Online Appendix

Securing Personal Space in the Crowd: Physical Crowdedness and Organic Mobile Usage

Contents

A. MOBILE FUNCTIONALITY CLASSIFICATION

Table A1. Examples of Mobile Apps by Functionality Categories

Functionality Category	App Store Genres	Examples
Social	Communication	Wechat, QQ, DingTalk, Sina Weibo
Information	News	Sina news, Tecent News
	Browser	Baidu browser, QQ browser
Entertainment	Music	Kugou Music, NetEase Music
	Reading	Baidu reading, Sougou reading
	Game	Three Kingdoms, QQ game
	Video	IQIYI, Youku, Tiktok
Shopping	Shopping	Jingdong, Taobao
Tool	Navigation	Gaode map, Baidu map, Didi
	Finance	Ping An Securities, Industrial & Commercial Bank of China
	Travel	12306, Qunar, Ctrip
	Education	IELTS, Graduate Exam Guide App, Youdao Dictionary
	Photo	Meitu Xiuxiu, B612
	Health	Keep, Daily yoga
	Living services	Alipay, Meituan, Dianping, 58.com
	Tools	Huawei app store, 360 weather, Baidu Pan

Table A2. Major Functionalities in Super Apps That Extend Beyond Their Market Category

Super App	App Category	Functionality Category	Specific Functionality	Associated URL Host
Wechat[1]	Social	Information	Subscription news	mp.weixin.qq.com
		Entertainment	Game center	game.weixin.qq.com
		Entertainment	Video/Live streaming	live.qcloud.com
		Shopping	Shopping*	jd.com
		Tool	Payment	pay.weixin.qq.com
		Tool	Finance*	tencentwm.com
QQ[1]	Social	Entertainment	Live streaming	live.qq.com
		Entertainment	Game Center	gamecenter.qq.com
		Entertainment	Video*	weishi.qq.com
		Entertainment	Tencent Animation*	ac.qq.com
		Entertainment	QQ music*	y.qq.com
		Entertainment	WeSing*	kg.qq.com
		Shopping	Shopping*	jd.com
		Tool	QQ payment	tenpay.com
		Tool	Exercise	yundong.qq.com
Tiktok	Entertainment	Social	Content release	creator.douyin.com
		Social	Sharing	imapi.douyin.com
		Social	Private message interaction	imapi.douyin.com
		Shopping	Shopping	ecombdapi.com
Kuaishou	Entertainment	Social	Content release	cp.kuaishou.com
		Social	Private message interaction	sixinpicnew.ksapisrv.com
		Shopping	Shopping	kwaixiaodian.com
Alipay	Tool	Shopping	Shopping*	m.taobao.com
Sina Weibo	Social	Entertainment	Watch videos	video.weibocdn.com

		Entertainment	Watch live streaming	live.weibo.com
		Shopping	Shopping	shop.sc.weibo.com
Taobao	Shopping	Tool	Payment*	mobilegw.alipay.com
Jingdong	Shopping	Tool	Payment*	jdpay.com
Pinduoduo	Shopping	Tool	Payment*	mobilegw.alipay.com
Meituan	Tool	Shopping	Meituan Youxuan	bi-mall.meituan.com
Baidu	Information	Entertainment	Watch video	nadvideo2.baidu.com
		Entertainment	Watch live streaming	live.baidu.com
		Entertainment	Reading books	novelapi.baidu.com
Little RedNote	Social	Entertainment	Watch videos	edith.xiaohongshu.com
		Shopping	Shopping	mall.xiaohongshu.com
Jinri Toutiao	Information	Entertainment	Watch video	toutiaoimg.com
Tencent News	Information	Entertainment	Watch videos*	vv.video.qq.com
QQ browser	Information	Entertainment	Read novel*	novel.html5.qq.com
		Entertainment	Watch videos*	vv.video.qq.com
UC browser	Information	Entertainment	Read novel*	shuqireader.com
		Entertainment	Watch videos	video.ums.uc.cn

Note: Functions marked with an asterisk (*) indicate features that involve external services integrated within the app, which redirect users to third-party platforms. These redirections result in URL hosts that are not native to the original app, but instead correspond to the destination domain. For example, when users initiate shopping activities within WeChat, they are directed to jd.com, an external e-commerce site, rather than a host under WeChat's domain. [1] While WeChat and QQ support a wide array of Mini Program functionalities, most serve as gateways that redirect users to external web-based services. As such, we do not include a detailed breakdown of Mini Program activity in this table.

B. RELATIONSHIPS BETWEEN CROWDEDNESS AND DIFFERENT FUNCTIONALITY USAGE RATIO

To gain deeper insights into how users allocate their organic mobile usage across functionality categories in crowded environments, we examine the ratio of usage duration devoted to each functionality categories. Specifically, we define five additional dependent variables: $SocRatio_{ij}$, $InfRatio_{ij}$, $EntRatio_{ij}$, $ShopRatio_{ij}$, and $ToolRatio_{ij}$, representing the proportion of total mobile usage duration that user i spend on social, information, entertainment, shopping and tool functionalities, respectively, during trip j. Results in Table B1 reveal that crowdedness significantly increases the proportion of social functionality usage ($p < 0.01$) while decreasing the share of shopping functionalities ($p < 0.01$). The ratio of information, entertainment and tool functionalities usage remains statistically unchanged ($p > 0.1$).

Table B1. Relationships between Crowdedness and Different Functionality Usage Ratio

	SocRatio	**InfRatio**	**EntRatio**	**ShopRatio**	**ToolRatio**
Crowdedness	0.004***	-0.001	0.001	-0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes
No. of Obs.	221416	221416	221416	221416	221416
R-Squared	0.2708	0.2928	0.3301	0.2801	0.3410

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,176 singleton observations are excluded from the estimation.

C. HETERGENEITY ACROSS MORNING AND EVENING PEAK HOURS

In this section, we further disaggregate peak hours into morning and evening periods and replicate the main analysis accordingly. As shown in the first two columns of Table C1, the relationship between crowdedness and mobile usage is positive in both time windows; however, the positive relationship is significantly stronger during morning peak hours compared with evening peak hours ($p < 0.1$). Moreover, Columns 3 to 12 of Table C1 indicate that across all five functionality categories, the positive relationships are consistently more pronounced during the morning peak than the evening peak.

These results align with the theoretical framework of personal space invasion, as morning peak hours are typically associated with greater urgency and time pressure as individuals commute to work (Van Hooff 2015, Zhou et al. 2017). This heightened urgency is likely to amplify the arousal from physical crowdedness, leading to an increased perception of personal space invasion. As a result, individuals may engage in stronger compensatory mobile usage during morning commutes compared to evening ones. This finding provides further empirical support for the personal space invasion theory framework.

Table C1. Heterogeneity across Morning and Evening Peak Hours for Different Functionality Category

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	UsageDuration		**SocDuration**		**InfDuration**	
Peak	Morning	Evening	Morning	Evening	Morning	Evening
Crowdedness	0.078***	0.039**	0.038***	0.032**	0.027**	0.026**
	(0.016)	(0.017)	(0.012)	(0.013)	(0.011)	(0.011)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	27873	27850	27873	27850	27873	27850
R-Squared	0.4935	0.4672	0.4437	0.4312	0.4824	0.4581

	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	EntDuration		**ShopDuration**		**ToolDuration**	
Peak	Morning	Evening	Morning	Evening	Morning	Evening
Crowdedness	0.038***	0.031**	0.011	0.004	0.043***	0.023**
	(0.012)	(0.012)	(0.007)	(0.008)	(0.011)	(0.011)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	27873	27850	27873	27850	27873	27850
R-Squared	0.4987	0.4710	0.4147	0.4034	0.4987	0.4727

*Note. * p<0.1, ** p<0.05, *** p<0.01.* 4,463 and 4,952 singleton observations are excluded from the estimations for morning and evening peak trips, respectively.

D. ROBUSTNESS CHECKS

In this section, we present additional analyses to assess the robustness of our findings. Our baseline specification includes user fixed effects and fully interacted Route × Day × Hour fixed effects, which absorb a broad set of common shocks within each route–time cell. While this specification substantially reduces potential confounding, it does not fully eliminate all sources of endogeneity. Accordingly, the following analyses are intended to provide complementary evidence on the robustness of the observed patterns.

We conduct several additional checks. First, we implement an instrumental variable (IV) approach (Section D1). Second, we perform subsample analyses focusing on regular passengers to address potential simultaneity bias (Section D2). In addition, we assess whether our results are overly influenced by WeChat, the dominant super app (Section D3), test the consistency of findings within super apps and at the individual app level (Sections D4 and D5), evaluate sensitivity to measurement error in the crowdedness variable (Section D6), and validate the results using an alternative proxy for prior subway experience (Section D7).

D1. Instrumental Variable Approach

To further examine the robustness of our results, we implement a two-stage least squares (2SLS) instrumental variable approach (Angrist & Krueger 1994). Instrumental variable should meet both relevance and exclusion restriction assumptions (Wooldridge 2010). In other words, the instrumental variable should be highly correlated with the endogenous variable and uncorrelated with the error. In this study, we introduce two instrumental variables. First, we employ $YesterdayCrowd_{ij}$, the one-day lagged value of $Crowdedness_{ij}$ on the same route as each user's focal route, as an instrumental variable for $Crowdedness_{ij}$ (Choi et al. 2023, James et al. 2023, Siebert & Zubanov 2010). Specifically, for trip j of user i, we use the average level of crowdedness at the same time on same route on the previous day and define this as $YesterdayCrowd_{ij}$. For example, if $Crowdedness_{ij}$ measures the level of crowdedness for trip j in Qingdao Line 2 taken by user i at 2pm on Tuesday, $YesterdayCrowd_{ij}$ represents the average crowdedness level on the trips with the same end stations at 2pm on Monday. The intuition is that lagged crowdedness and current crowdedness are correlated because of persistent daily patterns in public transit. However, conditional on the fixed effects including user and Day × Hour × Route fixed effects, any influence of lagged crowdedness on current mobile usage operates primarily through its effect on current crowdedness.

Second, we use the average crowdedness during the same hour on the same day on trips of the same length along Line 3, denoted as $Line3Crowd_{ij}$ as an additional instrumental variable. For example, if $Crowdedness_{ij}$ measures the level of crowdedness for trip j on Qingdao Line 2 taken by user i at 2 pm on a particular day, $Line3Crowd_{ij}$ represents the average crowdedness level of trips on Qingdao Line 3 at 2pm on the same day and with the same length as trip j taken by user i. Qingdao Line 3, like Line 2, is a high-traffic subway line located in the main urban area. Given their similar travel demand patterns, crowdedness on Line 3 serves as a strong predictor for crowdedness on Line 2 due to the network-level demand interactions within the subway system, satisfying the relevance condition. Additionally, conditional on the inclusion of rich fixed effects, the influence of Line 3 crowdedness on mobile usage on Line 2 operates primarily through its effect on crowdedness on Line 2.

We assess the validity of the instrumental variables used in our analysis. The coefficients for the IVs in the first stage are all statistically significant (coefficient of *CrowdLine3* = 0.159, $p < 0.01$; coefficient of *YesterdayCrowd* = 0.294, $p < 0.01$). The strength of IVs is assessed with a first-stage Sanderson-Windmeijer multivariate F-test for excluded instruments ($p < 0.01$), the Kleibergen-Paap rank statistic ($p < 0.01$), and the Cragg-Donald statistic, exceeding the Stock-Yogo critical value for a 10% maximal IV size. The Hansen J statistic for testing over-identification returns a p-value of 0.63, which is greater than 0.10, suggesting that the null hypothesis of instrument exogeneity cannot be rejected. These diagnostic tests collectively affirm the strength and validity of our instrumental variables.

Tables D1 – D4 present the results of the 2SLS analyses using the two instrumental variables, which are consistent with our main findings. Specifically, we observe a significantly positive relationship between crowdedness and organic mobile usage, particularly pronounced for social functionality usage for users with shorter previous subway trips, during off-peak hours and surrounded by different-age groups.

Table D1. 2SLS Results for Diverse Functionality Usage

	(1) UsageDur	(2) SocDur	(3) InfDur	(4) EntDur	(5) ShopDur	(6) ToolDur
Crowdedness	0.222***	0.181***	0.008	0.134***	-0.008	0.035

	(0.049)	(0.035)	(0.030)	(0.034)	(0.020)	(0.035)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	198061	198061	198061	198061	198061	198061
R-Squared	0.0009	-0.0015	0.0004	-0.0008	-0.0003	0.0011

Note. * p<0.1, ** p<0.05, *** p<0.01. 9,185 singleton observations are excluded from the estimation.

Table D2. 2SLS Results for Users with Short and Long Previous Subway Trips

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	UsageDuration		**SocDuration**		**InfDuration**	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.259***	0.145*	0.198***	0.127**	0.042	-0.017
	(0.067)	(0.078)	(0.047)	(0.056)	(0.042)	(0.048)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	104640	89513	104640	89513	104640	89513
R-Squared	0.0001	0.0019	-0.0026	0.0007	0.0011	-0.0004
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	EntDuration		**ShopDuration**		**ToolDuration**	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.162***	0.077	-0.004	0.006	0.078*	-0.011
	(0.047)	(0.052)	(0.028)	(0.031)	(0.047)	(0.055)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	104640	89513	104640	89513	104640	89513
R-Squared	-0.0024	0.0010	-0.0002	0.0002	0.0015	-0.0003

Note. * p<0.1, ** p<0.05, *** p<0.01. 8,504 and 4,589 singleton observations are excluded from the estimation for users with short- and long-length previous subway trips respectively.

Table D3. 2SLS Results During Peak and Off-Peak Hours

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	UsageDuration		**SocDuration**		**InfDuration**	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	1.903	0.270***	0.903	0.269***	1.882	-0.013
	(5.574)	(0.065)	(0.720)	(0.045)	(1.416)	(0.040)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	52438	140480	52438	140480	52438	140480
R-Squared	-0.6753	-0.0001	-0.2513	-0.0066	-1.5201	-0.0004
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	EntDuration		**ShopDuration**		**ToolDuration**	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	1.745*	0.132***	0.510*	-0.025	1.023	0.030
	(1.055)	(0.043)	(0.305)	(0.025)	(0.839)	(0.045)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	52438	140480	52438	140480	52438	140480
R-Squared	-1.0872	-0.0009	-0.2617	-0.0013	-0.3836	0.0010

Note. * p<0.1, ** p<0.05, *** p<0.01. 5,160 and 9,168 singleton observations are excluded from the estimations for peak and off-peak trips, respectively.

Table D4. 2SLS Results for the Same- and Different-Age Crowdedness

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	UsageDur	**SocDur**	**InfDur**	**EntDur**	**ShopDur**	**ToolDur**
SameCrowdedness	0.107**	0.031	0.017	0.037	-0.014	0.091**
	(0.053)	(0.039)	(0.034)	(0.037)	(0.021)	(0.039)

DifferentCrowdedness	0.172***	0.171***	0.001	0.119***	0.001	-0.014
	(0.054)	(0.038)	(0.034)	(0.037)	(0.022)	(0.039)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	197913	197913	197913	197913	197913	197913
R-Squared	0.0002	-0.0016	0.0003	-0.0010	-0.0005	-0.0010

Note. * p<0.1, ** p<0.05, *** p<0.01. For the independent variable of same/different-age crowdedness, we use the $YesterdayCrowd_{ij}$ of same/different-age group and $Line3Crowd_{ij}$ of same/different-age group as instrumental variables. 9,183 singleton observations are excluded.

To assess the sensitivity of our IV estimates to potential violations of the exclusion restriction, we conduct a plausibly exogenous sensitivity analysis following Lu et al. (2018) and Conley et al. (2012). This approach evaluates how the estimated coefficients change under bounded deviations from the exclusion restriction.

$$Y = X\beta + Z\gamma + \varepsilon,$$

$$X = Z\Pi + V,$$

where Y is the dependent variable, X is a set of endogenous explanatory variables, ε is the disturbance term, Z is a set of instruments that are presumably uncorrelated with ε, and V is the error term. The traditional instrumental variable studies assume zero correlation between Z and ε, namely the perfect exclusion restriction or $\gamma = 0$. Instead, "plausibly exogenous" method (Lu et al., 2018) loosens such traditional assumption to form confidence interval bounds of β. Specifically, they propose that γ approaches zero but will never be exactly zero and such a deviation from zero assumption and the related sensitivity analysis can be assessed. By replacing the original assumption of $\gamma = 0$, it assumes γ follows a Gaussian prior distribution,$\gamma \sim \boldsymbol{N}(0, \delta^2)$, which leads to a Gaussian distribution for $\hat{\beta}$ of interest (Conley et al., 2012). The sensitivity analysis aims to test whether our models are robust under potentially moderate deviations from exclusion restrictions (i.e., $\gamma = 0$), suggesting that the instruments are "plausibly exogenous" (Conley et al., 2012). In line with (Conley et al., 2012), we obtain the estimate for δ from a reduced form model that regresses our dependent variable on the two instruments and control variables. And we estimate the parameter β using the local-to-zero (LTZ) approximation method developed by Conley et al. (2012) and plot its 90% confidence interval under different levels of δ (from 0.5*SE to 2*SE) in Figure D1. Figure shows that the estimated relationships between crowdedness and usage duration are consistently significant.

The sensitivity analysis suggests that our models are robust under potentially moderate deviations from exclusion restrictions (i.e., $\gamma = 0$), suggesting that these two instruments are "plausibly exogenous" (Conley et al., 2012).

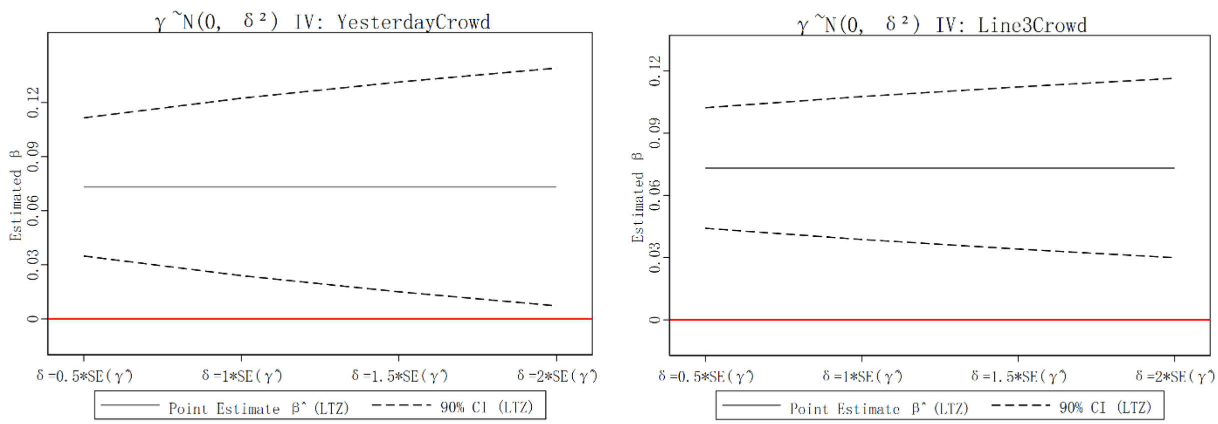

Figure D1. Plausibly Exogenous Test Results

D2. Simultaneity Concern

The observed positive relationship between crowdedness and mobile usage might be influenced by individuals' choice of public transit over driving due to the motivation of using their smartphones. To address this simultaneity concern, we conduct subsample analyses focusing on regular passengers of Qingdao Line 2. Regular passengers are defined as those who use the subway on more than 80% of the days per week. This distinction helps to exclude users who may have chosen to take the subway on a particular day due to specific, external factors, such as using the subway to engage with their smartphones, thus reducing potential biases from those with a more discretionary choice of transportation. By focusing on regular passengers, who have stable and habitual commuting patterns primarily driven by practical commuting needs (rather than the desire to use smartphones during transit), we mitigate the risk of simultaneity, as their decision to take the subway is less likely to be influenced by smartphone-related motivations.

The findings on regular passengers, presented in Tables D5 – D7, align with our main results.[1]

[1] We are unable to compare users with short and long prior trip lengths due to their high correlation with trip regularity.

Additionally, applying different thresholds to define regular passengers (e.g., 70% and 90%) produce consistent results. These results address the simultaneity concern.

Table D5. Relationship between Crowdedness and Diverse Functionality Usage for Regular Users

	(1) UsageDur	(2) SocDur	(3) InfDur	(4) EntDur	(5) ShopDur	(6) ToolDur
Crowdedness	0.125**	0.071*	0.006	0.054	-0.010	0.072
	(0.058)	(0.041)	(0.037)	(0.036)	(0.021)	(0.044)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	3459	3459	3459	3459	3459	3459
R-Squared	0.6074	0.5373	0.6019	0.5458	0.6064	0.6918

Note. * p<0.1, ** p<0.05, *** p<0.01. 4,351 singleton observations are excluded.

Table D6. Heterogeneous Relationships During Peak and Off-Peak Hours for Regular Passengers

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		SocDuration		InfDuration	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	-0.096	0.179**	-0.026	0.079	-0.119	0.009
	(0.122)	(0.077)	(0.105)	(0.049)	(0.094)	(0.049)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	699	2220	699	2220	699	2220
R-Squared	0.7017	0.6133	0.6613	0.5717	0.6863	0.6027
	(7)	(8)	(9)	(10)	(11)	(12)
	EntDuration		ShopDuration		ToolDuration	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	-0.040	0.082*	-0.109**	0.037	0.007	0.072
	(0.089)	(0.048)	(0.054)	(0.029)	(0.100)	(0.056)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	699	2220	699	2220	699	2220
R-Squared	0.6796	0.5545	0.6370	0.6365	0.7328	0.7130

Note. * p<0.1, ** p<0.05, *** p<0.01. 1,281, 3,610 singleton observations are excluded from the estimations for peak and off-peak trips. respectively.

Table D7. Analysis of Same- and Different-Age Crowdedness for Regular Users

	(1) UsageDur	(2) SocDur	(3) InfDur	(4) EntDur	(5) ShopDur	(6) ToolDur
SameCrowdedness	0.069	0.041	0.015	0.008	0.018	0.070*
	(0.059)	(0.042)	(0.038)	(0.037)	(0.021)	(0.041)
DifferentCrowdedness	0.096*	0.053	-0.002	0.051	-0.019	0.039
	(0.058)	(0.043)	(0.038)	(0.037)	(0.023)	(0.041)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	3459	3459	3459	3459	3459	3459
R-Squared	0.6072	0.5369	0.6019	0.5458	0.6066	0.6921

Note. * p<0.1, ** p<0.05, *** p<0.01. 4,351 singleton observations are excluded.

D3. WeChat Effects

Our findings might be predominantly influenced by dominant super app WeChat, which offers multi-category services. To address this concern, we replicate the main analysis while specifically excluding

WeChat usage. The results, presented in Tables D8 – D11 indicate that while the magnitude of the relationships between crowdedness and social functionality usage decreases slightly, owing to WeChat being the most popular social app, the overall results align closely with our main findings. The relationships between crowdedness and mobile usage remains significantly positive and is notably more pronounced for social functionality usage for users with shorter previous subway trips, during off-peak hours and surrounded by the different-age groups. These results address the concern that our findings might be excessively driven by WeChat usage alone.

Table D8. Relationships between Crowdedness and Functionality Usage Excluding Wechat

	(1) UsageDur	(2) SocDur	(3) InfDur	(4) EntDur	(5) ShopDur	(6) ToolDur
Crowdedness	0.108***	0.057***	0.044***	0.052***	0.016***	0.059***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	221416	221416	221416	221416	221416	221416
R-Squared	0.3672	0.3121	0.3535	0.3500	0.3107	0.3784

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,176 singleton observations are excluded from the estimation.

Table D9. Heterogeneous Relationships for Users with Short and Long Previous Subway Trips Excluding Wechat

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		SocDuration		InfDuration	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.116***	0.094***	0.058***	0.052***	0.047***	0.038***
	(0.008)	(0.009)	(0.005)	(0.006)	(0.005)	(0.006)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	113149	102294	113149	102294	113149	102294
R-Squared	0.3919	0.3936	0.3308	0.3471	0.3788	0.3850
	(7)	(8)	(9)	(10)	(11)	(12)
	EntDuration		ShopDuration		ToolDuration	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.056***	0.047***	0.017***	0.017***	0.062***	0.051***
	(0.006)	(0.006)	(0.003)	(0.004)	(0.006)	(0.006)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	113149	102294	113149	102294	113149	102294
R-Squared	0.3797	0.3753	0.3388	0.3444	0.3874	0.4198

Note. * p<0.1, ** p<0.05, *** p<0.01. 11,174 and 8,975 singleton observations are excluded from the estimation for users with short- and long-length previous subway trips respectively.

Table D10. Heterogeneous Relationships During Peak and Off-Peak Hours Excluding WeChat

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		SocDuration		InfDuration	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	0.072***	0.116***	0.036***	0.068***	0.029***	0.048***

	(0.011)	(0.007)	(0.007)	(0.005)	(0.007)	(0.005)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	58192	156335	58192	156335	58192	156335
R-Squared	0.4348	0.3926	0.3840	0.3395	0.4190	0.3865
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	EntDuration		**ShopDuration**		**ToolDuration**	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	0.044***	0.049***	0.012**	0.018***	0.038***	0.066***
	(0.008)	(0.005)	(0.005)	(0.003)	(0.008)	(0.005)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	58192	156335	58192	156335	58192	156335
R-Squared	0.4326	0.3736	0.3579	0.3524	0.4366	0.4092

Note. * p<0.1, ** p<0.05, *** p<0.01. 6,946 and 14,119 singleton observations are excluded from the estimations for peak and off-peak trips, respectively.

Table D11. Analysis of Same- and Different-Age Crowdedness Excluding Wechat

	(1) **UsageDur**	**(2)** **SocDur**	**(3)** **InfDur**	**(4)** **EntDur**	**(5)** **ShopDur**	**(6)** **ToolDur**
SameCrowdedness	0.023***	0.010***	0.010***	0.009**	0.006**	0.019***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
DifferentCrowdedness	0.097***	0.053***	0.039***	0.048***	0.013***	0.049***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	221256	221256	221256	221256	221256	221256
R-Squared	0.3671	0.3120	0.3534	0.3500	0.3107	0.3783

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,168 singleton observations are excluded.

D4. The Relationship between Crowdedness and Functionality Usage within Super Apps

It is possible that how users allocate their time across various single-function non-super apps differs from how they allocate time across multiple functionalities within super apps. To address this concern, we replicate the main analysis using only super app usage. The results, presented in Tables D12 and D13, show that the positive relationships between crowdedness and mobile use continues to be strongest for social functionality usage within super apps. These findings confirm that the heightened preference for social functionality under crowded conditions persists even within super apps.

Table D12. Relationships between Crowdedness and Different Functionality Usage for Super Apps

	SocDuration	**InfDuration**	**EntDuration**	**ShopDuration**	**ToolDuration**
Crowdedness	0.067***	0.040***	0.028***	0.008***	0.003***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.001)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes
No of Obs.	221416	221416	221416	221416	221416
R-Squared	0.3164	0.3606	0.3186	0.2930	0.1955

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,176 singleton observations are excluded from the estimation.

Table D13. Relationships between Crowdedness and Different Functionality Usage Ratio for Super Apps

	SocRatio	InfRatio	EntRatio	ShopRatio	ToolRatio
Crowdedness	0.009***	0.002**	-0.001***	-0.004***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes
No of Obs.	221416	221416	221416	221416	221416
R-Squared	0.2822	0.3299	0.3022	0.2887	0.3181

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,176 singleton observations are excluded from the estimation.

D5. The Relationship between Crowdedness and Mobile Use at the App Level

We also test the robustness of our results across different levels of mobile usage measurement. While the main analysis is based on functionality-level usage, we replicate it using app-level usage duration as an alternative dependent variable. Specifically, the usage duration of each super app is assigned to its primary category as defined in app stores. Tables D14 and D15 show consistent results that the positive relationships still hold for social functionality using app-level usage duration.

Table D14. App-level Analysis of the Relationship between Crowdedness and Mobile Usage

	(1) SocDuration	(2) InfDuration	(3) EntDuration	(4) ShopDuration	(5) ToolDuration
Crowdedness	0.072***	0.061***	0.049***	0.016***	0.058***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes
No. of Obs.	221416	226834	221416	221416	221416
R-Squared	0.3175	0.1159	0.3516	0.3101	0.3806

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,176 singleton observations are excluded from the estimation.

Table D15. Relationship between Crowdedness and Different App Usage Ratio

	(1) SocRatio	(2) InfRatio	(3) EntRatio	(4) ShopRatio	(5) ToolRatio
Crowdedness	0.004***	-0.001	0.001	-0.004***	0.0004
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes
No. of Obs.	221416	221416	221416	221416	221416
R-Squared	0.2717	0.2946	0.3316	0.2789	0.3419

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,176 singleton observations are excluded from the estimation.

D6. Measurements of Crowdedness

To address the concern about the measurement errors of crowdedness, we replicate our main analysis while either (1) right-censoring the crowdedness variable by setting upper and lower bounds at 0 and 5, respectively, or (2) injecting random noise into the crowdedness variable to address concerns about measurement errors. The results of each approach are displayed in Tables D16 – D19 (Tables D20 – D23). These findings are consistent with the main results of our study, effectively alleviating concerns regarding the measurement accuracy of the crowdedness variable.

Additionally, we estimate passenger volume by dividing the number of telecom users by the telecom provider's market penetration rate, following a widely used approach in prior research (e.g., Andrews et al. (2016)). Nevertheless, to address concerns about potential measurement error in extrapolating total metro ridership from our telecom sample, we conduct a robustness check using an alternative crowdedness measure based on actual daily ridership data from Qingdao Line 2. Specifically, for each day, we calculate an identification ratio by dividing the number of telecom users by the official daily ridership, and then use this ratio, rather than the market penetration rate, to estimate total passenger volume. The results, shown in Tables D24 – D27, remain consistent with our main findings, alleviating concerns regarding this source of measurement error.

Table D16. Relationships between Bounded Crowdedness and Diverse Functionality Usage

	(1) UsageDur	(2) SocDur	(3) InfDur	(4) EntDur	(5) ShopDur	(6) ToolDur
Crowdedness	0.114***	0.073***	0.043***	0.052***	0.016***	0.059***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	221369	221369	221369	221369	221369	221369
R-Squared	0.3629	0.3171	0.3536	0.3500	0.3107	0.3784

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,175 singleton observations are excluded from the estimation.

Table D17. Heterogeneous Relationships between Bounded Crowdedness and Mobile Use by Average Previous Subway Trip Length

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		SocDuration		InfDuration	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.121***	0.100***	0.074***	0.067***	0.047***	0.038***
	(0.008)	(0.009)	(0.006)	(0.007)	(0.005)	(0.006)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	113126	102271	113126	102271	113126	102271
R-Squared	0.3877	0.3894	0.3354	0.3520	0.3788	0.3850
	(7)	(8)	(9)	(10)	(11)	(12)
	EntDuration		ShopDuration		ToolDuration	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.056***	0.047***	0.016***	0.018***	0.062***	0.051***

	(0.006)	(0.006)	(0.003)	(0.004)	(0.006)	(0.006)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	113126	102271	113126	102271	113126	102271
R-Squared	0.3798	0.3754	0.3388	0.3445	0.3874	0.4199

Note. * p<0.1, ** p<0.05, *** p<0.01. 11,172 and 8,975 singleton observations are excluded from the estimation for users with short- and long-length previous subway trips respectively.

Table D18. Heterogeneous Relationships between Bounded Crowdedness and Mobile Use During Peak and Off-Peak Hours

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	UsageDuration		**SocDuration**		**InfDuration**	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	0.074***	0.125***	0.046***	0.088***	0.029***	0.047***
	(0.011)	(0.008)	(0.008)	(0.006)	(0.007)	(0.005)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	58192	156286	58192	156286	58192	156286
R-Squared	0.4313	0.3880	0.3885	0.3445	0.4190	0.3866
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	EntDuration		**ShopDuration**		**ToolDuration**	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	0.044***	0.049***	0.012**	0.017***	0.038***	0.067***
	(0.008)	(0.005)	(0.005)	(0.003)	(0.008)	(0.005)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	58192	156286	58192	156286	58192	156286
R-Squared	0.4326	0.3736	0.3579	0.3524	0.4366	0.4093

*Note. * p<0.1, ** p<0.05, *** p<0.01.* 6,946 and 14,120 singleton observations are excluded from the estimations for peak and off-peak trips, respectively.

Table D19. Analysis of Same- and Different-Age Crowdedness with Bounded Crowdedness

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	UsageDur	**SocDur**	**InfDur**	**EntDur**	**ShopDur**	**ToolDur**
SameCrowdedness	0.024***	0.013***	0.010**	0.009**	0.006**	0.019***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
DifferentCrowdedness	0.103***	0.067***	0.039***	0.048***	0.013***	0.050***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	221209	221209	221209	221209	221209	221209
R-Squared	0.3629	0.3170	0.3534	0.3500	0.3107	0.3784

*Note. * p<0.1, ** p<0.05, *** p<0.01.* 14,167 singleton observations are excluded.

Table D20. Relationships between Noise-Injected Crowdedness and Diverse Functionality Usage

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	UsageDur	**SocDur**	**InfDur**	**EntDur**	**ShopDur**	**ToolDur**
Crowdedness	0.100***	0.061***	0.037***	0.049***	0.015***	0.052***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	221416	221416	221416	221416	221416	221416
R-Squared	0.3626	0.3168	0.3534	0.3499	0.3106	0.3783

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,176 singleton observations are excluded from the estimation.

Table D21. Heterogeneous Relationships between Noise-Injected Crowdedness and Mobile Use

by Average Previous Subway Trip Length

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		**SocDuration**		**InfDuration**	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.107***	0.087***	0.060***	0.056***	0.041***	0.033***
	(0.008)	(0.009)	(0.006)	(0.006)	(0.005)	(0.006)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	113149	102294	113149	102294	113149	102294
R-Squared	0.3874	0.3892	0.3350	0.3517	0.3786	0.3849
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	EntDuration		**ShopDuration**		**ToolDuration**	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.053***	0.046***	0.016***	0.016***	0.055***	0.044***
	(0.006)	(0.006)	(0.003)	(0.004)	(0.005)	(0.006)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	113149	102294	113149	102294	113149	102294
R-Squared	0.3797	0.3753	0.3388	0.3444	0.3872	0.4197

Note. * p<0.1, ** p<0.05, *** p<0.01. 11,174 and 8,975 singleton observations are excluded from the estimation for users with short- and long-length previous subway trips respectively.

Table D22. Heterogeneous Relationships between Noise-Injected Crowdedness and Mobile Use During Peak and Off-Peak Hours

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		**SocDuration**		**InfDuration**	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	0.066***	0.106***	0.037***	0.071***	0.025***	0.039***
	(0.011)	(0.007)	(0.008)	(0.005)	(0.007)	(0.005)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	58192	156335	58192	156335	58192	156335
R-Squared	0.4311	0.3876	0.3884	0.3441	0.4189	0.3864
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	EntDuration		**ShopDuration**		**ToolDuration**	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	0.042***	0.046***	0.015***	0.015***	0.035***	0.056***
	(0.008)	(0.005)	(0.005)	(0.003)	(0.008)	(0.005)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	58192	156335	58192	156335	58192	156335
R-Squared	0.4326	0.3735	0.3580	0.3523	0.4365	0.4090

*Note. * p<0.1, ** p<0.05, *** p<0.01.* 6,946 and 14,119 singleton observations are excluded from the estimations for peak and off-peak routes, respectively.

Table D23. Analysis of Same- and Different-Age Crowdedness with Noise-Injected Crowdedness

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDur	**SocDur**	**InfDur**	**EntDur**	**ShopDur**	**ToolDur**
SameCrowdedness	0.010**	0.008**	0.004	0.003	-0.001	0.009**
	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)
DifferentCrowdedness	0.095***	0.061***	0.035***	0.042***	0.013***	0.047***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	221256	221256	221256	221256	221256	221256

R-Squared	0.3625	0.3168	0.3533	0.3498	0.3107	0.3781

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,168 singleton observations are excluded.

Table D24. Relationships between Crowdedness and Mobile Usage with the Crowdedness Calculated using Actual Ridership

	(1) UsageDur	(2) SocDur	(3) InfDur	(4) EntDur	(5) ShopDur	(6) ToolDur
Crowdedness	0.115***	0.073***	0.044***	0.053***	0.016***	0.059***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	221416	221416	221416	221416	221416	221416
R-Squared	0.3629	0.3170	0.3535	0.3500	0.3107	0.3784

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,176 singleton observations are excluded from the estimation.

Table D25. Heterogeneous Analysis for Users with Short and Long Previous Subway Trip with the Crowdedness Calculated using Actual Ridership

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		SocDuration		InfDuration	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.123***	0.099***	0.074***	0.066***	0.048***	0.038***
	(0.008)	(0.009)	(0.006)	(0.007)	(0.005)	(0.006)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	113149	102294	113149	102294	113149	102294
R-Squared	0.3877	0.3893	0.3353	0.3519	0.3788	0.3849
	(7)	(8)	(9)	(10)	(11)	(12)
	EntDuration		ShopDuration		ToolDuration	
PrevTripLength	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.058***	0.048***	0.017***	0.018***	0.062***	0.051***
	(0.006)	(0.006)	(0.003)	(0.004)	(0.006)	(0.007)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	113149	102294	113149	102294	113149	102294
R-Squared	0.3798	0.3753	0.3388	0.3444	0.3874	0.4198

Note. * p<0.1, ** p<0.05, *** p<0.01. 11,174 and 8,975 singleton observations are excluded from the estimation for users with short- and long-length previous subway trips respectively.

Table D26. Heterogeneous Analysis During Peak and Off-Peak Hours with the Crowdedness Calculated using Actual Ridership

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		SocDuration		InfDuration	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	0.073***	0.128***	0.045***	0.089***	0.028***	0.049***
	(0.011)	(0.008)	(0.008)	(0.006)	(0.007)	(0.005)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	58192	156335	58192	156335	58192	156335
R-Squared	0.4313	0.3879	0.3885	0.3444	0.4190	0.3865
	(7)	(8)	(9)	(10)	(11)	(12)
	EntDuration		ShopDuration		ToolDuration	
PeakHour	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak
Crowdedness	0.044***	0.051***	0.012**	0.019***	0.036***	0.068***
	(0.008)	(0.005)	(0.005)	(0.003)	(0.008)	(0.006)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes

No. of Obs	58192	156335	58192	156335	58192	156335
R-Squared	0.4327	0.3736	0.3579	0.3524	0.4365	0.4092

*Note. * p<0.1, ** p<0.05, *** p<0.01.* 6,946 and 14,119 singleton observations are excluded from the estimations for peak and off-peak trips, respectively.

Table D27. Analysis of Same- and Different-Age Crowdedness with the Crowdedness Calculated using Actual Ridership

	(1) UsageDur	(2) SocDur	(3) InfDur	(4) EntDur	(5) ShopDur	(6) ToolDur
SameCrowdedness	0.023***	0.012***	0.010***	0.009**	0.006**	0.019***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)
DifferentCrowdedness	0.099***	0.064***	0.037***	0.048***	0.013***	0.047***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	221256	221256	221256	221256	221256	221256
R-Squared	0.3692	0.3226	0.3551	0.3510	0.3117	0.3823

Note. * p<0.1, ** p<0.05, *** p<0.01. 14,168 singleton observations are excluded.

D7. Alternative Measure of Previous Subway Experiences

In this section, we introduce three alternative measures of previous subway experience: the total length of previous subway trips, the total number of distinct days on which trips were taken, and the aggregated level of crowdedness encountered during those prior trips. Specifically, $TotalTripLength_i$ captures the total number of stations traveled by user i during the first week of the observation period. $TripDays_i$ denotes the number of distinct days on which user i took at least one subway trip during the same period. $TripCrowd_i$ captures the aggregated level of crowdedness experienced by user i across all subway trips taken during that week. As shown in Table D28, the positive relationships between crowdedness and organic mobile use are stronger for users with shorter, fewer, and lower-crowdedness prior subway experience than for those with longer, more days of, and more crowded experiences, respectively.

Table D28. Sub-sample Results of Alternative Measure of Previous Experiences

	(1)	(2)	(3)	(4)	(5)	(6)
	UsageDuration		**UsageDuration**		**UsageDuration**	
	TotalTripLength		TripDays		TripCrowd	
Moderator	Lower	Higher	Lower	Higher	Lower	Higher
Crowdedness	0.118***	0.108***	0.114***	0.101***	0.119***	0.104***
	(0.008)	(0.011)	(0.008)	(0.008)	(0.008)	(0.010)
#Trips / 4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	135923	78621	104610	111645	128141	86300
R-Squared	0.3931	0.3834	0.4165	0.3456	0.4049	0.3641

Note. * p<0.1, ** p<0.05, *** p<0.01. 12,969, 8,079, 12,191, 7,146, 13,539 and 7,612 singleton observations are excluded for the estimation of Columns (1)- (6).

E. SURVEYS

E1. Survey Items

Table E1 shows the specific measurement items used in the survey, most of which were adapted from established research and refined according to our context. Specifically, we first measured our primary independent variable, perceived crowdedness, using an item developed by Maeng et al. (2013) for evaluating a room setting, which we adapted to a subway carriage context. Participants rated their perception on a 7-point Likert scale, where 1 indicated "strongly uncrowded" and 7 "strongly crowded." In addition, to validate the effectiveness of our contextual manipulation, participants were asked to confirm whether their simulated subway journey occurred during peak or off-peak hours, and whether they were surrounded by individuals from the same or different age groups.

Subsequently, we assessed various constructs for the proposed mechanism (i.e., personal space invasion) and potential alternative mechanisms (i.e., mobile immersion, stress, network connectivity, boredom, and desire for distraction). To measure personal space invasion, we adapted items from Jiang et al. (2013), which were originally developed to assess perceived intrusiveness, particularly the extent to which individuals feel their personal space is acknowledged or unsolicitedly invaded. Building on this foundation, we incorporated three fundamental functions of personal space—protection of self-esteem, privacy, and maintenance of a sense of control—as conceptualized by Altman (1975), Dosey and Meisels (1969), Edney et al. (1976), Horowitz et al. (1964). This integration led to the development of seven distinct items to measure personal space invasion. These items assess the extent to which surrounding individuals impact a respondent's self-esteem, perceived privacy, and sense of control, as well as the overall degree to which personal space is respected.

We adapted measures for mobile immersion, stress, and boredom from Andrews et al. (2016), Durante and Laran (2016), and Vodanovich and Watt (2016), respectively, with minor modifications to align with the subway carriage context. The items measuring desire for distraction were adapted from Peck and Childers (2003), who originally developed them to assess individuals' need for tactile interaction with products in retail environments. We revised these items to capture individuals' desire to mentally disengage from their immediate surroundings while on the subway. Moreover, we developed our own set of measures for perceived network connectivity problems. These items were specifically designed to assess the stability of network connections, the frequency of disconnections, and the overall availability of mobile service within the subway environment.

The measures used to assess smartphone usage intention—our key outcome variable—were adapted from Limayem et al. (2007), who originally developed them to evaluate users' intentions to adopt World Wide Web technologies. We modified these items to capture intentions related to general smartphone usage, as well as usage intentions across specific functionality categories: social, information, entertainment, shopping, and tool functionalities. To ensure respondents clearly understood each category, we provided specific examples of representative functionalities.

We also control for a wide range of factors that could potentially affect individuals' smartphone usage behavior. These include demographic factors (age, gender, and income), prior subway travel patterns (average trip duration and frequency over the past week), and smartphone usage behaviors (smartphone usage tenure, general preference for using smartphones during subway trips, and the frequency of using social, information, entertainment, shopping, and tool functionalities).

Table E1. Survey Item Measurements

Variable / Construct	Measurement items	Source
Crowdedness	How crowded do you feel the subway carriage is now? [Strongly uncrowded (1) to Strongly crowded (7)]	Maeng et al. (2013)
Peak Hour Trip	I am currently riding the subway during a morning peak hour.	
Surrounding Social Composition	People around me are of the same age as I am.	
Personal space invasion	(1) I feel that people around me in this subway carriage are intrusive. (2) I feel that people around me in this subway carriage intrude my privacy. (3) People around me in this subway carriage do not respect my need for personal space. (4) I feel that I cannot control the distance between myself and others in this subway carriage. (5) The presence of those around me in this subway carriage limits my ability to control my personal space. (6) I feel that my self-worth is being threatened in this subway carriage. (7) The people around me in this subway carriage make it difficult for me to feel confident and safe in this space.	Jiang et al. (2013)[a]

Mobile Immersion	(1) I am usually eager to get away by myself in this subway carriage. (2) During this subway ride, I would like to spend the time quietly.	Andrews et al. (2016)
Stress	(1) I find it hard to wind down in this subway carriage. (2) I find it difficult to relax in this subway carriage. (3) I have a lot of nervous energy in this subway carriage. (4) I find myself getting agitated in this subway carriage. (5) I find that I am very irritable in this subway carriage. (6) I feel that I am rather touchy in this subway carriage.	Durante and Laran (2016)[b]
Network connectivity problem	(1) I anticipate connection issues when using mobile networks in this subway carriage. (2) I believe mobile networks are inaccessible in this subway carriage. (3) I expect disconnections with the mobile network in this subway carriage.	
Feeling of boredom	(1) I think my surroundings are unexciting. (2) I think my surroundings are boring. (3) I feel that my surroundings are dull and 'blah.'	Vodanovich and Watt (2016)[c]
Desire for distraction	(1) I can't help but want to distract myself from the surroundings. (2) I feel comfortable after distracting myself from the surroundings. (3) It is important for me to distract from the surroundings	Peck and Childers (2003)[c]
Smartphone usage intention	(1) I intend to use my smartphones / social / information / entertainment / shopping / tool functionality rather than doing anything else in this subway carriage. (2) My intensions are using my smartphones / social / information / entertainment / shopping / tool functionality rather than doing anything else in this subway carriage. (3) If I could, I would like to use my smartphones / social / information / entertainment / shopping / tool functionality in this subway carriage.	Limayem et al. (2007)
Age	18~25; 26~30; 31~35; 36~40; 41~45; 46~50; above 51	
Gender	Male; Female	
Income	< 5000 RMB; 5000~8000 RMB; 8000~10000 RMB; 10000~15000 RMB; 15000~20000 RMB; > 20000 RMB	
Average previous subway trip duration	Please recall your subway trips in the last week. How many minutes did you spend on average per trip? Less than 10 minutes, 10-20 minutes, 21-30 minutes, 31-40 minutes, 41-50 minutes, more than 50 minutes.	
Average previous subway trip frequency	How frequently do you take the subway on a weekly basis? Less than 5 times; 5-10 times; More than 10 times	
Smartphone usage tenure	For how many years have you been using smartphones? Less than 1 year; 1 to 3 years; 3 to 5 years; 5 to 10 years; more than 10 years	
Smartphone usage during subway trips	I always use my smartphone when I am on the subway.	
Social, information, entertainment, shopping, and tool functionality usage frequency	In the past month, how frequently have you used social, information, entertainment, shopping, and tool functionalities? [Scale from "Never" (1) to "Very often" (6)]	Elhai et al. (2016)

Note. Unless otherwise noted, items are measured using a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7). [a] Two original items deemed irrelevant, namely 'The other party was overly persistent in getting me to respond' and 'I felt that the other party was harassing me during the interaction.' were excluded from our study as our study does not focus on individual interactions. [b] Two original items, namely 'I am in a state of nervous tension' and 'I find myself getting upset' were excluded from our study due to concerns regarding the length of the questionnaire. [c] Only three items are included in our study due to concerns regarding the length of the questionnaire.

E2. Pilot Survey

Before launching the full survey, a pilot test was carried out to verify the effectiveness of manipulating crowdedness and user contexts. For this purpose, 50 participants for each of the eight scenarios were recruited from the online survey platform Credamo (https://www.credamo.com/). Respondents completed a brief questionnaire that included measures of perceived crowdedness, time context (peak vs. off-peak hours), and social context (same-age vs. different-age group).

The results confirmed that the manipulations functioned as intended. Participants in low-crowdedness scenarios (Scenarios 1, 2, 5, and 6) reported significantly lower levels of perceived crowdedness than those in high-crowdedness scenarios (Scenarios 3, 4, 7, and 8), with mean ratings of 1.94 versus 4.42 ($p < 0.01$). The peak vs. off-peak manipulation was also effective: participants in peak-hour scenarios (Scenarios 1 and 3) were significantly more likely to report their trip as occurring during peak hours compared to those in off-peak scenarios (Scenarios 2 and 4), with mean ratings of 5.85 versus 1.92 ($p < 0.01$). Likewise, participants in same-age scenarios (Scenarios 5 and 7) were significantly more likely to perceive surrounding individuals as being of the same age group compared to those in different-age scenarios (Scenarios 6 and 8), with mean ratings of 5.99 versus 2.02 ($p < 0.01$).

E3. Survey Quality Assessment

In the formal survey, after excluding responses that failed the attention and manipulation checks, we retained 315 valid samples for analysis. The effectiveness of the experimental manipulations—crowdedness, peak-hour timing, and age-related social context—was confirmed, as detailed in Panel A of Table E2. Participants in low-crowdedness scenarios perceived the subway carriage as significantly less crowded than those in high-crowdedness scenarios (1.79 vs 4.63, $p < 0.01$). Likewise, those in peak-hour scenarios more strongly agreed that they were traveling during a peak period compared to participants in off-peak scenarios (6.41 vs 1.41, $p < 0.01$). Additionally, participants in same-age group scenarios were more likely to perceive that they were surrounded by individuals of a similar age, compared to those in different-age group scenarios (6.32 vs 1.38, $p < 0.01$). Furthermore, Panel B of Table E2 presents a balance check for the final sample, showing that the control variables, such as demographics, past subway usage, and smartphone usage behavior are statistically insignificant among the scenarios. It demonstrates that the scenarios are comparable, affirming the effectiveness of the random assignment of participants to each scenario.

Table E2. Manipulation and Balance Check for Control Variables

	All samples		**Peak Hour**		**Off-Peak Hour**		**Same-Age Group**		**Diff-Age Group**	
	Uncrowded (Scenarios 1, 2, 5, 6)	Crowded (Scenarios 3, 4, 7, 8)	Uncrowded (Scenario 1)	Crowded (Scenario 3)	Uncrowded (Scenario 2)	Crowded (Scenario 4)	Uncrowded (Scenario 5)	Crowded (Scenario 7)	Uncrowded (Scenario 6)	Crowded (Scenario 8)
Panel A: Manipulation checks										
Crowdedness	1.79	4.63	1.63	4.46	1.84	4.53	1.79	4.71	1.90	4.86
	(0.81)	(1.11)	(0.73)	(1.19)	(0.93)	(1.27)	(0.77)	(0.79)	(0.82)	(1.09)
	$p < 0.01$		$p < 0.01$		$p < 0.01$		$p < 0.01$		$p < 0.01$	
Peak Hour			6.41 (0.67)		1.41 (0.61)					
			$p < 0.01$							
Same Age							6.32 (0.67)		1.38 (0.61)	
							$p < 0.01$			
Panel B: Balance checks of control variables										
Age	2.87	2.96	2.76	2.88	3.03	3.02	2.95	2.97	2.76	2.94
	(1.42)	(1.56)	(1.36)	(1.71)	(1.7)	(1.76)	(1.63)	(1.42)	(0.98)	(1.26)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Gender	0.31	0.3	0.32	0.27	0.29	0.28	0.37	0.29	0.26	0.4
	(0.46)	(0.46)	(0.47)	(0.45)	(0.46)	(0.45)	(0.49)	(0.46)	(0.45)	(0.5)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Income	3.38	3.23	3.12	3.02	3	2.94	3.12	3.37	4.19	3.71
	(1.59)	(1.37)	(1.5)	(1.37)	(1.59)	(1.37)	(1.52)	(1.31)	(1.5)	(1.34)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Average subway trip duration	3.21	3.33	3.32	3.32	3.23	3.43	3.23	3.11	3.07	3.43
	(1.07)	(1.1)	(1.11)	(1.06)	(1.28)	(1.21)	(1.04)	(0.93)	(0.89)	(1.14)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Average Subway trip frequency	2.82	2.92	2.71	3.12	2.71	2.66	2.7	3.17	3.12	2.77
	(1.25)	(1.25)	(1.36)	(1.27)	(1.13)	(1.32)	(1.3)	(1.22)	(1.15)	(1.11)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Smartphone usage tenure	4.38	4.48	4.46	4.51	4.45	4.45	4.37	4.51	4.26	4.46
	(0.69)	(0.63)	(0.64)	(0.64)	(0.57)	(0.65)	(0.72)	(0.61)	(0.8)	(0.61)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Smartphone usage during subway trips	5.78	5.88	5.93	5.95	5.48	5.87	5.53	5.6	6.1	6.09
	(0.91)	(0.89)	(0.93)	(1.02)	(0.96)	(0.97)	(0.93)	(0.74)	(0.69)	(0.7)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Social func usage freq	5.36	5.28	5.56	5.39	5.19	5.23	5.35	5.17	5.31	5.34
	(0.63)	(0.67)	(0.55)	(0.54)	(0.75)	(0.6)	(0.57)	(0.57)	(0.64)	(0.94)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Infor func usage freq	4.53	4.59	4.46	4.39	4.32	4.53	4.33	4.66	4.95	4.83
	(0.92)	(0.88)	(0.92)	(1)	(0.75)	(0.91)	(1.13)	(0.76)	(0.62)	(0.75)

	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Enter func usage freq	5.11	5.1	5.07	5.32	4.84	4.98	5	4.86	5.48	5.26
	(0.79)	(0.74)	(0.69)	(0.65)	(0.86)	(0.82)	(0.76)	(0.73)	(0.77)	(0.66)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Shop func usage freq	4.52	4.43	4.46	4.66	4.61	4.17	4.16	4.29	4.86	4.66
	(0.96)	(1.01)	(0.74)	(0.73)	(1.12)	(1.31)	(0.92)	(0.83)	(0.95)	(0.94)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	
Tool func usage freq	4.2	4.18	4.27	4.29	4.06	4	4	4.26	4.43	4.2
	(0.89)	(0.9)	(0.9)	(0.87)	(0.85)	(0.93)	(0.93)	(0.92)	(0.83)	(0.87)
	$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$		$p > 0.1$	

Note. *p*-values denote the statistical significance of a differences between scenarios. Standard deviations are presented in parentheses.

The measurement model analysis demonstrates adequate reliability, as well as convergent and discriminant validity of the constructs. According to results presented in Table E3, the Composite Reliability (CR) and Cronbach's Alpha (CA) for all constructs exceed 0.7, affirming the reliability of our construct measurements. The Average Variance Extracted (AVE) surpasses 0.50, and the square root of AVE exceeds the values of other items within the same row or column, showcasing adequate convergent and discriminant validity of our measures. Furthermore, Table E4 illustrates that all factor loadings exceed 0.7, with values ranging between 0.75 and 0.97. This finding further validates that the measurement items are appropriately associated with their respective constructs.

Table E3. Reliability, Convergent Validity, and Discriminant Validity Test Results

	AVE	CR	CA	Inter-Construct Correlations											
				1	2	3	4	5	6	7	8	9	10	11	12
1. PSI	0.658	0.931	0.914	0.811											
2. MI	0.869	0.93	0.851	0.237	0.932										
3. ST	0.698	0.933	0.914	0.788	0.381	0.836									
4. NCP	0.77	0.909	0.851	0.463	0.242	0.473	0.878								
5. BO	0.86	0.948	0.918	0.333	0.474	0.483	0.353	0.927							
6. DD	0.814	0.929	0.889	0.342	0.51	0.468	0.326	0.646	0.902						
7. SPUI	0.626	0.834	0.701	0.31	0.173	0.172	0.048	0.206	0.201	0.791					
8. SFUI	0.787	0.917	0.865	0.207	-0.009	0.09	-0.004	0.038	0.012	0.362	0.887				
9. IFUI	0.916	0.971	0.954	-0.111	-0.04	-0.157	-0.237	-0.243	-0.149	-0.077	0.135	0.957			
10. EFU	0.892	0.961	0.939	0.003	-0.03	-0.026	-0.03	0.098	0.084	0.227	0.058	0.095	0.944		
11. SFUI	0.931	0.976	0.963	-0.066	-0.054	-0.115	-0.126	-0.154	-0.158	-0.065	0.125	0.382	0.147	0.965	
12. TFUI	0.925	0.974	0.96	-0.088	-0.08	-0.072	-0.205	-0.151	-0.108	-0.027	0.152	0.444	0.127	0.348	0.962

Note. Personal Space Invasion (PSI); Mobile Immersion (MI); Stress (ST); Network Connectivity Problem (NCP); Boredom (BO); Desire for Distraction (DD); Smartphone Usage Intention (SPUI); Social Functionality Usage Intention (SFUI); Information Functionality Usage Intention (IFUI); Entertainment Functionality Usage Intention (EFUI); Shopping Functionality Usage Intention (SFUI); Tool Functionality Usage Intention (TFUI). The diagonal cells in the table indicate the square root of the AVE for each construct.

Table E4. Factor Analysis Results

	PSI	MI	ST	NCP	BO	DD	SPUI	SFUI	IFUI	EFU	SFUI	TFUI
PSI1	0.827											
PSI2	0.827											
PSI3	0.831											
PSI4	0.85											
PSI5	0.772											
PSI6	0.761											
PSI7	0.807											
MI1		0.917										
MI2		0.947										
ST1			0.865									
ST2			0.881									
ST3			0.825									
ST4			0.864									
ST5			0.8									
ST6			0.773									
NCP1				0.926								
NCP2				0.935								
NCP3				0.761								
BO1					0.912							
BO2					0.939							
BO3					0.93							
DD1						0.922						
DD2						0.911						
DD3						0.874						
SPUI1							0.849					
SPUI2							0.758					
SPUI3							0.764					
SFUI1								0.899				
SFUI2								0.868				
SFUI3								0.894				
IFUI1									0.961			
IFUI2									0.956			
IFUI2									0.955			
EFUI1										0.949		
EFUI2										0.943		
EFUI3										0.941		
SFUI1											0.964	
SFUI2											0.962	
SFUI3											0.97	
TFUI1												0.962
TFUI2												0.96
TFUI3												0.964

E4. The Heterogeneity Analysis across Temporal, Social Contexts and Individual Traits

We utilized SmartPLS to examine heterogeneous path effects across temporal and social contexts depicted in Table E5. Columns 2 – 5 of Table E5 illustrate that crowdedness heightens users' perception of personal space invasion across all conditions. The heightened perceived personal space invasion leads to increased mobile phone usage, particularly for social functionalities, during off-peak hours and when users are surrounded by individuals from different age groups. The relationship between perceived personal space invasion and social functionality usage intention is positive and statistically significant in the off-peak hour condition (0.467, $p < 0.05$) and in the different-age group condition (0.431, $p < 0.1$). In contrast, the relationship is not statistically significant during peak hours (0.282, $p > 0.1$) or when users are surrounded by same-age individuals (0.32, $p > 0.1$).

Table E5. The PLS Results for Different Scenarios

	(1) All Samples	(2) Peak Hour	(3) Off-Peak Hour	(4) Same-Age Group	(5) Different-Age Group
Mechanism of Personal Space Invasion (PSI)					
Crowdedness → PSI	**0.676*** **	**0.661*** **	**0.695*** **	**0.607*** **	**0.711*** **
PSI → Smartphone Usage	**0.517*** **	**0.509*** **	**0.661*** **	**0.538***	**0.391***
PSI → Social Func Usage	**0.376*** **	0.282	**0.467****	0.32	**0.431***
PSI → Infor Func Usage	0.038	0.052	0.133	0.431	-0.3
PSI → Enter Func Usage	0.035	0.236	0.096	0.191	-0.361
PSI → Shop Func Usage	-0.006	-0.007	0.185	-0.236	-0.108
PSI → Tool Func Usage	-0.067	-0.015	0.212	0.065	-0.446
Mechanism of Mobile Immersion (MI)					
Crowdedness → MI	0.021	-0.006	0.026	-0.067	0.09
MI →Smartphone Usage	**0.087***	0.076	0.161	0.119	0.014
MI → Social Func Usage	-0.045	-0.212	-0.112	0.204	0.125
MI → Infor Func Usage	**0.186*** **	0.016	0.136	0.301	**0.361****
MI → Enter Func Usage	-0.089	0.123	-0.188	-0.053	-0.226
MI → Shop Func Usage	0.046	-0.026	0.059	0.104	0.073
MI → Tool Func Usage	0.01	-0.12	0.201	0.125	-0.07
Mechanism of Stress (ST)					
Crowdedness→ ST	**0.514*** **	**0.521*** **	**0.462*** **	**0.453*** **	**0.618*** **
ST →Smartphone Usage	**-0.297*** **	**-0.435****	-0.175	-0.341	-0.124
ST → Social Func Usage	-0.139	-0.137	-0.138	-0.212	-0.112
ST → Infor Func Usage	-0.078	-0.086	-0.327	-0.348	0.224
ST → Enter Func Usage	-0.12	-0.174	-0.295	-0.069	0.061
ST → Shop Func Usage	-0.032	0.192	**-0.451****	0.364	-0.013

ST → Tool Func Usage	0.104	-0.051	-0.047	0.162	0.352
Mechanism of Network Connectivity Problem (NCP)					
Crowdedness → NCP	**0.358*** **	0.211	**0.464*** **	**0.27** **	**0.5*** **
NCP →Smartphone Usage	**-0.117** **	-0.025	-0.013	-0.309	-0.197
NCP → Social Func Usage	**-0.116* **	-0.194	0.071	-0.108	-0.27
NCP → Infor Func Usage	**-0.147** **	-0.245	-0.046	-0.033	**-0.307** **
NCP → Enter Func Usage	-0.006	-0.217	0.108	-0.019	0.016
NCP → Shop Func Usage	-0.037	-0.043	0.056	-0.111	-0.237
NCP → Tool Func Usage	**-0.177*** **	-0.138	-0.165	**-0.284* **	-0.257
Mechanism of Boredom (BO)					
Crowdedness→ BO	**0.125** **	0.173	**0.187* **	-0.029	**0.176* **
BO →Smartphone Usage	0.057	-0.063	-0.002	0.063	0.116
BO → Social Func Usage	0.032	-0.108	0.144	-0.01	**0.329* **
BO → Infor Func Usage	**-0.22*** **	0.015	-0.144	-0.227	-0.141
BO → Enter Func Usage	0.082	0.283	0.145	0.156	-0.083
BO → Shop Func Usage	-0.069	-0.025	0.034	-0.147	-0.004
BO → Tool Func Usage	-0.113	0.168	-0.222	-0.174	-0.131
Mechanism of Desire for Distraction (DD)					
Crowdedness→ DD	**0.14** **	0.139	**0.193* **	0.013	**0.216* **
DD →Smartphone Usage	0.051	-0.021	0.067	-0.007	**0.279* **
DD → Social Func Usage	-0.027	0.021	0.045	-0.348	-0.193
DD → Infor Func Usage	0.037	0.118	**0.267* **	-0.053	-0.099
DD → Enter Func Usage	0.084	-0.192	0.162	-0.003	0.238
DD → Shop Func Usage	-0.078	-0.179	-0.099	0.095	0.017
DD → Tool Func Usage	0.011	-0.158	0.132	0.018	0.123

Note. * p<0.1, ** p<0.05, *** p<0.01

Additionally, we examine the moderating effect of users' average previous subway trip length. To this end, users were divided into two groups based on the mean of average previous trip duration.[2] Table E6 presents the PLS results for both groups, which are consistent with our main findings. Specifically, the positive relationship between crowdedness and perceived personal space invasion is stronger among users with shorter trip durations (0.698, $p < 0.01$) than those with longer trips (0.637, $p < 0.01$). Similarly, the relationship between perceived personal space invasion and smartphone usage intention is more pronounced in the low-duration group (0.606, $p < 0.01$) compared to the high-duration group (0.356, $p < 0.01$). This pattern is also observed for social functionality usage (0.428, $p < 0.01$; 0.312, $p < 0.05$). All the results align well with the main findings.

Table E6. The PLS Results for Low- and High- Average Trip Duration

[2] We use the median value as the threshold and obtain the consistent results.

	Low Average Trip Duration	High Average Trip Duration
Crowdedness → PSI	**0.698*** **	**0.637*** **
PSI →Smartphone Usage	**0.606*** **	**0.356*** **
PSI → Social Func Usage	**0.428*** **	**0.312** **
PSI → Infor Func Usage	0.043	0.068
PSI → Enter Func Usage	0.026	0.121
PSI → Shop Func Usage	-0.127	0.193*
PSI → Tool Func Usage	-0.151	0.023

The survey, which employs a refined identification strategy based on the random assignment of participants to varied scenarios, corroborates our empirical findings: crowdedness is positively associated with organic smartphone usage, with the relationship being particularly stronger for social functionalities, especially during off-peak hours, when surrounded by individuals from different age groups, and among users with shorter prior subway trip durations. Furthermore, the survey provides direct evidence supporting the mediating role of perceived personal space invasion in the relationship between crowdedness and smartphone usage, particularly for social functionalities. It also provides evidence indicating that alternative mechanisms proposed in prior research are less consistent with the observed findings.

E5. The Role of Different Functionalities in Creating Digital Personal Space

To delve deeper into the role of the five functionality categories (social, information, entertainment, shopping and tool functionality) in fostering digital personal space, we expanded our survey by incorporating items that directly assess how different mobile functionalities contribute to the three core dimensions of personal space—self-esteem (SE), privacy (PV), and sense of control (CT). To systematically test the role of different functionalities in creating digital personal space, we adapted well-established survey items from the literature. Specifically, each mobile functionality's ability to protect self-esteem was measured using two items (*SE1, SE2*) from the Rosenberg Self-Esteem Scale (Rosenberg et al. 1995). Individuals' perceived privacy when using each mobile functionality was assessed using three items (*PV1, PV2, PV3*) adapted from Chang et al. (2018). The extent to which mobile functionalities enable users to feel in control of their environment and interactions was measured using three items (*CT1, CT2, CT3*) from Consiglio et al. (2018). All items were measured on a 7-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). The specific survey items are provided in the first column of Table E7.

The results indicate that social functionalities consistently outperform other functionalities across all three dimensions of digital personal space. Specifically, social functionalities score significantly higher in helping users feel valued and acknowledged (*SE1, SE2*; $p < 0.01$), being perceived as more private, with activities and information handled in a more securely protected manner (*PV1, PV2, PV3*; $p < 0.01$), and offering users a stronger sense of control over their environment (*CT1, CT3*; $p < 0.01$). These findings empirically validate our argument that social functionalities are the most effective in fulfilling the core functions of personal space in the digital realm, reinforcing their role as the primary means of reclaiming personal space in crowded conditions.

Table E7. The Extent to Which Mobile Functionality Categories Support Digital Personal Space

Items		Mean	SD	Difference from Social Functionality
[*SE1*] I feel that I am a person of worth, at least on an equal plane with others.	Social	5.61	0.88	-
	Information	5.19	1.12	$p < 0.01$
	Entertainment	4.73	1.21	$p < 0.01$
	Shop	4.97	1.14	$p < 0.01$

	Tool	4.95	1.17	$p < 0.01$
[*SE2*] I feel that I can be recognized or acknowledged by others.	Social	5.88	0.88	-
	Information	5.21	1.14	$p < 0.01$
	Entertainment	4.85	1.26	$p < 0.01$
	Shop	5.03	1.23	$p < 0.01$
	Tool	4.9	1.21	$p < 0.01$
[*PV1*] I think I am engaging in private/sensitive/confidential activities.	Social	5.97	1.09	-
	Information	4.75	1.45	$p < 0.01$
	Entertainment	4.53	1.4	$p < 0.01$
	Shop	5.68	1.04	$p < 0.01$
	Tool	4.37	1.46	$p < 0.01$
[*PV2*] I think it can store my private/sensitive/confidential information.	Social	6.23	1.07	-
	Information	5.01	1.46	$p < 0.01$
	Entertainment	4.75	1.38	$p < 0.01$
	Shop	5.92	1.12	$p < 0.01$
	Tool	4.57	1.49	$p < 0.01$
[*PV3*] I believe my private information is not shared or used without my consent.	Social	5	1.5	-
	Information	4.71	1.47	$p < 0.01$
	Entertainment	4.74	1.49	$p < 0.01$
	Shop	4.46	1.71	$p < 0.01$
	Tool	4.76	1.35	$p < 0.01$
[*CT1*] I would have control over my surroundings.	Social	5.54	1.06	-
	Information	5.13	1.17	$p < 0.01$
	Entertainment	5.04	1.3	$p < 0.01$
	Shop	5.09	1.33	$p < 0.01$
	Tool	5.13	1.19	$p < 0.01$
[*CT2*] I would feel in control over the usage.	Social	5.68	0.98	-
	Information	5.46	1.01	$p < 0.01$
	Entertainment	5.53	1.14	$p < 0.1$
	Shop	5.58	1.1	$p > 0.1$
	Tool	5.42	1.12	$p < 0.01$
[*CT3*] I can exercise control and autonomy over my decisions.	Social	5.97	1.05	-
	Information	5.4	1.22	$p < 0.01$
	Entertainment	5.57	1.12	$p < 0.01$
	Shop	5.41	1.27	$p < 0.01$
	Tool	5.29	1.15	$p < 0.01$

Note. The items begin with "When I use social/information/entertainment/shopping/tool functionalities," and are measured in the 7-point Likert scale of strongly disagree (1) to strongly agree (7).

REFERENCES

Altman I (1975) *The environment and social behavior: privacy, personal space, territory, and crowding* (Brooks/Cole Publishing Company).

Andrews M, Luo X, Fang Z, Ghose A (2016) Mobile ad effectiveness: Hyper-contextual targeting with crowdedness. *Mark. Sci. 35*(2): 218-233.

Angrist J, Krueger AB (1994) Why do World War II veterans earn more than nonveterans? *J. Labor Econ. 12*(1): 74-97.

Chang Y, Wong SF, Libaque-Saenz CF, Lee H (2018) The role of privacy policy on consumers' perceived privacy. *Government Information Quarterly 35*(3): 445-459.

Choi AA, Rhee K-E, Yoon C, Oh W (2023) The Cost of Free: The Effects of "Wait-for-Free" Pricing Schemes on the Monetization of Serialized Digital Content. *MIS Q. 47*(3): 1073-1100.

Consiglio I, De Angelis M, Costabile M (2018) The effect of social density on word of mouth. *J. Consum. Res. 45*(3): 511-528.

Dosey MA, Meisels M (1969) Personal space and self-protection. *J. Pers. Soc. Psychol. 11*(2): 93.

Durante KM, Laran J (2016) The effect of stress on consumer saving and spending. *J. Mark. Res. 53*(5): 814-828.

Edney JJ, Walker CA, Jordan NL (1976) Is there reactance in personal space? *J. Soc. Psychol. 100*(2): 207-217.

Elhai JD, Levine JC, Dvorak RD, Hall BJ (2016) Fear of missing out, need for touch, anxiety and depression are related to problematic smartphone use. *Comput. Hum. Behav. 63*: 509-516.

Horowitz MJ, Duff DF, Stratton LO (1964) Body-buffer zone: exploration of personal space. *Arch. Gen. Psychiatry 11*(6): 651-656.

James TL, Qiao Z, Shen W, Wang GA, Fan W (2023) Competing for Temporary Advantage in a Hypercompetitive Mobile App Market. *MIS Q. 47*(3).

Jiang Z, Heng CS, Choi BC (2013) Research note—privacy concerns and privacy-protective behavior in synchronous online social interactions. *Inf. Syst. Res. 24*(3): 579-595.

Limayem M, Hirt SG, Cheung CM (2007) How habit limits the predictive power of intention: The case of information systems continuance. *MIS Q. 31*(4): 705-737.

Liu L, Wang Y, Xu Y (2024) A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data. *Am. J. Polit. Sci. 68*(1): 160-176.

Maeng A, Tanner RJ, Soman D (2013) Conservative when crowded: Social crowding and consumer choice. *J. Mark. Res. 50*(6): 739-752.

Pan Y, Qiu L (2022) How ride-sharing is shaping public transit system: A counterfactual estimator approach. *Prod. Oper. Manag. 31*(3): 906-927.

Peck J, Childers TL (2003) Individual differences in haptic information processing: The "need for touch" scale. *J. Consum. Res. 30*(3): 430-442.

Rosenberg M, Schooler C, Schoenbach C, Rosenberg F (1995) Global self-esteem and specific self-esteem: Different concepts, different outcomes. *Am. Sociol. Rev.*: 141-156.

Siebert WS, Zubanov N (2010) Management economics in a large retail company. *Manage. Sci. 56*(8): 1398-1414.

Van Hooff ML (2015) The daily commute from work to home: Examining employees' experiences in relation to their recovery status. *Stress and Health 31*(2): 124-137.

Vodanovich SJ, Watt JD (2016) Self-report measures of boredom: An updated review of the literature. *J. Psychol. 150*(2): 196-228.

Wooldridge JM (2010) *Econometric analysis of cross section and panel data* (MIT press).

Zhang H, Zheng E, Mehra A (2023) Information Transparency and Market Efficiency in Blockchain-enabled Marketplaces: Role of Traders' Analytical Ability. *Available at SSRN 4434399*.

Zhou L, Wang M, Chang CH, Liu S, Zhan Y, Shi J (2017) Commuting stress process and self-regulation at work: Moderating roles of daily task significance, family interference with work, and commuting means efficacy. *Pers. Psychol. 70*(4): 891-922.