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# Leveraging Electronic Health Records (EHR) for Mental Health Care in Underserved Communities: A Systematic Literature Review

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## ABSTRACT

Mental health disorders are prevalent globally, and many patients, particularly in under-represented populations, continue to have restricted access to high-quality care. The study aims to assess the use of EHR-based predictive models to detect and address mental health concerns in underrepresented populations. A systematic literature review was conducted in the Scopus and PubMed databases, covering articles published between 2017 and 2024, with a focus on the use of EHRs and their impact on mental health innovations among underserved populations. There is evidence that EHRs can enhance access to and diagnosis of mental health disorders. Nonetheless, the restrictions include infrastructure, financial, and data privacy issues. This enables the diagnosis of patients who exhibit potential danger signals, allowing for timely action to be taken. Mental health outcomes could be enhanced through EHR-based predictive analytics, as it can identify patients at risk early on. Nevertheless, issues still need to be addressed, such as infrastructure and clinician training, data privacy, and the need to engage underserved populations.

## INTRODUCTION

Mental health disorder is a major global public health issue that affects about 970 million people in the world today. (WHO, 2022). Certain underserved communities, such as economically disadvantaged populations, ethnic minorities, and rural or remote regions, are disproportionately affected by mental health challenges. However, these groups are more prone to mental health disorders but stand at a great disadvantage in engaging with care. These aspects are compounded because there are issues like socioeconomic deprivation, mental health issues, and the few health facilities available. (Kirkbride *et al.*, 2024). This may include a dearth of mental health practitioners in rural areas, resulting in long distances to access care. On the other hand, ethnic minorities suffer from cultural barriers and Stigma, which makes it difficult for them to seek help. (Jacob, 2017). This underlines the need to come up with ways of bridging the gap in access to mental health care, especially with early diagnosis and treatment of mental disorders among society's vulnerable sections.

To avoid the escalation of issues regarding mental health, proper identification of psychological distress must be conducted. It can also help reduce the severity of symptoms, improve overall well-being, and prevent the development of chronic issues. Nevertheless, the delay in detection remains a crucial issue among the underserved population. Such chronic illness and disability can result from prolonged undiagnosed mental health conditions. (Kirkbride *et al.*, 2024). These delays are expected because these communities have limited exposure to basic check-ups and lack most healthcare resources. Also, people have other barriers that include limited information, finances, and fear of discrimination, which make it difficult for them to seek mental health services. (Corrigan *et al.*, 2014). Thus, there is a need to more effectively screen and treat such disorders with the help of models that will detect these disorders in their early stages, especially among vulnerable population groups.

Another strategy discussed among the strategic approaches is the adoption of EHR, followed by integrating it with predictive analysis. EHR systems are used in most healthcare organizations to store patient records, and they are useful in making clinical decisions (Ondogan *et al.*, 2023).

Predictive analytics refers to the use of algorithms and machine learning techniques that utilize data to predict mental health issues before a clinical diagnosis is made. Predictive models can analyze health data (including symptoms, medical history, and demographics) and help identify individuals at risk for psychological distress. (Islam *et al.*, 2024). This early identification means there is an increased chance of more proactive care, which is important for those in underserved communities who have limited access to mental health services. Prediction can help the patient's first preventive intervention earlier, easing the disease burden associated with unattended mental health issues.

However, the accuracy of EHR-based predictive models depends on the quality of the data. Information contained within an EHR is often collected in the context of a clinical visit, but it is not always sufficient to identify mental health risks.

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Structured questionnaires can be integrated into EHR systems to improve predictive models. Most of these questionnaires will help you assess psychological well-being, levels of stress, and other aspects not typically captured during a normal clinical visit. For instance, asking questions about an individual's life stressors, social support, or sleep patterns can provide additional context for predictive models to more accurately predict mental health risks. Combining data from questionnaire surveys alongside EHR records will enhance prediction analytics as a whole and contribute to a clearer picture of an individual's mental health status that can lead to intervention earlier.

Several challenges exist regarding the use of EHR-based predictive analytics and questionnaire-based data collection to improve mental health outcomes in underserved communities. Among the barriers, a lack of trust in healthcare systems and new technologies is a key one.

Many individuals living in underserved communities may be skeptical of AI-powered solutions for mental health, as they have concerns about privacy, data security, or the impersonal nature of these technologies. Thus, mistrust of healthcare systems may stem from underlying discrimination or systemic inequities in the history of healthcare. (Prall *et al.*, 2024; Akil, 2023). As a result, they must be transparent, culturally sensitive, and user-centered to truly benefit people. These solutions can be developed and implemented by involving communities, which can help increase trust and induce the perception of relevance and benefit to these technologies.

Implementing predictive analytics in underserved communities is another challenge; infrastructure is needed. In such areas, many healthcare facilities lack the necessary infrastructural technological support, as well as the resources and qualified staff required to adopt and maintain advanced technologies. However, in certain instances, circumstances such as a lack of access to fast internet or outdated computer systems may limit the efficient use of predictive tools. To address this issue, there is a need to enhance the health facilities and the education of the healthcare providers. To ensure that predictive analytics can be effectively integrated into the healthcare system for underserved communities, it is crucial to provide the necessary resources and support.

Nevertheless, there is a significant potential for increasing the efficiency of mental health outcomes when using EHR-based predictive analytics. These models can be used to identify who is most likely to develop mental health conditions, thus allowing those victims who are affected to be attended to before the conditions worsen, and this will lead to improved overall mental health. In addition, utilizing questionnaire data in EHRs will enhance the efficiency of these models, facilitating the possibility of intervention by healthcare providers. However, significant challenges prevent predictive analytics from being achieved in aspects of trust, infrastructure, and availability. There are various ways through which predictive analytics has the potential to positively impact the access to mental health services gap for underserved communities, such as risk investment in equality and an emphasis on cultural competence in mental health services. Therefore, this study aims to evaluate the role of EHR-based predictive models in early identification and intervention for mental health issues in underserved communities.

## LITERATURE RIREVIEW

### Mental Health Disparities in Underserved Communities

Community-based disparities in mental health are still a critical social issue, as many vulnerable groups of people are experiencing certain levels of psychological problems. For instance, people with low family income, racially or ethnically diverse persons, and people living in rural areas are more vulnerable to depression, anxiety, or PTSD. (Morales *et al.*, 2020). Among these populations, economic instability, employment, and housing instability have a range of tangible effects on levels of psychological distress, stemming from their various social determinants of health. In addition, experiences such as violence, social discrimination, and social exclusion contribute to the development of mental health disorders and, thus, an unhealthy life cycle. (Williams *et al.*, 2019; Akil, 2024). Untreated mental health conditions can also lead to drug use, higher suicide rates, and higher physical illness rates, which is a testament to the lack of adequate service provision to underserved communities.

These communities argue for the importance of early detection and intervention services because many people in the population experience psychological distress. Nevertheless, there are inherent impediments in structures and systems that make it challenging for an individual to seek professional help or seek such help in the first place.

However, this delay prolongs the disease duration, increases the hospitalization rate, and poor treatment outcomes. Hence, the early recognition of alerts and intervention approaches is crucial when dealing with the community's population. Predictive analytics integrated with EHRs has become a possible solution for bridging the gap in mental health and identifying those at high risk of being referred for support services. (Nemesure *et al.*, 2021; Akil, 2024).

### Barriers to Mental Healthcare Access

Financial access issues represent the main barrier keeping underserved communities from receiving mental health care. Mental health services are unaffordable to many due to a lack of health insurance or high out-of-pocket costs. (Rapfogel, 2022). While even people with insurance coverage have limits such as high deductibles, co-pays, and limited mental health coverage, these add additional financial burdens. In addition, funding for public mental health programs is usually not sufficient, which results in long waits and restricted access to services for low-income people. (Hodgkinson *et al.*, 2017). Mental healthcare remains financially unavailable to many people, which makes them delay seeking help until their mental health worsens to the point of requiring emergency care.

Challenges of geographical disparities are also a major concern, especially when mental health professionals and facilities are insufficient in rural areas. Since many people travel long distances to seek specialized healthcare, there are issues with treatment being delayed and a higher cost of transportation. (Syed *et al.*, 2013; (Akil, 2019).

At present, access to mental health is usually a challenge in rural areas, and most of these individuals seek health from general practitioners who cannot offer mental health services because of the lack of the required training. This implies that the majority of the cases remain undiagnosed or inadequately treated in such cultures, and hence, mental health disorders become a concern in such civilizations.

Mental health care access faced several barriers, including cultural and linguistic ones. Mental illness is one of the most stigmatized diseases, and many people with the corresponding problems are scared to ask for help since there is such a stigma around it. Mental health consumers also espouse cultural beliefs about mental health, where some may reject biomedical interventions and turn to other healing modalities, even if they are experiencing symptoms (Subu *et al.*, 2022).

Moreover, due to misinterpretations and wrong diagnoses, language barriers hinder communication between patients and healthcare providers. These challenges are driven by the shortage of mental health professionals with cultural competence, making it harder to achieve when people from diverse backgrounds seek to access providers who are fully aware of their unique cultural experiences and perspectives.

Many systemic barriers, including fragmentation of the healthcare systems and lack of integration of mental health services in general practice, impede access to mental health care. Primary care providers and mental health specialists fail to coordinate to provide adequate mental health care to many people who seek care in general medical settings. (Modi *et al.*, 2022). Moreover, there is a disparity in mental health funding and policy prioritization in underserved communities that compounds the problem of the lack of development of mental health infrastructure in these communities. Together, these barriers result in a large treatment gap such that a large number of individuals with psychological distress will have minimal access to treatment.

**EHR-Based Predictive Analytics for Early Identification of Psychological Distress**

The integration of predictive analytics in EHR has been recognized as an innovative approach to enhancing mental health care access in underserved populations. Big data analytic tools and machine learning approaches are employed to process a considerable amount of patient information and identify patterns and the aetiology of mental disorders. (Nemesure *et al.*, 2021). To this extent, risk prediction models for psychological distress effectively measure the threat level posed by EHR variables, such as medical history, prescription history, and social factors. These models alert the healthcare givers early to take necessary action to forestall the spread of mental health diseases. (Coley *et al.*, 2021).

In other related studies, predictive analytics prove useful in screening individuals who are considered high risk for diseases such as depression, PTSD, and suicide risk. These models apply patterns from patient information to determine when a patient starts feeling some mental stress, but has not yet been diagnosed with any disorder. (Garriga *et al.*, 2022). Furthermore, using predictive analytics in primary care clinics will enable general practitioners to have on-hand decision aids to refer clients for early diagnosis and treatment from mental health specialists. This is particularly advantageous in areas with limited access to health facilities or professional mental health care providers. The enhancement in the early detection strategies can be made more effective by integrating the use of predictive analytics within general practice, which will reduce the prevalence of untreatable mental illness.

**Challenges and Ethical Considerations in Implementing Predictive Analytics**

The potential benefits of predictive analytics in EHR for mental healthcare require several obstacles to be addressed before they can be achieved within this healthcare environment. Using patient data for predictive modelling in health applications raises ethical concerns about patient confidentiality and consent standards, such that they receive information. (Yadav *et al.*, 2023). Patient information protection in healthcare organizations is governed by the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR), which are data protection laws. Furthermore, data sharing and patient consent must be standardized to establish clear rules regarding predictive analytics systems. Machine learning algorithms trained on non-representative datasets may yield an inaccurate assessment of minority populations. (Mehrabi *et al.*, 2021). Preventive models created without diverse and inclusive data inputs may inaccurately classify or disregard mental health issues selectively for some demographic groups. To eliminate bias, researchers and developers must ensure that their predictive analytics tools utilize data sets that accurately represent the experiences of underserved communities. However, healthcare providers often lack expertise in incorporating predictive models into their practice workflows. (Smith *et al.*, 2023). Healthcare providers must be trained and benefit from user-friendly decision support tools to leverage predictive analytics to develop mental health screening and intervention strategies.

## MATERIALS AND METHODS

This systematic review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a clear, comprehensive, and credible investigation into the role of Electronic Health Records in mental health care for underserved communities across the United States (Page *et al.*, 2021).

### Search Strategy

A comprehensive search was conducted for published articles up to 2024 in databases including PubMed, Web of Science, Scopus, and Google Scholar. The search terms used were: "Electronic Health Records," "Mental Health Care," "Underserved Communities," "EHR implementation," "Mental Health Electronic Records," "Barriers to EHR adoption," "Mental health outcomes," and "EHR use in primary care." Boolean operators (AND/OR) were applied to combine the search terms with filters, excluding non-peer-reviewed articles and limiting the results to those published in English. Additionally, the bibliographies of selected papers were reviewed to identify other relevant publications related to the research topic.

### Inclusion Criteria

- Research focuses on using Electronic Health Records in mental health care settings, particularly in underserved communities in the United States.
- Studies published from 2017 to 2024 examine EHR adoption, challenges, benefits, and outcomes in mental health care.
- Peer-reviewed journal articles that discuss EHR systems, their integration into mental health practices, and their impact on care delivery in underserved populations.
- Articles present experimental, observational, or qualitative data on EHR implementation and mental health care outcomes.

### Exclusion Criteria

- Studies are not related to EHR implementation or use in mental health care.
- Articles discussing non-EHR health information technologies or studies that do not focus on underserved communities.
- Research published in languages other than English or studies lacking full-text access.
- Technical reports, reviews, editorials, commentaries, and conference abstracts.

### Study Selection

Two independent investigators initially screened titles and abstracts of all the retrieved articles based on the inclusion and exclusion criteria. Following the initial screening, full-text articles were reviewed to determine final eligibility. When disagreements arose, the two reviewers discussed the issue, and a third reviewer was consulted to reach a consensus. A PRISMA flow diagram was used to outline the study selection process, including the number of records identified, included, and excluded, as well as the reasons for exclusion.

### Data Extraction

Two reviewers extracted data using a structured form designed for this review. The form was tailored to capture relevant information aligned with the research objectives. The following data were extracted:

**Study Characteristics:** Author(s), publication year, country, and study design (e.g., observational, experimental, qualitative).

**EHR System Details:** Type of EHR system used, functionalities, integration with mental health services, and challenges in implementation.

**Impact on Mental Health Care:** Outcomes related to the effectiveness of EHR use in improving care for underserved populations, including enhanced access to care, improved documentation, and improved patient outcomes.

**Methodological Details:** Data collection methods, analytical techniques, and statistical methods (e.g., regression analysis, thematic analysis).

The data extraction process was reviewed for inter-rater reliability by a second reviewer. Any discrepancies were resolved through discussion or, if necessary, consultation with a third reviewer.

### Data Synthesis

A qualitative synthesis was conducted to summarize the findings of the included studies. Given the heterogeneity of study designs and methodologies, a meta-analysis was not performed. Instead, a narrative approach was adopted to highlight key trends in the adoption of EHRs in mental health care, the barriers to their implementation, and their overall impact on underserved communities. Comparative evaluations were made where possible, examining similarities and differences in findings across different EHR systems, settings, and outcomes.

### Ethical Considerations

Each study reviewed in the present systematic review was conducted per the guidelines described in peer-reviewed journals; no new experiments on humans or animals were conducted for this review. Since this work relies on published literature, it does not require ethical clearance.

**Table 1:** Summary of the Included Studies

| Study Title | Authors | Country | Study Design | Methodology | Key Findings on HER Adoption and Impact | Mental Health Care Application(s) |
|---|---|---|---|---|---|---|
| A Help or a Hindrance: The Role of Electronic Health Records in Implementing New Practices in Community Mental Health Clinics | (Matthews & Stanhope, 2020) | USA | Mixed-Methods | Mixed-effects regression, Chart reviews | EHR availability did not influence initial fidelity to person-centered care planning (PCCP) but improved post-implementation fidelity | Community mental health clinics, person-centered care planning |
| Implementation of an EHR-integrated web-based depression assessment in primary care: PORTAL-Depression | (Franco *et al.*, 2024) | USA | Quality Improvement (QI) | Observational, survey, and administrative data | EHR integration improved depression assessment workflows, but financial and personnel constraints challenged sustainability | Primary care, depression screening, and patient portal integration |
| Adoption of Electronic Health Records among Substance Use Disorder Treatment Programs: Nationwide Cross-Sectional Survey Study | (Frimpong *et al.*, 2023) | USA | Cross-Sectional | National Survey, Statistical analysis | Increased EHR adoption in substance use disorder programs from 2014 to 2017, with organizational factors influencing adoption | Substance use disorder treatment programs, opioid epidemic management |
| Electronic health record adoption in US hospitals: the emergence of a digital "advanced use" divide | (Adler-Milstein *et al.*, 2017) | USA | Cross-Sectional | Logistic regression, Survey data analysis | Widespread EHR adoption, but hospitals, particularly critical-access ones, lag in adopting advanced EHR functions like performance measurement and patient engagement. | Hospital-based mental health services, patient engagement |

## RESULTS AND DISCUSSION

Based on the database search, 840 records were identified. Excluded prior to screening: 443 records were excluded as duplicates, 97 were filtered out by automated eligibility scanning, and 107 were excluded for other reasons. This led to the screening of 193 records, of which 53 were deemed unfit for further use. Thus, of the 140 reports that were required to be retrieved, 64 were not retrieved; therefore, only 76 were evaluated for their eligibility. Of these, 36 reports were excluded because they were not pertinent to the topic of interest, 24 others did not provide adequate information, or the studies that were reported in these papers were not comprehensive, and 12 others were excluded because the theoretical model underlying the study was flawed or there was inadequate empirical validation of the model. In total, four studies were selected for systematic review analysis (Figure 1).

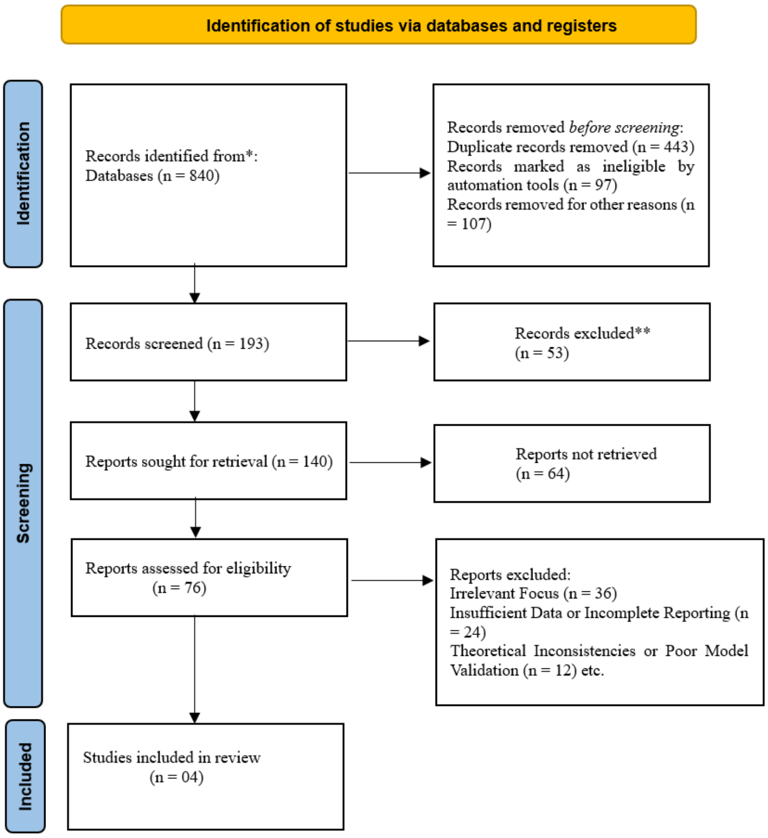


**Figure 1:** The PRISMA flow diagram

### Discussion

The implementation of EHR in mental health care amongst underserved populations reveals that improved accessibility and early diagnosis are feasible. An EHR system that contains all patient information lets patients at risk for mental health conditions be identified early, before conditions worsen. It is particularly beneficial to those who belong to low-income residents in rural places or regions where few mental health workers are available and where services are comparatively inaccessible. These models apply machine learning algorithms to data collected from clinical visits to ensure the early signs of depression, PTSD, or anxiety can be detected before causing more serious health complications (Garriga *et al.*, 2022). These models can help healthcare providers be more proactive in the treatments they administer, which may help prevent long-term mental health issues in patients. The fact that EHRs can enhance the integration of mental health services in primary care organizations suggests a clear correlation between EHRs and the accessibility of mental health services. EHR systems provide the necessary information to healthcare providers and other stakeholders to make informed decisions addressing the needs of patients at risk. Early detection and intervention are essential in the underprivileged community, where access to psychiatrists and other mental health professionals is scarce. (Matthews & Stanhope, 2020). Moreover, EHRs make it easier for patients to access mental health care without traveling long distances, as such facilities can be scarce, especially in rural areas due to poor infrastructure. (Syed *et al.*, 2013).

However, implementing the EHR system poses several challenges. The Main challenges affecting the implementation of these systems include limited infrastructure, especially in developing countries. EHR systems can also be challenging to implement due to the lack of proper infrastructure and trained workforce in many healthcare facilities. This is exacerbated by the fact that implementing and maintaining EHRs is expensive, as well as training employees to effectively use these systems. There is a risk of suboptimal EHR systems in these communities if there is insufficient financial backing or help. (Prall *et al.*, 2024).

Furthermore, issues related to data privacy and patient consent remain major concerns. Some of the challenges that arise with mental health data concern the privacy and security of patient information. HIPAA and GDPR offer some guard against this, but concerns that occur with predictive analytics in EHRs include informed consent and data protection (Yadav *et al.*, 2023).

The next crucial issue is bias in the models that help make some of the predictions. If such EHR systems are not trained on diverse and representative data, they will be unable to capture the mental health risks, especially among minority populations. It might also find out that their prognoses will be off at times, causing some people to be left out or categorized in the wrong groups. They should incorporate fairness to address this issue when diagnosing people from different backgrounds, as this affects their mental health risks. (Mehrabi *et al.*, 2021). Telemedicine requires standards for EHR systems to ensure coherence in data collection, integration, and analysis. A lack of standardization can also lead to compatibility issues, making it challenging for healthcare stakeholders to manage and utilize data effectively in their operations.

Hence, future research should concentrate on real-time interventions to increase the future utilization of EHR systems in mental health care delivery. Integrating telemedicine and mobile health with EHR systems can improve the early detection and management of patients who need the effective utilization of telepsychiatry in their treatment. Real-time interventions can be constructive in several cases to reduce the need for emergency care and improve patient outcomes. (Garriga *et al.*, 2022). Furthermore, as AI is also being incorporated into EHRs, the best practices for implementing AI in mental health care should also be established. These should address some issues, including algorithmic bias and the lack of transparency, to ensure that AI enhances clinical decision-making. (Mehrabi *et al.*, 2021).

It is also important to address another issue of digital health equity, ensuring that such communities receive the benefits that EHR systems introduce. The improvement of using EHR systems has significant potential in enhancing mental health care for the population. Still, the systems should be made more available to people at different income levels or living in remote areas. This involves adapting EHR systems to the local culture and providing low-income and rural populations with access to the necessary technology and digital literacy skills to use them effectively. Addressing digital inequality is crucial to ensuring that disadvantaged groups can access and benefit from new opportunities in digital health. (Williams *et al.*, 2019).

## CONCLUSION

In conclusion, the use of EHRs in mental health care significantly increases the accessibility of care, especially among vulnerable groups. Appropriate levels of EHR include the added value of utilizing the predictive analytical element, which helps in the early identification of vulnerable individuals for whom preventive measures can be taken to efficiently manage or effectively prevent the progression of their mental health complications. This has been a significant challenge to the full implementation of EHRs due to several factors, including infrastructure, financial, and privacy issues. Modern development trends, including the incorporation of artificial intelligence (AI) and real-time prediction of outcomes, can improve the mental health care of the population. These issues should be addressed in policy recommendations, which include the need to enhance data privacy laws regarding mental health information, coordination of schemes, cooperation among policymakers, healthcare providers, and technology leaders, increased awareness of digital health, and improvement of the digital environment in rural regions. Moreover, further studies should be devoted to enhancing the efficiency of mental health risk assessment in real-time, discussing the ethical implications of using AI in EHR, and considering the outcomes of implementing EHR interventions on improving the long-term mental health state. By implementing these recommendations, the benefits of EHR systems in supporting the accessibility and effectiveness of mental health care in the targeted, underprivileged populations can be amplified.

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