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A longitudinal study of a mHealth app and regional policies on the uptake of postpartum depression referral after positive screening in Shenzhen

Chaoyang Yan^{1†}, Ruoyun Cao^{1†}, Xinxin Hu^{2†}, Yancen Hu³ and Huimin Liu^{3*}

Abstract

Background Postpartum depression (PPD) has received widespread attention. Shenzhen has been running a large-scale program for PPD since 2013. The program requires mothers to self-assess when applying information technology to PPD screening beginning in 2021. The purpose of this study was to conduct a longitudinal analysis of the impact of mHealth apps on the health-seeking behaviors of PPD patients.

Methods Longitudinal data from districts in the Shenzhen Maternal and Child Health Management Information System (MCHMIS) for ten years was used in this study. Referral success rate (RSR, successful referrals to designated hospitals as a percentage of needed referrals) was used to assess health-seeking behavior. Trend χ^2 tests were used to assess the overall trend of change after the implementation of mHealth in ten districts in Shenzhen. Interrupted Time Series Analysis (ITSA) was employed to assess the role of the mHealth app in changing patient health-seeking behaviors.

Results For the results of the trend χ^2 tests, the ten districts of Shenzhen showed an upward trend. For the ITSA results, different results were shown between districts. Nanshan district, Longhua district, and Longgang district all demonstrated an upward trend in the first-year application of the mHealth app. Nanshan district and Longgang district both exhibited an upward trend in terms of sustained effects.

Conclusions There is a difference in the performance of the mHealth app across the ten districts. The results show that the three districts with better health resource allocation, Nanshan, Longgang, and Longhua districts, demonstrated more significant mHealth app improvements. The mHealth app's functions, management systems, and health resource allocation may be potential factors in the results. This suggests that when leveraging mHealth applications, the first step is to focus on macro-level area resource allocation measures. Secondly, there should be effective process design and strict regulatory measures. Finally, there should also be appropriate means of publicity.

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Keywords Postpartum depression, mHealth, Referral success rates, Interrupted time series

Introduction

Postpartum depression background

Postpartum depression (PPD) has been identified as a major public health issue worldwide. It refers to depressive symptoms that occur in the latter stages of pregnancy or within four weeks of giving birth, with a prevalence rate of roughly 6–20% and an incidence rate of roughly 15% worldwide [1, 2]. Notably, the prevalence could rise to between 24.2 and 32.53% in China [3] and is often higher in economically disadvantaged countries [2, 4, 5]. This condition not only impairs maternal quality of life but also adversely affects the mother-infant bond and the child's development [4, 6, 7].

Current research on the subject focuses primarily on risk factor identification and screening for perinatal depression. Screening for PPD could identify women at high risk and lead to appropriate interventions [8]. Systematic screening programs have been developed in countries such as the USA, UK, and Sweden to identify high-risk populations [9, 10]. Some studies have focused on screening for PPD using a variety of tools [11]. Relatively few studies have been conducted after patient screening. Such a study would be more meaningful, as it might be more directly responsive to the effects of coping measures on PPD improvement.

The shift from screening to patient behavior improvement has received relatively less attention. Changes in patient health-seeking behavior could better highlight the role of screening effectiveness. In terms of patient behavior change, it is necessary to change patient behavior in order to effectively manage PPD, and studies of screening rates alone cannot do this [12]. Therefore, research on behavioral change in PPD patients could more effectively contribute to a practical improvement in the health of the population.

Changes in patients' health-seeking behavior require indicators to be measured to determine the impact of the PPD intervention. Some research in China has used qualitative methods to seek factors influencing PPD healthcare-seeking behavior [13]. However, there is a lack of evidence from real-world quantitative studies in China to explore the effects of behavior change in PPD patients. Given the importance of the above, the referral success rate (RSR) was utilized in this study for analysis. Referral success rate (RSR) is the proportion of successful referrals to patients recommended for referral, an indicator of the effect of health-seeking behaviors among patients.

Implementation of PDD screening in Shenzhen using the mHealth app

Shenzhen, a relatively economically developed city in China, established a comprehensive maternal mental healthcare system in 2013, extending across all ten districts of the city. The program mandates the use of the Edinburgh Postnatal Depression Scale (EPDS) during postnatal visits and the 42nd-day postpartum check-up in hospitals [3]. Targeting over 150,000 women annually, this program aims to identify and refer mothers who screen positive for further mental health care. Specifically, by facilitating timely referrals, the program seeks to alleviate PPD and promote maternal health across various districts.

Shenzhen has implemented an innovative Internet-based strategy to expand PPD screening coverage and facilitate effective referrals. In 2021, Shenzhen used WeChat (China's most popular messaging app) to build a mHealth app for PPD patients [14]. Mothers could be screened for PPD directly on their cell phones, and once the screening was completed, the results were automatically indicated on the interface, and advice was given on the need for further medical attention.

The interface of the mHealth app is shown in Fig. 1. The mHealth app generates a healthcare number for each mother, as well as a record section. The mHealth app creates a psychological screening feature that prompts the mother to complete the psychological screening in a timely manner and marks with different colored circles whether the psychological screening was completed at different stages of the delivery period. The mHealth app will suggest referrals based on the results of the psychological screening to help patients with PPD seek better treatment.

Shenzhen has adopted a mHealth app into its three-tier maternal and child healthcare network, as shown in Fig. 2. Whether completed at the postpartum visit or returned to the birthing hospital at 42 days postpartum, Edinburgh postnatal depression test (EPDS) results are collected through the mHealth app and transmitted in real-time to the Maternal and Child Health Management Information System (MCHMIS). Medical staff could review and manage cases in a timely manner.

In this study, we aim to determine whether mHealth applications can enhance the health-seeking behaviors of postpartum depression (PPD) patients across ten districts in Shenzhen. A longitudinal analysis of policies, support measures, and resource allocation among districts is utilized in this study to identify the strengths and limitations of mHealth apps. As a result, evidence will be collected to guide the optimization of mobile healthcare

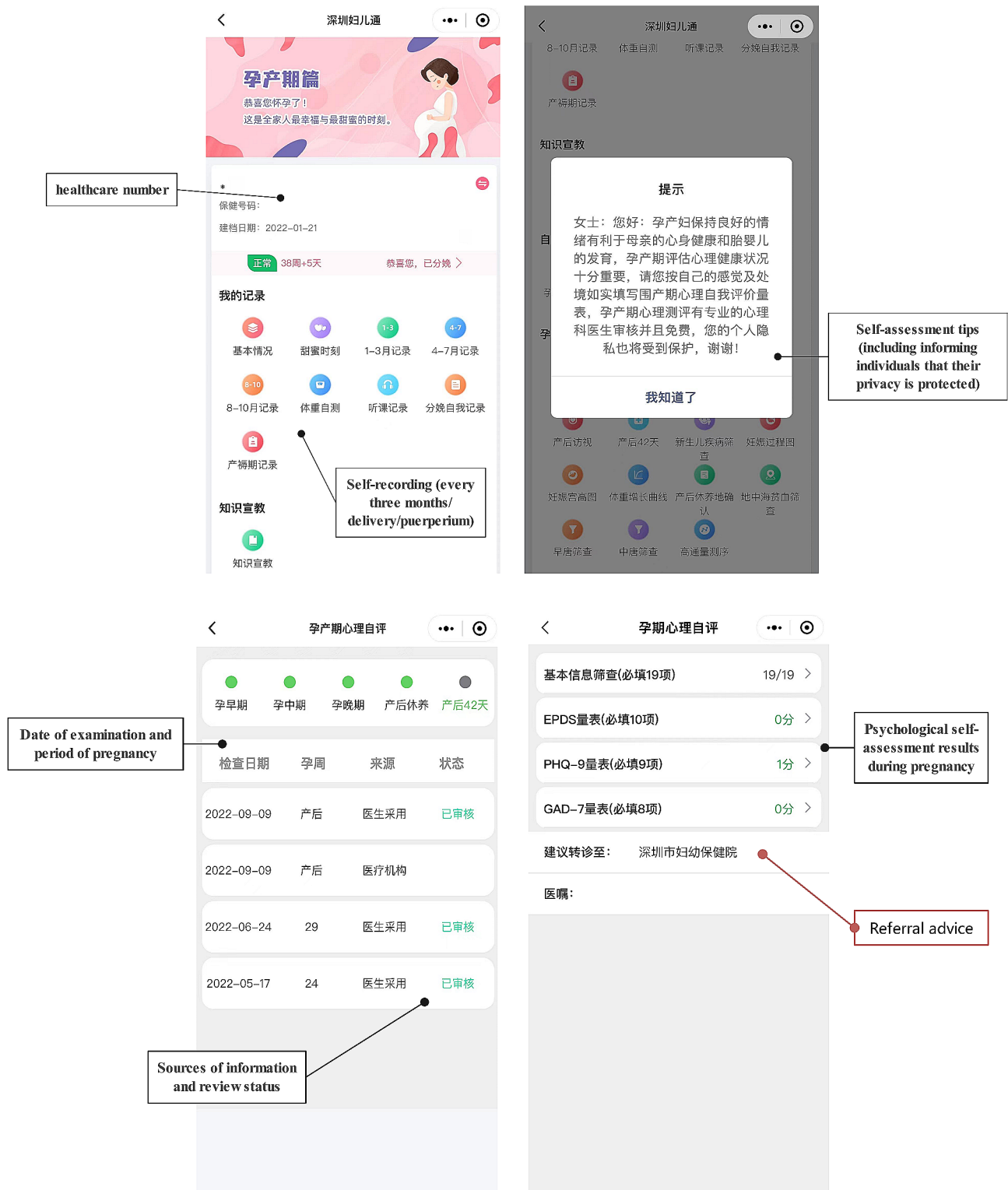


Fig. 1 Interfaces for mHealth

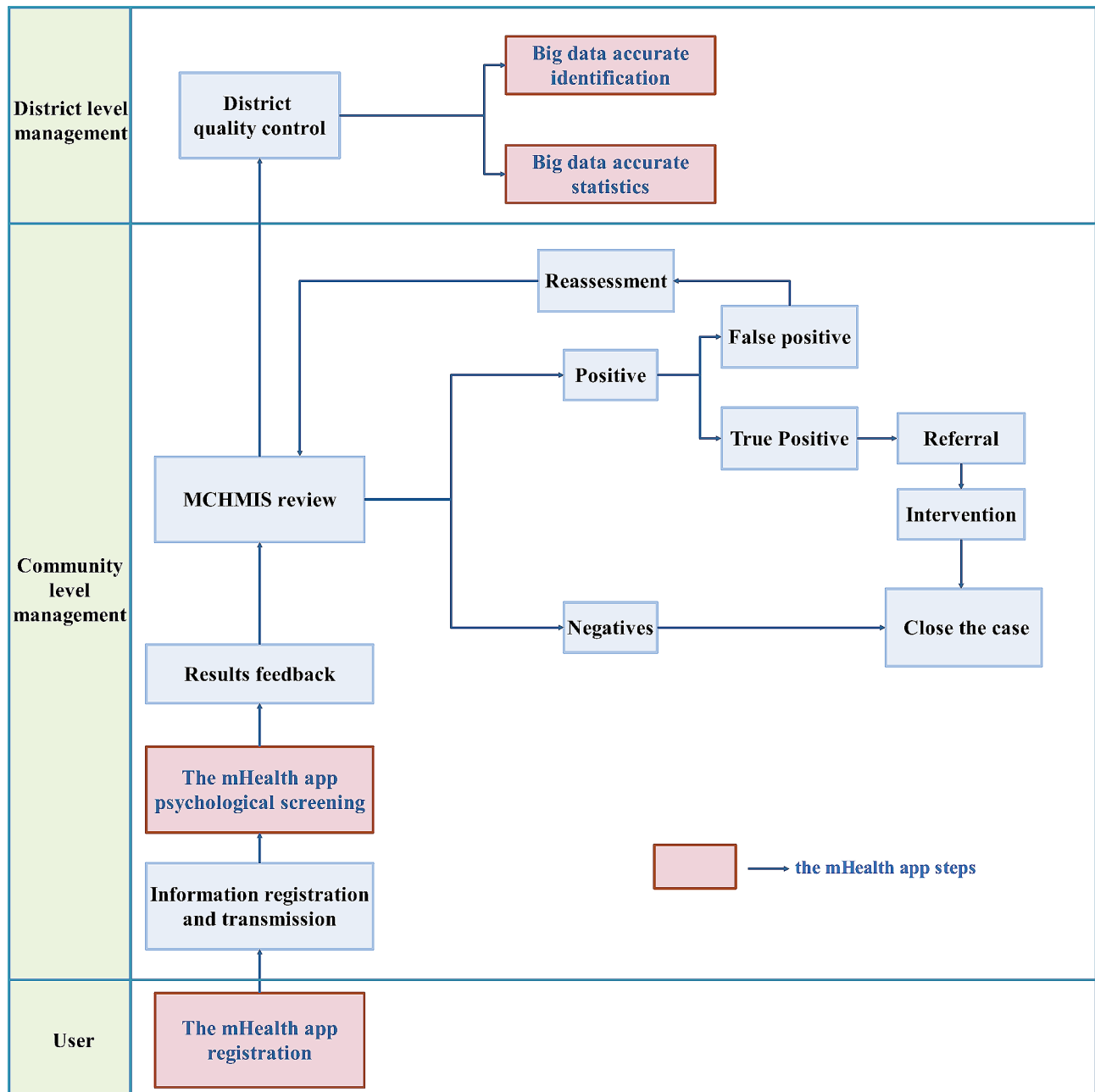


Fig. 2 Process of Shenzhen PPD screening program

applications so that mental health services can be provided more effectively.

Method

Data sources

Data for this retrospective study was sourced from routine health information recorded in the MCHMIS. Data were collected on women screened for depression between January 2013 and December 2022 in ten districts of Shenzhen. Initially, data were collected and entered manually by designated staff at each facility, including

community health service organizations and midwifery institutions. After the mHealth app was introduced in 2021, data was collected and results were transported in real time to MCHMIS. Quality control of the data is carried out by the Maternal and Child Health Hospital at the city and district levels and is reflected in such measures as quarterly supervisory inspections, the establishment of a quality control team, and the organization of numerous trainings.

Variable and definitions

Referral success rate Changes in patient behavior could be adequately reflected by the RSR. $RSR = \text{number of successful referrals} / \text{number of referrals} * 100\%$. Positive depression patients are informed by the mHealth app or healthcare workers that their screening result is abnormal. Only instances of presumed false positives, such as errors in form completion, are addressed by rejecting and requesting a resubmission of the screening form. The referral process is meticulously tracked: healthcare workers confirm whether patients have followed through with their referrals to the specified institutions via follow-up phone calls and manage these cases accordingly. Only when these steps are documented in the MCHMIS is the referral considered successful and included in the RSR numerator.

Statistical method

Trend χ^2 test and interrupted time series analysis (ITSA) were applied in this study. Trend χ^2 was used to analyze changes in RSR across districts in the past ten years. ITSA was employed to evaluate the role of the mHealth app intervention in changing patient health-seeking behavior in a PPD screening program after the mHealth app was adopted in 2021. The model was fitted using segmented regression, which enabled us to statistically assess changes in the intervention over time [15]. The segmented regression model for the single-group ITSA was.

$$Y_t = \beta_0 + \beta_1 \text{time} + \beta_2 \text{intervention} + \beta_3 \text{post} + \varepsilon_t.$$

Where the outcome variable at moment t was denoted by Y_t and a continuous variable of time was represented by time . The dummy variable for the occurrence of the intervention was represented by intervention , which took the value of 0 before the intervention and 1 after the intervention. A continuous time variable after the start of the intervention was represented by post . The initial

level of the outcome variable was represented by β_0 as the intercept term.

The estimate of the slope of change in disease before the intervention was represented by β_1 . The direct estimate of the change in the variable in the first year after the intervention was represented by β_2 , in response to the immediate effect of the intervention. The slope of the variable after the intervention compared to the pre-intervention trend, which responds to the sustained effect, was represented by β_3 . The residuals at moment t were denoted by ε_t , meaning that there was no variation explained by the regression model.

SPSS 25.0 was used for trend χ^2 , and STATA software 13 was applied to the ITSA model (generalized least squares were utilized for autocorrelation treatment), with statistical significance at $p < 0.05$.

Result

Figure 3 reflects the work of the PPD screening program in Shenzhen over a ten-year period. In terms of PPD referral rates, the city has a linear upward trend ($p < 0.001$) over the decade. The referral rate increased steadily from 75.72% in 2014 to 91.03% in 2019. There was a slight decrease in 2019–2020, and the percentage of increase accelerated in 2020–2022 until it reached 98.52% in 2022. 2018 had the highest number of follow-ups, reaching 7,566. In terms of RSR across the city, RSR has a linear trend ($p < 0.001$). RSR has steadily risen over a ten-year period from 5.89% in 2014 to 57.39% in 2022, with the number of successful referrals surpassing 3,000. There is a slight decrease in the number of successful referrals from 2018 to 2020, and continues to rise after 2020. The screening program was carried out stably.

Figure 4 shows a linear trend ($p < 0.05$) in PPD RSR in all districts. Among them, Nanshan District, Guangming District, Dapeng District, Luohu District, Longhua District, and Longgang District all saw faster growth. Before 2020, Nanshan District had a low level of RSR, but it improved by 10% from 2020 to 2021. In the first four

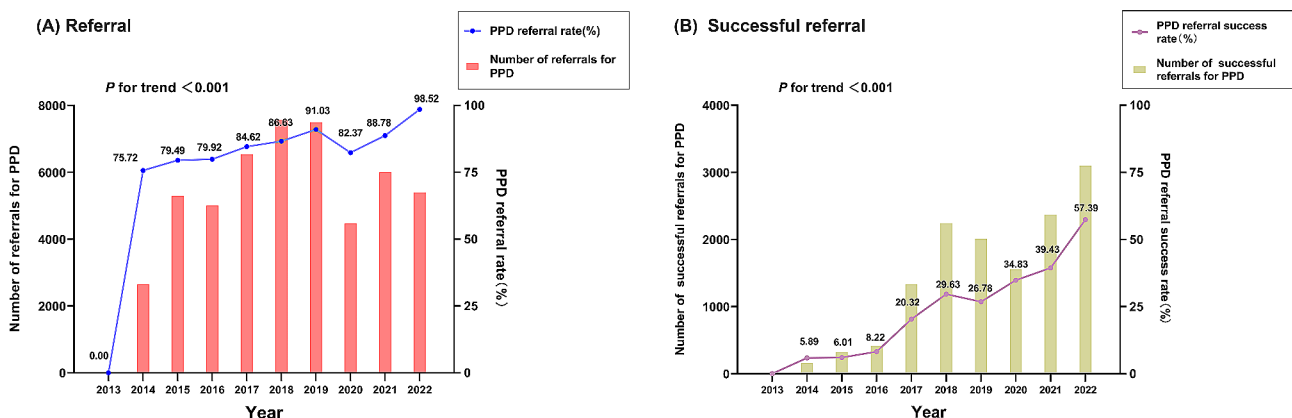


Fig. 3 Changes in referral rates and RSR in Shenzhen over a 10-year period

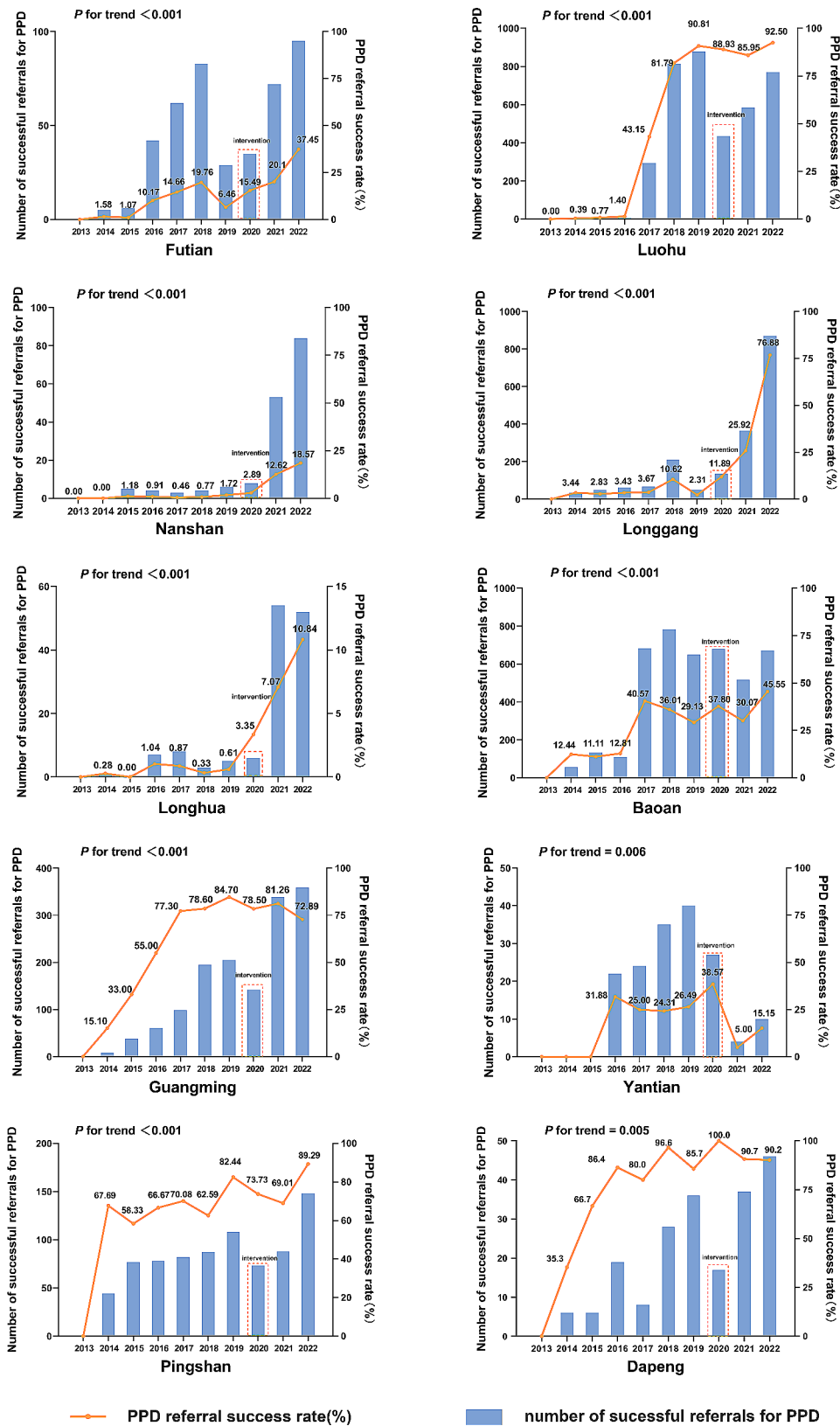


Fig. 4 PPD RSRs in ten districts of Shenzhen

years, Guangming District saw a tremendous increase, rising from 15.10 to 77.30%. In 2020, Dapeng District achieved a 100% success rate in referrals. Luohu District increased from 1.40% in 2016 to 90.81% in 2019. Longhua District has a lower level, below 1% from 2014 to 2019, rising to 10.84% by 2022. Longgang District has an overall upward trend, with a faster rate of increase in the latter four years.

The PPD RSR in Pingshan District, Baoan District, and Futian District is on a slow upward trend. Pingshan District has a higher starting point, with an RSR of 67.69% in 2014 alone, the highest among the ten districts, so it is growing more slowly. Baoan District has a lower RSR, all of which is below 50%. Futian District climbed steadily between 2014 and 2022, from 1.58 to 37.45%. With a general declining trend, Yantian District saw a greater decline in 2021 compared to the previous year, falling from 38.57 to 5.00%.

Table 1 exhibits the results of the ITSA of PPD RSRs. Based on the meaning of equations β_1 , β_2 , and β_3 described above, β_1 shows the trend in RSR before the mHealth app application. Before the mHealth app was implemented (before 2021), the PPD RSR in Nanshan District improved at a rate of 0.34% annually ($p=0.018$). In Pingshan District, Guangming District, Dapeng District, Baoan District, Luohu District, and Longgang District, the RSRs increased with a yearly average of 2.76% ($p=0.008$), 10.89% ($p=0.016$), 8.60% ($p=0.015$), 4.87% ($p=0.029$), 14.93% ($p=0.004$), and 0.96% ($p=0.008$), respectively, before the intervention. The remaining districts were not statistically significant at this time. Nanshan, Longhua and Longgang districts had lower RSR trends than the other districts prior to the implementation of the mHealth app, so it is necessary to systematically analyze the reasons for the lower trends before implementation.

For β_2 and β_3 , which are of greater interest to most ITSA studies, they measure the first-year effect of the intervention and the sustained effect after the intervention. They are more representative of the effect of the mHealth app. In terms of presenting the immediate

effect of the mHealth app intervention β_2 , Nanshan District saw an average increase in PPD RSR of 9.87% in the first year of the intervention ($p<0.001$). Longhua District increased by 6.09% in the first year of the intervention ($p=0.004$). During the implementation of the mHealth app, Longgang District experienced an average increase in PPD referral success of 20.78% ($p<0.001$) in the first year of the intervention.

In terms of achieving a sustained effect β_3 , Nanshan and Longgang districts increased with a trend of 5.73% ($p<0.001$) and 42.54% ($p<0.001$) per year on average, respectively, after the imposition of the mHealth app intervention. The p -values of the remaining districts were greater than 0.05, which was not statistically significant for the time being.

In summary, the best performers in terms of the immediate and sustained effects of the mHealth app interventions in the PPD screening program are the Longgang, Nanshan, and Longhua districts. All three districts had a considerable increase in the PPD RSRs in the first year of the intervention, and Nanshan and Longgang districts also had a greater trend of increase after the intervention. The reasons for the significant increase in PPD RSRs in these three districts deserve continued exploration.

Discussion

Trends in RSRs and the impact of the mHealth app in terms of shifts in patient health-seeking behavior were analyzed through the analysis of trend χ^2 test and ISTA, and it was found that the effects of the mHealth app implementation showed differences across districts. The mHealth app itself, the regulatory system for the mHealth app, and the state of external health resource allocation may be related to the result.

Optimizing patient engagement and healthcare system efficiency with mHealth technology integration

The functionality of the mHealth app enhances patient convenience and engagement, a key factor in its effectiveness. The mHealth app allows individuals to be screened in a private setting through simple actions on a mobile

Table 1 ISTA results for referral success rates

District	β_1 (%)	SE	P	β_2 (%)	SE	P	β_3 (%)	SE	P
Nanshan	0.34	0.11	0.018	9.87	0.72	<0.001	5.73	0.74	<0.001
Pingshan	2.76	0.65	0.008	-12.65	6.42	0.106	20.93	9.41	0.077
Guangming	10.89	3.02	0.016	-13.10	13.67	0.382	-21.99	13.42	0.162
Dapeng	8.60	2.37	0.015	-22.60	16.74	0.235	-8.96	18.44	0.648
Baoan	4.87	1.60	0.029	-15.26	11.54	0.243	10.79	12.88	0.440
Yantian	1.45	1.89	0.497	-27.30	9.33	0.061	7.56	9.71	0.493
Futian	2.21	1.08	0.096	1.30	7.71	0.873	15.18	8.53	0.135
Luohu	14.93	3.38	0.004	-19.48	20.37	0.376	-9.00	20.45	0.675
Longhua	0.28	0.13	0.074	6.09	1.19	0.004	1.97	1.67	0.291
Longgang	0.96	0.22	0.008	20.78	2.51	<0.001	42.54	4.26	<0.001

phone, alleviating privacy concerns (a key barrier in mental health assessment) and greatly increasing the likelihood that individuals will engage in services [16, 17]. The mHealth app also has a timely reminder function that not only informs patients of the assessment results but also provides information about the referral hospital. Previous studies have shown that timely and convenient information delivery increases patient engagement with healthcare services, and immediate feedback could facilitate a series of real-time evaluations and treatments [18]. The mHealth app greatly contributes to patient health-seeking behaviors and improves the efficiency of the referral process.

The mHealth app realized the information interaction with MCHMIS (see Fig. 5). The use of the mHealth app changes the way paper-based questionnaires were collected in the past and complements the back-end data of the MCHMIS to obtain more accurate and comprehensive data [19, 20]. This integration helps to reduce the overall cost of healthcare delivery and expand the use of screening services, thereby improving RSR [21, 22]. Meanwhile, the mHealth app promotes accurate identification of populations and precise management of patients through the regulation of information [23]. The mHealth app collects personal data and feeds the information back to MCHMIS for review, and this review process avoids false positives and enhances the reliability of the results. Patients found to have positive screening

results are provided with timely referrals and interventions, thus overseeing the entire screening and referral process.

Since the program was launched in Shenzhen, 150,000 people have been screened during pregnancy each year. After the implementation of the mHealth app, the screening rates in Shenzhen has reached more than 95% in the past two years, and the referral rates and RSRs have even increased significantly. There has not yet been a large-scale data analysis of PPD and evaluation of the effectiveness of the mHealth app implementation in other cities in China. This study in Shenzhen provides frontier experience and evidence for the utilization of mHealth to assist PPD screening and intervention in major regions in the future.

Factors influencing mHealth effect: resources, policy, and management

Additionally, the increase in RSRs may also be related to the design of the publicity package and the design of the regulation. In terms of publicity, Longgang District collaborated with Longgang Media to promote patient knowledge and awareness of PPD, which may have contributed to the usage of the mHealth app and patient healthcare-seeking behaviors [24]. Nanshan District conducts special quality control on the work status of the whole district every month, monitoring and providing feedback and rectification through the data in the

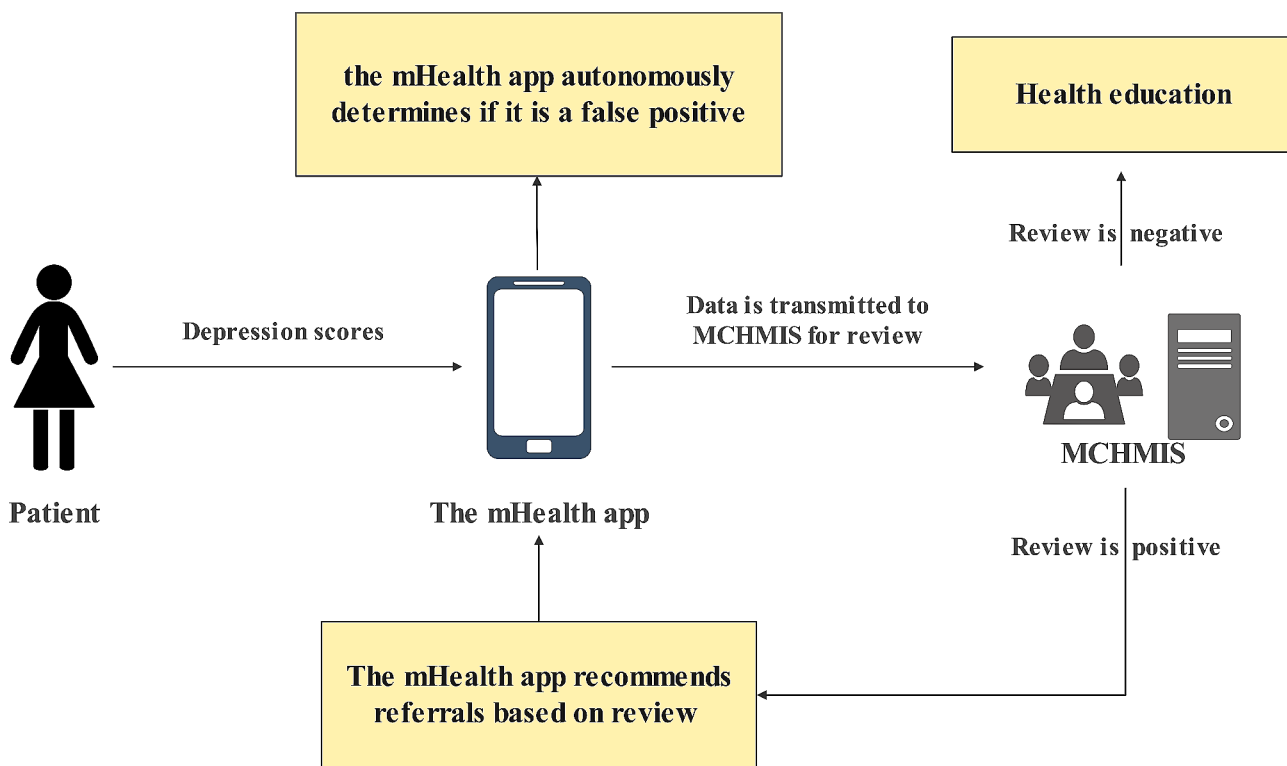


Fig. 5 Information interaction between the mHealth app and MCHMIS

back-end of the mHealth app to promote the efficiency of the whole workflow. Longhua District collected frequent data through precision medicine provided by the mHealth app to provide personalized and continuous management for patients, supervising the referral of high-risk mothers [18].

Moreover, changes in patient behavior may also be linked to the allocation of health resources. Districts with more abundant health resources have demonstrated effective mHealth implementation [25]. In the Nanshan district, abundant resources (including substantial government funding and strong talent development measures) supported frequent quality control measures based on the data from the mHealth app, facilitating timely interventions. Longgang District demonstrated the benefits of a supportive policy system and effective multi-sectoral collaboration. Patients identified by the mHealth app as needing referrals are efficiently directed to the psychiatric department of the district's Maternal and Child Health Center, which works closely with the obstetrics department to ensure a seamless flow of services. Meanwhile, Longhua District's success is due to its strong management. The district benefits from highly supportive management staff and a standardized and organized way of operating to ensure the effective implementation of health interventions. The examples from the three districts above indicate that the process of improving RSR for patients is not only dependent on the implementation of the mHealth app but also on the level of local resource allocation. The reason for the lower trend in these three districts that appeared in the results section before the implementation of the mHealth app may also be related to the fact that the advantages mentioned above were not fully exploited.

However, the use of the information function is not effectively utilized in districts with poor health resource allocation [26]. Healthcare workers in some areas not only lacked a comprehensive understanding of the mHealth app's functions but also spent little time explaining its use to patients in their clinical work, which further hindered the use of the mHealth app by new mothers. In addition, the referral process faces coordination challenges in districts where specialized psychiatric facilities are unavailable. Typically, referrals are made to different agencies and departments, where delays in data processing could disrupt the continuity of care, which is critical for effective mental health integration. There is a need to strengthen the management and engagement of referral departments to ensure seamless service delivery. Also, the mHealth app could be much less effective in districts with insufficient administrators where the process of the mHealth app doesn't form a closed loop.

In conclusion, resource allocation plays a very important role in supporting the functionality of the mHealth

app. This firstly suggests that there is a need to strengthen staff training and increase investment in specialized staff. Secondly, use the mHealth app to promote process standardization. Clarify the responsibilities and obligations of each section, promote multisectoral cooperation, and avoid the lack of service links. Finally, processes such as patient PPD positive determination criteria, follow-up process, patient prognosis management, and feedback need to be supported by an efficient management system. The future utilization of the mHealth app in conjunction with improved health resource allocation deserves deeper study.

Limitations to the study

Firstly, relevant studies would be more thorough and robust in the future if more time-series data were accessible. Secondly, this study only focused on the maternal situation within 42 days postpartum. Although the proportion of women with high levels of PPD at 3 years postpartum is increasing [27], further tracking of the data would also require more time for refinement. In this case, the intervention of the mHealth app had a significant effect on PPD RSRs in all three districts, thus making our study more credible. Finally, as the mHealth app is implemented, it may have an impact on other healthcare measures, such as the childcare facilities and the parental leave system, but these data are not available due to patient privacy concerns. We will analyze the whole mHealth system more comprehensively in the future when such data become available.

Conclusion

The study found that the effect of implementing the mHealth app differ across districts. The mHealth app's function, the management system, and the macro-environment will all have an impact on its implementation effect. This suggests that in the future, attention needs to be paid to the design of the supporting system, and more attention needs to be paid to supplementing resources in areas with fewer health resources to utilize the mHealth app for effective referrals.

Abbreviations

EPDS	Edinburgh Postnatal Depression Self-Assessment Scale
ITSA	Interrupted time series analysis
MCHMIS	Maternal and Child Health Management Information System
PPD	Postpartum depression
RSR	Referral success rates

Acknowledgements

The authors acknowledge funding from the Shenzhen Pingshan District Science and Technology Innovation Bureau. They also acknowledge Shenzhen Maternity and Child Healthcare Hospital for its full support of the study. In addition, they would like to acknowledge all the health workers who participated in the PPD screening and intervention in Shenzhen as well as the patients who volunteered to participate in the PPD program.

Author contributions

CYY (Soochow University) conducted the research, drafted the original manuscript, and contributed to conceptualization. RYC (Soochow University) developed the methodology, performed formal analysis, and assisted in drafting the original manuscript. XXH (ShenZhen Pingshan Maternal and Child Health Hospital) provided supervision and was responsible for funding acquisition. YCH (Shenzhen Maternity and Child Healthcare Hospital) managed data curation. HML (Shenzhen Maternity and Child Healthcare Hospital) contributed resources and participated in reviewing and editing the manuscript. All authors have read and approved the final manuscript for publication.

Funding

This study was supported by the Scientific Research Project of Health System in Pingshan District, Shenzhen, China [Project No.: 202182]. This funding helped the publication of research findings, though the research assistant was not involved in the design of the study, analysis, interpretation of data, or writing of the manuscript.

Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

This study was approved by the Medical Ethics Committee of Affiliated Shenzhen Maternity & Child Healthcare Hospital of Pingshan District, Shenzhen [No.: (2024) 003]. The study was agreed to by each woman in writing, and the raw data were kept strictly confidential.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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Received: 8 May 2024 / Accepted: 1 August 2024

Published online: 14 August 2024

References

- Balan I, Patterson R, Boero G, Krohn H, O'Buckley TK, Meltzer-Brody S, et al. Brexanolone therapeutics in post-partum depression involves inhibition of systemic inflammatory pathways. *eBioMedicine*. 2023;89:104473. <https://doi.org/10.1016/j.ebiom.2023.104473>
- World Health Organization, United Nations Population Fund. Mental health aspects of women's reproductive health: a global review of the literature. 2009:168.
- Jiang L, Wu D, Chen S, Zhao G, Wang Y, Duan W, et al. Towards universal screening for postpartum depression in China: lessons learned from a comprehensive prevention programme in Shenzhen. *Matern Child Health J*. 2022;26:2109–17. <https://doi.org/10.1007/s10995-022-03482-7>
- Putnam KT, Wilcox M, Robertson-Blackmore E, Sharkey K, Bergink V, Munk-Olsen T, et al. Clinical phenotypes of perinatal depression and time of symptom onset: analysis of data from an international consortium. *Lancet Psychiatry*. 2017;4:477–85. [https://doi.org/10.1016/S2215-0366\(17\)30136-0](https://doi.org/10.1016/S2215-0366(17)30136-0)
- Patton GC, Romaniuk H, Spry E, Coffey C, Olsson C, Doyle LW, et al. Prediction of perinatal depression from adolescence and before conception (VIHCS): 20-year prospective cohort study. *Lancet*. 2015;386:875–83. [https://doi.org/10.1016/S0140-6736\(14\)62248-0](https://doi.org/10.1016/S0140-6736(14)62248-0)
- Slykerman RF, Hood F, Wickens K, Thompson JMD, Barthow C, Murphy R, et al. Effect of lactobacillus rhamnosus HN001 in pregnancy on postpartum symptoms of depression and anxiety: a randomised double-blind placebo-controlled trial. *EBioMedicine*. 2017;24:159–65. <https://doi.org/10.1016/j.ebiom.2017.09.013>
- Howard LM, Molyneux E, Dennis C-L, Rochat T, Stein A, Milgrom J. Non-psychotic mental disorders in the perinatal period. *Lancet*. 2014;384:1775–88. [https://doi.org/10.1016/S0140-6736\(14\)61276-9](https://doi.org/10.1016/S0140-6736(14)61276-9)
- Braverman J, Roux JF. Screening for the patient at risk for postpartum depression. *Obstet Gynecol*. 1978;52:731–6.
- Lilliecreutz C, Josefsson A, Mohammed H, Josefsson A, Sydsjö G. Mental disorders and risk factors among pregnant women with depressive symptoms in Sweden—A case-control study. *Acta Obstet Gynecol Scand*. 2021;100:1068–74. <https://doi.org/10.1111/aogs.14051>
- US Preventive Services Task Force, Curry SJ, Krist AH, Owens DK, Barry MJ, Caughey AB, et al. Interventions to prevent perinatal depression: US preventive services task force recommendation statement. *JAMA*. 2019;321:580–7. <https://doi.org/10.1001/jama.2019.0007>
- Venkatesh KK, Zlotnick C, Triche EW, Ware C, Phipps MG. Accuracy of brief screening tools for identifying postpartum depression among adolescent mothers. *Pediatrics*. 2014;133:e45–53. <https://doi.org/10.1542/peds.2013-1628>
- Mazoruk S, Meyrick J, Taousi Z, Huxley A. The effectiveness of health behavior change interventions in managing physical health in people with a psychotic illness: a systematic review. *Perspect Psychiatr Care*. 2020;56:121–40. <https://doi.org/10.1111/ppc.12391>
- Xue W, Cheng KK, Liu L, Li Q, Jin X, Yi J, et al. Barriers and facilitators for referring women with positive perinatal depression screening results in China: a qualitative study. *BMC Pregnancy Childbirth*. 2023;23:230. <https://doi.org/10.1186/s12884-023-05532-6>
- Zhang W, Liu L, Cheng Q, Chen Y, Xu D, Gong W. The relationship between images posted by new mothers on WeChat moments and postpartum depression: cohort study. *J Med Internet Res*. 2020;22:e23575. <https://doi.org/10.2196/23575>
- Wagner AK, Soumerai SB, Zhang F, Ross-Degnan D. Segmented regression analysis of interrupted time series studies in medication use research. *J Clin Pharm Ther*. 2002;27:299–309. <https://doi.org/10.1046/j.1365-2710.2002.00430.x>
- Deng Z, Hong Z, Ren C, Zhang W, Xiang F. What predicts patients' adoption intention toward mHealth services in China: empirical study. *JMIR mHealth uHealth*. 2018;6:e172. <https://doi.org/10.2196/mhealth.9316>
- Xue Wenqing, Cheng KK, Liu Lu L, Qiao J, Xin Y, Jingmin et al. Barriers and facilitators for referring women with positive perinatal depression screening results in China: a qualitative study. *BMC Pregnancy Childbirth*. 2023;23.
- Grossman JT, Frumkin MR, Rodebaugh TL, Lenze EJ. mHealth assessment and intervention of depression and anxiety in older adults. *Harv Rev Psychiatry*. 2020;28:203–14. <https://doi.org/10.1097/HRP.0000000000000255>
- Singh Y, Jackson D, Bhardwaj S, Titus N, Goga A. National surveillance using mobile systems for health monitoring: complexity, functionality and feasibility. *BMC Infect Dis*. 2019;19:786. <https://doi.org/10.1186/s12879-019-4338-z>
- Marcano Belisario JS, Jamsek J, Huckvale K, O'Donoghue J, Morrison CP, Car J. Comparison of self-administered survey questionnaire responses collected using mobile apps versus other methods. *Cochrane Db Syst Rev*. 2015;2015. <https://doi.org/10.1002/14651858.MR000042.pub2>
- Ben-Zeev D, Razzano LA, Pashka NJ, Levin CE. Cost of mHealth versus clinic-based care for serious mental illness: same effects, half the price tag. *Psychiatr Serv*. 2021;72:448–51. <https://doi.org/10.1176/appi.ps.202000349>
- Iribarren SJ, Cato K, Falzon L, Stone PW. What is the economic evidence for mHealth? A systematic review of economic evaluations of mHealth solutions. *PLoS ONE*. 2017;12:e0170581. <https://doi.org/10.1371/journal.pone.0170581>
- Lee H, Uhm KE, Cheong IY, Yoo JS, Chung SH, Park YH, et al. Patient satisfaction with mobile health (mHealth) application for exercise intervention in breast cancer survivors. *J Med Syst*. 2018;42:254. <https://doi.org/10.1007/s10916-018-1096-1>
- Puljak L. Using social media for knowledge translation, promotion of evidence-based medicine and high-quality information on health. *J Evidence-Based Med*. 2016;9:4–7. <https://doi.org/10.1111/jebm.12175>
- Greenberg AJ, Haney D, Blake KD, Moser RP, Hesse BW. Differences in access to and use of electronic personal health information between rural and urban residents in the United States. *J Rural Health*. 2018;34. <https://doi.org/10.1111/jrh.12228>
- Ariiriguzoh S, Amodu L, Sobowale I, Ekanem T, Omidiora O. Achieving sustainable e-health with information and communication technologies in Nigerian

rural communities. *Cogent Social Sci.* 2021;7:1887433. <https://doi.org/10.1080/23311886.2021.1887433>

27. Wu D, Jiang L, Zhao G. Additional evidence on prevalence and predictors of postpartum depression in China: a study of 300,000 puerperal women covered by a community-based routine screening programme. *J Affect Disord.* 2022;307:264–70. <https://doi.org/10.1016/j.jad.2022.04.011>

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