An adaptive data-driven architecture for mental health care applications: a systematic review

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Background. In an era of rapid technology innovations our lives are gettingincreasingly associated with digital systems. Eventually, every human action leaves a digital data which makes it an invaluable resource. In such context, data driven architectures are crucial in organizing, manipulation and presenting data for positive computing through ensemble machine learning models. Furthermore, the covid pandemic stressed a significant need of an adaptable mental health care architecture inclusive of machine learning predictive models which has the potential to benefit vast population which identify individuals at higher risk of developing various mental health disorders.

Objective. Hence, the research is to develop an adaptable mental health care architecture that leverages data-driven approaches and ensemble machine learning models, to effectively organize, manipulate, and present data for positive computing. The adaptive data-driven architecture enables interventions tailored to various types of mental health disorders and promoting positive computing. This, in turn, would reflect improved mental health care outcomes and increased accessibility for individuals with diverse mental health conditions.

Method. Following PRISMA guidelines, we conducted a systematic literature review in the WoS database to identify the existing strengths and limitations of software architecture relevant to our adaptive design. The systematic review was registered in PROSPERO (CRD42023444661). Additionally, a mapping process was employed to derive essential paradigms serving as the foundation for our architecture design. To validate the architecture based on its features, a Likert scale was utilized by the professional experts.

Results. Through the review we identified six fundamental paradigms crucial for designing the architecture. Building upon these paradigms, we designed an adaptive data-driven architecture, which was subsequently validated by professional experts which yielded a mean score above 4 for each assessed feature, affirming the architecture's effectiveness. To further test the architecture's practical application, a pandemic anxiety prediction prototype architecture was designed.

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ABSTRACT

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INTRODUCTION

In recent years, there has been a growing awareness of the importance of mental health and well-being. With the rise of mental health issues worldwide, policymakers, scholars, and healthcare professionals are actively seeking innovative approaches to offer effective care and support to those who require it. A promising and evolving method involves the implementation of data-driven mental health care systems and machine learning algorithms. The aim of data-driven mental health care systems is to harness vast amounts of information collected from various sources, including electronic health records, wearable devices, and patient-reported outcomes. (Aggarwal & Girdhar 2022) (An et al. 2022). Data-driven mental health care systems gather, analyze, and interpret data to generate valuable insights that provide decision-making in mental health care. Within these systems, machine learning models play a crucial role by uncovering patterns that healthcare practitioners could potentially overlook. By applying complex algorithms to the collected data, these models can then make predictions based on their data analysis. The capacity of data-driven mental health care systems to offer customized and precise interventions is a notable advantage, particularly during pandemics like covid (Arivoli et al. 2022). The machine learning data-driven systems have the potential to significantly impact each patient's specific needs by analyzing individual data, including socio-demographic information, medical history, and behavioral patterns. The complexity of this task would be overwhelming for human efforts alone. In this data-driven system, machine learning algorithms undergo a series of events, which include data collection and dataset extraction. Subsequently, they handle various aspects such as data preprocessing, encompassing data filtration, handling missing values, noise reduction, tokenization, vectorization, manipulation, data presentation, and final report visualization. Data-driven systems and machine learning are inherently interconnected (Thieme et al. 2020), serving as the foundation of any decision support system that depends on valuable data (Khumprom & Yodo 2019). The data within these systems is typically classified into structured, unstructured, and semi-structured formats (Siriyasatien et al. 2018) which is then processed and analyzed. The initial stage of the data collection process for decision-making involves gathering data from sources like social networking sites (e.g., Facebook, Twitter) (Alharbi & Fkih 2022), existing datasets acquired through surveys, cohort studies, etc., or through direct face-to-face interviews, among other methods. The subsequent step involves comprehending and interpreting this diverse data, which may include spatial data, sensor data, graphs, and real-time transactions (Burkom et al. 2021). Data-driven decision support systems offer user-friendly access, enabling the integration of various data sources, intuitive data manipulation, and diverse conceptual reporting of the interpreted results. The significance of data-driven systems lies in the reliability of Data-driven Decision Making (DDDM). The DDDM framework comprises various stages, including data collection, organization, analysis, summarization, synthesis, and prioritization (Yu et al. 2021). Consequently, the healthcare domain will persist in relying on data and machine learning models to steer the transformation process, necessitating a dependable and adaptive machine learning data-driven architectural framework. As data is collected from diverse sources through multiple channels and in various formats, it becomes crucial to design an interoperable framework that ensures a smooth and secure process flow prior to the actual manipulation by ensemble models. It should promote reusability, automated machine learning prediction and human decision support (Alreshidi & Ahmad 2019). As revealed from the initial search, limited research focused on architecture for mental health care systems particularly on machine learning based data-driven systems. Therefore, this research investigates various existing data-driven architectural patterns, not limited to mental health care but also encompassing other health care applications. By doing so, the study aims to identify strengths and limitations, enabling the development of an adaptive architecture that addresses these issues effectively.

BACKGROUND STUDY

This study aims on design of an adaptive data-driven architectures, which focuses to conduct a systematic review to identify key architectural strengths and limitations in this domain. (Kaur et al. 2018) centered around big data analytics in the healthcare domain, leading to the design of four crucial pillars: Patient-Centric Care, incorporating health records, drug history, patient behavior, and preferences, Real-time Patient Monitoring through wearable sensors, Predictive Analysis of diseases, and Enhancement of treatment methods. A healthcare architecture was developed, comprising four layers: data source, storage, security, and a machine learning-based application layer. The primary emphasis was placed on security and privacy within this architecture. (Patel & Gandhi 2018) focused on big data analytics in the healthcare domain, employing ensemble models. Despite the notable advantages of using big data analytics combined with machine learning, the review highlighted key challenges associated with managing the variety of data structures, data storage and management, as well as data integration and processing. A systematic literature review was carried out on cyber-physical systems (CPS) that encompass the integration of sensing, computing, and communication to monitor, control, and interact with physical processes. The main objective was to identify successful solutions that could serve as valuable guidance for architects and practitioners in their healthcare projects. The synthesis of the search results generated a knowledge base of software architectures for healthcare CPS, encompassing stakeholders' interests, functional and non-functional requirements, quality aspects, architectural views and styles, and the components of architectural designs (Plaza et al. 2018). On the other hand, (Avci et al. 2020) focuses on discussing software architectures for extensive data systems, carefully considering the application domain, architectural viewpoints, architectural patterns, architectural concerns, quality attributes, design methods, technologies, and stakeholders. This systematic literature review thoroughly examines big data software designs, assessing evidence while also exploring the interrelationship between the data extraction area and quality parameters. A survey and comparison of Big Data architectures are carried out, covering multiple application domains (Macak et al. 2020). The study involves selecting representative architectures from each domain to provide guidance to researchers and practitioners in their respective fields. Furthermore, a cross-domain comparison is conducted to identify similarities and differences among the domain-specific architectures. The study concludes by presenting practical guidelines to aid Big Data researchers and practitioners in constructing and improving their architectures, leveraging insights gathered from this research. (Schymanietz et al. 2022) focuses on Data-Driven Service Innovation (DDSI), which involves integrating data and analytics into the domain as an analytical unit. The research involved systematic and expert reviews, with data as the primary source, exploring and synthesizing various attributes and terms related to data science to enhance organizational capabilities. (Mukhiya et al. 2022) study introduced a user profiling model for reference architecture, aiming to adapt and personalize interventions according to individual user needs. Building upon the proposed reference architecture, an open-source framework for an adaptive Intervention Design and Planning Tool was developed. The framework underwent evaluation through a combination of case study, expert evaluation, and software quality metrics, assessing factors such as adaptability, scalability, reusability, security, interoperability, and modifiability. However, it is worth noting that the evaluation did not cover other critical metrics on reliability, data quality, and performance. (Khan et al. 2022) conducted comprehensive and systematic research, encompassing articles from 2011 to 2021, focusing on the analysis of the healthcare domain in disease diagnosis using data analytics. The findings from this study indicated that integrating advanced hybrid machine learning-based models and cloud computing applications could lead to several benefits in the healthcare sector. These advantages include cost reduction in treatments, decreased simulation time, and improved quality of care. Policymakers can promote the adoption of these technologies to encourage researchers and practitioners to develop more sophisticated disease diagnosing models, ultimately elevating the overall quality of patient treatment. The study also emphasized that architectures for cognitive computing with hybrid machine learning are essential tools for the data-driven analysis of healthcare big data, offering promising avenues for the future. Based on the above background study, several key findings emerge. Firstly, it is evident that there is a lack of extensive research conducted on mental health care applications. Secondly, there exists a research gap in analyzing data-driven architecture from the perspective of machine learning which is critical contributor in mental health care. Lastly, recent trends highlight the need for an adaptive architecture capable of accommodating various mental health disorders to achieve cost and time savings. These identified research gaps serve as the basis for undertaking this systematic literature review.

METHODOLOGY

The systematic review draws inspiration from (Xiao & Watson 2017) and Preferred reporting items for systematic reviews and meta-analyses (Moher et al. 2009). Figure 1 depicts the complete PRISMA flowchart, detailing the stages from the initial phases to the ultimate article selection. Figure 2 presents a visual representation of the method we employed for conducting our systematic literature review. The initial phase of our systematic literature review involves identifying research problems and questions using the PICOC model provided in Table 1. Next, search strings and online repositories are identified to conduct the initial extraction of research articles. Subsequently, a set of inclusion and exclusion criteria are established to filter the relevant literary works from these primary studies. The final step entails literature extraction based on this filtering process, involving the setup of a quality checklist to assess the literature works and assign them a quality score.

Figure 1. PRISMA Flow chart

Figure 2. Systematic literature review method

The initial design of the data extraction form and quality assessment checklist, as well as the development of the search strategy, were done by the first two authors. A review meeting involving all four authors was conducted to assess the research design strategy. During this meeting, the two remaining authors provided valuable suggestions and recommendations to address any discrepancies.

Table 1. PICOC model

Data preparation, analysis, and interpretation were the responsibilities of the third and fourth authors. All collected data was meticulously recorded and stored in an Excel spreadsheet to ensure accuracy and transparency. To minimize bias, the first and second authors independently validated the extracted data. In a subsequent review meeting, all final studies were compared, and each author expressed their agreement or disagreement with the identified results. These findings were thoroughly discussed among the authors. In cases where differences in opinions arose, the variations were carefully examined and deliberated upon until a consensus was reached among the team.

Research problem and questions

The purpose of the systematic literature review is to identify key challenges in existing data-driven architectures in mental health care domain. This is achieved after conducting an initial background study on data-driven systems and machine learning models. The research questions were formulated based on the PICOC model, as presented in Table 1. The background study and PICOC model led to the framing of the following research questions.

RQ 1: What are the strengths and limitations in existing data-driven architecture studies?

RQ 2: What are key essential paradigms (KEP) for designing adaptive data-driven architecture?

The knowledge synthesized from RQ1 becomes the foundation for addressing RQ2. The insights gained from understanding the strengths and limitations of existing architecture studies help in formulating the key essential paradigms required for designing adaptive data-driven architectures that can overcome the identified limitations and build on the strengths. The process of mapping strengths and limitations to derive KEP is illustrated in Figure 3.

Figure 3: Mapping process of review results to derive KEP

1. Identify strengths and limitations: Review each study individually and identify the strengths and limitations of the data-driven architectural patterns discussed in the study.
2. Thematic categorization: Group together the identified strengths and limitations that have similar implications or characteristics. For example, if multiple studies mention

"interoperability", “exchangeability” as a strength or limitation, categorize it under the theme of "Data service".
3. Frame KEP: Based on the categorized strengths and limitations, frame KEP that are critical for a data-driven architectural pattern. These paradigms represent the necessary aspects that should be present in any effective data-driven architecture.
4. Validate and refine: Ensure that the identified KEP which foster design of data-driven architectural patterns. Validate the mapping with relevant experts to refine and improve the clarity and comprehensiveness of KEP.

Literature search and screening

The literature search involved identifying search strings and selecting appropriate standard repositories. Initially, the focus of the literature review was on architectural frameworks in mental health care data-driven systems. However, this preliminary search yielded very few relevant literary works within our scope. As a result, the search was broadened to encompass the health care domain, and the search strings identified were data-driven, mental health care architecture, health care architecture, and machine learning. To ensure reliability, the Web of Science (WoS) was chosen as the repository collection for accessing credible studies. The search strings were utilized to extract articles published between 2016 and 2023. A specific set of inclusion and exclusion criteria was employed to scrutinize the relevant articles initially, as listed in Table 2.

Table 2. Inclusion and exclusion criteria

Extraction and data synthesis

An initial screening on title and abstract is done, 419 articles were included for quality assessment. After validation of the inclusion and exclusion criteria, there were 122 records. A set of quality assessment questions was framed based on which the articles were assessed and selected for the final research study which is given in Table 3.

Table 3. Quality checklist

Score for each assessment question is given in range 0-1, where 0 is doesn’t meet quality checklist, 0.5 partial meets the checklist and 1 meets the quality questions. Finally, the articles with an average score of more than 70% is taken for final study. Table 4 illustrates the quality assessment score for the final 17 articles for review study.

Table 4. Quality assessment

RESULTS AND DISCUSSION

RQ1 assessment

To address RQ1, the review and discussion of results for each article included in the final study for the research questions are discussed here. (Shalom et al. 2016) designed a new PICARD architecture for practical continuous clinical guideline (GL) based decision support for multiple task types for data-driven and user-driven modes. The architecture was designed with a key emphasis on interoperability facilitated by APIs and continuous evaluation, which incorporated clinicians' input rather than relying solely on simulation tools. Validation efforts encompassed technical competency, functionality, and direct clinical evaluation. Given the system's reliance on critical patient data, the architecture would have been detailed to incorporate robust data privacy measures. (Vinci et al. 2016) outlines different perspective of research methods employed to propose an enterprise architecture as evaluation model for the municipal and regional management of a Mental Health Care Network that includes computerized information systems and specific indicators of spatial and temporal dimensions of mental health care matrix. This theoretical model aids in expansion of mental health improvement in localities where its poorly managed. The key limitation is that it relies on the specific context of the Psychosocial Care Network, and its applicability to other regions or countries may vary. Furthermore, the availability and accuracy of data needed for real-time monitoring and evaluation could pose challenges which would demand digitalized system for continuous evaluation and data analytics. A common smart object architecture, which liberates data and meta-data for re-use across the various components and layers in the architecture, serves as the cornerstone for a data-centric architectural vision for the IoT. (Schooler et al. 2017) examined the correlation between Edge and Fog computing, employing data-centric networking as a model to optimize meta-data-driven processes. It explored software-defined strategies to control data flows upstream, including the placement of analytics and data caching in the network. The study recommended implementing software-defined techniques to manage upstream data flows, facilitating improved decision-making regarding the placement of data analytics and caching in the network. It is focused on specific environments, like edge and fog computing which could limit the generalizability of the findings to other contexts and feasibility in all network infrastructures. (Olsen 2017) focus is on implementing enterprise architecture (EA) in the Norwegian health sector through exploratory study. It identifies several challenges that hindered the establishment of a generalized EA, such as unclear roles, ineffective communication, low EA maturity and commitment, and complex EA tools. These challenges ultimately attributed to three main factors: the lack of clarity in the EA concept, difficult EA terminology, and the complexity of EA frameworks. This thrives a need for a generalized architecture addressing the challenges, which could be customized based on complete and clear requirements communication from health care stakeholders.

(Mendez & Jabba 2018) investigated on the IoT health architecture concerning communication protocols to tackle the crucial issue of interoperability. It proposed an IoT connected healthcare architecture for heart monitoring, utilizing the Constrained Application Protocol and Message Queue Telemetry Transport communication protocols. The architecture comprises key elements such as personal IoT devices, gateways, communication protocols, fog computing, and cloud computing. Although a hybrid solution is proposed to address this, there might still be challenges in optimizing the system's integration and performance and require further investigation on impact of the Manager component's location in the Fog stage of the architecture, which could have implications for the system's overall effectiveness. (Chmielewski et al. 2018) investigated the practical experiences and architectural concepts used to collect and process biomedical data in a large-scale system aimed at monitoring elderly patients. Key requirements for healthcare applications, such as data security, authorized access, reliability, efficiency, and context awareness, were achieved through user authorization, sensor configurations, patient profile management, and biomedical data monitoring with reliable wireless transmission to server services. The study implemented an architecture for a mobile application that integrated data from diverse sources, including Microsoft BS Band 2 through Microsoft Health API, FreeStyleLibre Sensor via NFC protocol, and various mobile phone sensors on the Android OS. But the architecture limits in exploring the interoperability requirement of health care applications. The integration of heterogeneous data sources from different manufacturers, might present data consistency and integration challenges in ensuring seamless compatibility and interoperability among these devices due to differences in data formats, communication protocols and APIs. (Handayani et al. 2019) implemented a health referral information system (HRIS) for patient, specimen and health care professional referral and adhered to TOGAF Open Group Architecture Framework. Qualitative methods through interviews and observations were conducted to frame the basic principles and scenario viewpoints. The study's effectiveness has not been assessed, and it fails to adequately address significant technical concerns regarding data scaling and security in the referral process. These aspects need careful consideration to ensure the reliability and safety of the system. A five-layer stakeholder-based blockchain architecture was developed for managing health records, encompassing primary, secondary, and tertiary stakeholders to validate approximately 30 requirements for a blockchain-based electronic health record (Beinke et al. 2019). The study also identified several major challenges in blockchain healthcare, such as low processing speed, data verification, access and authorization issues, limited scalability, and inadequate computational power. (Zhuang et al. 2020) primarily addressed the significant challenge of data coordination, with a particular focus on ensuring security and privacy rules are maintained among health information systems. The proposed three-layer architecture involves the use of smart contracts functions within the interfacing layer to facilitate specific actions when health facilities request data from one another. To ensure data security during the exchange between layers, reliable metadata becomes crucial for the interfacing layer to authenticate and retrieve the original data. The primary limitation is the setup requirement for each participating health care facility which must provide at least one blockchain node to the system Patients may also need to contribute blockchain nodes, like mobile devices, to exchange and store their personal health records from medical devices. The model's performance can be influenced by the properties of the blockchain nodes. If a single node generates a massive number of transactions simultaneously through the blockchain adapter, it can exhaust all memory and cause the node to malfunction before data is sent to the blockchain.

Health Information Systems (HIS) reference architecture was designed, and domain analysis was conducted on various sub-domains, including hospital, primary care, outpatient care, pediatric, and diabetic care, to explore stakeholder issues and concerns. Feature modeling was utilized to represent the extracted domain features, using views and a comprehensive approach that incorporated 17 predefined stakeholder viewpoints (Tummers et al. 2021). While the study demonstrated the effectiveness of applying software architecture design methods in the healthcare domain and derived an architecture adaptation for a University hospital in Japan, scalability of the RA were not extensively tested across multiple different HIS scenarios. (Nadhamuni et al. 2021) proposed an enterprise architecture to tackle the challenges of interoperability and standardization. This architecture adopts a five-layer model: source layer, datastore layer, event integration layer, distributed processing layer, and data analytics layer. It also incorporates a consent layer for individual consent management, adhering to the digital lifecare security strategy in compliance with government policies. However, effectively handling the significant heterogeneity of data and facilitating smooth data exchange among different channels requires further in-depth investigation and exploration. A fog-based 4+1 view architecture was devised to improve real-time data transmission and minimize network latency among IoT devices (Ilyas et al. 2022). In IoT-enabled healthcare systems, a major obstacle is the traffic delay caused by distant cloud servers. To overcome this limitation, a decentralized fog computing paradigm is adopted, placing computing resources like storage, processing models, network devices, and infrastructure at the network edge, in close proximity to the data sources and end-users. Although the research has shown improved performance by reducing network latency, it does have limitations in terms of security and privacy quality aspects. (Blobel et al. 2022) proposed an ontology-based generic reference architecture utilizing Universal Type Theory and system-theoretical approaches, to address the challenges of multi-disciplinary interoperability in various domains. The proposed architecture model allows for harmonizing and mapping diverse specifications and standards without requiring revisions. It offers a policy-driven, system-oriented solution to transform health and social care ecosystems, bridging gaps between different languages and provide various representation styles. Conceptualization, security, natural language processing through AI models, semantic interoperability are core factors for technology adaptation for transforming health care systems. Developing and maintaining a comprehensive ontology-based reference architecture model can be time-consuming and complex, especially when integrating multiple domains and communities. Additionally, ensuring the interoperability of diverse systems and specifications may encounter technical challenges and compatibility issues.

(Aldabbas et al. 2022) designed an architecture of IoT healthcare systems which analyses real time health data of the patients for personalized drug recommendations. The main challenge of such smart health care systems is mining significant data from sensor devices over network traffic. It collaborated clustering and machine learning models for disease identification. The primary emphasis of the study was on employing ensemble models for data mining and manipulation but lacks to address the security concerns pertaining to cloud-based application. (Perez et al. 2023) proposed distributed architecture, aimed at providing an accompaniment service for the elderly and dependents. The significant contribution is a comprehensive set of architectural patterns, which streamline the deployment of the service across various technologies, actors, and development scenarios. The architecture was evaluated for different parameters including quality and commercial aspects. While the work has introduced conceptual, technical, and deployment architectures to support implementation and scalability, there may still be constraints in addressing interoperability as it relies on numerous technologies and manufacturers, making it challenging to integrate diverse functionalities. In the healthcare sector, the adoption of healthcare-specific APIs has been increasing, enabling interoperability and secure electronic data transfer between health IT systems and third-party applications. Although these APIs offer valuable benefits, there are also challenges and weaknesses that need to be addressed for achieving full interoperability (Mishra et al. 2023). It proposed a framework to enhance interoperability which is crucial factor in health care systems through the use of Application Programming Interface. The framework uses API LED Connectivity based proposed for health care systems for API integration in experience, process and system layers. The study falls short in adequately addressing data privacy and security concerns during the transfer of information between various health IT systems and third-party applications. (Upadhyay et al. 2023) proposed an IoT architecture integrated with cloud system which aids the medical center to monitor the individuals at home through wearable sensors. It explores the limitations of an existing system concerning transfer of sensor data to control devices and monitoring centers that are affected by external noise, error prone survival tracking techniques using ECG, which could be reduced by machine learning models, improving sensor quality, managing data, real-time communication and patient monitoring. While the study suggests improving IoT systems with a suitable power absorption through conceptual model, the practical implementation and effectiveness of such models through narrowband IoT and scheduling mechanisms require further investigation. Table 5 below shows the summary of strength and limitation features identified in each review study.

Table 5. RQ1 summary

RQ2 assessment

KEP are important for architecture design because they serve as foundational principles and guidelines that ensure the effectiveness, efficiency, and reliability of the designed architecture. By integrating these KEP into the architecture design, organizations can construct data-driven systems that exhibit robustness, reliability, and adaptability to cater to the dynamic requirements of users and stakeholders. Figure 4 illustrates KEP for data-driven architectural framework derived from our review studies to answer RQ2. In our proposed approach, we have identified six essential elements that form the foundation of any data-driven architectural pattern:

1. Data Security: Ensuring data security is of utmost importance, including proper authentication and authorization, as well as maintaining the privacy of medical data.
2. Data Availability: Ensuring data availability is crucial for scalability, performance and preventing failures. Load balancing techniques are employed to distribute the data load efficiently.
3. Data Quality: Maintaining data quality is essential to enable effective data manipulation. This includes handling missing data through imputation techniques and data augmentation for completeness, ensuring consistency by standardizing data formats and performing data cleaning to address inconsistencies, outliers, and errors. Additionally, data validity is ensured through outlier detection and expert verification, which serves as the basis for machine learning manipulations.
4. Data Manipulation: Data manipulation is critical for machine learning algorithms to enable automated prediction and analysis which involves parameter tuning, feature selection, model selection and evaluation for machine learning models.
5. Data as a Service: Implementing data as a service ensures distributed data management, promoting interoperability and exchangeability between different applications.
6. Data Representation: Proper data representation is necessary for contextualization, allowing for insightful comparisons and trend analytics.

These six KEP foster designing robust and effective data-driven architectures that can address various challenges and requirements in healthcare domain.

The mapping matrix of RQ1 results to RQ2 KEP is given in Table 6. In this representation, a checkmark (✓) indicates the presence of a strength or limitation in the corresponding study for a specific KEP. The matrix allows for a clear visualization of the strengths and limitations identified in each study and how they are mapped to KEP. Figure 5 provides frequency chart between different studies and KEP. From the figure, we can determine data manipulation aspects have been relatively less emphasized which provides scope for further research and development. Therefore, our proposed adaptive data-driven architecture incorporates dedicated layers specifically designed for data manipulation.

Figure 4: KEP for data-driven architecture

Table 6. Mapping matrix between studies and KEP
Figure 5: Frequency chart of studies and KEP

Designing an adaptive data-driven architecture based on KEP involves creating a flexible and responsive system that can dynamically adjust and optimize its processes based on the mental health care requirements. KEP identified in Figure 4 serve as guiding principles for shaping the architecture's structure and functionalities. The adaptive data-driven architecture for mental health care application is given in Figure 6. KEP is distributed across the designed adaptive data-driven mental health care architecture. The KEP based distribution is as follows. Data security is of utmost importance in any organization, especially in mental health care, where sensitive and personal information is being handled. Role-based access control (RBAC) and multi-factor authentication (MFA) are two crucial data security measures that play a pivotal role in safeguarding sensitive data. RBAC allows mental health care organizations to assign specific access privileges to different users based on their roles and responsibilities (Garg et al. 2023). This helps prevent unauthorized access to sensitive data and ensures that each user can only access the information necessary for their job functions. MFA adds an extra layer of security by requiring users to provide multiple forms of authentication, like using hash functions (Midha et al. 2023). Data anonymization is another critical aspect of data security. By removing or encrypting personally identity from datasets, organizations can protect the privacy of individuals while still allowing data analysis and research. However, the challenge lies in maintaining data utility while anonymizing, as overly aggressive anonymization can compromise data integrity and research potential. Mental health organizations must comply with relevant laws and regulations, to protect patient confidentiality and avoid legal repercussions. Audit logs and monitoring play a crucial role in detecting and responding to potential security breaches. By monitoring access logs and system activities, organizations can identify suspicious behavior and take appropriate action promptly. Fraud analytics is an emerging field that uses advanced data analytics techniques to detect and prevent fraudulent activities (Ai et al. 2022). By applying machine learning algorithms and anomaly detection methods to transaction data, mental health organizations can proactively identify and mitigate fraudulent behavior.

Figure 6: Adaptive data-driven mental health care architecture

Data availability is vital in mental health care to ensure that critical information is accessible when needed. Auto-scaling infrastructure allows the system to dynamically allocate resources based on demand (Santos et al. 2020). This ensures that the system can handle varying workloads and maintain high availability, even during peak times. Geo proximity routing is a technique used to route data traffic to the nearest data center or server location based on the user's geographical location (Meena et al. 2021). This reduces latency and ensures faster data access for users from different regions. Data sharding involves horizontally partitioning data across multiple servers or databases. This improves data retrieval and scalability (Niya et al. 2020).

Data quality is essential for accurate analysis and decision-making in mental health care. Data cleaning involves identifying and correcting errors, inconsistencies, and missing values in the dataset (Sorkhabi et al. 2020). Data standardization is the process of transforming data into a consistent format and structure. Standardized data allows for easier integration and analysis across different systems. Data validation ensures that data meets specific criteria and conforms to predefined rules. Automated validation checks help identify data discrepancies and ensure data accuracy, but validation rules must be regularly updated to adapt to changing data requirements. Ethical data handling compliances involve adhering to ethical principles and regulations related to data collection, usage, and storage (Wilton 2017). Mental health care organizations must prioritize data privacy, informed consent, and data anonymization to protect patient rights.

Data manipulation is a critical part of machine learning model development. Parameter tuning involves fine-tuning model parameters to optimize performance. Feature engineering focuses on selecting or creating relevant features to enhance model accuracy and predictive power. Model selection and training involve choosing the most suitable machine learning algorithm and training the model on the dataset. Evaluation is the process of assessing the model's performance on a separate test dataset to measure its accuracy, precision, recall, and other metrics (Nithya et al. 2017). The feedback loop enables continuous improvement by incorporating new data and refining the model based on mental health professional feedback and real-world scenarios. Monitoring and maintenance ensure that the model remains accurate and up-to-date over time. Regular model monitoring helps identify concept drift and data changes that might affect model performance, while maintenance involves periodic retraining and updates.
Data service involves making data accessible and usable across different platforms and systems. Platform-agnostic compatibility ensures that data services are not tied to any specific platform, allowing seamless integration with various devices and applications. Interoperability standards facilitate data exchange and communication between different systems (Fysarakis et al. 2019). Adopting common data formats and protocols ensures smooth data flow and reduces integration challenges. API Integration enables data services to interact with external applications and services, promoting collaboration and information sharing across different platforms.

Data representation plays a crucial role in conveying insights and information to stakeholders. Report and data visualization present data in a visually appealing and easy-to-understand manner, making it simpler for users to interpret complex data. Epidemiological analysis involves analyzing and interpreting health-related data to identify patterns and trends, facilitating evidence-based decision-making in mental health care. Trend Analytics enables the identification of long-term patterns and developments in data, allowing organizations to make informed predictions and strategic decisions. Counsellor and patient profiles store important information about mental health professionals and patients, supporting personalized and effective treatment plans. Scheduling and referral features help manage appointments and referrals efficiently, ensuring smooth coordination among healthcare providers and optimizing patient care. Assessment and treatment features assist mental health professionals in evaluating patients' conditions and delivering appropriate treatments based on data-driven insights.

Expert review of proposed data-driven architecture

We have gathered around 10 professional experts for evaluation of adaptive data-driven architecture for mental health care. Following the completion of the architectural design, expert evaluations were carried out to validate the suitability of the proposed architecture. The architecture assessment instrument focused on maturity levels, process and practices, ease of use, applicability and flexibility. Table 7 shows compilation of validating criteria covering 11 features which are used during the expert review session and the mean value of each criterion. We used 5-points Likert scale (van den Bergh et al. 2020) (Perez-Benito et al. 2020) (Paes et al. 2021) (Tungpantong et al. 2022) to record the feedback from experts.

Table 7. Expert review analysis instrument

Figure 7: Radar chart of architecture evaluation results

Radar chart of evaluation results ins provided in Figure 7. The radar values represent validating feature and their respective mean values. The features are essential factors that have been evaluated in the context of the system or application under consideration. Each feature is assigned a numerical mean value, ranging from 1 to 5, where 1 indicates the strongly disagree level, and 5 represents strongly agree level. Upon analyzing the radar chart, we observe that the mean values for the constraints are generally high, with most falling above the point of 4.0. This implies that the identified features have been largely well-handled and do not impose significant limitations on the architecture. Among the features, feasibility stands out with the highest mean value of 4.712, suggesting that the architecture is highly feasible for implementation in mental health care domain. Conversely, constraint accuracy has the lowest mean value of 4.01, implying that it might be an area requiring further attention to encompass machine learning prediction. The radar chart also demonstrates an interesting pattern, with constraints comprehensiveness, mutual exclusion, and adaptability forming a cluster of similar mean values (4.62, 4.375, and 4.702, respectively). This indicates that these constraints share common characteristics and might be interconnected in some way, warranting a more in-depth investigation. Furthermore, features relevancy, understandability and applicability display moderate mean values (4.31, 4.106, and 4.405, respectively), signifying that they are adequately addressed but may still have room for enhancement to optimize the system's overall performance.

CASE STUDY

Pandemic anxiety prediction application (PAPA) was prototyped from the proposed adaptive data-driven mental health care architecture. During pandemic, anxiety disorders are major concern and it requires machine learning predictions to be applied on huge population sample (Albagmi et al. 2022). In event of pandemic, government could use PAPA, where it triggers mental health screening of vulnerable populations in targeted high-risk premises. It uses machine learning anxiety prediction models to predict anxiety levels and suggest online or nearby mental health counselling services. This also keeps track of mental health analytics which helps government in data driven decision making. Basic process flow diagram of PAPA is given in Figure 8. Data sources of PAPA are from online data sets, anxiety assessments instruments like Generalized Anxiety Disorder-7 (Camargo et al. 2021), and reports from mental health care centers. All these sources are categorized accordingly would help to render this data as an independent service for other functionalities to facilitate data exchangeability and interoperability between government health care institutions for referral. The data security is achieved through multi-factor authentication. Authorization is achieved through restricted user role base access only for government entity, respective health care professional and user. Privacy is maintained through encryption mechanisms and consent management to store data. Also, user identity is masked as anonymous for machine learning training data set. It is periodically archived and backed up in cloud servers for scalability and load balancing. Standard processes of ML algorithm like data cleaning, pre-processing, parameter tuning, feature and model selection, and prediction are done in anxiety prediction model. Based on the participant’s assessment response and social media data like tweet, Facebook, anxiety prediction model is continuously trained. This application could potentially aid in the early identification of individuals experiencing pandemic-related anxiety. Early prediction would allow for timely intervention and support to mitigate the impact on mental health. Also, accurate prediction of pandemic anxiety levels could help allocate mental health resources more efficiently, directing support to those who need it the most during periods of heightened anxiety. By predicting pandemic anxiety levels for individuals, mental health care providers could offer more personalized and tailored treatment plans to address specific needs and coping mechanisms.

Figure 8: Process flow of pandemic anxiety prediction application

CONCLUSION

In conclusion, the adaptive data-driven architecture for mental health care applications represents a transformative leap towards personalized, efficient, and compassionate healthcare services. By harnessing the power of data analytics, machine learning, and advanced technologies, this architecture empowers mental health professionals, government agencies with data-driven insights and evidence-based decision-making capabilities. The main goal of this study was to investigate the prominent strengths and limitations encountered in current healthcare software architectures. The research revolves around formulating an adaptive, data-driven architecture capable of effectively mitigating these identified limitations and enhancing on strengths using key essential paradigms. The adoption of an adaptive data-driven architecture for mental health care applications could have several significant impacts like personalized Treatment to provide personalized treatment plans considering patients' profile, and responses to interventions, leading to more effective and tailored mental health care. The architecture's adaptability enables real-time monitoring of patients' mental health indicators through assessment tools. In cases of deterioration, timely interventions can be initiated, preventing potential harm and ensuring prompt support. By analyzing large-scale mental health data, the adaptive architecture can identify patterns and trends that may contribute to improved diagnostic accuracy and prognosis for mental health disorders and its ability to optimize resources and treatment plans can lead to cost-effective mental health care, reducing unnecessary expenditures and maximizing the impact of interventions. With personalized customization from the adaptive architecture and remote mental health care options, it can help reduce stigma and access barriers. Patients can access support discreetly, enhancing mental health care utilization. Overall, an adaptive data-driven architecture in mental health care applications has the potential to revolutionize the delivery of mental health services, providing more effective, personalized, and accessible care to individuals in need. The proposed architecture underwent thorough evaluation by subject matter experts, which confirmed its adaptability for diverse mental health disorders. The radar values provided valuable insights into the strengths and weaknesses of the proposed architecture concerning the identified features. The high mean values for most constraints demonstrate the effectiveness of the system design in addressing these factors. However, the disparities in mean values prompt further analysis and refinement to ensure the architecture’s robustness. By leveraging these insights, application designers and stakeholders can make informed decisions to fine-tune the architecture, ultimately enhancing its adaptability and effectiveness in dealing with various mental health disorders. However, it is important to note that the review's scope was limited to peer-reviewed journal articles accessible through the Web of Science databases. Therefore, it did not encompass other types of publications from other databases which could be considered as a limitation of this study. Moving forward, the future scope of research involves in development of pandemic anxiety prediction application, aiming to identify the technical challenges associated with implementation of proposed adaptive architecture. This would provide valuable insights into refining and enhancing the software architecture to effectively address real-world scenarios and to improve mental health care.

Author Contributions: Experiment design, including the establishment of inclusion/exclusion criteria and search keywords, was conducted by A.S. and H.S. They also focused on developing a quality assessment checklist and designing data extraction form for extracting relevant data from selected studies. A review meeting was then organized with all authors to verify and obtain their consent. Data preparation, analysis, and interpretation were carried out by S.H.A.H. and A.M.N. A.S. drafted the manuscript and incorporated feedback from co-authors during the revision process. H.S., S.H.A.H., and A.M.N. were responsible for overseeing the review process and subsequent revisions of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Figure 1

PRISMA Flow chart

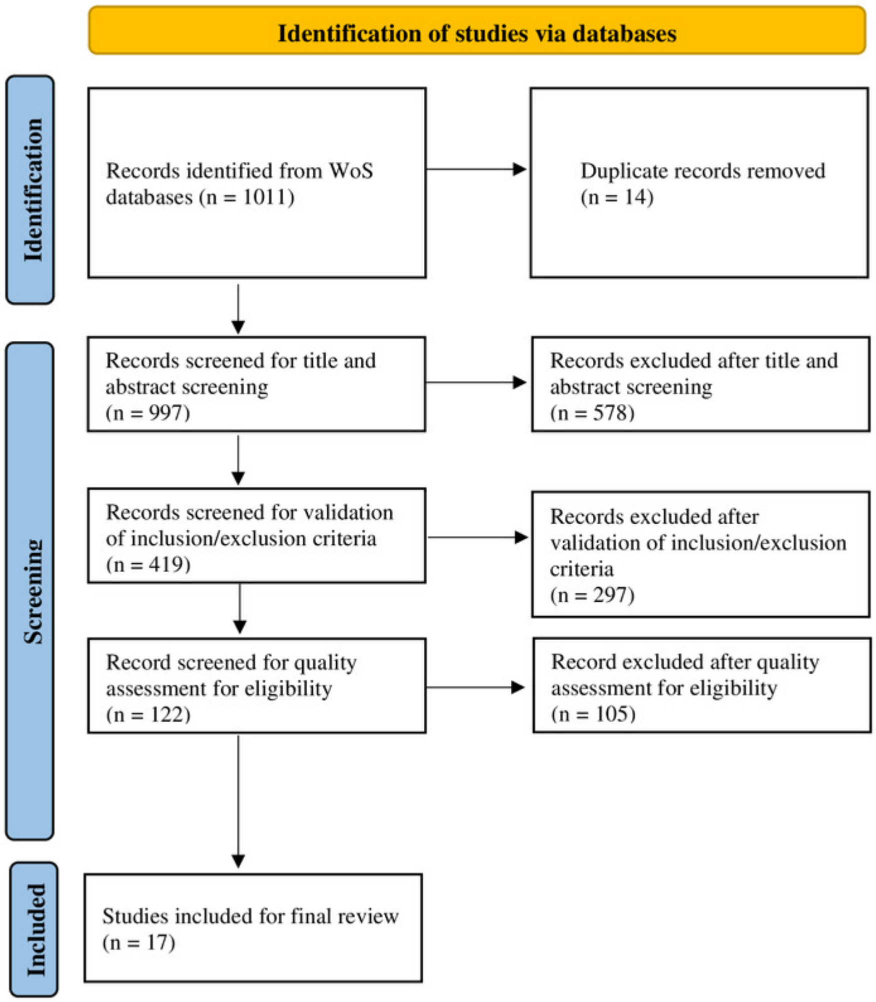
Identification of studies via databases
Identification
Records identified from WoS databases (n = 1011)
Duplicate records removed (n = 14)
Screening
Records screened for title and abstract screening (n = 997)
Records excluded after title and abstract screening (n = 578)
Records screened for validation of inclusion/exclusion criteria (n = 419)
Records excluded after validation of inclusion/exclusion criteria (n = 297)
Record screened for quality assessment for eligibility (n = 122)
Record excluded after quality assessment for eligibility (n = 105)
Included
Studies included for final review (n = 17)

Figure 2

Systematic literature review method

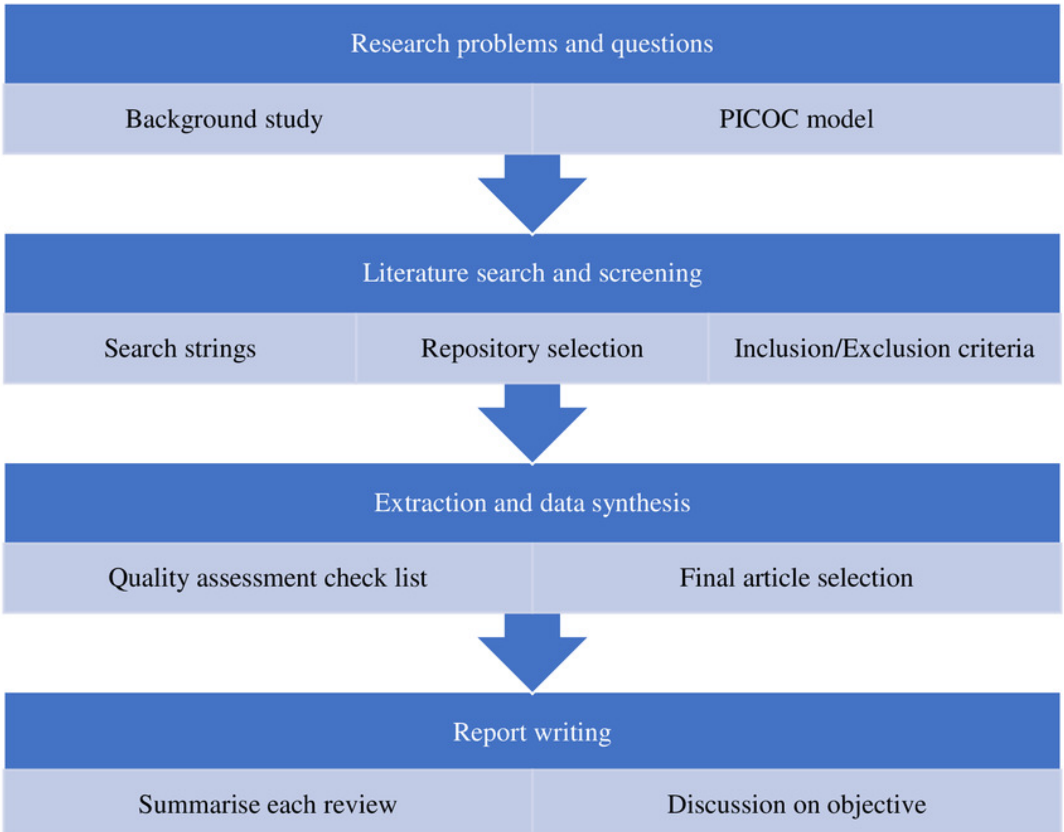
Research problems and questions
Background study
PICOC model
Literature search and screening
Search strings
Repository selection
Inclusion/Exclusion criteria
Extraction and data synthesis
Quality assessment check list
Final article selection
Report writing
Summarise each review
Discussion on objective

Figure 3

Mapping process of review results to derive KEP

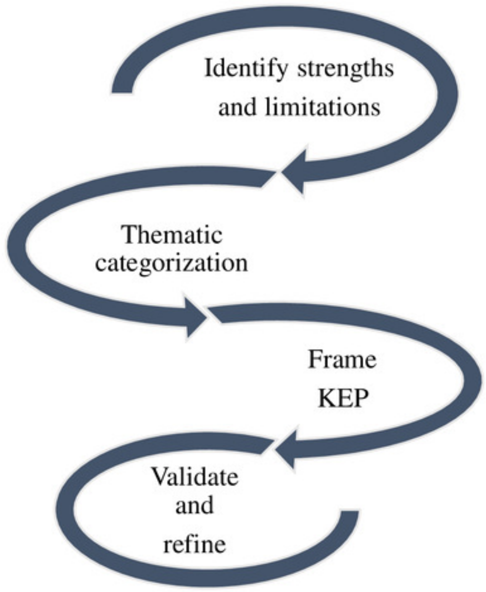
Identify strengths
and limitations
Thematic
categorization
Frame
KEP
Validate
and
refine

Figure 4

KEP for data-driven architecture

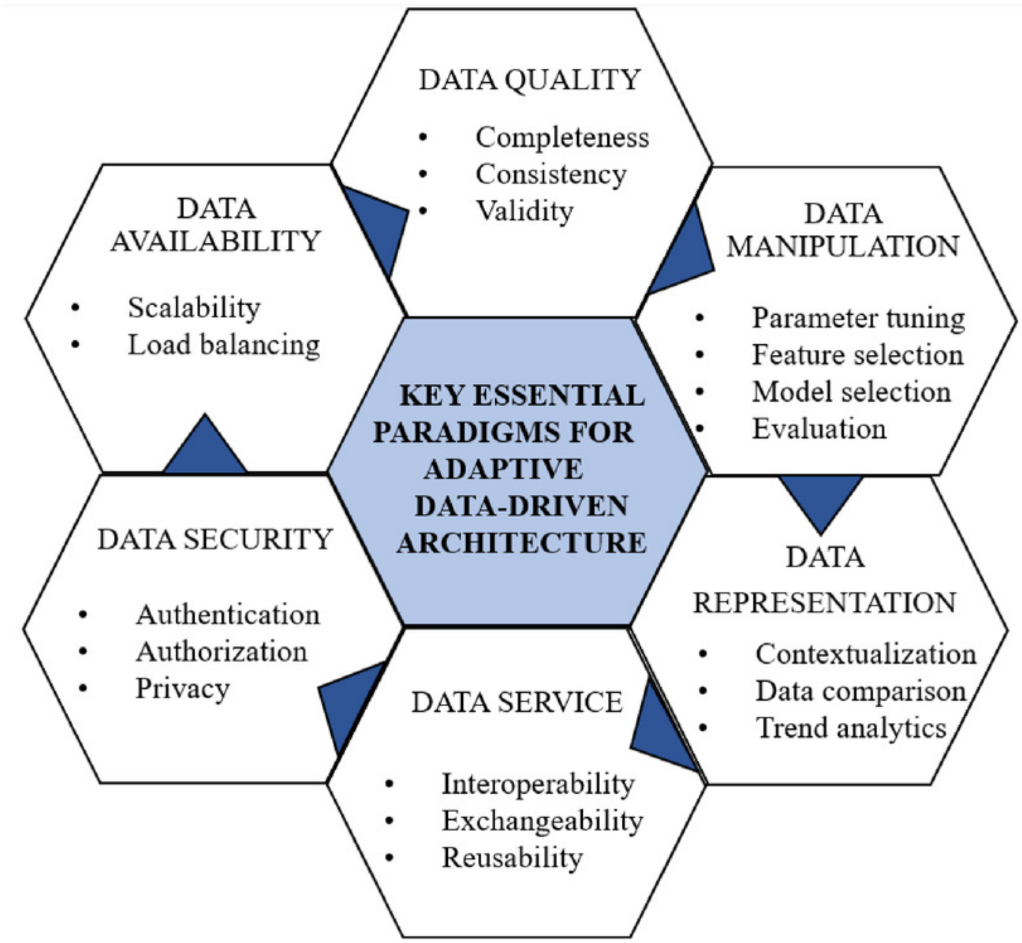
DATA QUALITY
Completeness
Consistency
Validity
DATA AVAILABILITY
Scalability
Load balancing
DATA MANIPULATION
Parameter tuning
Feature selection
Model selection
Evaluation
KEY ESSENTIAL PARADIGMS FOR ADAPTIVE DATA-DRIVEN ARCHITECTURE
DATA SECURITY
Authentication
Authorization
Privacy
DATA REPRESENTATION
Contextualization
Data comparison
Trend analytics
DATA SERVICE
Interoperability
Exchangeability
Reusability

Figure 5

Frequency chart of studies and KEP

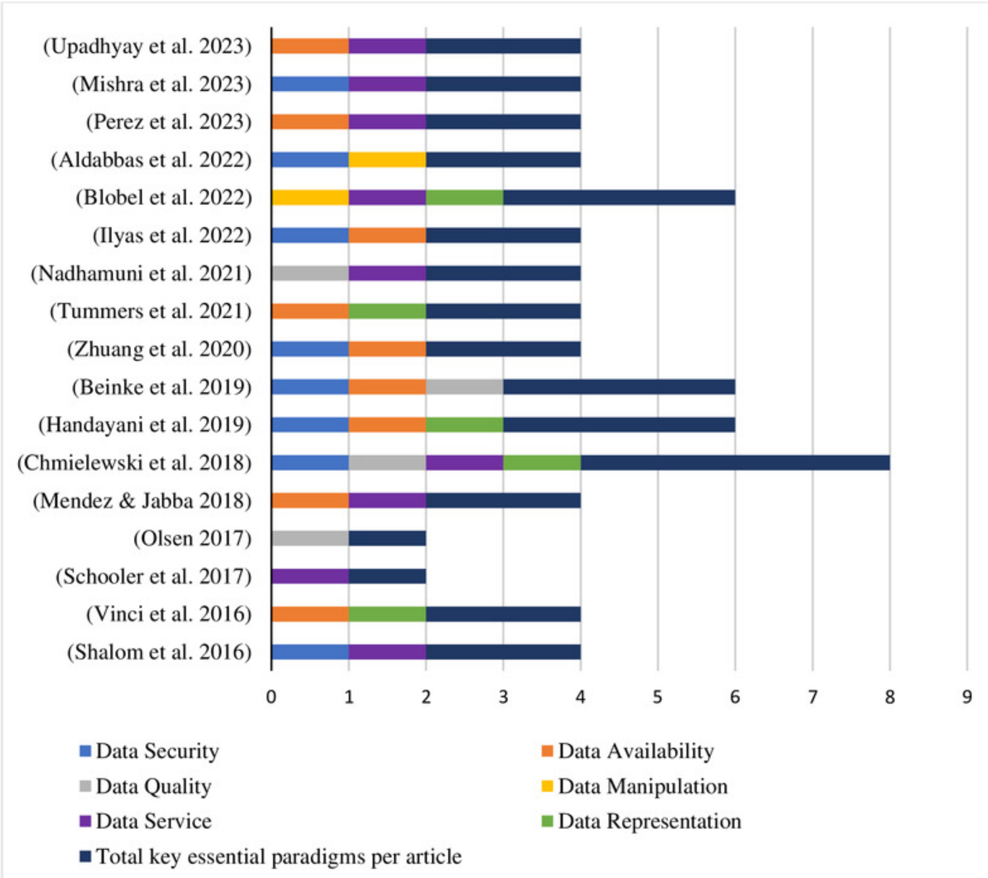
(Upadhyay et al. 2023)
(Mishra et al. 2023)
(Perez et al. 2023)
(Aldabbas et al. 2022)
(Blobel et al. 2022)
(Ilyas et al. 2022)
(Nadhamuni et al. 2021)
(Tummers et al. 2021)
(Zhuang et al. 2020)
(Beinke et al. 2019)
(Handayani et al. 2019)
(Chmielewski et al. 2018)
(Mendez & Jabba 2018)
(Olsen 2017)
(Schooler et al. 2017)
(Vinci et al. 2016)
(Shalom et al. 2016)
0 1 2 3 4 5 6 7 8 9
Data Security
Data Availability
Data Quality
Data Manipulation
Data Service
Data Representation
Total key essential paradigms per article

Figure 6

Adaptive data-driven mental health care architecture


User layer
Epidemiological analysis by public health agency
Assessment and treatment tools
Report and data visualisation
Counsellor and patient interaction
Scheduling and referral
Trend Analytics
Security layer
Role based access control
Data anonymization
Mental health regulatory compliance
Multi factor authentication
Audit logs and monitoring
Fraud Analytics
Scalable service layer
Auto-scaling infrastructure
Geo proximity routing
Data sharding
API Integration
Interoperability standards
Platform agnostic compatibility
ML decision support layer
Data quality
Data cleaning
Data standardization
Data validation
Data quality assessments
Ethical data handling compliances
Data manipulation
Parameter tuning
Feature engineering
Model selection and training
Evaluation
Feedback loop
Monitoring and maintenance

Figure 7

Radar chart of architecture evaluation results

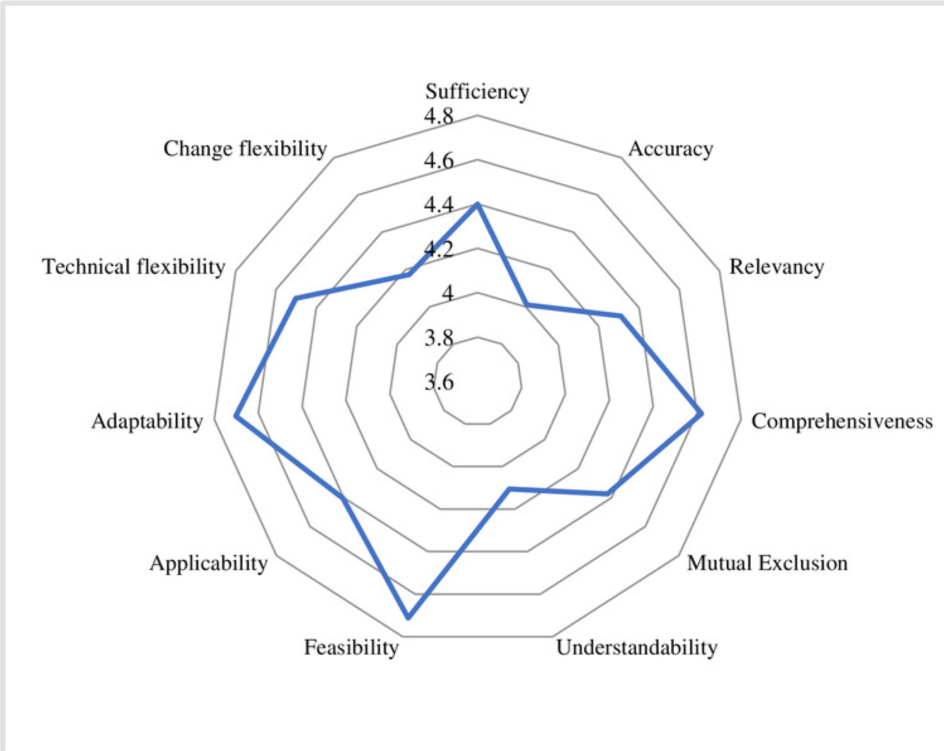
Sufficiency
4.8
4.6
4.4
4.2
4
3.8
3.6
Accuracy
Relevancy
Comprehensiveness
Mutual Exclusion
Understandability
Feasibility
Applicability
Adaptability
Technical flexibility
Change flexibility

Figure 8

Process flow of pandemic anxiety prediction application

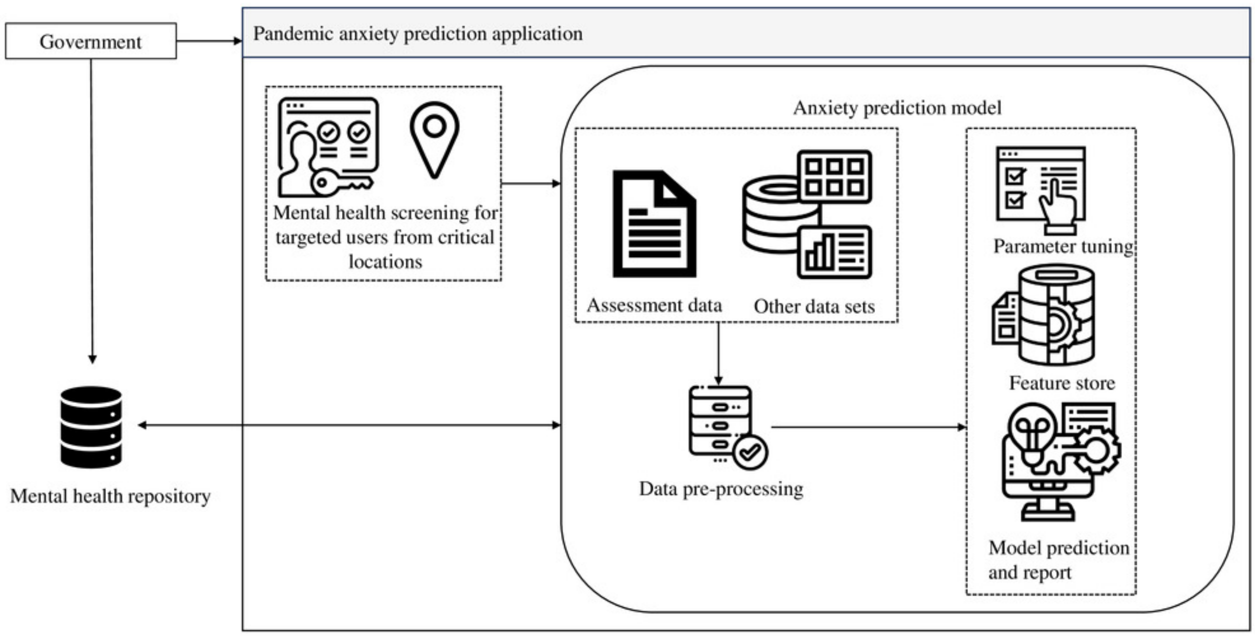

Table 1(on next page)

PICOC model

Table 1. PICOC model

Components	Description
Population	Architectural patterns
Intervention	Data-driven health care systems
Comparison	NA
Outcomes	Identifying the strengths and weaknesses of data-driven systems architecture
Contexts	Review of strength and weaknesses of different architectural patterns used in data-driven systems

Table 2(on next page)

Inclusion and exclusion criteria

Table 2. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Article corresponds to data-driven architectural framework in healthcare domain	Articles only with machine learning algorithms without any architectural study
Article corresponds to data-driven architecture using machine learning algorithms	Articles which do not focus on data-driven architecture
Articles including referential architecture for data driven systems	Editorial notes/letters/mini -review
Articles in English	Duplicate publications
Articles which are fully accessible	Restricted access

Table 3 (on next page)

Quality checklist

Table 3. Quality checklist

Quality assessment	Answer
Is there practical implementation of data-driven architecture?	Yes/Partly/No
Is machine learning aspect of data-driven systems covered?	Yes/Partly/No
How relevant is the article with respect to research objectives?	
Is research methodology clearly explained?	Yes/Partly/No
Is results and analysis referenced with existing works?	Yes/Partly/No
Are all the study questions answered?	Yes/Partly/No

Table 4(on next page)

Quality assessment

1 Table 4. Quality assessment

Index	Q1	Q2	Q3	Q4	Q5	Q6	Total	%
1	1	0	0.5	1	1	1	4.5	0.75
2	0.5	0	1	1	1	1	4.5	0.75
3	1	0.5	1	0.5	1	0.5	4.5	0.75
4	1	0	1	1	1	1	5	0.83
5	0.5	0.5	1	1	0.5	1	4.5	0.75
6	1	0	0.5	1	1	1	4.5	0.75
7	0.5	1	1	0.5	1	1	5	0.83
8	1	0	1	1	1	1	5	0.83
9	0.5	1	1	1	1	1	5.5	0.92
10	1	0.5	0.5	1	0.5	1	4.5	0.75
11	1	0.5	1	0.5	1	0.5	4.5	0.75
12	1	0	1	1	0.5	1	4.5	0.75
13	1	0	1	1	1	0.5	4.5	0.75
14	1	0	1	1	0.5	1	4.5	0.75
15	1	0	1	1	1	0.5	4.5	0.75
16	1	1	1	1	1	0.5	5.5	0.92
17	1	0	0.5	1	1	1	4.5	0.75

2

Table 5(on next page)

RQ1 summary

Table 5. RQ1 summary

Study	Strengths	Limitations
(Shalom et al. 2016)	Interoperability	Security and privacy
(Vinci et al. 2016)	Contextualization	Availability & Accuracy
(Schooler et al. 2017)	Reusability	Scalability
(Olsen 2017)	Consistency	Clarity and completeness
(Mendez & Jabba 2018)	Interoperability	Performance
(Chmielewski et al. 2018)	Security, authorized access, reliability, efficiency, and context	Data consistency and interoperability
(Handayani et al. 2019)	View point contextualization	Data scaling and security
(Beinke et al. 2019)	Security and privacy	Performance, data validation, and scalability
(Zhuang et al. 2020)	Security and privacy	Performance
(Tummers et al. 2021)	View point contextualization	Scalability
(Nadhamuni et al. 2021)	Interoperability and standardization	Data consistency and interoperability
(Ilyas et al. 2022)	Performance	Security and privacy
(Blobel et al. 2022)	Interoperability, Contextualization, Security, Data manipulation	Interoperability
(Aldabbas et al. 2022)	Data manipulation	Security and privacy
(Perez et al. 2023)	Scalability	Interoperability
(Mishra et al. 2023)	Interoperability	Data privacy and security
(Upadhyay et al. 2023)	Data exchangeability	Performance

Table 6 (on next page)

Mapping matrix between studies and KEP

Table 6. Mapping matrix between studies and KEP

Study	Data Security	Data Availability	Data Quality	Data Manipulation	Data Service	Data Representation
(Shalom et al. 2016)	√				√	
(Vinci et al. 2016)		√				√
(Schooler et al. 2017)					√	
(Olsen 2017)			√			
(Mendez & Jabba 2018)		√			√	
(Chmielewski et al. 2018)	√		√		√	√
(Handayani et al. 2019)	√	√				√
(Beinke et al. 2019)	√	√	√			
(Zhuang et al. 2020)	√	√				
(Tummers et al. 2021)		√				√
(Nadhamuni et al. 2021)			√		√	
(Ilyas et al. 2022)	√	√				
(Blobel et al. 2022)				√	√	√
(Aldabbas et al. 2022)	√			√		
(Perez et al. 2023)		√			√	
(Mishra et al. 2023)	√				√	
(Upadhyay et al. 2023)		√			√	

Table 7(on next page)

Expert review analysis elements

Table 7. Expert review analysis elements

Element	Validating criterion (feature)	Mean Value
Maturity Levels	The maturity levels are compliant in all stages of data processing (Sufficiency)	4.400
	Is data redundancy and noise reduction achieved (Accuracy)	4.010
Process and Practices	All processes and practices are generalizable to domain-relevant application (Relevancy)	4.310
	It covers all processes impacting the domain (Comprehensiveness)	4.620
	Process and Practices are analyzed, and they are distinct (Mutual Exclusion)	4.375
Ease of use	Is the architectural framework easy to understand (Understandability)	4.106
	Is the architecture feasible to implement (Feasibility)	4.712
Applicability	Is it practically applicable to mental health care domain (Applicability)	4.405
Flexibility	Is it adaptable to different mental health care systems (Adaptability)	4.702
	Technical flexibility to adapt different technologies (Technical flexibility)	4.501
	Flexible to be customized for accommodating changes (Change flexibility)	4.172