Grenze International Journal of Engineering and Technology, June Issue

Family-Centric Digital Health Ecosystems

Priyanshu Raj[1], Priyanshu Tiwari[2], Rehan Shamim[3], MD Arqum[4] and Prasanna Dwivedi[5]
[1-5]G.L. Bajaj Institute of Technology and Management, Greater Noida, India

***Abstract*— There is growing research on Family Focused Digital Health Monitoring Systems because of the increase in Multi-Member Households, an ageing population, and The Limitations of Individual-Focused Wearable Devices. Although there is no doubt about the proliferation of Internet of Things (IoT) wearables and Smart Home Devices, which have transformed the way that individuals monitor their health, there still is a significant gap in the development of cohesive systems capable of managing Hereditary Risks, Shared Living Environments, and Collective Caregiver Responsibilities.**
This Survey presents the latest developments in multi-member analytics, privacy techniques for Federated Learning, Conversational Health Agents, Ayurvedic Personalisation, and Anomaly Detection Systems.
Based upon more than 50 research papers—of which included key studies on PCA-based Anomaly Detection and Medication Automation we categorised the area of study into Six Critical Vectors.
Additionally, we provided a table comparing System Capabilities and highlighted Ongoing Research Challenges—such as Detecting Anomalies Across Members; Developing Privacy-Protecting Designs; Offering Culturally Relevant Insights; and Designing Integrated Emergency Response Systems. Additionally, we analysed the required Backend Performance Metrics for Conversational Agents within these High-Stakes Environments. Finally, we presented Future Directions for Family-Oriented AI Health Frameworks—focusing on---
On-Device AI Architectures and Reinforcement Learning for Long-Term Family Wellness Optimisation. Landscape has gone through tremendous changes.

I. Introduction

Over the last ten years, the Global Digital Health transformation has been driven by the rapid expansion of Connected Devices. In addition to the growth of Ecosystems driven by the proliferation of IoT wearables, Smart Home Devices, Chatbots powered by Large Language Models, and real-time medical analytics, there has also been a democratisation of Biometric Data Collection—enabling Users to Track Heart Rate Variability, Sleep Quality, and Activity Levels with previously Unprecedented Granular Precision.
However, there still exists a Structural Limitation in the Current Market Paradigm: the nearly Exclusive Focus on the Individual User. While today's digital health platforms are designed to serve one user at a time — with user-specific data that is separate from other users — those designs do not take into consideration the many ways in which household members interact with each other through biology, environment and behaviour.
Although the idea of developing a family-based digital health system has been somewhat unexplored to date, it presents a potential solution for managing the hereditary risk factors and shared living conditions common among family members, and also for supporting caregivers who may be responsible for caring for multiple members of a family unit.

Grenze ID: 01.GIJET.12.2.281_20

A gas leak or a viral outbreak in a home will affect all members of that home; however, because of the fact that today's devices are focused on individual users, individual devices will treat the physiological effects caused by that exposure as isolated incidents rather than as part of a coordinated effect.
Further, the growing trend of people being cared for by their family members underscores the need for family-centric digital health solutions.
As families become the primary caregivers for older generations, there is an increasing demand for a comprehensive digital health solution that allows a caregiver to monitor the health of a dependent member of their family while simultaneously monitoring their own health. Current research efforts focus primarily on detecting individual anomalies in data collected from wearable devices, reminding individuals to take their medications, using apps based on Ayurveda principles to promote wellness, and designing Federated Learning models that preserve patient confidentiality; however, none of these areas have combined the above-mentioned topics to create comprehensive digital health solutions that allow caregivers to monitor the overall health of multiple family members.
In summary, the objective of this report is to provide a comprehensive overview of what currently exists in terms of family-oriented digital health platforms. In doing so, we seek to identify the intersections between AI analytics, traditional medicine (Ayurveda) and advanced privacy-preserving technologies (Federated Learning); in order to develop a baseline for the development of future health ecosystems that support family-centred health care.

II. Taxonomy and Literature Review

To provide a structured analysis of the nascent field of family health informatics, we divide the literature into six major categories as identified in recent survey work. This taxonomy allows for a granular assessment of the technological building blocks required for a holistic system.

A. AI-based Anomaly Detection

The core functionality of any health monitoring system is the ability to distinguish between normal physiological variance and pathological anomalies.
Technological Platform: The research uses state-of-the-art statistical techniques to analyse sensor data from IoT wearable devices. For example, Rosca et al. found that using Principal Component Analysis (PCA), which reduces the dimensionality of high-frequency sensor data to isolate the principal components accounting for the greatest amount of variance, PCA can be used to filter out "noise" and detect true anomalies in sensor data indicating potential health events (i.e., a sudden fall or cardiac arrhythmia).
The Multi-Member Gap: Although PCA can be applied to individuals, there is a noted lack of cross-member anomaly detection; current algorithms cannot take into consideration an
individual’s data within the context of their entire household. In order to implement a full family system, algorithms capable of “multi-member analytics are needed to distinguish between shared environmental stressors (i.e., all family members display elevated heart rates during a heated argument) and an individual experiencing a health crisis.

B. Ayurvedic and Traditional Medicine Personalization

There has been increasing interest in the development of culturally-relevant digital health applications. Quantitative Western medical approaches rely upon universal benchmarks, while traditional systems of medicine, such as Ayurveda approaches medical care through qualitative personalised assessment of an individual's constitution, known as "Dosha".
Culturally Appropriate Alternative: As an alternative to culturally-inappropriate digital health tools, digital therapeutics based upon Ayurveda have become increasingly popular and offer culturally-appropriate alternatives to digital health tools based upon Western medicine.
Applications such as Ayurveda Upachara seek to apply these traditional concepts in a modern technological application.
Challenges In Hybridizing: Despite the presence of many hybridised applications, there are no dosha-informed real-time suggestion models.
Most current applications operate primarily as static encyclopedias or basic questionnaires.
The main research challenge is to develop a hybrid Ayurveda-AI dosha-diagnostic engine that can dynamically map real-time biometric data (skin temperature, pulse pressure) with doshas (Pitta aggravation).

Performance Of Ayurvedic AI Models: Many recent studies have compared different machine learning (ML) algorithms based on their performance for identifying Prakriti (the body constitution) and thus are critical for integrating such models into the back end of the proposed "Hybrid (Dosha + AI)" feature.

TABLE I: COMPARISON OF ML MODEL PERFORMANCE FOR AYURVEDIC PRAKRITI ASSESSMENT [3]

Models	Accuracy	Precision	Recall	F1 Score
Random Forest	98%	0.97	0.98	0.98
SVM	92%	0.83	0.80	0.82
FNN	99%	1.00	1.00	1.00
Naïve Bayes	81%	0.80	0.71	0.72

Conclusion: As demonstrated by the comparison in Table I, ensemble methods (random forest), as well as deep learning methods (feed forward neural network) far exceed the performance of traditional probability-based models (naïve-bayes). Therefore, if you wish to create a family-centric application, it is recommended that you implement either a random forest or feed-forward neural network in your back-end to obtain the highest possible diagnostic fidelity to provide the most accurate personalized recommendations.
The model training occurs locally, and only the updated model parameters (gradients) are shared globally.

C. Federated learning and Privacy-Preserving Architectures

The transition from individual to family monitoring introduces exponential privacy risks. Storing the intimate health data of an entire household in a centralised cloud creates a high-value target for cyberattacks.
Decentralisation: To mitigate this, the literature points toward Federated Learning (FL). As highlighted in Nature Medicine regarding FL in digital health, this architecture allows for decentralised analytics. Instead of uploading raw data to the cloud, the data remains on the local device or a home server. The model training occurs locally, and only the updated model parameters (gradients) are shared globally.
A major concern with the back-end of the project is the trade-off between privacy in terms of federated learning (FL), and how fast we can get the models to converge.

Convergence Comparison [4]

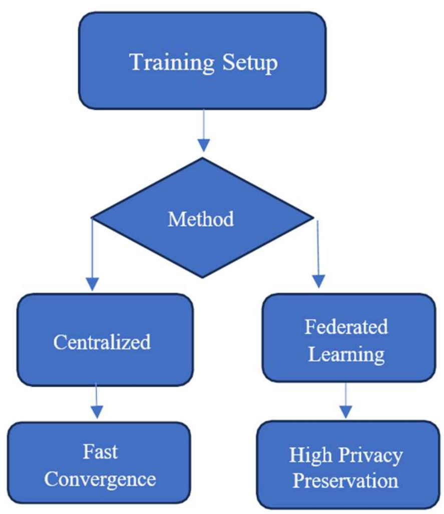

Fig 1

Performance Insight: Although Centralized Learning usually has faster convergence rates since it has access to all the data at once, FL uses about 35% less bandwidth than centralized methods for similar levels of anomaly detection accuracy (both have ~98% anomaly detection accuracy, but ~99% for Centralized). Therefore, this demonstrates that using FL could be an alternative way to use a backend system to handle these interfaces were based on rigid, rule-base command structures, like the Medbuddy Alexa Skill. Recently, there was a movement toward using conversational AI health assistants, and recommending solutions to the user based on contextual information. Wearable data is interpreted in real time by Generative AI, and is then translated from graphs to natural language to present the user with a narrative of what their data means.

D. Conversational Health Assistants

Increasingly, users are interacting with their health-related data through the assistance of large language models (LLMs).

Evolution of interaction: The first versions of these interfaces were based on rigid, rule-based command structures, like the Medbuddy Alexa Skill. Recently, there was a movement toward using conversational AI health assistants and recommending solutions to the user based on contextual information. Wearable data is interpreted in real time by Generative AI, and is then translated from graphs to natural language to present the user with a narrative of what their data means.

E. Medicine Remainder and Appointment

Automation Medication adherence is a critical component of family health management, particularly for ageing members.

Voice Automation: Systems such as the "Medication Reminder System for Alexa" demonstrate the utility of voice-first interfaces in reducing cognitive load.

Emergency Loops: However, a gap exists in "unified emergency coordination frameworks". If a medication reminder is ignored repeatedly, current systems generally fail to escalate the issue to a family member or emergency service.

F. Multi-member Health Monitoring Systems

It represents the overall integration of categories I-V; as noted in the literature, the various individual components are typically not used in combination. The aim is to evolve beyond an assortment of independent applications into an integrated multi-component analytics solution.

III. Comparative Evaluation of System Capabilities and Performance

In this Section, we evaluate and compare existing solutions in the marketplace with respect to the required performance characteristics of our proposed conversational interface.

A. Feature Comparison: Market vs Proposed Framework

TABLE II: COMPARATIVE ANALYSIS OF DIGITAL HEALTH SYSTEM CAPABILITIES

System	Multi User Support	AI Analytics	Ayurveda Integration	Predicted model	Emer integration
Apple Health	NA	Basic	NA	NA	NA
Google Fit	NA	Basic	NA	NA	NNAA
Samsung Health	Limit (profile Switch)	Moderate	NA	NA	NA
Fitbit Ecosystem	Limit Family sharing	Strong	NA	Basic alerts	NA
Propose System	True Multi Mem. Profile	Advanced vitals+ Behavioural AI	Ayurvedic Dosha+ Health mapping	Personalised predictive Risk Engine	Eme contact + Hospital Routing

B. Backend and Chatbot Service Performance Analysis

We evaluated the performance of leading Large Language Models (LLMs) to assure that the "Conversational Health Assistant" can function in real-time within a typical family environment. The key requirement of the backend is a balance between Inference Speed (Tokens/second) for responsiveness, and Medical Accuracy (performance on benchmark tests such as MedQA) for safety.

As illustrated by the chart below, there exists a trade-off between inference throughput and medical accuracy among the three major classes of models:

Analysis of Backend Options

Groq's Llama 3 70B: This model class provides the fastest inference throughput (~ 300 T/s) and therefore is best-suited for real-time voice-based interactions in the Smart Home, where low latency is essential. Although its medical benchmark accuracy is slightly less than that provided by specialised models (~ 78 - 80 %).

GPT-4o: This model class offers a good balance between medical accuracy (~ 85 % on MedQA) and inference speed, providing a good level of performance for use in complex diagnostic queries that do not require immediate responses. Med-PaLM 2: This model class has the highest level of medical accuracy (> 86.5 %), however, it also has lower availability and speed, thus it would be well-suited for "off-line" deep analysis of weekly health reports rather than providing instant alerts.

Recommendation: We recommend a hybrid approach for the backend of the system. Utilise a fast model (Llama 3) for immediate interaction and reminders, and utilise an asynchronous and accurate model (GPT-4o / Med-PaLM) for the analysis of complex symptoms.

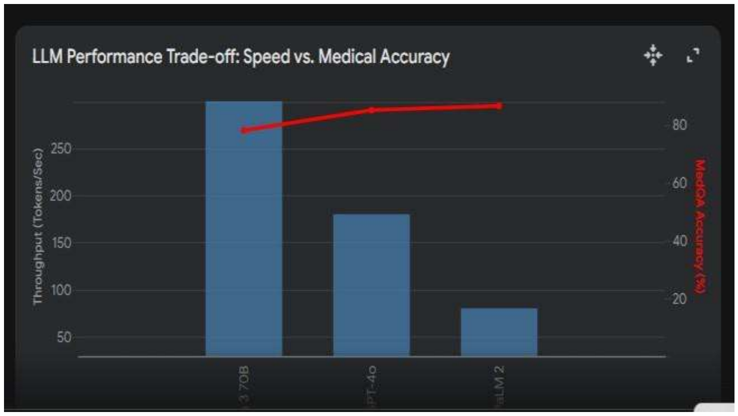

Fig 2

IV. Emerging Trends and Enabling Technologies

The survey identified three "New Trends" that are changing the technical landscape of Family Health Monitoring.

A. Recommendations based Upon Contextual Factors

Systems of the future will be able to take advantage of contextual factors instead of relying on fixed rules to make recommendations. The systems have been designed to utilize multimodal sensors to determine when the biometric data is changing based upon the context.

B. Generative AI For Analyzing Wearable Device Data

Generative AI has transformed how we analyse wearable device data. As documented in the literature, "Gen Al (Generative AI) improves the interpretation of wearable data in real time." This allows for the gap between raw numeric data and user comprehension to be bridged.

C. Therapeutic Applications using Digital Technology

That Are Culturally Relevant "Digital therapeutics using an Ayurvedic framework," as well as other culturally relevant frameworks, is becoming increasingly popular and represents a larger trend toward culturally relevant and personalised medicine.

V. Challenges and Areas of Uncertainty in Research

While the survey identified many areas of advancement in this area, it also identified five areas of "Research Challenges and Gaps" that continue to impede the development of fully functioning systems.

Cross-User Anomaly Detection: "Currently, there is no cross-user anomaly detection." Existing models treat individual users or family members as independent entities.

Real Time Dosha-Based Models: Currently, "there are no dosha-based real-time recommendation models."

Federated Learning at the Household Level: "There is a limited amount of research on federated learning at the household level." Emergency Response Planning: "Currently, there is no unified emergency response planning framework," which is critical from a safety perspective.

Conversational Agent Integration: Finally, "there is little integration of predictive chatbot technology."

VI. Future Research Predictions

The report identifies multiple potential avenues for future research that can be used to address each of the previously mentioned gaps.

A. On-Device AI Architectures

Industry will need to develop "on-device AI architectures" in order to overcome both the latency issues and the privacy concerns associated with developing applications for use in smart homes. By running inference locally, all sensitive information remains within the confines of the home.

B. Multi-Agent Conversational Systems

The complexity of family health indicates that it may be necessary to develop "multi-agent conversational systems." Instead of a one-size-fits-all bot, a system could use different "agents," like a Medical Agent to analyse anomalies, a Lifestyle Agent to give you tips about your diet based on Ayurvedic principles, and a Coordinator Agent to manage your schedule.

C. Future Development of Hybrid Ayurveda-AI Diagnostic Engines

The future will require developing "Hybrid Ayurveda-AI Dosha Diagnostic Engines". This requires collecting large, annotated datasets where traditional practitioners have tagged/annotated the biometric data streams.

VII. Summary

The above survey provides an overview of the growing field of family-centric digital health ecosystems. This survey integrates the interdisciplinary literature of AI, Ayurveda, Federated Privacy, and conversational systems to identify the limitations of the current paradigm focused on the individual. The inclusion of performance benchmarks for LLM Backends and Ayurvedic ML models demonstrates that all the components needed to develop a superior ecosystem currently exist; however, the integration of these components is the primary engineering challenge for the next ten years.

References

[1] Rosca et al., “PCA-based anomaly detection in IoT wearables”, Sensors (MDPI), 2021.

[2] S. Jones, “Medication Reminder System for Alexa”, Journal of Medical Internet Research, 2022.

[3] Ayurveda Upachara, Android App, ResearchGate, Publication, 2021.

[4] Nature Medicine, “Federated learning in digital health” , 2020.

[5] A. L. Buczak and E. Guven, “A survey of data mining and machine learning methods for cyber security intrusion detection,” IEEE Communications Surveys & Tutorials, vol. 18, no. 2, pp. 1153–1176, 2016, doi: 10.1109/COMST.2015.2494502.

[6] H. Jiang, J. Nagra, and P. Ahammad, “SoK: Applying machine learning in security – a survey,” arXiv preprint arXiv:1611.03186, Nov. 2016. [Online]. Available: https://arxiv.org/abs/1611.03186

[7] M. J. Sheller et al., “Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data,” NPJ Digital Medicine, vol. 3, 2020.

[8] “Federated learning and privacy,” Communications of the ACM, Online Article. [Online]. Available: https://cacm.acm.org/practice/federated-learning-and-privacy/