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Assistive Digital Technologies for Adherence Monitoring and Evaluation Using Multimodal Patient Data

Aneta Buchtelová[1,2]
Vojtěch Malina[1]
Milada Luisa Šedivcová[1]
Jan Kašpar[1]
Ondřej Pelák[1]

[1] Faculty of Biomedical Engineering, Czech Technical University in Prague, Department of Information and Communication Technologies in Medicine, José Martího 269/31, 162 52, Praha 6 – Veleslavín, email: aneta.buchtelova@fbmi.cvut.cz
[2] Faculty of Biomedical Engineering, Czech Technical University in Prague, Department of Natural Sciences

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Abstract Adherence to therapeutic recommendations is a key determinant of treatment effectiveness across medical disciplines, yet its reliable assessment remains challenging in real-world settings. This paper presents an assistive digital framework for adherence monitoring and evaluation based on multimodal patient-generated data. The proposed system integrates wearable-derived physiological data, mobile self-reported behavioral inputs, and contextual clinical information into a unified assessment pipeline. An interpretable algorithmic approach combining categorical evaluation, normalization, and weighted aggregation is introduced to quantify daily adherence. The framework emphasizes transparency, flexibility, and practical usability rather than black-box prediction models. Pilot study confirmed technical feasibility, reliable data integration, and high user acceptance, supporting the applicability of the approach in real-world conditions.

Key words assistive technology, mobile application, multimodal data, health, wearable technologies

1. INTRODUCTION

Adherence to therapeutic recommendations represents a critical determinant of treatment effectiveness across a wide range of medical domains. Insufficient adherence to prescribed behavioral, pharmacological, or lifestyle interventions is associated with reduced clinical outcomes, increased healthcare costs, and diminished quality of life [1]. Despite its recognized importance, adherence remains difficult to monitor objectively, particularly outside controlled clinical environments. Traditional approaches relying on patient self-reporting or sporadic clinical assessments often fail to capture the dynamic and context-dependent nature of everyday patient behavior [2,3].

Recent advances in digital health technologies have created new opportunities for continuous and unobtrusive adherence monitoring. Wearable sensors, mobile health applications, and connected medical devices enable the collection of diverse patient-generated data reflecting physiological signals, behavioral patterns, and subjective experiences [4,5]. When combined, such multimodal patient data provide a more comprehensive view of adherence-related behavior than any single data source alone. However, the increasing volume and heterogeneity of these data also introduce significant challenges related to integration, interpretation, and meaningful clinical utilization [6].

Assistive digital technologies aim to address these challenges by supporting both patients and healthcare professionals through intelligent data processing, feedback mechanisms, and decision support. Within the context of digital therapeutics, assistive systems can facilitate personalized monitoring, early detection of non-adherence, and adaptive interventions tailored to individual patient needs [7]. A key requirement for such systems is the availability of transparent and interpretable methods for translating raw multimodal data into actionable adherence indicators that can be understood by end users without advanced technical expertise [8].

This paper presents a technological and algorithmic framework for adherence monitoring based on multimodal patient-generated data. The proposed approach integrates data from wearable devices, mobile self-reporting tools, and clinically relevant measurements into a unified adherence evaluation model. A weighted daily adherence score is introduced to enable standardized assessment across heterogeneous parameters while preserving flexibility for different therapeutic contexts. The framework has been implemented within an assistive digital system and preliminarily verified through application in a pilot observational study, demonstrating its feasibility for real-world adherence monitoring. By focusing on system architecture, data integration, and algorithmic design, this work contributes to the development of scalable assistive digital technologies supporting adherence within digital therapeutic pathways.

2. SYSTEM ARCHITECTURE

The proposed assistive digital system was designed to support continuous adherence monitoring through the integration of heterogeneous patient-generated data sources. The architecture follows a modular and scalable design, enabling flexible adaptation to different therapeutic contexts and monitored parameters. The system combines wearable-based physiological sensing, mobile self-reporting, and clinically relevant measurements into a unified data processing pipeline.

2.1 Data Acquisition Layer

The data acquisition layer consists of multiple sources capturing complementary aspects of patient behavior and physiological state. First, wearable devices are used to continuously monitor objective physiological and activity-related parameters, such as sleep duration, physical activity, and daily routines. These devices enable passive, unobtrusive data collection in real-world conditions, minimizing patient burden and recall bias.

Second, a custom mobile application serves as a self-reporting interface for collecting subjective and behavioral data. Through short daily questionnaires, patients report variables relevant to therapeutic adherence, including perceived stress, lifestyle behaviors, and task completion. The application is designed to ensure high usability and compliance by limiting interaction time and employing simple input mechanisms.

In addition to patient-generated data, selected clinically relevant measurements may be incorporated when available. These measurements, obtained during routine clinical visits or remote assessments, provide contextual validation and enhance the interpretability of digitally collected data. Together, these sources form a multimodal dataset reflecting both objective and subjective dimensions of adherence.

2.2 Data Synchronization and Integration

A critical component of the system architecture is the temporal synchronization and integration of heterogeneous data streams. Data originating from wearable devices, mobile self-reports, and clinical measurements differ in sampling frequency, timing, and format. To address this heterogeneity, all data are aligned to a common temporal reference, typically a daily observation window.

Wearable-derived parameters are aggregated into daily summaries using predefined rules corresponding to the monitored therapeutic objectives. Self-reported data are time-stamped at the moment of user input and linked to the same daily window. Clinical measurements are associated with the closest relevant time interval and treated as contextual inputs rather than continuous signals. This synchronization strategy enables consistent pairing of multimodal data for downstream adherence evaluation.

2.3 Data Processing and Normalization

Following integration, raw data undergo preprocessing and normalization to ensure comparability across parameters. Continuous variables are transformed into clinically or behaviorally meaningful categories based on predefined thresholds. These thresholds may reflect recommended therapeutic targets, clinical guidelines, or empirically derived reference ranges.

Each parameter is subsequently mapped onto a normalized adherence scale, allowing heterogeneous inputs to be combined within a single evaluation model. This normalization step is essential for maintaining interpretability and preventing dominance of any single data modality. The resulting normalized values form the input to the adherence scoring algorithm described in the subsequent section.

2.4 Adherence Evaluation and Feedback Layer

The adherence evaluation layer implements the algorithmic logic for computing daily adherence scores based on weighted combinations of normalized parameters. Weighting coefficients allow prioritization of parameters according to therapeutic relevance or individual patient profiles. The output of the evaluation is a continuous adherence score, complemented by a categorical classification to support intuitive interpretation.

To facilitate user engagement and clinical usability, adherence results are presented through a simplified visual feedback mechanism based on a traffic-light model. This representation enables rapid identification of high, moderate, or low adherence states and supports timely behavioral adjustments or clinical interventions. The feedback layer is designed to function both as a patient-facing motivational tool and as a clinician-facing monitoring aid.

2.5 System Scalability and Extensibility

The proposed architecture is intentionally designed to be extensible. Additional data sources, such as new wearable sensors or external health information systems, can be incorporated without altering the core evaluation logic. Similarly, therapeutic plans can be customized by modifying parameter sets, thresholds, and weights, allowing the system to support diverse clinical scenarios.

This modular approach supports future expansion toward advanced analytics, including machine learning–based personalization and predictive modeling. By separating data acquisition, processing, and evaluation layers, the system provides a robust foundation for scalable assistive digital technologies aimed at adherence monitoring in digital therapeutic applications. Figure 1 provides a conceptual overview of the system architecture and the flow of multimodal patient data across system components.

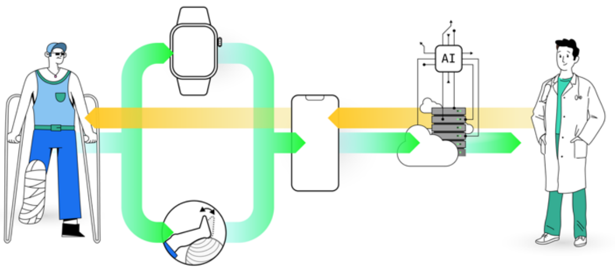

Figure 1 - Conceptual overview of the assistive digital system for adherence monitoring using multimodal patient data. Patient-generated data are continuously collected via wearable sensors and self-reporting via mobile application, processed in a cloud-based environment, and translated into interpretable feedback supporting both patient engagement and clinical oversight.

3 ALGORITHMIC FRAMEWORK FOR ADHERENCE EVALUATION

The proposed assistive digital system incorporates an algorithmic framework designed to transform heterogeneous multimodal patient data into a unified and interpretable indicator of therapeutic adherence. Given the diversity of monitored parameters and therapeutic contexts, the framework emphasizes transparency, modularity, and clinical interpretability, allowing its application across different digital therapeutic scenarios without reliance on opaque or black-box models.

3.1 Parameter Evaluation and Normalization

Each monitored parameter is first evaluated independently according to predefined behavioral or clinical thresholds derived from therapeutic recommendations, clinical guidelines, or empirical reference values. These thresholds define adherence-related categories reflecting the degree to which patient behavior aligns with the prescribed therapeutic plan. To support intuitive interpretation by both patients and healthcare professionals, a three-level traffic-light model is applied, distinguishing optimal adherence, partial adherence, and non-adherence.

Following categorical evaluation, adherence levels are transformed into normalized numerical values to enable aggregation across heterogeneous data modalities. This normalization step maps categorical states onto a bounded numerical scale between zero and one, ensuring that parameters with different units, sampling frequencies, and measurement characteristics can be compared and combined within a single evaluation framework. By preserving a direct correspondence between categorical meaning and numerical representation, the normalization process maintains interpretability while enabling quantitative analysis.

3.2 Weighted Aggregation and Adherence Scoring

To quantitatively summarize adherence across heterogeneous monitored parameters, a weighted aggregation approach is employed. Each monitored parameter i is first assigned a categorical adherence level corresponding to the traffic-light classification, where green indicates optimal adherence, yellow partial adherence, and red non-adherence. These categorical levels are encoded as discrete values $x_i \in \{0,1,2\}$.

To ensure normalization and comparability across parameters, the categorical values are transformed into normalized adherence scores s_i according to:

$$s_i = \frac{x_i}{2}$$

where $s_i \in [0,1]$ represents the normalized adherence contribution of parameter i.

Each parameter is assigned a weighting coefficient w_i reflecting its relative importance within the therapeutic plan. The daily adherence score A_{day} is then computed as a weighted average of normalized parameter values:

$$A_{\text{day}} = \frac{\sum_{i=1}^{k} w_i \cdot s_i}{\sum_{i=1}^{k} w_i}$$

where k denotes the total number of monitored parameters. The resulting adherence score is bounded within the interval $[0,1]$, enabling intuitive interpretation and longitudinal comparison.

This formulation ensures flexibility, as both the set of monitored parameters and their corresponding weights can be adapted to different therapeutic contexts without altering the core computational logic.

3.3 Adherence Classification and Clinical Interpretability

For practical deployment in assistive digital systems, the continuous adherence score is further translated into categorical adherence states using predefined decision thresholds. This classification yields three adherence levels corresponding to high, moderate, and low adherence, enabling rapid interpretation and actionable feedback without requiring numerical expertise.

The combination of continuous scoring and categorical classification balances analytical precision with clinical usability. While continuous scores support detailed monitoring, trend analysis, and research applications, categorical adherence states facilitate real-time feedback, patient motivation, and clinical decision support. This dual representation enhances the applicability of the framework across patient-facing and clinician-facing interfaces and supports timely identification of adherence-related risks within digital therapeutic pathways.

4 VALIDATION AND PILOT STUDY

The proposed assistive digital architecture and adherence evaluation framework were implemented and preliminarily validated through application in a pilot observational study. The primary objective of this validation was to assess the technical feasibility, reliability of multimodal data integration, and practical applicability of the system in real-world conditions, rather than to evaluate clinical efficacy.

The pilot study involved longitudinal collection of multimodal patient-generated data, including wearable-derived physiological parameters, daily self-reported behavioral inputs, and selected clinically relevant measurements. Data were collected over multiple consecutive days, enabling repeated daily adherence evaluation within naturalistic settings. This design allowed verification of system robustness under realistic usage patterns and confirmed the feasibility of continuous adherence monitoring outside controlled clinical environments.

The system successfully synchronized heterogeneous data streams characterized by different temporal resolutions, formats, and acquisition mechanisms into a unified daily evaluation window. Data preprocessing, normalization, and weighted aggregation procedures were applied consistently across all observation periods, resulting in stable and interpretable daily adherence scores. No significant data loss, synchronization failures, or system-level inconsistencies were observed during the pilot phase, indicating reliable operation of the data acquisition and processing pipeline.

In addition to technical validation, user interaction with the system was assessed to evaluate usability and acceptance. Participants demonstrated high compliance with daily self-reporting and minimal interaction burden, supporting the practicality of the assistive digital approach. The traffic-light–based adherence feedback was perceived as intuitive and easily interpretable, enabling meaningful user engagement without requiring detailed technical explanations.

Overall, the pilot application confirms the feasibility of the proposed assistive digital technologies for adherence monitoring based on multimodal patient data. While the pilot study was not designed to assess long-term clinical effectiveness within the scope of this paper, it provides a robust proof of concept demonstrating reliable system operation in real-world conditions. Detailed quantitative and clinical outcomes of the pilot study are reported in a separate manuscript that is currently under peer review. The present paper therefore focuses on the technological architecture and algorithmic framework enabling adherence monitoring, rather than on clinical outcome evaluation.

5 DISCUSSION

This paper presented an assistive digital framework for adherence monitoring based on multimodal patient-generated data, with an emphasis on system architecture and algorithmic design rather than clinical outcome evaluation. The proposed approach addresses a key challenge in digital therapeutics: transforming heterogeneous data streams into interpretable and actionable adherence indicators that can support both patients and healthcare professionals in real-world settings.

A central contribution of this work lies in the design of a transparent and modular adherence evaluation framework. Unlike black-box approaches that rely on complex predictive models, the proposed method prioritizes interpretability by combining categorical evaluation, normalization, and weighted aggregation. This design choice enhances clinical acceptability and facilitates integration into patient-facing and clinician-facing digital tools, where clear and understandable feedback is essential for sustained engagement and trust [9,10,11].

The use of multimodal patient-generated data represents a significant advantage over traditional adherence assessment methods [3]. By integrating objective wearable-derived parameters with subjective self-reported inputs and contextual clinical measurements, the system captures multiple dimensions of patient behavior that are often overlooked in single-source approaches [12]. This multimodal perspective enables more robust adherence monitoring and provides a foundation for identifying behavioral patterns and adherence-related risks that may not be detectable through isolated measurements.

From a technological perspective, the proposed system demonstrates the feasibility of continuous adherence monitoring outside controlled clinical environments. The pilot study confirmed reliable data acquisition, synchronization, and processing under naturalistic usage conditions. High user compliance and positive acceptance of the feedback mechanism further support the practicality of assistive digital technologies for long-term adherence monitoring. Importantly, the traffic-light–based feedback model offers an intuitive balance between simplicity and informational value, supporting timely behavioral adjustments without overwhelming users.

Several limitations of the presented work should be acknowledged. The pilot validation was conducted on a limited sample and over a relatively short observation period, restricting generalizability and precluding conclusions regarding long-term clinical effectiveness. Additionally, parameter thresholds and weighting schemes were defined based on current therapeutic assumptions and may require further refinement and personalization. The framework is intentionally flexible to accommodate such adaptations, but systematic validation across diverse clinical contexts remains necessary.

Future research should focus on extending the proposed framework through larger-scale studies and longer monitoring periods to evaluate its impact on adherence behavior and clinical outcomes. The modular architecture also enables integration of advanced analytical methods, such as adaptive weighting strategies or machine learning–based personalization, while preserving the interpretability of core adherence indicators. Moreover, further exploration of bidirectional feedback mechanisms may enhance patient engagement and support personalized digital therapeutic pathways [13,14].

Overall, this work contributes to the growing field of assistive digital technologies by demonstrating a practical and interpretable approach to adherence monitoring using multimodal patient data. By bridging wearable sensing, mobile self-reporting, and algorithmic evaluation within a unified framework, the proposed system offers a scalable foundation for future digital therapeutic applications and adherence-focused interventions.

6 CONCLUSION

This paper introduced an assistive digital framework for adherence monitoring based on multimodal patient-generated data, emphasizing system architecture and an interpretable algorithmic evaluation approach. By integrating wearable data, mobile self-reports, and contextual clinical information, the proposed system enables continuous adherence assessment in real-world settings.

The presented framework provides a transparent and flexible method for transforming heterogeneous data into a unified adherence indicator that is understandable to both patients and healthcare professionals. Pilot study confirmed the technical feasibility and practical usability of the approach. Overall, the proposed solution represents a scalable foundation for future adherence-focused digital therapeutic applications.

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