https://doi.org/10.32394/pe/208660

U Venkatesh[1], Varkey Nadakkavukaran Santhosh[1], Ashoo Grover[2], Om Prakash Bera[3], Ashish Joshi[4], R Durga[5]

SYSTEMATIC QUALITY EVALUATION OF MOBILE HEALTH APPLICATIONS USING SELENIUM WEB SCRAPING APPROACH

[1]Department of Community Medicine & Family Medicine, All India Institute of Medical Sciences, Gorakhpur, Uttar Pradesh, India
[2]Implementation Research, Indian Council of Medical Research, Ansari Nagar, New Delhi, India
[3]Civil Registration and Vital Statistics, Global Health Advocacy Incubator (GHAI), Washington, USA
[4]Public health, University of Memphis School of Public Health, Memphis, USA
[5]Department of Dentistry, All India Institute of Medical Sciences, Gorakhpur, Uttar Pradesh, India

ABSTRACT

BACKGROUND. Mobile health applications have emerged as powerful tools for improving public health, but their rapid proliferation raises concerns regarding quality, effectiveness, and security.
OBJECTIVE. This study aimed to systematically evaluate the quality of health applications on the Google Play Store in India, focusing on physical, mental, and social health domains.
MATERIAL AND METHODS. Python and Selenium-based web scraping approach was used to extracted data available from the Indian version of Google Play Store using domain-specific keywords. Applications were screened based on preset criteria. The Mobile App Development and Assessment Guide (MAG) was used to evaluate the application quality across eight domains. Kruskal-Wallis test and partial least squares regression analysis were used for analysis.
RESULTS. From 866 applications, 322 met eligibility criteria (182 physical, 84 mental, 56 social health). Commercial organizations dominated development. Social health applications demonstrated higher download volumes and superior quality across multiple MAG domains, with higher overall scores (35.18 ± 12.05) compared to physical (26.95 ± 11.27) and mental health applications (26.25 ±1 1.62). Quality metrics influenced user ratings differently across health domains, with weak correlation between MAG scores and ratings for physical health applications.
CONCLUSIONS. The study reveals significant variability in mHealth application quality, with concerning deficiencies in privacy and security. Findings highlight the need for enhanced regulatory oversight and quality standards in India's evolving digital health ecosystem.

Key words: *mHealth, MAG, smartphone apps, E-health, Health mobile apps*

INTRODUCTION

The World Health Organization (WHO) defines mobile health (mHealth) as the use of smartphones, sensors, personal digital assistants, wireless monitoring devices, or other wireless technologies for public health and medical practice (1). It has emerged as a powerful tool to enhance and streamline healthcare delivery across diverse populations. Mobile applications, specifically designed to run on smartphones or tablets, serve multiple healthcare functions, from promoting health and preventing diseases to assisting individuals with chronic illnesses in managing their conditions and improving treatment adherence (2). The ubiquity of smartphones has transformed these devices into highly accessible and cost-effective platforms for healthcare delivery and research. Their widespread adoption across different ages, races, and socioeconomic statuses enables researchers and healthcare providers to reach diverse population samples inexpensively (3).

The mHealth market demonstrates remarkable growth potential, with projections indicating a compound annual growth rate of 17.6% from 2021 to 2028 (4). This expansion has been further accelerated by the COVID-19 pandemic, which significantly increased downloads and usage of various mHealth applications (5). Contemporary health applications offer diverse features, including tracking physical activity, monitoring dietary habits, supporting mental health, and enhancing social interactions (6). Smartphone and internet penetration in India have surged, with rural internet users reaching over 425 million, enabling digital health interventions (7). Leveraging mHealth, can enhance healthcare access by delivering preventive and curative services remotely. Its scalability, cost-effectiveness, and ability to provide real-time health monitoring make it particularly effective in underserved rural regions.

Mental and physical health apps are essential tools for promoting healthy behaviours, managing chronic conditions, and improving overall wellbeing through accessible, personalized interventions (8). These apps empower users to monitor, track, and enhance their physical fitness and mental resilience, making them integral components of digital health solutions (9). Social health was included under the broad category of mHealth apps because social connectedness and support are critical determinants of overall health and wellbeing (10). Mobile health apps targeting social engagement can effectively reduce isolation and enhance health outcomes, justifying their inclusion in this study (11,12).

However, the rapid proliferation of mHealth applications raises critical concerns regarding their quality, effectiveness, and security. The absence of standardized evaluation creates a significant gap in literature in assessing the multi-dimensional aspects of these applications, particularly in their practical healthcare applications (13). This is especially relevant in emerging markets like India, where smartphone penetration continues to increase rapidly while regulatory oversight of digital health solutions remains in development (14).

Health applications collect and process extensive user data, from physiological parameters like heart rate to behavioral metrics such as sleep patterns, food intake, and physical activity. While this data collection enables personalized health interventions, it simultaneously raises important questions about data privacy and security protocols (15). The fragmented nature of application development, with contributions from commercial organizations, public institutions, and individual developers, necessitates comprehensive quality assessment to guide users toward high quality digital health solutions. This fragmentation in the health app ecosystem makes it crucial to assess application quality using standardized tools (16).

In India, Android smartphones dominate the mobile device market, with over 95% market share compared to iOS devices (17). This overwhelming preference for Android is driven by the availability of affordable handsets across various price points, making them accessible to a broader segment of the population across diverse socioeconomic backgrounds. Given this predominance of Android usage among Indians, the present study strategically focused on analyzing health applications available on the Google Play Store rather than Apple's iOS Store (18). This targeted approach allowed us to evaluate the digital health solutions most relevant and accessible to the majority of Indian users. This study aims to systematically evaluate the quality of health applications available on the Indian version of Google Play Store, with a specific focus on features supporting physical, mental, and social health domains. A Python and Selenium-based web scraping methodology will be employed to extract relevant data, facilitating a structured assessment of these applications.

METHODOLOGY

Study design and ethical considerations. The current study was observational in design and received ethical approval from the Institutional Ethics Committee (Reference Number: IHEC/AHMS-GKP/BMR/109/2022; Date: 23-04-2022) prior to commencement of data extraction and analysis.

Search strategy. A systematic approach was adopted to evaluate the quality of health applications available on the Indian version of Google Play Store, with specific focus on physical, mental, and social health domains. The keywords were extracted through a comprehensive literature review conducted using the PubMed database. Relevant articles pertaining to digital health, mHealth, and related interventions were identified, and domain-specific terms related to physical, mental, and social health were manually collated from articles to generate a comprehensive list. Table 1. presents the domain specific keywords used in the study.

Data extraction. All Google Play Store searches were conducted without authentication to a Google account to minimize algorithm bias and personalization effects (19). Google Play Store organizes and displays app ratings, reviews, and related metadata based on the user's country-specific Play Store version. In this study, data were extracted exclusively from the Indian version of the Google Play Store using a device and IP address located in India (20). The data extraction process employed automated web scraping techniques utilizing Python programming language with the Selenium library. Custom-developed bots were programmed to systematically extract application data from the Google Play Store at specified intervals. This method was chosen over manual extraction to ensure consistency, minimize human error, and enable

Table 1. Domain-specific keywords derived from literature review

Physical Health	Exercise, Physical Health, Fitness, Health, Weight Loss, Diet, Wellness, Workout, Healthy Lifestyle, Physical Activity, Health Education, Health Monitor, Calorie Tracker, Weight Management, Physical Fitness, Nutrition Guide, Health Assessment, Fitness Coaching, Health Tips, Healthy Eating, Physical Wellness, Healthy Habits, Yoga, Physical Health
Mental health	Mental Health, Stress, Self-Care, Self-Improvement, Meditation, Sleep, Mindfulness, Stress Management, Psychoeducation, Mental Wellbeing
Social Health	Social Health, Social Wellbeing, Social Support, Social Engagement, Social Interaction, Social Wellness, Social Connectivity, Social Hub, Communication

efficient collection of large volumes of data at regular intervals. Manual methods would have been time-consuming, prone to inconsistencies, and impractical for maintaining up-to-date datasets across numerous applications. Automated bots allowed for systematic, reproducible, and scalable data gathering, which was essential for the study's accuracy and reliability. For each keyword search, the first 30 applications were included in the dataset to provide a representative sample of available applications within each health domain. This automated data extraction process was carried out over a period of 3 months, with bots programmed to retrieve data at weekly intervals to capture updates and changes in app information.

The following parameters were extracted for each application: application name, developer information, release date, last update timestamp, number of downloads, application category, application description, and average user ratings of the applications. All extracted data was organized and stored in a spreadsheet for subsequent analysis. The data extraction process was started on May 1st, 2024 and was completed on July 30, 2024.

Screening criteria. All the duplicates were removed from the organized spreadsheet. Two independent reviewers performed screening of the applications, evaluating the names, descriptions, screenshots, videos, and supplementary information available on the Play Store landing pages. Any disagreements between reviewers were resolved through discussion, and if consensus was not reached, a third reviewer adjudicated the final decision. Applications were included in the final analysis if they met three specific criteria: relevance to physical, mental, or social health domains, application updated within the last three years and presence of user ratings and reviews. Applications were excluded if they were not available in English language or if they were primarily designed for donations or clinical trial recruitment.

Quality assessment. The quality of the selected mobile health applications was evaluated using the validated Mobile App Development and Assessment Guide (MAG) (21). This standardized tool enabled objective evaluation of various application parameters including usability, functionality, reliability, and content quality. MAG is an effective tool for the quality evaluation of health applications based on previous research (21-23). MAG was selected for this study instead of the more commonly used Mobile App Rating Scale (MARS) due to its broader scope and greater relevance to current health app evaluation demands. While MARS focuses on engagement, functionality, aesthetics, and information quality, MAG offers a more comprehensive framework consisting of eight distinct criteria specifically designed to address key aspects of application quality (21).

The quality assessment was conducted independently by two experts in digital health. These experts were not involved in the data extraction process. Each expert assessed all selected applications using the MAG framework to ensure comprehensive and reliable evaluation. To maintain objectivity and minimize bias, the assessment process was conducted in a blinded manner, with each expert evaluating the applications independently without prior discussion of their findings. The final MAG scores for each application were calculated by taking the average of the scores provided by both experts across all assessment criteria.

The MAG framework encompasses eight domains: Usability (14 items) evaluates ease of use, functionality, and accessibility; Privacy (14 items) examines user data handling, terms of service, and consent mechanisms; Security (9 items) assesses encryption, password management, and cybersecurity measures; Appropriateness and Suitability (2 items) evaluates benefit explanation and expert involvement; Transparency and Content (2 items) ensures scientific evidence use and ethical adherence; Safety (7 items) identifies potential risks and compliance with medical standards; Technical Support and Updates (2 items) addresses update impacts on data integrity and technical support availability; and Technology (4 items) assesses performance, resource usage, and data recovery mechanisms. The scoring methodology employed a binary scale where each item was scored as "Yes" (1 point) or "No" (0 points). Total scores for each application were calculated by summing scores across all eight domains, with a maximum possible score of 54 representing highest quality and a minimum possible score of 0 indicating lowest quality.

Data analysis. The data analysis process began with data cleaning where missing data were handled through exclusion. Descriptive statistics (frequency, percentage, and mean) summarized key attributes of the applications and MAG scores. The Shapiro-Wilk test confirmed non-normal data distribution, necessitating a non-parametric Kruskal-Wallis test for comparing mean MAG scores across application types. Partial Least Squares regression (PLS) analysis was employed since there was a significant multicollinearity among independent variables and a non-normal data distribution. Separate PLS analyses were conducted for each app category with average user rating as the dependent variable and developer type, last update, number of downloads, total number of ratings, and MAG domain scores as independent variables. The level of significance was set at $P \leq 0.05$.

RESULTS

A total of 866 applications were initially retrieved from the Google Play Store. After removing 494 duplicates, 358 unique applications proceeded to the screening stage. Following the application of exclusion criteria related to relevance, recency of updates, and language availability, 322 applications met the eligibility criteria and were included in the final assessment. Of these, 182 (56.5%) focused on physical health, 84 (26.1%) on mental health, and 56 (17.4%) on social health. (Figure 1).

General characteristics of the included applications. Majority of health applications were developed by commercial organizations (96.1% physical, 94.0% mental, 96.5% social), with minimal contributions from public institutions and individual developers. None of the included applications were developed by academic or research institutes. Most applications had been updated within the last year

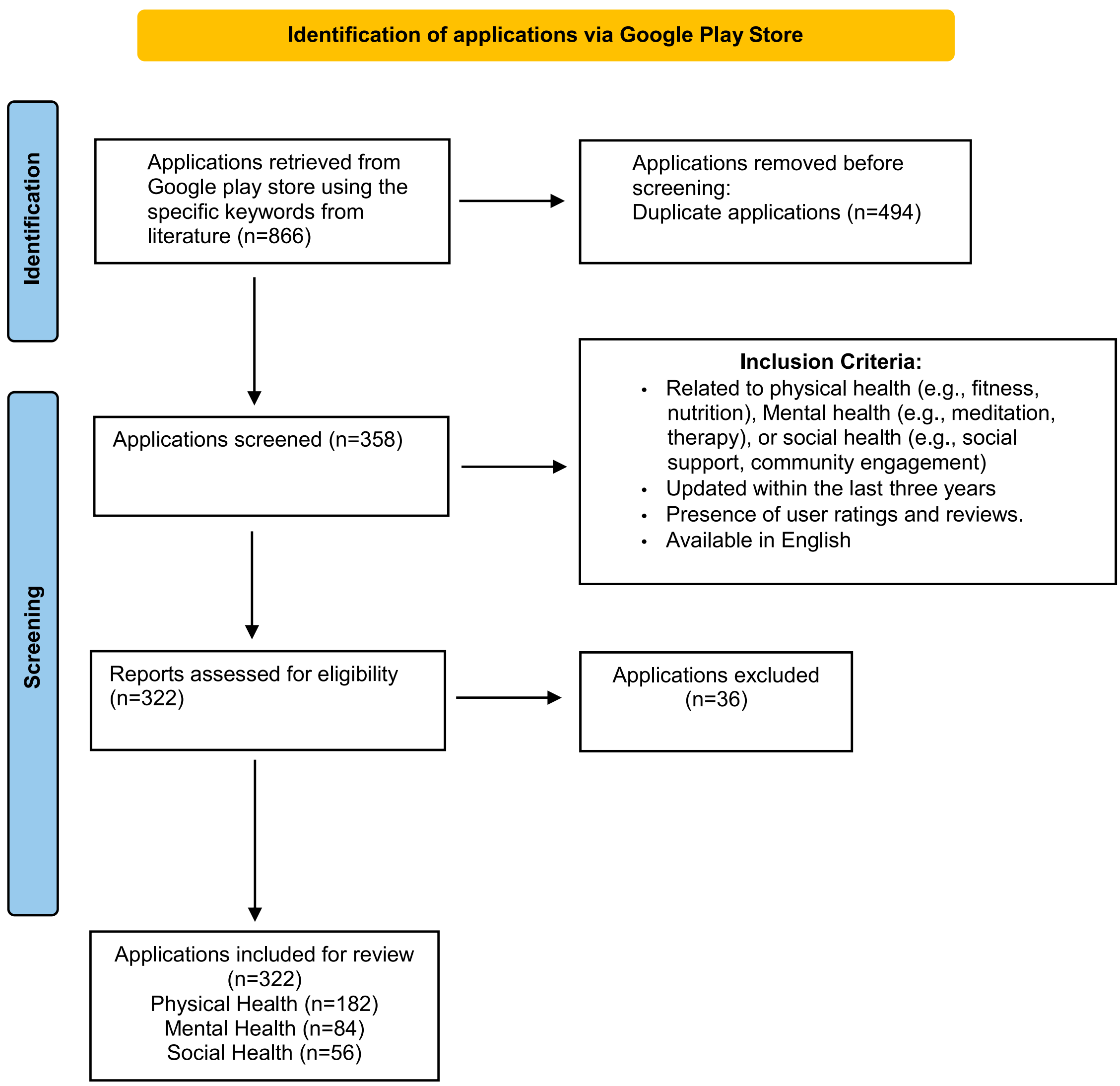

Figure 1. Flow diagram showing the data extraction methods for the applications from Google Play store

(97.3% physical, 98.8% mental, 94.7% social). Social health applications demonstrated the highest proportion of downloads exceeding 10 million (43.8%), compared to physical (8.8%) and mental health applications (2.4%). Majority of applications across all health domains received high user ratings between 4-5 stars (75.3% physical, 77.4% mental, 69.6% social) (Table 2).

Quality Assessment Using MAG. Social health applications were consistently rated higher when compared to both physical and mental health applications across most MAG domains. The mean total MAG score for social health applications (35.18 ± 12.05) was significantly higher than scores for physical health applications (26.95 ± 11.27) and mental health applications (26.25 ± 11.62).

In the domain-specific analysis, social health applications demonstrated significantly higher scores in usability (6.47 ± 1.69), privacy (11.07 ± 4.04), security (7.00 ± 2.56), appropriateness and suitability (1.53 ± 0.66), transparency and content (1.33 ± 0.79), and technical support and updates (1.14 ± 0.93) compared

Table 2. Comparison of the key attributes of the selected applications in various domains (N = 322)

Key attributes	Physical health n = 182 (%)	Mental health n = 84 (%)	Social health n = 56 (%)
Developer type			
Public Institution	2 (1.1%)	3 (3.6%)	0 (0%)
Commercial Organization	175 (96.1%)	79 (94.0%)	55 (96.5%)
Individual	5 (2.8%)	2 (2.4%)	1 (1.8%)
Last Update			
Within 1 year	177 (97.3%)	83 (98.8%)	54 (94.7%)
Within 1-2 years	2 (1.1%)	1 (1.2%)	2 (3.5%)
Within 2-3 years	3 (1.6%)	0 (0%)	0 (0%)
Number of Downloads			
less than 1000	7 (3.8%)	1 (1.2%)	2 (3.5%)
1000 – 10,000	13 (7.2%)	18 (21.4%)	10 (17.5%)
10,000 – 100,000	36(19.8%)	21 (25.0%)	7 (12.3%)
> 100,000 – 1,000,000	57 (31.3%)	33 (39.3%)	7 (12.3%)
> 1,000,000 – 10,000,000	53 (29.1%)	9 (10.7%)	5 (8.8%)
> 10,000,000	16 (8.8%)	2 (2.4%)	25 (43.8%)
Average user ratings			
< 3	4 (2.2%)	1 (1.2%)	2 (3.6%)
3 – < 4	41 (22.5%)	18 (21.4%)	15 (26.8%)
4 – < 5	137 (75.3%)	65 (77.4%)	39 (69.6%)
All values are expressed as frequency with percentages (in parentheses).			

Table 3. Comparison of the mean scores of various domains of MAG

MAG domains	Physical health	Mental health	Social health	H	P-value
Usability	4.74 ± 1.46[a]	4.38 ± 1.46[a]	6.47 ± 1.69	59.69	0.001*
Privacy	9.44 ± 4.24[a]	9.43 ± 4.61[a]	11.07 ± 4.04	9.73	0.001*
Security	4.74 ± 3.42[a]	4.40 ± 3.00[a]	7.00 ± 2.56	28.84	0.001*
Appropriateness and suitability	1.16 ± 0.53[a]	1.26 ± 0.54[a]	1.53 ± 0.66	20.42	0.001*
Transparency and content	0.95 ± 0.84[a]	1.01 ± 0.77[a]	1.33 ± 0.79	9.77	0.008*
Safety	2.76 ± 2.23	2.48 ± 1.98	3.68 ± 3.19	4.61	0.100*
Technical support and updates	0.42 ± 0.80[a]	0.46 ± 0.80[a]	1.14 ± 0.93	32.70	0.001*
Technology	2.73 ± 1.12	2.73 ± 1.24	2.95 ± 0.89	0.95	0.622
Total Score	26.95 ± 11.27[a]	26.25 ± 11.62[a]	35.18 ± 12.05	24.10	0.001*

MAG – Mobile App Development and Assessment Guide; All values are expressed as mean ± standard deviation. The statistical test used: Mann-Whitney post hoc test following a significant Kruskal-Wallis test; *P ≤ 0.05 is considered a statistically significant association. Lowercase letter “a” indicates that post hoc test is statistically significant with the social health group (in the row).

to both physical and mental health applications. However, no significant differences were observed in the safety domain (*P*=0.100) and technology domain (*P*=0.622) across the three app categories (Table 3).

Factors influencing average user ratings. PLS regression analysis of health app ratings reveals distinct influences across categories. For physical health applications, average user ratings show weak positive relationship with number of downloads (r = 0.118) and total user ratings (r = 0.113), while a negative coefficient for last update (r = -0.112) suggests outdated applications receive lower ratings. However, the model explains only 10% of rating variance (R^2 = 0.10). In mental health applications, technology (r = 0.451) and appropriateness (r = 0.410) scores strongly predict higher ratings, whereas safety (r = -0.270) and privacy (r = -0.192) concerns negatively impact perceptions. With R^2 = 0.26, these factors explain a greater share of variance. For social health applications, application downloads (r = 0.210) positively influence ratings, but technology (r = -0.136) and safety (r = -0.103) concerns lower them, with an R^2 of 0.23 (Table 4).

DISCUSSION

Digital health-based interventions enhance healthcare accessibility, enable real-time monitoring, and facilitate personalized disease management. Their integration improves health outcomes by optimizing early diagnosis, treatment adherence, and remote patient care (24). The current study reveals significant variations in the quality of mHealth applications available on the Google Play Store in India. It offers insights into the present state of the mHealth ecosystem across physical, mental, and social health domains. The findings have important implications for users, developers, healthcare providers, and regulatory bodies.

The overwhelming dominance of commercial organizations in the development of health applications across all three domains reflects the market-driven nature of the mHealth landscape in India. These applications were developed specific for Indian users. This commercial orientation reflects global trends where profit-driven entities play a key role in advancing digital health innovation (25). The limited involvement of public institutions represents a missed opportunity for governments and healthcare systems to influence the quality and accessibility of digital health solutions, especially considering that National Digital Health Mission of India emphasizes leveraging technology to improve healthcare delivery (26). The high frequency of application updates observed across all categories suggests active maintenance efforts by developers. This might reflect the competitive nature of rapidly evolving digital health market in India, where maintaining technological relevance is crucial for user retention (27).

In the present study the download patterns revealed striking differences across health domains. The social

Table 4. PLS regression coefficients showing impact of app characteristics and quality metrics on average user ratings across health app categories

Independent Variables	Physical Health App	Mental Health App	Social Health App
Application characteristics			
Developer type	0.030	-0.100	-0.098
Last update	-0.112	0.000	-0.139
Number of downloads	0.118	0.136	0.210
Total number of user ratings	0.113	0.056	0.104
MAG domains			
Usability	0.029	0.152	0.101
Privacy	-0.021	-0.192	0.060
Security	-0.017	-0.005	0.013
Appropriateness and suitability	0.016	0.410	0.051
Transparency and content	0.056	-0.085	-0.030
Safety	0.012	-0.270	-0.103
Technical support and updates	-0.030	-0.106	-0.070
Technology	-0.054	0.451	-0.136
Total score	-0.010	-0.175	-0.098
Model R^2	0.10	0.26	0.23

PLS - Partial Least Squares; Independent variable: Average user ratings; Positive coefficients suggest positive influence on average ratings, while negative coefficients indicate negative impact.

health applications demonstrated significantly higher download volumes, with almost half of the applications (43.8%) exceeding 10 million downloads compared to physical and mental health applications. This disparity may reflect the broader appeal of social connectivity features and the potential stigma associated with dedicated mental health applications in the Indian cultural context (28). The observed download distribution pattern in this study is consistent with the findings of Wang et al., who identified social attributes, source credibility, and legal considerations as key factors influencing user behaviour within the social dimension (29). The present study observed that despite lower download volumes, mental and physical health applications maintained high user ratings, with over 75% receiving 4-5 stars. This requires further investigation, as it suggests that while these applications reach smaller audiences, they potentially deliver satisfactory experiences to their specific user bases. Understanding healthcare customer needs is essential for successfully positioning and sustaining this large markets (30).

Social health applications demonstrated superior quality across multiple MAG domains, particularly in usability, privacy, security, and content transparency. Their higher overall scores may be attributed to the inherent focus on user engagement and data sharing that characterizes social platforms, necessitating robust privacy and security measures. This finding aligns with research indicating that digital interventions incorporating social support often employ more refined user experience designs and robust security measures compared to applications focusing solely on individual health management (31). The superior performance might also reflect the competitive landscape of social media platforms that has established higher baseline standards for user interface design and data protection (32).

Despite their prevalence, physical and mental health applications exhibited concerning quality gaps, particularly in privacy and security domains. This finding resonates with Huckvale et al., who identified similar deficiencies in depression and smoking cessation applications, with 81% transmitted data for advertising and marketing purposes (33). Such deficiencies raise significant concerns given the sensitive nature of health data processed by these applications. The pattern of lower quality scores in privacy and security domains observed across all application categories underscores a pervasive challenge in the mHealth ecosystem, suggesting potential regulatory gaps in the Indian digital health landscape.

The PLS regression analysis performed in the study revealed that quality metrics influence user ratings differently across health domains. For mental health applications, technology features and appropriateness significantly predicted higher user ratings, suggesting that users prioritize functionality and relevance when evaluating mental health tools. However, safety and privacy concerns showed negative correlations with ratings, potentially indicating limited user awareness regarding these critical aspects. This finding aligns with previous research indicating that mental health applications users often prioritize immediate utility over privacy considerations (34).

The weak correlation between MAG quality scores and user ratings for physical health applications suggests a potential disconnect between user perception and objective quality metrics. This phenomenon has been documented in studies indicating that user ratings often reflect subjective experiences rather than objective quality criteria (35,36). For social health applications, the positive influence of download numbers on ratings may indicate network effects, where perceived value increases with broader adoption. However, the negative impact of technology and safety concerns on ratings demonstrates that social health applications users remain sensitive to performance and security issues.

A key strength of this study is its robust methodology, integrating automated data extraction with structured quality assessment. Web scraping enabled unbiased data collection, while the validated MAG framework ensured objective, multidimensional evaluation.

Limitations and future directions. The present study has certain limitations. It assesses only applications from the Google Play Store, excluding iOS applications, though Android users form the majority of the smartphone market in India. While the MAG framework provides a comprehensive evaluation, its binary scoring system may not capture subtle variations in application quality. Future research should address these limitations by incorporating cross-platform studies including both Android and iOS applications. This would provide more comprehensive insights into the broader mHealth ecosystem. Additionally, investigating applications available in regional Indian languages would enhance understanding of digital health accessibility across diverse linguistic communities. Qualitative studies focussing on objective quality metrics with user feedback could further elucidate the relationship between application quality and user satisfaction.

This study highlights the need for stronger regulations in health applications development and distribution in India. Significant quality variations, particularly in privacy and security, suggest self-regulation is insufficient. Certification mechanisms or quality standards could help guide users and encourage developers to prioritize evidence-based design and data protection.

CONCLUSION

The present study provides a comprehensive assessment of the quality landscape of health applications available on the Google Play Store in India, with specific focus on physical, mental, and social health domains. The findings reveal significant variability in application quality, with social health applications demonstrating superior performance across multiple quality dimensions compared to physical and mental health counterparts. The concerning deficiencies identified in privacy and security domains across application categories highlight the need for enhanced regulatory oversight and quality standards in the rapidly evolving Indian digital health ecosystem. As mHealth expands, systematic quality evaluation is crucial for guiding users to secure digital health solutions and providing developers with clear benchmarks for improvement.

Funding
This study was supported by the Indian Council of Medical Research (ICMR) under the Extramural Research Grant (Project No: Adhoc/191/2022/SBHSR.), titled
"Evaluating the impact of digital Health Interventions to enhance physical and mental wellbeing of individuals living in the urban poor settings of Gorakhpur".

REFERENCES

1. mHealth: New horizons for health through mobile technologie | WHO | Regional Office for Africa. 2025 [cited 2025 Mar 13]. Available from: https://www.afro.who.int/publications/mhealth-new-horizons-health-through-mobile-technologie
2. Joshi V, Joshi NK, Bhardwaj P, Singh K, Ojha D, Jain YK. The Health Impact of mHealth Interventions in India: Systematic Review and Meta-Analysis. Online J Public Health Inform. 2023 Sep 4;15:e50927.
3. Wilson K. Mobile cell phone technology puts the future of health care in our hands. CMAJ Can Med Assoc J. 2018 Apr 3;190(13):E378–9.
4. Amagai S, Pila S, Kaat AJ, Nowinski CJ, Gershon RC. Challenges in Participant Engagement and Retention Using Mobile Health Apps: Literature Review. J Med Internet Res. 2022 Apr 26;24(4):e35120.
5. Behar JA, Liu C, Kotzen K, Tsutsui K, Corino VDA, Singh J, et al. Remote health diagnosis and monitoring in the time of COVID-19. Physiol Meas. 2020 Nov 10;41(10):10TR01.
6. Zheng S, Edney SM, Goh CH, Tai BC, Mair JL, Castro O, et al. Effectiveness of holistic mobile health interventions on diet, and physical, and mental health outcomes: a systematic review and meta-analysis. eClinicalMedicine. 2023 Nov 18;66:102309.
7. Pramshu. IndBiz | Economic Diplomacy Division. 2023 [cited 2025 Mar 13]. India had over 700 mn active internet users by Dec '22: Report. Available from: https://indbiz.gov.in/india-had-over-700-mn-active-internet-users-by-dec-22-report/
8. Farzandipour M, Sharif R, Anvari S. Effects of mhealth applications on military personnel's physical and mental health: A systematic review. Mil Psychol Off J Div Mil Psychol Am Psychol Assoc. 2025;37(3):199–207.
9. Mahmood A, Kedia S, Wyant DK, Ahn S, Bhuyan SS. Use of mobile health applications for health-promoting behavior among individuals with chronic medical conditions. Digit Health. 2019;5:2055207619882181.
10. Francis J, Cross D, Schultz A, Armstrong D, Nguyen R, Branch-Smith C. Developing a smartphone application to support social connectedness and wellbeing in young people with cystic fibrosis. J Cyst Fibros Off J Eur Cyst Fibros Soc. 2020 Mar;19(2):277–83.
11. Liu Z, Wang C, Yang D, Luo S, Ding Y, Xu W, et al. High engagement in mobile peer support is associated with better glycemic control in type 1 diabetes: A real-world study. J Diabetes Investig. 2022 Nov;13(11):1914–24.
12. Balki E, Hayes N, Holland C. Effectiveness of Technology Interventions in Addressing Social Isolation, Connectedness, and Loneliness in Older Adults: Systematic Umbrella Review. JMIR Aging. 2022 Oct 24;5(4):e40125.
13. Palanichamy T, Sharma MK, Chandra PS, Kandavel T. Development and validation of an instrument for the assessment of internet use in the Indian context. Ind Psychiatry J. 2023;32(1):120–9.
14. Mukhopadhyay A, Bagchi KK, Udo GJ. Exploring the Main Factors Affecting Mobile Phone Growth Rates in Indian States. J Knowl Econ. 2023 Apr 25;1–23.
15. Khatiwada P, Yang B, Lin JC, Blobel B. Patient-Generated Health Data (PGHD): Understanding, Requirements, Challenges, and Existing Techniques for Data Security and Privacy. J Pers Med. 2024 Mar 3;14(3):282.
16. Zych MM, Bond R, Mulvenna M, Martinez Carracedo J, Bai L, Leigh S. Quality Assessment of Digital Health Apps: Umbrella Review. J Med Internet Res. 2024 Oct 10;26:e58616.
17. Statista. [cited 2025 Mar 13]. India: mobile OS share 2023. Available from: https://www.statista.com/statistics/262157/market-share-held-by-mobile-operating-systems-in-india/

18. Agarwal N, Biswas B. Doctor Consultation through Mobile Applications in India: An Overview, Challenges and the Way Forward. Healthc Inform Res. 2020 Apr;26(2):153–8.
19. Shen N, Levitan MJ, Johnson A, Bender JL, Hamilton-Page M, Jadad A (Alex) R, et al. Finding a Depression App: A Review and Content Analysis of the Depression App Marketplace. JMIR MHealth UHealth. 2015 Feb 16;3(1):e3713.
20. Farag N, Noë A, Patrinos D, Zawati MH. Mapping the Apps: Ethical and Legal Issues with Crowdsourced Smartphone Data using mHealth Applications. Asian Bioeth Rev. 2024 Jul;16(3):437–70.
21. Llorens-Vernet P, Miró J. The Mobile App Development and Assessment Guide (MAG): Delphi-Based Validity Study. JMIR MHealth UHealth. 2020 Jul 31;8(7):e17760.
22. Llorens-Vernet P, Miró J. Standards for Mobile Health-Related Apps: Systematic Review and Development of a Guide. JMIR MHealth UHealth. 2020 Mar 3;8(3):e13057.
23. Miró J, Llorens-Vernet P. Assessing the Quality of Mobile Health-Related Apps: Interrater Reliability Study of Two Guides. JMIR MHealth UHealth. 2021 Apr 19;9(4):e26471.
24. Gold N, Yau A, Rigby B, Dyke C, Remfry EA, Chadborn T. Effectiveness of Digital Interventions for Reducing Behavioral Risks of Cardiovascular Disease in Nonclinical Adult Populations: Systematic Review of Reviews. J Med Internet Res. 2021 May 14;23(5):e19688.
25. Stoumpos AI, Kitsios F, Talias MA. Digital Transformation in Healthcare: Technology Acceptance and Its Applications. Int J Environ Res Public Health. 2023 Feb 15;20(4):3407.
26. Mantri M, Sunder G, Kadam S, Abhyankar A. A perspective on digital health platform design and its implementation at national level. Front Digit Health. 2024 Apr 11;6:1260855.
27. Al Dahdah M, Mishra RK. Digital health for all: The turn to digitized healthcare in India. Soc Sci Med. 2023 Feb 1;319:114968.
28. Stigma associated with mental health problems among young people in India: a systematic review of magnitude, manifestations and recommendations | BMC Psychiatry | Full Text. [cited 2025 Mar 20]. Available from: https://bmcpsychiatry.biomedcentral.com/articles/10.1186/s12888-020-02937-x
29. Wang C, Qi H. Influencing Factors of Acceptance and Use Behavior of Mobile Health Application Users: Systematic Review. Healthcare. 2021 Mar 22;9(3):357.
30. Radu G, Solomon M, Gheorghe CM, Hostiuc M, Bulescu IA, Purcarea VL. The adaptation of health care marketing to the digital era. J Med Life. 2017;10(1):44–6.
31. López Seguí F, Pratdepàdua Bufill C, Rius Soler A, de San Pedro M, López Truño B, Aguiló Laine A, et al. Prescription and Integration of Accredited Mobile Apps in Catalan Health and Social Care: Protocol for the AppSalut Site Design. JMIR Res Protoc. 2018 Dec 21;7(12):e11414.
32. Moorhead SA, Hazlett DE, Harrison L, Carroll JK, Irwin A, Hoving C. A new dimension of health care: systematic review of the uses, benefits, and limitations of social media for health communication. J Med Internet Res. 2013 Apr 23;15(4):e85.
33. Huckvale K, Torous J, Larsen ME. Assessment of the Data Sharing and Privacy Practices of Smartphone Apps for Depression and Smoking Cessation. JAMA Netw Open. 2019 Apr 5;2(4):e192542.
34. Iwaya LH, Babar MA, Rashid A, Wijayarathna C. On the privacy of mental health apps. Empir Softw Eng. 2023;28(1):2.
35. Sun Y, Zhang Y, Gwizdka J, Trace CB. Consumer Evaluation of the Quality of Online Health Information: Systematic Literature Review of Relevant Criteria and Indicators. J Med Internet Res. 2019 May 2;21(5):e12522.
36. Roberts AE, Davenport TA, Wong T, Moon HW, Hickie IB, LaMonica HM. Evaluating the quality and safety of health-related apps and e-tools: Adapting the Mobile App Rating Scale and developing a quality assurance protocol. Internet Interv. 2021 Apr 1;24:100379.

Received: 04.05.2025
Accepted for publication: 25.07.2025

Address for correspondence:
Dr U Venkatesh
Department of Community Medicine & Family Medicine,
All India Institute of Medical Sciences,
Gorakhpur, Uttar Pradesh, 273008, India
email: Venkatesh2007mbbs@gmail.com