting for the life expectancy of the U.S. Smartphone overuse often results in decreased life quality and health outcomes. Evidence suggests that excessive smartphone use exacerbates work-life balance challenges, leading to poor physiological, psychological, and relational well-being (Magni et al. 2023).

Current strategies for combating digital overuse primarily rely on access restrictions and incentives, which can be effort-consuming and costly (Allcott et al. 2022). A cost-effective and sustainable alternative is to enhance real-life social engagement, a process in which smartphones themselves can play a facilitating role (Chang et al. 2022). First, smartphones are highly portable and support instant communication anytime and anywhere, minimizing the barriers of social interaction. Building on this, smartphones also facilitate the formation and activation of social networks, fostering the organizing and sustaining of group social activities. Here, we define social network activation as the process of initiating communication with contacts within one's social network. In this study, we examine whether and how smartphone-enabled social network activation paradoxically reduces overall smartphone use. We hypothesize that contacts embedded in cohesive groups of a social network have a stronger influence than periphery contacts on promoting downstream social engagement, leading to a reduction in smartphone use when properly activated.

To test this hypothesis, we leverage data sets collected from a series of longitudinal studies that tracked participants' smartphone use, social networks, and physical activities. We construct the K-Core, a metric that captures a node's centrality while also considering the cohesion of the group in which the node sits. We identify social network activation in real-time and track its evolution for each participant, combining self-reported social network structure information and real-time mobile communications. Our results show that a one-standard-deviation increase in the K-Core of the activated contacts leads to a 6.46-minute reduction in daily screen time, representing a 3.68 % decrease in total smartphone use. The results remain robust after controlling for non-topological social factors, including social intimacy, trust, relation length, and personality. Moreover, mediation analysis suggests that activating high-K-Core contacts reduces individuals' smartphone use by improving the steps walked, resulting in reduced digital use.

Our study contributes to the literature on combating digital addiction by providing a novel, cost-effective strategy for reducing smartphone overuse that does not require significant finance and effort input. Our findings suggest that strategically activating social ties via smartphones can reduce overall screen time, even though the process itself requires screen time. We also contribute to the literature that studies the impact of social interaction on human behavior and well-being. Prior research heavily relies on social interaction volume as the social engagement metric, little attention has been paid to the structure of social networks. We demonstrate that activating different parts of a social network has heterogeneous effects on human behavior and well-being. Specifically, activating contacts within cohesive social groups helps curb smartphone overuse, potentially because these contacts foster broader group social engagement. Our findings also have practical implications for healthcare interventions and lifestyle enhancement strategies, offering insights for practitioners aiming to promote healthier digital behaviors and social engagement.

2. Literature

2.1. Smartphone Overuse

Modern smartphones support rich tasks including gaming, live streaming and video-watching, which can be addictive. Smartphone overuse, also known as “smartphone addiction” or “ problematic smartphone use ”, is characterized by excessive or compulsive use of smartphones, which results in negative health and quality of life. First, smartphone overuse can cause negative impacts on users’ physical health. Evidence shows that constant smartphone use can cause computer vision syndrome (CVS) including eye fatigue, dryness, blurred vision and other eye-related discomforts (Choi et al. 2018). Excessive use of digital devices at bedtime can also reduce sleep duration and quality and increase daytime sleepiness (Carter et al. 2016). Second, smartphone overuse can detrimentally affect mental health. Benefiting from the portability and connectivity of the mobile platform, smartphones can facilitate the use of social media, whose misuse can cause damage to mental health. For example, by studying the staggered introduction of Facebook in US colleges, Braghieri et al. (2022) find that using Facebook has significant and negative effects on student mental health due to the social comparison on the online community. Another study using cross-sectional survey examined the relationship between smartphone overuse and overall mental health with 655 participants. The results show that excessive smartphone use is associated with higher levels of depression, anxiety and stress (Khan et al. 2023). Third, smartphone overuse can impose challenges on cognitive capability, negatively impact productivity. Alotaibi et al. (2022) find that overusing smartphone can increase cognitive load, limiting engagement in productive activities and negatively impacting academic and work performance.

Researchers and software developers have designed various approaches to help users reduce digital overuse, a process named "digital detox". Existing digital detox strategies primarily rely on access restrictions and incentives. Using a randomized experiment, Allcott et al. (2022) find that either providing users with incentives or allowing users to set limits on screen use can effectively reduce social media use, suggesting that digital overuse is a habit forming as well as a self-control problem. Others recommend using applications for limiting the time and managing the types of digital use. For example, Schmuck (2020) find that digital detox applications (apps; e.g., iOS Screen Time) can reduce smartphone overuse and its consequences on well-being that originate from the misuse of social networking sites (SNSs). Although the above strategies are proven to be effective in reducing digital use, they typically require considerable effort or financial input.

2.2. Social Engagement

Humans are inherently social beings. Appropriate social engagement has significant benefits for individuals’ physical and mental health, contributing to a higher quality of life (Umberson &

Karas Montez 2010). Social engagement refers to the participation in social activities that encompasses interacting with others, forming and maintaining social relationships, and playing meaningful roles within a community.

Social engagement enhances physical health. First, engaging in social groups can result in interpersonal competition and social influence, which have been shown to be effective at motivating individuals to walk more steps, fostering physical health by reducing sedentary life styles (Hydari et al. 2022). Moreover, the received social support has been shown to be positively associated with physical activity levels, where social support is exchanged through interpersonal social interactions (Lieber et al. 2024).

Social engagement improves mental health. First, social engagement provides individuals with companionship, emotional support, and information support, contributing to one's mental health conditions (Yan & Tan 2014). In contrast, a constant lack of engagement may lead to social isolation. When individuals are socially isolated, they usually have no or little regular social interaction or sufficient contacts to connect with. Evidence suggests that the lack of social engagement is highly associated with many negative health consequences such as anxiety, depression, and suicide (Garnett F. & Curtin C. 2023).

3. Hypothesis Development

3.1. How Smartphones-Enabled Social Interaction (not necessarily Social Network Activation) Reduces Screen Time (Enhances Real-Life Activity Engagement)

1. Smartphones are highly portable and support instant communication anytime and anywhere, minimizing the barriers of social interaction.
2. Smartphones also facilitate the formation and activation of social networks, fostering the organizing and sustaining of group social activities.

Hypothesis 1 *Using smartphones to activate social networks reduces screen time.*

3.2. How Activating High-K-Core Contacts Reduces Screen Time

Contacts embedded in cohesive groups of a social network have a stronger influence than periphery contacts on promoting downstream social engagement, leading to a reduction in smartphone use when properly activated.

Hypothesis 2 *Using smartphones to activate contacts with a high-K-core in a social network reduces screen time.*

Hypothesis 3 *Social network activation reduces screen time by increasing the steps walked.*

4. Model

4.1. Specification for Smartphone Screen Time

$$\text{Screen Time}_{it} = \beta_0 + \beta_1 \cdot \text{Nodes}_{it} + \alpha \cdot X_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (1)$$

$$\begin{aligned}\text{Screen Time}_{it} = \beta_0 + \beta_1 \cdot \text{Nodes}_{it} + \beta_2 \cdot \text{K-Core}_{it} \\ + \beta_3 \cdot \text{Nodes}_{it} \cdot \text{K-Core}_{it} \alpha \cdot X_{it} + \theta_i + \lambda_t + \varepsilon_{it}\end{aligned} \quad (2)$$

4.2. Logistic Model for Smartphone Addiction

In the previous section, we discussed the impact of the characteristics of social networks on general mobile phone adoption. In this section, we focus on the impact of the characteristics of social networks on mobile phone addiction. To the best of our knowledge, there is no definitive metric for the measurement of smartphone overuse. Therefore, we identify the observations with extremely high screen time and label them as smartphone addictions. Specifically, we define that an individual i is addicted to their smartphone on day t if $ScreenTime_{it}$ is above the top 10% of an individual's total observations. Then we create a dummy variable $Addiction_{it}$ for each observation. Thereafter, we estimate the probability of smartphone overuse with a logistic model using the above two metrics for smartphone overuse:

$$\ln\left(\frac{\Pr(\text{ Addiction }_{it}=1|\boldsymbol{X}_{it})}{1-\Pr(\text{ Addiction }_{it}=1|\boldsymbol{X}_{it})}\right)=\beta_0+\beta_1\cdot\text{Nodes}_{it}+\alpha\cdot X_{it}+\theta_i+\lambda_t+\varepsilon_{it} \tag{3}$$

$$\begin{aligned}\ln\left(\frac{\Pr(\text{ Addiction }_{it}=1|\boldsymbol{X}_{it})}{1-\Pr(\text{ Addiction }_{it}=1|\boldsymbol{X}_{it})}\right)=&\beta_0+\beta_1\cdot\text{Nodes}_{it}+\beta_2\cdot\text{K-Core}_{it}\\&+\beta_3\cdot\text{Nodes}_{it}\cdot\text{K-Core}_{it}\alpha\cdot X_{it}+\theta_i+\lambda_t+\varepsilon_{it}\end{aligned} \tag{4}$$

$Addiction_{it}$ measures whether a user i is addicted to a smartphone on a given day t. $Pr\left(\text{ Addiction }_{it}=1\mid\boldsymbol{X}_{it}\right)$ refers to the conditional probability that $Addiction_{it}$=1 when the independent variables are taking the values of X. Our objective is to examine whether activating contacts with particular network features could curb smartphone addiction. We estimate the probability of smartphone addiction with specification 2. It should be noted that we try multiple criteria for smartphone addiction as robustness checks.

5. Results

5.1. Effects of Social Network Activation on Smartphone Overuse

5.2. Logistic Model for Smartphone Addiction

Instead of estimating general smartphone use, we identify observations of users when they were addicted to smartphones on a certain day. By doing this, we investigate whether network features could benefit reducing the probability of being addicted to smartphones. Figure **??** (Appendix I) shows the distribution of average individual screen time for different purposes. Figure **??** (Appendix I)shows the distribution of individual smartphone addiction rates (addicted days/ total days) with varying addiction threshold value N in criteria 2. Table **??** shows the estimation for smartphone overuse. The first three columns represent the results for addiction to non-communication smartphone use; columns 4-5 represent the results for addiction to communication-driven smartphone use; columns 6-9 show the results for overall smartphone overuse. We can find that K-core reduces the probability of smartphone overuse for all kinds of screen use.

6. Mechanism

$$\text{Screen Time}_{it}=\beta_0+\beta_1\cdot\text{Nodes}_{it}+\alpha\cdot X_{it}+\theta_i+\lambda_t+\varepsilon_{it} \tag{5}$$

$$\text{Steps}_{it}=\beta_0+\beta_1\cdot\text{Nodes}_{it}+\alpha\cdot X_{it}+\theta_i+\lambda_t+\varepsilon_{it} \tag{6}$$

$$\text{Screen Time}_{it}=\beta_0+\beta_1\cdot\text{Steps}_{it}+\alpha\cdot X_{it}+\theta_i+\lambda_t+\varepsilon_{it} \tag{7}$$

Table 1 **Effects of Social Network Activation on Smartphone Overuse**

VARIABLES	(1) Screen Time	(2) Screen Time	(3) Screen Time	(4) Screen Time	(5) CommFreq.	(6) Characters
Contacts	-1.301***					
	(0.111)					
OutNetwork-Contacts		-1.157***	-1.140***	-1.130***	9.284***	289.494***
		(0.120)	(0.120)	(0.120)	(0.098)	(2.405)
Nodes		-2.147***	-2.618***	-1.701***	22.977***	654.423***
		(0.279)	(0.332)	(0.425)	(0.472)	(9.910)
K-Core				-1.276***	-1.105***	-21.866***
				(0.308)	(0.263)	(6.676)
Nodes × K-Core				-0.197***	-0.204***	-2.645*
				(0.055)	(0.061)	(1.379)
Trust			0.154	0.285	0.265	-9.496
			(0.504)	(0.505)	(0.387)	(10.432)
Close			-1.660	0.158	9.596***	262.310***
			(1.224)	(1.255)	(0.993)	(26.116)
Position			0.636***	0.761***	-2.424***	-61.894***
			(0.134)	(0.135)	(0.111)	(3.001)
RelationLength		0.448***	0.404***	-1.687***	-47.941***	
			(0.085)	(0.085)	(0.067)	(1.784)
Constant	254.912***	255.430***	255.409***	254.428***	40.708***	945.351***
	(2.753)	(2.744)	(2.756)	(2.781)	(2.394)	(58.313)
Observations	105,318	105,318	105,318	105,318	105,318	105,318
R-squared	0.346	0.346	0.346	0.347	0.597	0.647
Communication	Full	Full	Full	Full	Full	Full
Unit F.E.	YES	YES	YES	YES	YES	YES
Day F.E	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes.

1. *Contacts = Nodes + OutNetwork-Contacts.*
2. *Dependent and independent variables are winsorized at 5%/95%.*

7. Conclusion and Discussion

7.1. Implications

As an intrinsic nature of human beings, socializing plays a significant role in self-achievement, fulfilling the sense of belonging, and maintaining mental health. Activating social networks and mobilizing social capital provides a potential vehicle for improving individuals' health behaviors. As a primary approach of ICTs, smartphone has been playing a crucial role in facilitating interpersonal social interaction. Whether smartphone-facilitated social interaction has similar benefits as physical social interaction is poorly understood. With this in mind, our study investigates how smartphone-based social network activation affects individuals' behavior and wellness.

Our study contributes to the literature from multiple aspects. First, our study advances the understanding of the impact of social engagement on individual behavior and well-being from social interaction volume to the structure of social networks. Our results suggest that activating and mobilizing contacts who are embedded in one's social network can increase group-level social engagement and thus reduce excessive smartphone use. Moreover, we find that activating different segments of one's social network can have varying effects on an individual's health behavior, highlighting the heterogeneity of these impacts. In contrast to much of the previous research, which primarily measures social interaction based on its frequency or volume, we adopt a more comprehensive approach. Utilizing social network analysis, we delve into a deeper exploration of an individual's social engagement. This approach enables us to not only assess the overall level of social engagement but also dissect the intricate structure of one's social network.

The second key advancement our study offers is shedding light on the intricate mechanisms underlying the heterogeneous effects of activating different parts of an individual's social network

Table 2 **Impact of Social Network Activation on Smartphone Addiction**

VARIABLES	(1) Addiction	(2) Addiction	(3) Addiction	(4) Addiction	(5) CommFreq.	(6) Characters
Contacts	-0.034***					
	(0.003)					
OutNetwork-Contacts		-0.028***	-0.028***	-0.027***	9.508***	297.950***
		(0.004)	(0.004)	(0.004)	(0.416)	(10.590)
Nodes		-0.076***	-0.076***	-0.071***	22.797***	664.630***
		(0.010)	(0.010)	(0.013)	(1.532)	(39.228)
K-Core				-0.034***		
				(0.010)		
Nodes × K-Core				-0.001		
				(0.002)		
Trust			0.015	0.018	0.292	-6.120
			(0.016)	(0.016)	(1.245)	(36.205)
Close			-0.067*	-0.031	6.700**	191.711**
			(0.038)	(0.039)	(3.279)	(97.407)
Position			0.013***	0.015***	-2.585***	-64.994***
			(0.004)	(0.004)	(0.385)	(10.164)
RelationLength			0.010***	0.009***	-1.672***	-48.129***
			(0.003)	(0.003)	(0.223)	(5.654)
Constant					45.051***	1,113.284***
					(5.328)	(150.169)
Observations	105,364	105,364	105,364	105,364	105,370	105,370
R-squared					0.295	0.372
Number of egoid	451	451	451	451	457	457
Communication	Full	Full	Full	Full	Full	Full
Unit F.E.	YES	YES	YES	YES	YES	YES
Day F.E	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes.
1. *Dependent variable is log odds of smartphone addiction.*
2. *Contacts = Nodes + OutNetwork-Contacts.*
3. *Dependent and independent variables are winsorized at 5%/95%.*

Previous studies have established that mobilizing social capital can yield positive outcomes, such as effective career threat management (Smith et al. 2012). However, we acknowledge the darker side, wherein activating specific segments of one's social network may lead to detrimental consequences, including social isolation, mistrust, and a decline in self-esteem (Pescosolido et al. 2010, Wahl 2012). Our research seeks to bridge this knowledge gap by closely examining the characteristics of the activated clusters within one's social network. Furthermore, our study takes a dynamic perspective, a departure from the predominantly static analyses prevalent in current social network research. We recognize the inherent nature of social interactions as dynamic and evolving over time (Emirbayer 1997). Therefore, by tracking changes in an individual's social network throughout our study, we aim to uncover the intricate dynamics of social interactions and their impact on health behavior.

Current research about social engagement has several limitations in analyzing an individual's social behavior. First of all, prior research traditionally takes the volume of social interaction as a metric of social engagement level relying on self-reported data (Onnela et al. 2014). In addition, current research in this field probes social interaction heavily, focusing on local interpersonal social activities (we use the term "local interpersonal social activities" to refer to the social interaction that directly involves the focal individual), which may lead to some limitations in the understanding of one's overall social behavior.

In summary, our research advances the current understanding of the relationship between social

Table 3 Mediation Effects of Steps

VARIABLES	(1) Screen Time	(2) Steps	(3) Screen Time
Steps			-0.002***
			(-22.06)
Nodes	-2.883***	107.083***	-2.646***
	(-8.66)	(10.43)	(-7.96)
OutNetwork-Contacts	-1.219***	34.112***	-1.143***
	(-10.13)	(8.80)	(-9.53)
K-Core	-1.775***	2.315	-1.770***
	(-6.45)	(0.27)	(-6.45)
Constant	230.789***	11,234.617***	255.715***
	(92.79)	(146.84)	(92.78)
Observations	105,318	105,318	105,318
R-squared	0.343	0.540	0.346
Communication	Full	Full	Full
Unit F.E.	YES	YES	YES
Day F.E	YES	YES	YES
r2_q	.	.	.
F	162.6	1779	177.7

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes.
1. *Contacts = Nodes + OutNetwork-Contacts.*
2. *Dependent and independent variables are winsorized at 5%/95%.*

networks and health behavior in three key ways: by providing a more comprehensive measurement of social engagement through social network analysis, by examining the mechanisms behind the heterogeneous effects of network activation, and by adopting a dynamic approach to the study of evolving social networks. These contributions collectively enhance the depth and breadth of knowledge in the field of social network analysis and its implications for health outcomes. Moreover, in future research endeavors, it becomes increasingly essential to conduct meticulous investigations into the nuanced ways in which both social disconnectedness and perceived isolation uniquely shape and influence an individual's utilization of smartphones.

7.2. Limitations

In the discussion of our findings, it is imperative to acknowledge the inherent limitations of our study. While our analysis offers valuable insights into the interplay between social network activation and smartphone utilization, it is crucial to recognize the following constraints: First, demographic homogeneity. Our study predominantly comprises students as participants. While this cohort provided us with valuable data, it may not be fully representative of the broader population. Different age groups and professional backgrounds may exhibit diverse smartphone usage patterns, potentially limiting the generalizability of our findings. Second, screen time is confounding. The method we employed to detect social network activation was based on mobile communication events, which inherently encompass screen time. This introduces an inherent challenge in isolating

Sobel-Goodman Mediation Tests

	Est	Std_err	z	P>|z|
Sobel	-0.238	0.025	-9.430	0.000
Aroian	-0.238	0.025	-9.422	0.000
Goodman	-0.238	0.025	-9.438	0.000

Indirect, Direct, and Total Effects

	Est	Std_err	z	P>|z|
a_coefficient	107.083	10.295	10.402	0.000
b_coefficient	-0.002	0.000	-22.342	0.000
Indirect_effect_aXb	-0.238	0.025	-9.430	0.000
Direct_effect_c'	-2.646	0.329	-8.039	0.000
Total_effect_c	-2.883	0.330	-8.744	0.000

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Proportion of total effect that is mediated:    0.082
Ratio of indirect to direct effect:             0.090
Ratio of total to direct effect:                1.090
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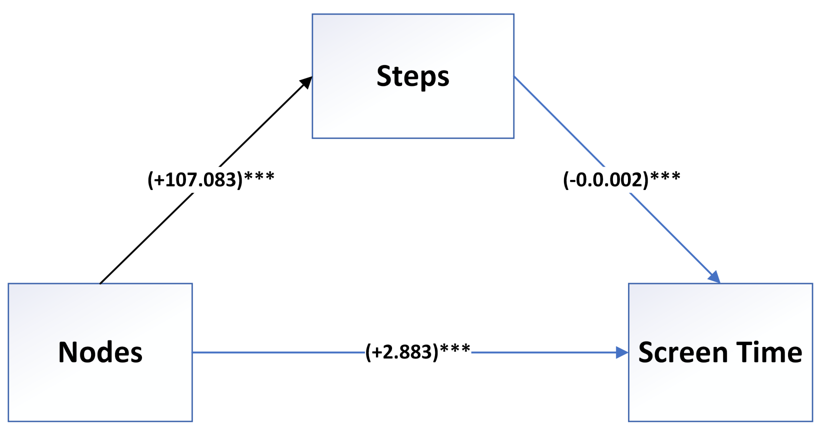

the precise influence of social network activation on smartphone usage independently, as these variables tend to overlap.In light of these limitations, it is advisable for future research to encompass a more diverse and inclusive participant pool spanning various age groups and professions. Additionally, refining our measurement techniques to disentangle the effects of screen time from social network activation could provide a more nuanced understanding of this intricate relationship."

Notes

[1]https://www.pewresearch.org/internet/fact-sheet/mobile/

[2]https://www.statista.com/statistics/1045353/mobile-device-daily-usage-time-in-the-us/

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Appendix A: Summary Statistics

A.1. Neighbour Borrowing from Closest 1 Wave, Complete Nodes

Table 4: Summary statistics for Neighbour Borrowing from Closest 1 Wave, Complete Nodes

Variable	Mean	Std. Dev.	Min.	Max.	N
Total	209.774	130.993	0	1072.863	105370
Comm.	29.244	39.023	0.009	1429.967	105370
NoComm.	180.531	130.221	-1429.967	1056.663	105370
Unlock Freq.	81.924	58.109	0	4691	105370
Degree Centrality	0.509	0.348	0	1	105370
Core Number	5.017	3.788	0	23	105370
Steps	118.063	54.748	2.6	642.26	105370
Sleep Relation Length	416.709	101.309	1	1171	105370
Naps	0.122	0.352	0	7	105370
Nap Relation Length	13.449	42.563	0	879	105370
Activated Network Nodes	2.972	2.405	0	27	105370
Inactive Network Nodes	7.765	7.218	-17	25	105370
Out-Network Contacts	5.865	5.59	0	95	105370
Contacts	8.837	6.827	1	99	105370
Network Edges	49.233	50.214	0	320	105370
Network Nodes	10.736	7.906	0	26	105370
Relation Relation Length	6.788	6.468	0	21	105370
Call Relation Length	10.717	29.469	0	1396.067	105370
In-Network Comm. Freq.	78.399	118.503	0	2313	105370
Out-Network Comm. Freq.	46.704	73.208	0	1764	105370
Call	2.883	4.32	0	117	105370
SMS	114.282	146.339	0	2640	105370
MMS	4.528	9.789	0	396	105370
WhatsApp	4.7	33.604	0	1231	105370
Trust	6.699	4.037	0	10	105370
Survey Contact Position	4.516	4.444	0	25	105370
Social Closeness	2.807	1.671	0	4	105370

Appendix B: Tables

Table 5 Results with Lagged Independent Variables

VARIABLES	(1) NonComm.	(2) NonComm.	(3) NonComm.	(4) Comm.	(5) Comm.	(6) Total Screen	(7) Total Screen	(8) Total Screen
Lagged Degree Centrality	2.729	3.448	4.893	6.333***	3.972**	9.062	7.420	4.895
	(5.292)	(5.224)	(5.138)	(1.819)	(1.615)	(5.582)	(5.268)	(5.138)
Lagged Core Number	-1.062**	-1.115**	-1.374***	-0.625***	-0.505***	-1.687***	-1.620***	-1.375***
	(0.501)	(0.500)	(0.485)	(0.185)	(0.178)	(0.503)	(0.490)	(0.485)
In-Network Nodes	-1.526***	-1.624***	-0.434	4.527***	4.627***	3.002***	3.003***	-0.484
	(0.377)	(0.396)	(0.451)	(0.189)	(0.190)	(0.425)	(0.436)	(0.451)
In-Network Inactive Nodes	-0.556***	-0.519***	-0.458**	1.136***	1.151***	0.580***	0.632***	-0.466**
	(0.175)	(0.175)	(0.205)	(0.075)	(0.075)	(0.170)	(0.171)	(0.204)
Out-Network Contacts	-0.362	-0.395	-0.756	-0.666***	-0.839***	-1.029	-1.234	-0.741
	(0.659)	(0.823)	(0.824)	(0.169)	(0.190)	(0.671)	(0.834)	(0.823)
Edges	0.061	0.053	0.100	0.097***	0.118***	0.159	0.171	0.099
	(0.114)	(0.122)	(0.124)	(0.028)	(0.029)	(0.116)	(0.126)	(0.124)
Steps		-0.183***	-0.194***		-0.033***		-0.216***	-0.195***
		(0.019)	(0.019)		(0.007)		(0.020)	(0.019)
Sleep Relation Length		-0.078***	-0.083***		-0.012***		-0.090***	-0.083***
		(0.008)	(0.008)		(0.004)		(0.008)	(0.008)
Trust		0.099	0.209		0.061		0.160	0.212
		(0.947)	(0.920)		(0.474)		(0.964)	(0.920)
Social Closeness		-1.747	-1.316		1.477		-0.271	-1.337
		(2.316)	(2.279)		(1.033)		(2.362)	(2.279)
Contact Position		0.689***	0.558***		-0.464***		0.225	0.559***
		(0.223)	(0.214)		(0.080)		(0.220)	(0.214)
Relation Length		0.432***	0.530***		-0.081		0.351**	0.523***
		(0.152)	(0.143)		(0.070)		(0.146)	(0.143)
In-Network Comm.Freq.			-0.013					0.137***
			(0.013)					(0.013)
Out-Network Comm.Freq.			-0.011					0.140***
			(0.017)					(0.017)
Call Time			-0.685***					0.309***
			(0.044)					(0.044)
Constant	156.588***	221.354***	237.243***	27.337	37.821*	183.925***	259.175***	237.301***
	(45.787)	(44.890)	(41.393)	(19.828)	(20.251)	(49.725)	(48.801)	(41.378)
Observations	81,823	81,823	81,823	81,823	81,823	81,823	81,823	81,823
R-squared	0.027	0.035	0.063	0.111	0.116	0.026	0.037	0.059
Number of egoid	445	445	445	445	445	445	445	445
Communication	Full	Full	Full	Full	Full	Full	Full	Full
Unit F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Day F.E	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes. Columns 1-3 represent the results for non-communication smartphone use estimated in equation 1; Columns 4-6 represent the results for communication-driven smartphone use (communication variables In-COMM and Out-COMM are not included as they comprise DV: communication use time); Columns 6-9 represent the results for overall smartphone use .