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A Global meta-analysis of digital divide in psychiatric population from 2004 to 2023

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This meta-analysis identified forty-eight unique samples (total number of participants =10,324) which reported rates of smartphone ownership (SO), current, and daily internet usership (IU) among adults with psychiatric disorders between 2004 and 2023. SO increased from 32% in 2012–2013 to 77% in 2020–2021; current IU rose from 65% in 2010–2011 to 87% in 2018–2019; daily IU grew from 30% in 2010–2011 to 58% in 2016–2017. Compared to US national data, the gap has narrowed by 8.9% for SO since 2012 and 10% for current IU since 2010. Individuals who are older, male, less educated, unemployed, and with psychosis diagnosis were at-risk of various digital disengagement. At the macro-level, regional income inequality was also associated with IU. Although the usage and device gaps have been substantially narrowed, continued monitoring is needed to ensure sustained improvements. The highly heterogeneous studies highlighted the need of establishing standardized outcome metrics to enhance cross-study comparability.

Digital technologies have become a fundamental part of our daily lives. In 2022, internet users constituted around 95.3–97.1% of the national population in the US, UK, and Hong Kong[1]. The COVID-19 pandemic further underscored the benefits of digital technologies, as restrictions on physical interactions highlighted their potential to enable broad access to services with reduced cost[2]. Since then, the digitalisation in various aspects of societal function has been a major focus of governments. While digital technologies are frequently promoted as a solution for reducing inequalities[3,4], their accessibility and usability remain shaped by entrenched structural and individual barriers[5]. Disadvantaged populations, particularly patients with psychiatric illnesses, may be disproportionately excluded as they fall behind in digital participation and face a new form of social inequality. The digital divide refers to the disparity in digital access, usage, and outcomes[6], which has direct and indirect detrimental impacts on patients with psychiatric illness. Direct impacts relate to the inaccessibility of digital health technologies (DHTs). DHTs aim to provide both physical and mental health care at reduced cost and with wider coverage, attracting significant interest from various national health services[7]. However, over-emphasis on developing DHTs may neglect the needs of the digitally disengaged population. Indirect impacts pertain to digitalising essential services, such as housing or employment opportunities[7], which risk further marginalising digitally disengaged patients.

The digital divide among the psychiatric population can be examined on two levels: the access and the usage gap. The access gap refers to the 'have' or 'have-not' internet access[6]. In recent years, due to high internet penetration rate in developed regions, the focus has shifted to the device gap[8], which relates to the device they use to access the Internet. Particularly, smartphones have a lower financial cost compared to personal computers, serving as a viable entry point for populations with limited resources[9]. The usage gap, on the other hand, explores how and why individuals with access use the internet, and focus on the disparities in usage patterns, digital skills, confidence, and acceptance[6,8]. As digital technologies evolve, becoming more affordable and increasingly user friendly, it can be anticipated that the existing gaps will continue to narrow. However, ongoing monitoring remains crucial to assess the pace and sustainability of this progress. Moreover, what constitutes meaningful participation is likely to shift over time. Beyond measuring general internet use, examining usage patterns, such as frequency and types of online activities, could provide deeper insights into how psychiatric populations adapt to societal digitalisation[10]. Previous research on internet use (IU) and smartphone ownership (SO) has produced varying results and conflicting conclusions regarding the existence of gaps between psychiatric and general populations[11,12], warranting a review to consolidate these findings. Additionally, a static snapshot of IU and SO may not fully capture the evolving nature of the divide. Examining longitudinal changes can reveal whether improvements have been consistent or whether periods of stagnation or regression have occurred. These insights are crucial for informing policy decisions and guiding interventions.

To the best of our knowledge, no prior review has examined the IU gap among psychiatric populations, and only one meta-analysis was conducted in 2016 which focused on mobile phone ownership among individuals with

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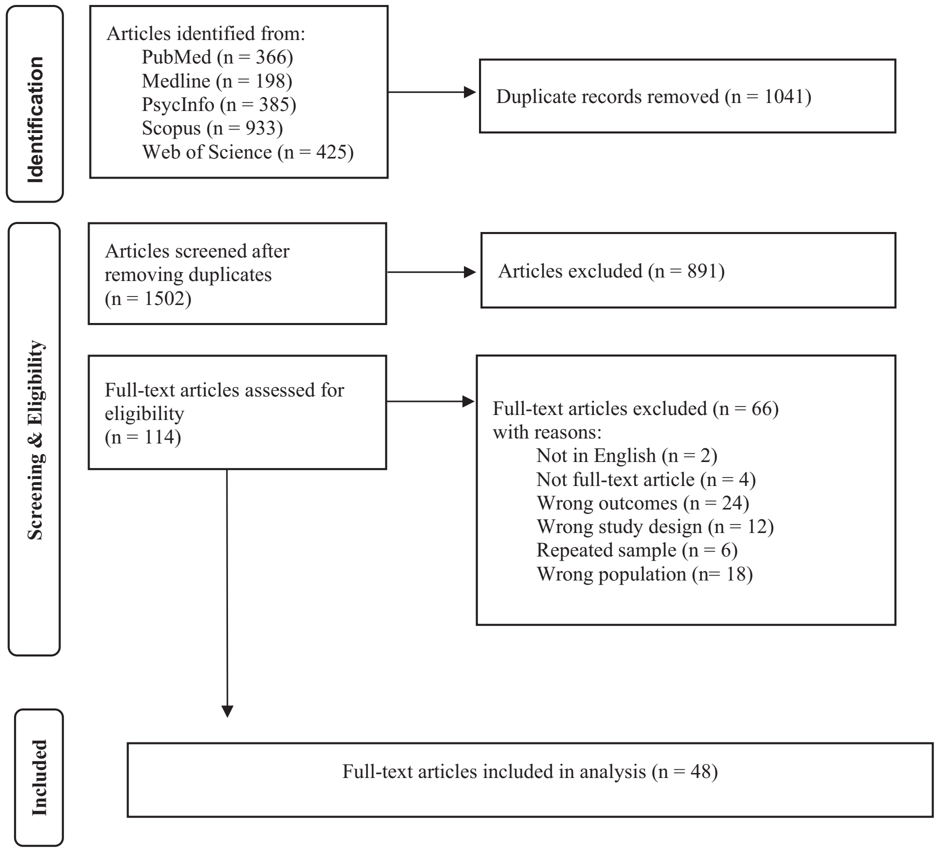

Fig. 1 | PRISMA Flowchart of the methodological steps taken to identify empirical studies included for meta-analysis. n = number of studies. Included and excluded studies extracted from PubMed, Medline, PsycInfo, Scopus, Web of Science on smartphone ownership and internet use among psychiatric populations, with reasons for exclusion.

psychosis. The study reported a significantly narrowed gap in mobile phone ownership between patients and the general population[13]. However, since 2016, technological advancements have been substantial. Smartphones have largely replaced traditional mobile phones and become the predominant mobile device. Merely owning a mobile phone may no longer be sufficient for patients to remain digitally connected within society. For instance, communication has largely transitioned from traditional text messages to social media platforms, and many DHTs now incorporate sophisticated functions that operate exclusively on smartphones. Moreover, the previous meta-analysis modelled temporal trends linearly. This approach may not account for variations in the pace of technological progress during different periods. Thus, an updated and more comprehensive meta-analysis on smartphone ownership (SO) is warranted.

Furthermore, contemporary models theorise that the digital divide is shaped by deeply rooted structural inequalities and individual-level vulnerabilities. According to Van Dijk's Resources and Appropriation theory, personal categories (e.g., age, gender, health/ability, etc.) and positional categories (e.g., education, household, nation) determine individuals' temporal, material, mental, social and cultural resources, which in turn influence their access and use of digital technologies[5]. Apart from socio-demographic and socio-economic determinants of the divide that have been examined extensively in non-psychiatric populations[8], illness chronicity and severity have been identified as illness specific barriers in psychiatric populations in previous studies[13]. Particularly, patients with psychosis have been highlighted to have lower levels of digital engagement compared to other severe mental illnesses[14]. Beyond individual barriers, the digital divide, understood as a dimension of social inequality, is closely interlinked with other systematic inequities. Macro-level determinants including regional disparities in information communication technology (ICT) infrastructures, social policy environments, as well as regional income inequality interact with the micro-level factors (individual and illness-related barriers)[15]. Indeed, prior research has indicated that higher regional income inequality significantly predicted lower internet usage[16]. Psychiatric populations, who are often socio-economically disadvantaged, may be disproportionately impacted by these systematic inequalities, and their intersecting vulnerabilities can further entrench their position on the disadvantaged side of the digital divide[5]. Addressing both societal and individual factors could better inform social policies directions and development of targeted interventions to further reduce the digital divide.

This is the first meta-analysis to investigate internet use and smartphone ownership in the psychiatric population. This review first examined the trend of SO, current and daily IU rates over the years among psychiatric populations. Then, potential factors relating to SO, current and daily IU were explored. Lastly, the device and digital usage gap between the psychiatric and general populations was investigated by comparison with national data. By addressing these areas, we hope to contribute to the broader discourse of the digital divide and support the efforts to reduce and improve equity in societies.

Results

The database search identified 2307 results, of which 48 studies were found to be eligible for this review, yielding a total sample size of 10, 324 (Fig. 1).

The mean age was 41.9 (median = 44, range = 27.7-69.5) (k = 45), 53.7% of the sample were identified as male (k = 47), 61.2% achieved education equivalent to or above high school (k = 32), 34.6% were engaged in open employment or had student status (k = 26), and 38.8% had a diagnosis of psychosis (k = 46). The studies were conducted across 17 countries/regions, 19 (39.6%) studies were from World Health Organisation (WHO Region of the Americas, 19 (39.6%) studies were from the WHO European Region, 6 (12.5%) studies were from the WHO Western Pacific Region, 1 (2.1%) was in the WHO African Region, and 1 (2.1%) was across multiple regions. Thirty-one studies (64.6%; n = 7045) reported the rate of current IU while 21 (43.8%; n = 3990) reported daily IU rates from 2004 to 2021, 27 (56.3%) studies (n = 5431) reported the rate of SO from 2012 to 2023 (Table 1).

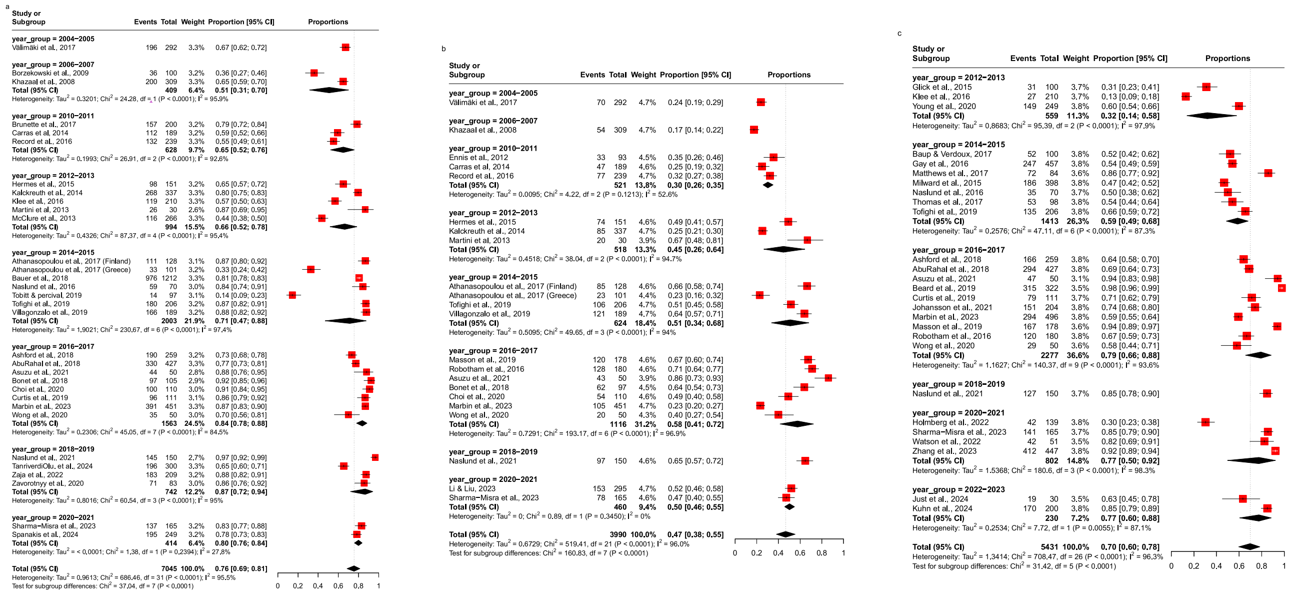

Fig. 2 | Forest plots of pooled estimates of internet user rates across periods. **a** Forest plot of pooled estimates of current internet user rates. Red squares indicate rates from individual studies, while black diamonds represent the pooled estimates for each period and the overall analysis. **b** Forest plot of pooled estimates of daily internet user rates. Red squares indicate rates from individual studies, while black diamonds represent the pooled estimates for each period and the overall analysis. **c** Forest plot of pooled estimates of smartphone ownership rates. Red squares show the rates from individual studies, and black diamonds depict the pooled estimates for each period and the overall analysis.

Longitudinal patterns of smartphone ownership and internet use

The pooled rate of current IU increased from 65% (95% $CI = 52–76\%$) in 2010–2011 to 87% (95% $CI = 72–94\%$) in 2018–2019 (Fig. 2a), daily IU rose from 30% (95% $CI = 26–35\%$) in 2010–2011 to 58% (95% $CI = 41–72\%$) in 2016–2017 (Fig. 2b). Additionally, SO increased from 32% (95% $CI = 14–58\%$) in 2012–2013 to 77% (95% $CI = 50–92\%$) in 2020–2021 (Fig. 2c). Significant bi-yearly sub-group differences were observed for all three outcomes ($p < 0.001$), with high heterogeneity ($I^2 = 95.5–96.3\%$; $\tau^2 = 0.67–1.34$). From 2010 to 2019, there was a marked increase in current IU within the psychiatric population, nearly catching up the general population. However, a possible drop was observed after 2018–2019 in the psychiatric population only while the US general population continued to increase. A similar trend was also observed for daily IU, though the rate remained much lower than that of the current IU (Fig. 3a). An accelerated growth in SO was noted in the psychiatric population, with the SO rate becoming comparable to the general US population by 2024. Nevertheless, since 2020, the rate of SO within the psychiatric populations may have experienced a slight drop and plateaued, while the general US population continued to see a steady increase (Fig. 3b). The leave-one-out sensitivity analysis did not reveal any samples that were influential to the pooled rates (Supplementary Figs. 1 & 2). By excluding studies with low quality, the sensitivity analysis revealed that the estimated rates were minimally affected (Supplementary Figs. 3 & 4). Funnel Plots and Egger's regression test detected no publication bias except for the rate of SO in 2016-2017 (Supplementary Figs. 5 & 6).

The exploratory meta-regression on the pandemic effect on digital engagement showed no significant association between the COVID-19 pandemic and current or daily IU, but a significant negative association were observed with SO (Estimate = −2.13, $SE = 0.92$, $p < 0.01$; Supplementary Table 2), though there were only two studies from 2020 onwards for current and daily IU and six for SO. Additionally, the sensitivity analysis conducted by excluding 2020-2021 studies revealed that the pooled SO rate decreased slightly from 70% (95% $CI = 60\%$ – 78%) to 68% (95% $CI = 57–77\%$) (Supplementary Fig. 7), indicating that the observed decline may not entirely driven by the studies in the COVID-19 period. However, due to the limited studies after 2020 for current and daily IU, this sensitivity analysis was not performed on these outcomes. Table 1

Predictors of digital engagement

For socio-demographic predictors, being male was significantly associated with lower rates of current, daily IU and SO. Older age was significantly associated with lower current IU and SO but not daily IU. Conversely, attaining a high school education was significantly associated with higher rates of current, daily IU and SO. Employment status was significantly associated with lower rates of current and daily IU but higher SO (Table 2). Risk of multicollinearity was insignificant for these predictors (VIF < 2). The multivariate regression model revealed that only attainment of high school education was significantly associated with higher rate of SO, current and daily IU. In addition, being male was also associated with higher daily IU. However, the models had small sample sizes ($k = 15–22$), and particularly the SO ($\tau^2 = 2.40$) and daily IU models ($\tau^2 = 2.71$) exhibited high heterogeneity (Supplementary Table 3).

For clinical predictors, having psychosis was significantly associated with lower current, daily IU and SO. For structural predictors, residing in a region with a higher Gini Index was significantly associated with a lower rate of current and daily IU but only a trend toward significance with higher rate of SO ($p = 0.063$; Table 2). The regional differences were also examined. The meta-regression revealed that WHO European regions had significantly lower SO rate than WHO Region of Americas (Supplementary Table 4). Subgroup analyses further supported this finding, showing a significant regional difference in SO (Supplementary Fig. 11). However, no significant differences were observed between regions for current and daily IU in either the meta-regression (Supplementary Table 4) or subgroup analyses (Supplementary Figs. 12 & 13).

Discussion

This is the first proportional meta-analysis of current and daily internet use (IU) and smartphone ownership (SO) among psychiatric populations from 2004 to 2023, including 48 unique samples with a total of 10,324 psychiatric populations across 17 regions. Current IU in psychiatric populations increased from 60% in 2010–2011 to 87% in 2018–2019, while SO rose from 32% in 2012–2013 to 77% in 2020–2021. Using US national data as a benchmark, psychiatric populations had nearly caught up with the general population in terms of current IU and SO by 2019. A possible decline was observed during 2020–2023, though additional data were required to

Fig. 3 | Pooled estimates of digital technology use in psychiatric populations. **a** Internet user rate across 2004–2021. Each bubble represents the internet user rate of an individual study, with point size proportional to sample size. Red points represent the World Health Organisation (WHO) African Region, green the European Region, blue the Region of the Americas, purple the Western Pacific Region, and grey an undefined region. The grey line shows the internet user trend of the general United States population (International Telecommunication Union[1] data, adapted by authors), while the pink and orange lines represent the pooled daily and current internet user trends of the psychiatric sample, respectively. **b** Smartphone ownership rate across 2012–2023. Each bubble represents the smartphone ownership rate of an individual study, with point size proportional to sample size. Red points represent the WHO African Region, green the European Region, blue the Region of the Americas, purple the Western Pacific Region, and grey an undefined region. The grey line shows the trend of the general United States population (International Telecommunication Union[1] data, adapted by authors). The orange line represents the trend of the psychiatric sample.

confirm this finding. The findings also revealed older, male, less educated individuals and patients with psychosis were at-risk subpopulations of digital disengagement. Being employed were less likely to use the internet but more likely to be smartphone owners. Residing in regions with higher Gini Index were less likely to use the internet.

The digital divide between psychiatric and general populations has narrowed substantially over the years. Current IU rates (87%) peaked in 2018–2019, while SO (79%) peaked in 2016–2017. The increased affordability of technology and the rise in popularity of smartphones may have contributed to this trend. For instance, the affordability of fixed broadband improved with a 2.7% drop in Gross National Income per capita price worldwide and a 4.5% drop in the US alone from 2008 to 2017[17]. Notably, the Canadian smartphone price index showed a remarkable 56.7% drop in prices from 2015 to 2021[18]. These comparable SO rates of the psychiatric and general population support previous research suggesting that smartphones are a viable entry point to close the device and usage gap for disadvantaged populations[9]. However, our meta-analyses suggested that the rate of daily IU appeared drastically lower than the rate of current IU, with nearly one-third of the current IU were not engaging daily. Although the number of studies assessing daily IU at each bi-yearly subgroup were limited, this preliminary finding points to potential barriers beyond accessibility and affordability, such as a lack of skills and interest[19]. Thus, the psychiatric populations may remain vulnerable to the usage gap. Therefore, simply categorising individuals into internet users and non-users may not effectively assess the digital divide. This highlights the need to constantly refine metrics of digital participation to better reflect meaningful engagement in the everchanging digital landscape.

Additionally, although more studies are needed to verify the findings, our meta-analyses suggested a potential decline in daily and current IU and SO after 2019, despite continued growth in the general population. A possible explanation is the impacts of COVID-19. Pandemic restrictions, such as lockdowns and social distancing measures, may have reduced access to some of the key resources of digital access for the psychiatric population, including public facilities offering free Internet[20], and to social networks that provide internet and device support. Our exploratory analysis partially supported this explanation, as the pandemic dummy variable was associated with lower SO rate, though the significance was not observed in current and daily IU, possibly due to the limited number of post-2020 studies for these outcomes. Sensitivity analysis excluding 2020-2021 studies yield a slightly dropped pooled estimate for SO. The pandemic restrictions may have isolated individuals with limited digital skills from support needed to maintain digital engagement. A study in the UK during the pandemic found that patients with severe mental illness (SMI) reported lower internet knowledge compared to the general public [14].These results suggested the vulnerability of the psychiatric population to fall back into poorer digital access and usage during sudden societal changes, warranting further monitoring of the divide and underscores the need for enhanced support to improve digital adaptability and independence among the vulnerable population.

The current study also identified several individual, clinical, and macro-level socioeconomic factors associated with current, daily IU and SO. Consistent with findings from non-psychiatric populations, older adults and individuals with lower educational levels were less likely to use the internet or own smartphones[21,22]. Conversely, digital disengagement was more common among men. One possible reason may be the lower perceived social benefits of digital technology. Previous research has shown that men with psychiatric disorders are less likely to seek help[23], which may reduce their motivation to engage digitally. Being employed was significantly associated with higher smartphone ownership but lower likelihood of current and daily internet use, highlighting unique challenges faced by the psychiatric population. This paradox may suggest that, although employed individuals could afford smartphones, many may work in blue-collar occupations, requiring them to work long hours in physically demanding tasks[24], leaving limited opportunities or motivations to develop digital skills. Hence, smartphone ownership does not necessarily translate to active digital engagement. Future research on the relationships between the types of occupation and SO and IU are needed. When accounting for

Table 1 | Included Study Characteristics and quality assessment

Region	Author, Year	Data collection time	Gini Index	N	Study Design	Sample description (psychosis %)	Age[a]	Male (%)	High school educated (%)	Employed[1]	Internet Use	Smartphone Ownership	JBI score
WHO Region of America													
United States	Borzekowski et al., 2009	Feb – Dec 07	40.8	100	Paper-based survey	SMI (72)	46.1 (10.1)	63	64	NA	Current	NA	Low
	Brunette et al., 2017	2010	40	200	Paper or Web-based survey	Peer support SMI user (NA)	37.9[c]	45.9	NA	NA	Current (12 months)	NA	Low
	Record et al., 2016	Mar 10 – Oct 11	40	239	Paper-based survey (Baseline)	Veterans with SMI (26)	54.3 (8.3)	89	56[3]	28.5	Current (1month) Daily	NA	Moderate
	Carras et al, 2014	2011	40.9	189	Paper-based survey	SMI (40)	41.7[c]	36.0	67.2	NA	Current Daily	NA	Low
	Glick et al., 2015	2012	40.9	100	Paper-based survey	SMI (29.2)	47 (10.7)	62.6	19	NA	NA	Yes	High
	McClure et al., 2013	2012[2]	40.9	266	Paper-based or web-based survey	Substance Use treatment outpatients (0)	44.1 (11.5)	64	60	49	Current (weekly)	NA	Moderate
	Young et al., 2020	Mar 12 – Apr 14	40.7	249	Face-to-face interview	SMI veterans (58.6)	54 (9.8)	90	68[3]	NA	NA	Yes	Low
	Klee et al., 2016	Jul -Dec 12	40.9	210	Paper-based survey	SMI veterans (24.3)	56.8 (9.8)	83.3	97.1	NA	Current	Yes	Low
	Hermes et al., 2015	Nov 2012 – Nov 2013	40.7	151	Paper-based survey	Veterans Substance use treatment outpatient (7.3)	52 (10.9)	94.6	94.1	NA	Current Daily	NA	Moderate
	Gay et al., 2016	Aug - Sep 14	41.5	457	Web-based survey	Schizophrenia (100)	41.3[b]	54	64[3]	40	NA	Yes (Access)	Low
	Matthews et al., 2017	Sep 13 – Oct 14	41.5	84	Web-based survey	Bipolar (0)	NA	NA	NA	NA	NA	Yes	Low
	Naslund et al., 2021	2017-2019	41.2	150	Paper-based survey (Baseline)	SMI (43.3)	28.4 (4.5)	42.7	85.3	18.7	Current Daily	Yes	Low
	Naslund et al., 2016	2014 - 2015	41.2	70	Paper-based survey (Baseline)	SMI (26)	47.1 (12.4)	40	45	20	Current	Yes	Low
	Tofighi et al., 2019	Feb – Aug 15	41.2	206	Paper-based survey	Substance use treatment inpatients (0)	43.7 (11.8)	91	71	28	Current (12 months) Daily	Yes	High
	Masson et al., 2019	Feb – Oct 16	41.1	178	Face-to-face interview and survey	Opiod treatment patients (0)	38.0 (10.4)	51	79	42	Daily	Yes	High
	Curtis et al., 2019	May 2016	41.1	111	Paper-based survey	Substance use treatment outpatient (0)	27.7 (5.1)	75.7	69.4	30.6	Current (weekly)	Yes	Low
	Ashford et al., 2018	May 2016	41.1	259	Paper-based survey	Substance use disorder (NA)	39.6 (12.2)	72.9	58.8	22.4	Current	Yes	Moderate
	Asuzu et al., 2021	May 2017 – Jan 2018	41.1	50	Paper-based survey	SMI (32)	35 (13)	52	72[3]	46	Current	Yes	
	Beard et al., 2019	Sep 2017 – Mar 2018	41.1	322	Web-based survey	Psychiatric clinic Inpatients (5.9)	33.5 (13.9)	43	NA	52.5	NA	Yes	Low

Table 1 (continued) | Included Study Characteristics and quality assessment

Region	Author, Year	Data collection time	Gini Index	N	Study Design	Sample description (psychosis %)	Age[a]	Male (%)	High school educated (%)	Employed[1]	Internet Use	Smartphone Ownership	JBI score
Brazil	Martini et al, 2013	2013[4]	52.7	30	Face-to-face interview	Bipolar (0)	36.0 (11.5)	66.9	NA	NA	Current Daily	NA	High
WHO European Region													
United Kingdom	Ennis et al., 2012[5]	Mar – Apr 2011	33.2	93	Web-based survey	Psychosis and other disorder (76.9)	34.6 (11.6)	70	NA	NA	Daily	NA	Low
	Milward et al., 2015	Mar – Jun 14	33.1	398	Paper-based survey	Substance Use treatment outpatients (0)	36 (7.7)	74	NA	19	NA	Yes	Low
	Tobitt & percival, 2019	2015	33.3	97	Face-to-face or phone interview	Psychosis placement patients (100)	54[c]	50.5	NA	NA	Current (3 months)	NA	Moderate
	Robotham et al., 2016	2016	33.1	241	Paper or Web-based survey	Psychosis vs Depression (50.2)	38.6	55.6	NA	NA	Current Daily	Yes	High
	Watson et al., 2022	Apr 20	32.8	51	Paper-based survey or phone interview	Psychosis (100)	41.4	45.1	NA	NA	NA	Yes	Moderate
	Spanakis et al., 2024	Jan – Mar 21	32.4	249	Paper or Web-survey or Phone Interview	SMI (48.2)	51.7	51.4	NA	24.5	Current (12 months)	NA	High
	Kuhn et al., 2024	May – Dec 2022	32.4	200	Web-based survey	Psychosis (100)	37.8	59	95	39	NA	Yes	Low
Germany	Kalckreuth et al., 2014	Feb – Jul 13	31.5	337	Face-to-face survey	Psychiatric clinic Inpatients, outpatients and day hospital patients (17.8)	46 (16.3)	42.7	43.4	33.6	Current Daily	NA	High
	Marbin et al., 2023[9]	Mar – Sep 16	31.4	496	Face-to-face interview	Psychiatric inpatients and day-clinic outpatients (27.0)	40.9[c]	58.7	NA	NA	Current Daily	Yes	Moderate
	Zavorotnyy et al., 2020	2018-2019	31.7	83	Paper-based survey	Schizophrenia vs Depression (28.9)	44.8 (14.4)	47.0	NA	NA	Current	NA	Moderate
	Just et al., 2024	Mar -May 23	31.7	30	Face-to-face interview and survey	Geriatric Psychiatric Clinic Inpatients and outpatients (10)	69.5 (8.8)	46.7	93.3	NA	NA	Yes	Moderate
Sweden	Johansson et al., 2021[8]	May – Oct 2017	28.8	204	Paper or Web-based survey or face-to-face interview	Bipolar, Depression and Anxiety (0)	33.1	27.5	65	47	NA	Yes (Access)	Low
	Holmberg et al., 2022	Jun 2021	26.8	139	Case manager report	Schizophrenia (100)	59 (10.8)	58	NA	NA	NA	Yes	Low
Finland	Välimäki et al., 2017	Mar 05 – Oct 06	27.6	297	Paper-based survey	Schizophrenia inpatients (100)	39.0[c]	59	49	NA	Current Daily	NA	High
Finland/ Greece	Athanasopoulou et al., 2017	Jun - Dec 2015	27.1/ 36	229	Paper-based survey	Schizophrenia spectrum disorder (100)	41[b]	58	67	13	Current Daily	NA	High
Switzerland	Khazaal et al., 2008	Jan – Apr 07	34.3	319	Paper-based survey	Psychiatric clinic Outpatients (33.2)	40 (11.4)	58.5	70[5]	12.9	Current Daily	NA	Moderate
France	Baup & Verdoux, 2017	Nov 2014 – Mar 2015	32.7	100	Face-to-face interview and survey	Psychiatric clinic Outpatients (41)	40.3 (12.4)	48	33	21	NA	Yes	Moderate

Table 1 (continued) | Included Study Characteristics and quality assessment

Region	Author, Year	Data collection time	Gini Index	N	Study Design	Sample description (psychosis %)	Age[a]	Male (%)	High school educated (%)	Employed[1]	Internet Use	Smartphone Ownership	JBI score
Israel	AbuRahal et al., 2018	Jan - May 2017	39	427	Paper-based survey	SMI vs Non-SMI (71)	41.2 (14.3)	47.5	82.6	38	Current Daily	Yes	High
Spain	Bonet et al., 2018	Feb – May 2017	35.8	105	Face-to-face interview and survey	Psychosis (100)	31.3 (38.1)	13	57.1	37.2	Current Daily	NA	Moderate
Croatia	Zaja et al., 2022	Dec 18 -Feb 20	28.9	209	Paper-based survey	Schizophrenia vs Depression inpatients (50.2)	40.7 (14.6)	59.8	89	44	Current	NA	High
Turkey	TanriverdiOluğ et al., 2024	Jun – Nov 19	43.8	300	Face-to-face interview	Schizophrenia vs Bipolar (50)	41.2 (11.5)	58	34.7	26	Current	NA	Low
WHO Western Pacific Region													
Australia	Villagonzalo et al., 2019	2014[7]	34.4	189	Face-to-face interview (Baseline)	Psychosis (100)	40.0 (11.1)	50.8	47.6	27.5	Current Daily	NA	Moderate
	Thomas et al., 2017	May – Jun 14	34.4	98	Paper-based survey	SMI (79)	NA	57	55.7	19.4	NA	Yes	Low
	Wong et al., 2020	2016[2]	33.7	50	Face-to-face interview	Schizophrenia outpatients (100)	40.5[c]	62	40	NA	Current Daily	Yes	Moderate
China	Li & Liu, 2023	Oct 20 – Jul 21	58.3	295	Paper-based survey	Home-dwelling SMI (58)	NA	44.1	58.3	NA	Daily	NA	Moderate
	Zhang et al., 2023	Feb 21 – Jan 22	46.6	447	online survey	SMI (28)	34.8 (14.3)	11.6	68.9[3]	74.3	NA	Yes	High
Hong Kong	Choi et al., 2020	Oct 2017 – Jan 2018	53.9	110	Paper-based survey	Schizophrenia (100)	39 (11.2)	63.6	66.4	27.3	Current Daily	NA	High
WHO African Region													
South Africa	Sharma-Misra et al., 2023	Aug – Nov 21	65	165	Paper-based survey	Schizophrenia (100)	41 (14.2)	54.5	23[3]	37.6	Current (3 months)	Yes	High
Unclassified													
Multiple regions	Bauer et al., 2018	March 2014 – Jan 2016	NA	1222	Paper-based survey	Bipolar Affective Disorder (0)	44 (13.8)	38	NA	NA	Current	NA	Moderate

[a] Mean (SD) unless otherwise specified.
[b] Median.
[c] Approximate mean calculated based on percentage of each age group or based on article description.
[1] Full-time, part-time open employment, full-time student.
[2] Based on the date of comparison data.
[3] Above high school.
[4] Based on article's acceptance date.
[5] Only part of the sample was included in the analysis as internet user was reported only for the psychosis group (n = 93), smartphone ownership was recorded with the specification of brands which may not have generalized representation, so it was excluded from analysis.
[6] Mandatory school or above.
[7] Based on ethics approval date.
[8] Only patients with psychiatric illnesses that were reported separately for digital outcomes were reported in this table
[9] Only information on smartphone use and internet use were reported here.
SMI Severe mental illness.

Table 2 | Individual Meta-Regression Models Results

	k	QM	τ^2	Estimate	SE	Z	CI Lower
Smartphone Owner							
Age	30	29.42***	0.67	-0.09***	0.02	-4.86	-0.13
Gender (Male)	31	10.28**	1.01	-0.02*	0.01	-2.45	-0.04
Gini Index	33	10.00**	1.03	0.05	0.28	2.62	0.03
High School Educated	24	13.58**	1.21	0.03*	0.01	2.52	-0.00
Employed	20	15.54***	0.55	0.03*	0.01	2.21	0.00
Psychosis	33	81.60***	1.09	-0.01***	0.00	-8.68	-0.02
Current Internet User							
Age	33	62.46***	0.88	-0.12***	0.02	-7.22	-0.15
Gender (Male)	33	18.48***	0.73	-0.02**	0.01	-3.25	-0.03
Gini Index	33	37.38***	1.85	-0.18***	0.03	-5.91	-0.24
High School Educated	26	68.06***	1.54	0.06***	0.01	7.94	0.05
Employed	23	12.81**	0.75	-0.05**	0.016	-3.07	-0.08
Psychosis	33	19.00***	0.72	-0.54**	0.17	-3.26	-0.87
Daily Internet User							
Age	26	12.01**	0.48	-0.01	0.01	-1.49	-0.03
Gender (Male)	27	16.86***	0.46	-0.02***	0.01	-2.76	-0.03
Gini Index	27	20.96***	0.79	-0.08***	0.02	-3.90	-0.12
High School Educated	21	54.60***	0.61	0.05***	0.01	6.80	0.03
Employed	16	53.39***	4.98	-0.20***	0.03	-7.25	-0.25
Psychosis	17	13.65**	0.20	-0.01*	0.00	-2.53	-0.01

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ after controlling for data collection time.

multiple socio-demographic variables simultaneously, only educational level remained a significant predictor for current IU and SO, while higher educational level and being male were associated with higher daily IU. However, given the small number of studies with complete socio-demographic data and high residual heterogeneity, the models were underpowered, and no firm conclusions should be drawn. Future studies with more comprehensive assessments of socio-demographic factors and their relationship with digital engagement are needed to clarify these associations.

Clinically, having psychosis was negatively associated with SO, current and daily IU. This corroborated with previous evidence that patients with psychosis had poorer digital skills[19]. Impaired cognitive functioning and negative symptoms, such as amotivation and asociality, may impaired their ability to develop digital skills and reduce their interest in social interaction and help-seeking behaviors[25], leading to digital disengagement, even in the most basic forms. Notably, the lowest rate of current IU was reported in community rehabilitation placement users with long-term psychosis[26], who were likely to represent those with more severe and chronic forms of illness among psychiatric populations. Thus, while telehealth and digital interventions are promising avenues for mental healthcare delivery, they may not reach the subgroups most in need without tailored strategies to address cognitive and motivational barriers, warranting reconsideration in the role of DHTs in the overall healthcare model.

On a macro-level, income inequality was significantly associated with current and daily internet use but not smartphone ownership. Regions with a higher Gini Index, exhibited less IU, suggesting that in areas with greater income inequality, internet access may be perceived as a privatized asset, discouraging use among disadvantaged individuals. For example, as of 2024, the US, a region with relatively high Gini Index, continues to struggle to provide affordable internet connectivity to disadvantaged populations[27]. In contrast, regions with a lower Gini Index, such as those in Europe, have made efforts to provide reliable and free public internet access[28], which may encourage IU without necessarily increasing SO or private internet subscriptions. This may partly explain the regional differences identified where SO was lower in the European regions compared to the Americas. These results highlighted the impacts of government social policies on the digital divide and reinforced "Internet for all" as a viable solution to mitigate the usage gap. However, policymakers should also consider ongoing technological advancements that may potentially raise the threshold of meaningful digital participation, necessitating individuals to own personal devices with constant internet access to remain socially and economically relevant. Furthermore, while the Gini Index reflects overall income inequality, it does not capture the specific distribution between wealthy and low-income populations. This limitation may partly explain why significant associations were observed for IU but not SO, as SO may depend more strongly on the proportion of disadvantaged individuals lacking resources rather than generalized inequality measures. Future research may consider examining regional income distribution and individuals' socio-economic status to provide better predictors of smartphone ownership.

One limitation of this study is the sample size. Although the overall sample size was relatively large, not all analyses had sufficient studies to achieve statistical power. For the bi-yearly subgroup analyses, there were three subgroups with less than three studies for current and daily IU, and two subgroups for SO. Therefore, caution in interpretation is warranted for these subgroup analyses. Moreover, only about half of the psychiatric patients reported daily IU, it was the least frequently measured across studies and was not assessed consistently across all time periods. Future research on digital inclusion among both general and disadvantaged populations should include daily IU as a standardized metric to enable more accurate and meaningful assessments of the usage gap in the evolving digital landscape. Furthermore, due to insufficient reporting across included studies, only multivariate meta-regressions on socio-demographic factors were conducted exploratively. The interaction between individual socio-demographic, illness-related, and macro-level socioeconomic factors was not explored. Additionally, only a very small number of studies were available post-2020 (2 studies for current and daily IU, and 6 studies for SO), making the exploratory analyses of the pandemic effects and post-pandemic trends underpowered. Findings related to potential post-COVID declines should be interpreted with caution until more post-pandemic data become available and future studies should continue to monitor the digital engagement trends to identify any possible widening of the divide.

Secondly, the included studies suffered from high methodological heterogeneity, particularly in operational definitions and timeframes used to assess "current" internet users. Measurement periods varied widely, ranging from weekly to yearly intervals, and some studies categorised users without clearly specifying the reference period. Such inconsistencies in strictness of criteria may make the outcomes vulnerable to inflation or underestimation, thereby obscuring true temporal trends. This lack of standardization underscores a broader concern regarding the constituents of a meaningful timeframe for assessing digital participation. Establishing consensus on internet usage is critical for ensuring comparability of findings across studies which warrants further investigation.

Thirdly, the regional distribution of studies was highly uneven, with only three conducted in Asia, one in Africa, and none in Southeast Asia. Although subgroup analyses were performed to explore regional effects and account for outcome heterogeneity, the limited representation of several regions resulted in underpowered analyses. This imbalance restricted the generalisability of the findings and highlighted the need for more geographically diverse research. Notably, this review utilized national data from the United States as a benchmark for comparison. While most of the included studies were conducted within the US, employing this reference to evaluate findings from studies conducted in other regions may introduce comparability bias. In particular, the digital divide also existed on a regional level due to differences in ICT infrastructures[29], and developing regions may be more vulnerable to the divide. We performed subgroup analyses restricted to U.S.-only studies to measure the changes in digital engagement within the same national reference frame. Although limited by small sample sizes, these analyses similarly reflected a narrowing of the digital divide since 2014 for both current internet use and smartphone ownership (Supplementary Figs. 16 & 17), which were largely consistent with the overall temporal trends. Nonetheless, this approach cannot fully account for cross-regional differences. Furthermore, we did not perform subgroup comparisons with healthy subjects by demographic characteristics (e.g., age or gender). The included sample was on average middle-aged with balanced gender distribution, making comparisons with the general population a reasonable benchmark. Therefore, future research should explore subgroup-specific digital divides, such as in older age groups to address the intersectionality between multiple disadvantaged status and develop region-specific benchmarks spanning multiple geographic areas to improve the robustness and generalizability of findings.

Fourthly, other variables, such as cognitive functioning, housing situation and income level, have been identified in prior research as factors influencing digital engagement but could not be examined in this meta-analysis due to insufficient reporting across included studies[26,30,31]. Although efforts were made to extract data on socio-economic status and living situation, these variables were rarely available and often unstandardized, which may partly explain the high residual heterogeneity observed in our analyses. Besides, while different psychiatric diagnoses may influence digital engagement, our analysis primarily distinguished between individuals with and without psychosis, as it was the most consistently reported diagnostic category across included studies. Other diagnoses, such as affective disorders or substance use disorders, were less frequently or inconsistently documented, making reliable analyses infeasible. Finally, only fundamental evaluation of the internet usage gap rather than examining specific online activities were reviewed in this study. It is possible that psychiatric populations differ from the general population not only in access but also in how they use the internet. Future research could examine specific types of internet use to provide a more nuanced understanding of the usage gap and to inform targeted interventions.

In conclusion, our findings suggest that the gap in internet usage and device ownership between the general population and psychiatric populations has substantially narrowed but may have widened since 2020, calling for continued monitoring of the gaps. Moreover, research on digital inclusion should shift focus on the patterns of internet use as a discrepancy between current and daily internet usage within the psychiatric population was observed. Individual factors including older age, male, lower education, diagnosis of psychosis and employment were found to be related with digital disengagement with varied directions. At macro-level, regional income inequality was also associated with internet use. Our results highlighted a complex relationship between these factors and the digital divide over time. Thus, it would be crucial to establish a standardized core outcome set for assessment of digital divide encompassing key socio-demographic factors (e.g., age, gender, living status, marital status or other social network indicators), socio-economic indicators (e.g., educational level, employment status, occupational type, income, standardized poverty measures), clinical variables (e.g., standardized diagnostic reporting, illness severity, cognitive functioning), and digital engagement metrics (e.g., digital usage patterns, device ownership, self-reported digital skills such as the Essential Digital Skills survey[19]). This would facilitate cross-study comparisons and comprehensive understanding of the digital divide, in support of the United Nation (UN) initiative to monitor and evaluate the maturity level of digital health in countries and institutions, implement digital health strategies and inform future policy development[15].

Methods

Literature Search and Selection Criteria

This review was pre-registered on PROSPERO (ID: CRD42024542674) and adhered to the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines[32] (Supplementary Table 1). A systematic search of PubMed, MEDLINE, PsycINFO, Scopus, and Web of Science was performed from database inception to 22 October 2024. The search strategy was designed to capture studies addressing the digital divide, internet use, and smartphone ownership in psychiatric populations. For the digital divide, we used the terms “digital divide”, “digital inequality”, “digital gap”, “technology inequality”, “digital disparities”, and “digital exclusion”. For internet use, we included “internet use”, “internet usage”, and “internet access.” For smartphone ownership, we included “smartphone ownership” and “smartphone access”. For psychiatric populations, search terms included “mental illness”, “mental disorder”, “psychiatric illness”, “psychiatric disorder”, “psychiatric disabilities”, “severe mental illness”, “schizophrenia”, “psychosis”, “bipolar”, “major depressive disorder”, “anxiety disorder”, “obsessive-compulsive disorder”, “mood disorder”, “substance use disorder”, “trauma-stressor related disorder”, and “eating disorder”. Within each conceptual group, terms were combined using the Boolean operator OR, and the resulting sets were combined using AND to form the final search string. Paper screening, data extraction, and quality assessment were conducted independently by two researchers (CTW Wong, HLJ Li), and disagreements were resolved through discussion with the research team.

Only peer-reviewed articles that were quantitative studies, published in English, and with separate categorical measurements on the rate of internet users (IU), smartphone owners (SO), or access among adults (aged over 18) diagnosed with any psychiatric illnesses were included. A smartphone is defined as a mobile phone with apps and internet capabilities. Studies were excluded if they, (1) did not measure SO and IU as categorical variables; (2) no separate information were reported for individuals with psychiatric illnesses; (3) involved samples with problematic internet use or internet abuse; or (4) were abstract, poster, qualitative studies, case reports, or reviews. For longitudinal studies with multiple follow-up studies, the study with the clearest definition and measurement period of IU and/or SO was chosen.

Data extraction and risk of bias assessment

The following information was systematically extracted from each study: (1) study and sample characteristics: sample size, study region, age, gender, educational level, employment, data collection period, and diagnosis; and (2) the rate and measurement period of SO and IU. When data collection period was not provided, the year used for national data comparison in the study, or the year of journal acceptance was extracted instead. The rates were extracted separately for different psychiatric diagnoses and study regions where possible. To reflect clearly the temporal relationship of the data, past users/owners were categorised as non-users or non-owners. IU was extracted along with their measurement period, IU was classified as current IU (non-daily internet usage, including user in the last 3 months, 12 months, monthly and weekly user) or daily IU, as the latter indirectly represented familiarity and regular usage of the internet that is distinct from simply having used the internet (Supplementary Table 5). The access rate of smartphones was used as equivalent as SO when SO was not provided. Gini Indices of the regions for the year closest to the midpoint of included study data collection year were obtained from the World Bank[33]. The Gini Index measures income inequality, where a higher index indicates higher degrees of inequality[34]. The quality of the studies included in the current review was assessed using the Joanna Briggs Institute (JBI) checklist[35] (Supplementary Table 6). The included studies were ranked according to their quality.

Statistical Analysis

Meta-analyses were conducted to examine the bi-yearly temporal trends for SO, current and daily IU among psychiatric populations. Studies were allocated to bi-yearly intervals using the midpoint of each study's data collection period to ensure sufficient sample size and account for rapid technological changes. Random-effects models were applied to the meta-analyses of proportions, with logit transformation used to stabilise variance and improve the normality assumptions. A normal approximation interval based on summary measures was used to estimate the confidence interval (CI)[36]. Meta-analyses were performed with data when at least 2 studies were available for an outcome and period. The Cochran's Q, Tau^2 and I^2 statistics were used to estimate heterogeneity between studies, with high heterogeneity indicated by an $I^2 > 75\%$. The robustness of results was tested by performing sensitivity analyses using the leave-one-out method and removing studies of low quality (ranking in the lower 75% quartile of quality score) to evaluate the changes in effect size in current IU and SO. Funnel plots and Egger's test were used to assess publication bias in current IU and SO. As the data for daily IU was relatively limited and concentrated within certain periods, sensitivity analysis and publication bias tests were not conducted.

Temporal trends were visualized by plotting bi-yearly pooled rates with locally weighted linear regression (LOESS) smoothing[37]. Following the methodology of a previous meta-analysis[13], as most included studies were conducted in the US, the corresponding US national data retrieved from International Telecommunication Union[1] was utilised as a benchmark for comparing SO and current IU. Since no equivalent national data were available on daily IU, comparisons were only made against current IU to examine the differences between having used the internet and regular internet use. To validate the changes in the usage and ownership gaps within the same national reference frame, sensitivity analyses were performed on US-only studies.

Separate meta-regressions were performed for age, gender, educational level, employment status, Gini index, and presence of psychosis on SO, current and daily IU, with year of data collection as controlled variable. The potential interrelated effects of sociodemographic variables (i.e., age, gender, employment status and educational level) were explored through multivariate meta-regression. Explorative meta-regression analyses were also conducted on the pandemic effects (pre-2020 vs post-2020), and WHO regional differences on the outcomes while controlling for the year of data collection. Sensitive analysis was conducted by excluding 2020-2021 studies when possible. Regional sub-group meta-analyses further complemented the results on regional differences in the outcomes.

All analyses were performed with R (version 4.4.2), using the R package "metafor"[36].

Data Availability
The datasets generated and/or analyzed during the current study are not publicly available, as they comprise extracted data from both open-access and subscription-based published studies. However, they are available from the corresponding author upon reasonable request.

Code availability
No custom code was used in the analysis but the R scripts used in the current study is available on reasonable request from the corresponding author.

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Author contributions

C.T.W.W. and S.K.W.C. are the chief investigators who conceptualised, designed the review protocol and developed the search strategy. C.T.W.W. and L.H.J.L. conducted systematic literature search and paper screening. C.T.W.W. conducted data extraction with L.H.J.L. and Y.S.V.C. C.T.W.W., H.K.H.T., W.T., C.L., and H.Z. conducted data analysis. C.T.W.W., H.K.H.T. and S.K.W.C. were responsible for writing the original draft and result visualisation. All authors revised and finalized the manuscript. All authors approved the content of the manuscript. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication.

Competing interests

The authors declare no competing interests.

Additional information

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