Research Review

Cesar Martinez

Department of Informatics and Mathematics, Mercer University

INFM480: Capstone Project for IT & Informatics

Dr. Long

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Capstone Project Research Resources

Project Title: Personal Health Coach Platform

1. Health Metric Models

This research determines **how the platform interprets user health data**.

Research established formulas and benchmarks used in health science, such as:

- BMI calculation
- Basal Metabolic Rate (BMR) formulas (Mifflin-St Jeor equation)
- Total Daily Energy Expenditure (TDEE)
- Recommended Daily Allowances (RDA) for nutrients
- Sleep recommendations by age
- Heart rate zones for exercise

Purpose in system:

- Establish baseline health metrics
- Compare user data against healthy ranges
- Generate recommendations

Sources:

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- TDEE multiplier:
  - Sedentary (1.2): Little or no exercise; desk job.
  - Lightly Active (1.375): Light exercise/sports 1–3 days/week.
  - Moderately Active (1.55): Moderate exercise/sports 3–5 days/week.
  - Very Active (1.725): Hard exercise/sports 6–7 days a week.
  - Extra Active (1.9): Very hard exercise, physical job, or training

2. Digital Health Platform Adoption

This research looks at **whether people actually want to use a platform like this**.

Questions you might investigate:

- Why do people avoid traditional health coaching?
- Are users comfortable sharing health data digitally?
- Do users trust AI-generated recommendations?

Purpose:

- Validate that the platform solves a real problem
- Support the research questions

Why People Avoid Traditional Health Coaching

Key Research Findings

Several studies in digital health and public health show that **cost, accessibility, and convenience** are the main barriers to traditional coaching or personalized health services.

Common barriers identified in research:

1. Cost

- Personal health coaching can cost **$100–$300 per session** depending on specialization.
- Many individuals cannot afford ongoing coaching.

Research fields supporting this:

- Preventive medicine
- Behavioral health intervention studies

2. Accessibility

- People in rural or underserved areas have **limited access to health professionals**.
- Scheduling appointments can be difficult for working individuals.

3. Time Constraints

- Traditional coaching requires regular appointments.
- Many individuals prefer **asynchronous or flexible digital tools**.

Example Finding

Studies on digital health interventions show that individuals are more likely to engage with health tools when they are **convenient, low-cost, and accessible through mobile or web platforms**.

How This Supports the Platform

The system addresses these issues by providing:

- automated health insights
- always-available recommendations
- low-cost digital access

Are Users Comfortable Sharing Health Data Digitally?

Key Research Findings

Research from **digital health adoption studies** shows that:

- Many users are willing to share health data **if privacy protections exist**.
- Trust increases when platforms clearly communicate how data is used.

Common concerns include:

- data privacy
- security breaches
- misuse of health information

However, surveys of wearable users and digital health platforms show:

- people regularly share data with:
    - fitness apps
    - wearable devices
    - telehealth platforms

Examples include:

- Apple Health
- Fitbit
- MyFitnessPal

Example Finding

Research in digital health adoption shows that **users are more willing to share personal health data when platforms demonstrate strong security protections and transparency in data usage policies.**

How This Supports the Platform

The project can include:

- secure data storage
- transparent privacy policies
- optional data-sharing settings

Trust in AI-Generated Health Recommendations

This is a **very important research area** because the platform includes an **AI chatbot module**.

Key Research Findings

Research in healthcare AI shows:

Users are more likely to trust AI recommendations when:

1. AI supports — not replaces — human expertise
2. Recommendations are **explainable**
3. The system uses **evidence-based guidelines**

Studies in medical AI show that:

- users prefer **AI-assisted recommendations** rather than fully automated medical decisions
- transparency increases trust

Example finding:

People are more likely to accept AI health recommendations when they understand **how the recommendation was generated and what data was used**.

How This Supports the Platform

The system could include:

- explanations for recommendations
- evidence-based references
- transparency in algorithms

Growth of Digital Health Platforms

Another important piece of research is that **digital health adoption is rapidly increasing**.

Major trends identified in health informatics research:

- Wearable devices are widely used
- Telehealth expanded significantly after COVID-19
- Many users track health data through mobile apps

Digital health platforms are increasingly used for:

- fitness tracking

- diet tracking
- sleep monitoring
- telemedicine

Example Research Conclusion

Studies in health informatics show that **digital health tools are increasingly used to support preventative health management and lifestyle monitoring.**

Sources:

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- Nascimento, I. J. B., et al. (2023). Barriers and facilitators to utilizing digital health technologies.
- Alzghaibi, H., et al. (2025). Adoption barriers and facilitators of wearable health devices.
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- Hassan, M., et al. (2024). *Barriers and facilitators of AI adoption in healthcare.* JMIR Human Factors.

3. Data Integration in Health Platforms

The system combines **multiple health data sources**, so research is needed on how systems combine data from different inputs.

Examples:

- Wearable data (steps, heart rate)
- Nutrition tracking apps
- Sleep trackers
- Medical test results

Research questions:

- How do health apps integrate multiple data sources?
- What challenges exist when combining health metrics?

A. Research on Integrating Multiple Health Data Sources

1. Interoperability and Integration of Digital Health Data

Source

Benson, T., & Grieve, G. (2016).
Principles of Health Interoperability: SNOMED CT, HL7 and FHIR. Springer.

Key findings:

Health systems integrate data using interoperability standards such as:

- **HL7**
- **FHIR (Fast Healthcare Interoperability Resources)**
- **SNOMED clinical terminology**

These standards allow different systems (wearables, EHRs, mobile apps) to **exchange health information in a consistent format**.

Why it supports the platform:

The system conceptually aggregates data from:

- wearables
- nutrition apps
- medical records

which requires **interoperability principles**.

2. Integrating Wearable Data with Health Systems

Source

Piwek, L., Ellis, D., Andrews, S., & Joinson, A. (2016).
The rise of consumer health wearables: Promises and barriers.
PLOS Medicine.

Key findings:

Wearable devices provide large volumes of health data including:

- heart rate
- activity levels
- sleep metrics

However, challenges include:

- inconsistent data quality
- device accuracy variation
- lack of standardized formats

Why this supports the project:

The platform integrates **wearable health metrics**, which makes this research directly relevant.

3. Mobile Health (mHealth) Data Integration

Source

Free, C., et al. (2013).
The effectiveness of mobile-health technologies to improve health care service delivery.
PLOS Medicine.

Key findings:

Mobile health platforms allow users to:

- collect health data through smartphones
- integrate wearable device information
- combine self-reported lifestyle data

However, effective integration requires:

- standardized APIs
- consistent data structures
- secure data transmission

Relevance:

The system collects:

- nutrition data

- sleep data
- exercise data

which are common mHealth inputs.

4. Personal Health Informatics Research

Source

Li, I., Dey, A., & Forlizzi, J. (2010).
A stage-based model of personal informatics systems.

Key findings:

Personal health platforms combine:

- automatically collected data (wearables)
- manually entered data (diet logs)
- medical records

Users rely on **data visualization and trend analysis** to interpret these combined data streams.

Relevance:

The dashboard concept fits exactly into **personal informatics system research**.

5. Health Data Aggregation Platforms

Source

Wang, Y., Kung, L., & Byrd, T. (2018).
Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations.

Key findings:

Health platforms can combine:

- biometric sensor data
- clinical health records
- lifestyle tracking data

to identify patterns and generate **predictive insights**.

Relevance:

The system integrates:

- biometric metrics
- health behaviors
- physiological indicators

to produce recommendations.

Challenges When Combining Health Data

This part is **important for the capstone limitations section**.

1. Data Standardization Problems

Different health devices and apps often use **different measurement formats**, which creates integration challenges.

Example:

- Heart rate may be stored as
  - BPM average
  - BPM per second
  - zone-based metrics

Research:

Piwek et al. (2016)

2. Data Accuracy and Reliability

Wearables may produce **inconsistent results** depending on:

- device brand
- sensor quality
- user movement

Example:

Sleep trackers and step counters can vary significantly in accuracy.

Research:

PLOS Medicine wearable studies.

3. Data Volume and Complexity

Combining multiple data streams creates **large datasets**, which require:

- efficient storage
- data cleaning
- analytics processing

Research:

Wang et al. (2018) big data healthcare analytics.

4. Privacy and Security Concerns

Combining multiple health datasets increases the **risk of data exposure**.

Health platforms must follow regulations such as:

- HIPAA
- GDPR

This ties directly into the **next research section on privacy and ethics**.

Sources:

- Benson, T., & Grieve, G. (2016).
  Principles of Health Interoperability: SNOMED CT, HL7 and FHIR. Springer.
- Free, C., et al. (2013).
  The effectiveness of technologies to improve health care service delivery.
  PLOS Medicine.

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  The rise of consumer health wearables: Promises and barriers. *PLOS Medicine.*
- Wang, Y., Kung, L., & Byrd, T. (2018).
  Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change.*

4. AI in Personalized Health Recommendations

Since the project includes **AI or rule-based recommendations**, you should research how recommendation systems work in health technology.

Examples:

- AI chatbots in healthcare
- rule-based health recommendation systems
- predictive health analytics

Purpose:

- Support the recommendation logic of the system

A. AI Chatbots in Healthcare

1. Conversational Agents for Health Care

Source

Laranjo, L., Dunn, A. G., Tong, H. L., et al. (2018).
Conversational agents in healthcare: A systematic review.
Journal of the American Medical Informatics Association (JAMIA).

Key findings:

- Healthcare chatbots can provide:
  - symptom guidance
  - health education
  - behavioral coaching
- Chatbots improve **user engagement and accessibility to health information**.
- They are especially useful for **preventive health monitoring and lifestyle management**.

Why this supports the platform:

the system uses an **AI chatbot module to provide recommendations and explanations** based on health metrics.

2. AI Chatbots for Behavior Change

Source

Bickmore, T., Schulman, D., & Yin, L. (2010).
Maintaining engagement in long-term interventions with relational agents.

Key findings:

AI conversational agents can encourage:

- increased physical activity
- better medication adherence
- improved lifestyle behaviors

Users often respond positively to **interactive conversational systems that simulate coaching interactions**.

Relevance:

The platform acts as a **digital health coach**.

Rule-Based Health Recommendation Systems

Many health applications use **rule-based systems derived from clinical guidelines**.

3. Clinical Decision Support Systems

Source

Sutton, R. T., et al. (2020).
An overview of clinical decision support systems.
NPJ Digital Medicine (Nature).

Key findings:

Clinical decision support systems analyze:

- patient health data
- medical guidelines
- health metrics

to generate recommendations such as:

- lifestyle advice
- risk alerts
- treatment suggestions

Why this supports the platform:

The recommendation engine compares user metrics against **evidence-based ranges** (BMI, sleep, activity, blood pressure).

Rule-Based Systems in Health Informatics

Source

Shortliffe, E. H., & Cimino, J. J. (2014).
Biomedical Informatics: Computer Applications in Health Care and Biomedicine.

Key findings:

Rule-based medical systems work by:

1. collecting health data
2. comparing values against medical guidelines
3. generating recommendations based on defined rules

These systems are widely used in:

- preventative care

- wellness applications
- clinical decision support tools

Predictive Analytics in Healthcare

Source

Raghupathi, W., & Raghupathi, V. (2014).
Big data analytics in healthcare: Promise and potential.

Key findings:

Health analytics systems can analyze large datasets including:

- wearable device data
- biometric measurements
- lifestyle behaviors

to detect patterns and predict health risks.

Examples include predicting:

- cardiovascular risk
- obesity trends
- sleep disorders

Relevance:

The platform detects trends such as:

- declining sleep quality
- increasing resting heart rate
- inadequate exercise levels.

Personalized Health Recommendation Systems

Source

Ricci, F., Rokach, L., & Shapira, B. (2015).
Recommender Systems Handbook.

Key findings:

Health recommender systems personalize recommendations by:

- analyzing user characteristics
- comparing behavior to health guidelines
- adapting suggestions based on user data trends.

This type of system is commonly used in:

- fitness apps
- nutrition tracking systems
- digital wellness platforms

Sources:

- Laranjo, L., Dunn, A. G., Tong, H. L., et al. (2018).
  Conversational agents in healthcare: A systematic review. *Journal of the American Medical Informatics Association.*
- Bickmore, T., Schulman, D., & Yin, L. (2010).
  Maintaining engagement in long-term interventions with relational agents.
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- Shortliffe, E. H., & Cimino, J. J. (2014).
  Biomedical Informatics.

5. Privacy and Ethical Considerations

Health data is extremely sensitive, so ethical research is important.

Topics:

- HIPAA considerations

- data privacy in digital health platforms
- user consent for health data collection
- risks of automated health advice

Purpose:

- demonstrate ethical awareness in the project

HIPAA and Health Data Protection

1. HIPAA Overview

Source

U.S. Department of Health & Human Services (HHS).
Health Insurance Portability and Accountability Act (HIPAA).

Key points:

HIPAA protects **Protected Health Information (PHI)** including:

- medical records
- biometric identifiers
- health test results
- health history
- healthcare services received

HIPAA requires:

- **secure storage of health data**
- **restricted access to data**
- **patient authorization before sharing data**

Relevance to the project:

The system collects health information such as:

- biometrics
- nutrition data
- sleep patterns
- wearable metrics

Therefore, the platform concept must include:

- encryption
- secure data storage
- restricted access

Data Privacy in Digital Health Platforms

2. Privacy Risks in Mobile Health Applications

Source

Dehling, T., Gao, F., Schneider, S., & Sunyaev, A. (2015).
Exploring the far side of mobile health: Information security and privacy of mobile health apps.
JMIR mHealth and uHealth

Key findings:

Many health applications collect sensitive data but fail to clearly disclose:

- how data is stored
- who can access the data
- how data may be shared

Major privacy risks include:

- third-party data sharing
- weak encryption
- unclear privacy policies

Why this supports the project:

The platform should include:

- transparent privacy policies
- secure data handling
- user control over data sharing

User Consent for Health Data Collection

Ethical Framework for Digital Health Data

Source

Mittelstadt, B. D., et al. (2016).
The ethics of algorithms: Mapping the debate.
Big Data & Society

Key findings:

Users should be informed about:

- what data is collected
- how algorithms use the data
- potential risks associated with automated decisions

Ethical digital health platforms should provide:

- **informed consent**
- **clear explanations of data usage**
- **user control over personal data**

Risks of Automated Health Advice

This is the **most important ethical concern for the project**.

4. Ethical Challenges of AI in Healthcare

Source

Topol, E. (2019).
High-performance medicine: The convergence of human and artificial intelligence.
Nature Medicine

Key findings:

AI systems in healthcare should:

- support human decision-making
- not replace medical professionals
- clearly communicate limitations

Risks of AI-generated health advice include:

- incorrect recommendations
- overreliance on automated systems
- misinterpretation of health data

5. Responsible AI in Healthcare

Source

World Health Organization (WHO).
Ethics and governance of artificial intelligence for health.

WHO identifies key ethical principles:

1. Protect human autonomy
2. Promote safety and transparency
3. Ensure accountability
4. Protect privacy and confidentiality

Relevance to the platform:

The system should include disclaimers such as:

"This platform provides informational health guidance and should not replace professional medical advice."

Ethical Design Principles for the Platform

Based on the research, the system should follow these design principles.

1. Data Protection

```
Encrypted data storage
Secure authentication
Limited access to sensitive information
```

2. Transparency

```
Explain how recommendations are generated
Show which health metrics triggered alerts
```

3. User Consent

```
Require explicit permission before collecting data
Allow users to delete their data
```

4. AI Safety

```
Provide recommendations as guidance, not diagnosis
Include medical disclaimers
Encourage consultation with healthcare professionals
```

Sources:

- Dehling, T., Gao, F., Schneider, S., & Sunyaev, A. (2015).
  Exploring the far side of mobile health: Information security and privacy of mobile health apps. *JMIR mHealth and uHealth.*
- Mittelstadt, B. D., et al. (2016).
  The ethics of algorithms: Mapping the debate. *Big Data & Society.*
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  High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine.*
- U.S. Department of Health & Human Services.
  Health Insurance Portability and Accountability Act (HIPAA).
- World Health Organization. (2021).
  Ethics and governance of artificial intelligence for health.