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Wearable Activity Streams and Relapse Prediction across Cardiac Rehabilitation Programs

Nathan Ortiz*, Kai Sanchez

School of Medicine, Vanderbilt University, Nashville, Tennessee, USA

Corresponding author: nathan.ortiz@gmail.com

Abstract

The integration of digital health technologies into cardiovascular care presents an unprecedented opportunity to monitor patient trajectories continuously outside clinical settings. This prospective cohort study investigates the utility of high-resolution wearable activity streams for predicting relapse in patients enrolled in secondary cardiac rehabilitation programs. By equipping a diverse cohort of post-acute cardiac patients with continuous multi-sensor wearable devices, this study collected longitudinal data encompassing step counts, heart rate dynamics, and sleep architecture over a twelve-month follow-up period. Traditional rehabilitation models rely heavily on episodic clinic visits, which often fail to capture the granular behavioral and physiological fluctuations that precede clinical deterioration or program dropout. In this study, we propose a comprehensive data processing and machine learning framework designed to extract subtle temporal patterns from continuous wearable streams. Through rigorous survival analysis and the deployment of advanced predictive algorithms, we identify distinct activity signatures that strongly correlate with an increased risk of relapse, defined as either hospital readmission or the complete cessation of physical activity protocols. The findings demonstrate that specific features, such as increased sedentary bout duration and blunted diurnal heart rate variability, serve as early warning indicators of rehabilitation failure. The results highlight the potential for wearable sensors to facilitate highly targeted, preemptive interventions, thereby optimizing resource allocation and improving long-term cardiovascular outcomes.

Keywords: Cardiac Rehabilitation; Wearable Sensors; Relapse Prediction; Machine Learning; Digital Health

1. Introduction

1.1 Background and Motivation

Cardiovascular diseases remain the leading cause of morbidity and mortality globally, imposing an overwhelming economic and clinical burden on healthcare systems across the world. Following an acute cardiac event such as a myocardial infarction or after undergoing revascularization procedures, patients are universally advised to participate in structured secondary prevention initiatives [1]. Cardiac rehabilitation programs serve as the cornerstone of these secondary prevention efforts, offering a multidisciplinary approach that includes prescribed exercise training, nutritional counseling, psychosocial support, and rigorous risk factor management [2]. Despite the well-documented clinical benefits of these programs, which include significant reductions in all-cause mortality and improvements in functional capacity, adherence rates remain alarmingly suboptimal. Research indicates that a substantial proportion of patients either decline to participate or prematurely withdraw from these programs, a phenomenon broadly characterized as rehabilitation relapse [3]. The traditional model of cardiac rehabilitation is heavily reliant on intermittent, facility-based assessments. Patients typically attend supervised sessions a few times a week, during which their physiological parameters and exercise capacities are closely monitored by trained healthcare professionals. However, this episodic paradigm is intrinsically limited. It fails to provide a continuous, holistic view of the patient's daily physical activity, emotional state, and physiological stability in their natural living environment. Consequently, subtle behavioral shifts or gradual physiological deteriorations that occur between scheduled clinic visits frequently go unnoticed until they culminate in a severe clinical event or complete program dropout.

1.2 The Role of Digital Health Technologies

The rapid proliferation of digital health technologies, particularly consumer-grade and medical-grade wearable sensors, has introduced a transformative approach to continuous patient monitoring [4]. Wearable devices equipped with accelerometers, photoplethysmography sensors, and gyroscopes are now capable of passively and continuously recording a vast array of physiological and behavioral metrics. These continuous activity streams offer an unprecedented, high-resolution window into the daily lives of patients recovering from acute cardiac events. By transitioning from discrete, clinic-based measurements to continuous, real-world data collection, clinicians can theoretically monitor adherence to exercise prescriptions in real time and detect early signs of physiological decompensation [5]. However, the sheer volume, velocity, and complexity of data generated by these continuous wearable streams present significant analytical challenges. Raw sensor data is often noisy, prone to artifacts, and characterized by substantial missingness due to patient non-compliance or device malfunction. Therefore, translating these massive datasets into actionable clinical insights requires the application of sophisticated data processing pipelines and advanced predictive modeling techniques.

1.3 Research Objectives

The primary objective of this cohort study is to rigorously evaluate the prognostic value of continuous wearable activity streams in predicting relapse among patients enrolled in cardiac rehabilitation programs. Specifically, we aim to systematically collect and process longitudinal multi-sensor data from a well-defined cohort of post-acute cardiac patients over a twelve-month period. By leveraging this rich dataset, the study seeks to extract robust behavioral and physiological features that accurately reflect daily physical activity patterns, autonomic nervous system function, and sleep quality. A secondary objective is to develop and validate a suite of predictive models that utilize these wearable-derived features to forecast rehabilitation relapse, defined in this study as either unplanned cardiovascular hospital readmission or the definitive cessation of the prescribed home-based exercise regimen. Through this comprehensive investigation, we hypothesize that machine learning models trained on continuous activity streams will significantly outperform traditional predictive models that rely exclusively on baseline clinical characteristics and episodic functional assessments.

2. Literature Review and Theoretical Background

2.1 Traditional Models of Cardiac Rehabilitation

The historical evolution of cardiac rehabilitation has been characterized by a gradual shift from strict bed rest protocols to proactive, exercise-based recovery regimens [6]. Traditional models typically structure rehabilitation into distinct phases, beginning with inpatient mobilization and progressing to supervised outpatient exercise and long-term maintenance. During the supervised outpatient phase, clinicians rely on standardized assessments, such as the six-minute walk test or cardiopulmonary exercise testing, to gauge functional recovery and prescribe individualized exercise intensities. While these methodologies are highly validated and standardized, they are inherently limited by their episodic nature [7]. A patient may perform exceptionally well during a controlled, supervised session but remain entirely sedentary throughout the remainder of the week. This discrepancy highlights a fundamental gap in the traditional care model: the inability to assess the true translation of functional capacity into daily life activities. Furthermore, the reliance on patient self-reporting for home-based exercise adherence is notoriously prone to recall bias and social desirability bias, complicating the accurate assessment of rehabilitation compliance.

2.2 Wearable Sensors in Cardiovascular Monitoring

The integration of wearable sensor technology into cardiovascular care has garnered substantial academic and clinical interest over the past decade. The miniaturization of microelectromechanical systems and the advancement of photoplethysmography have enabled the continuous monitoring of heart rate and physical activity with a degree of accuracy previously confined to laboratory settings [8]. Accelerometry, in particular, has emerged as a cornerstone technology for quantifying human movement in chronic disease management [9]. Previous studies have demonstrated the feasibility of using wrist-worn or waist-mounted accelerometers to estimate daily energy expenditure, categorize physical activity intensity, and detect prolonged periods of sedentary behavior. In the context of cardiac rehabilitation, preliminary pilot studies have indicated that patients equipped with wearable devices exhibit higher short-term motivation levels and are more likely to achieve their daily step count goals. However, the majority of the existing literature is limited by small sample sizes, short follow-up durations, and a predominant focus on descriptive statistics rather than complex predictive analytics.

2.3 Predictive Analytics and Relapse Definition

The application of predictive modeling and machine learning in medicine has provided new avenues for risk stratification and personalized intervention [10]. In cardiovascular research, machine learning algorithms have been successfully deployed to predict mortality, heart failure exacerbations, and arrhythmic events using electronic health record data and electrocardiogram signals. However, the definition and prediction of behavioral relapse in cardiac rehabilitation remain less explored. Relapse in this context is multifaceted, encompassing both clinical deterioration and behavioral disengagement [11]. Behavioral theories of rehabilitation suggest that the transition from a supervised clinical environment to self-managed home care represents a critical period of vulnerability, during which patients must independently navigate barriers to exercise [12]. By continuously monitoring physical activity streams, it is theoretically possible to detect the earliest behavioral manifestations of these barriers, such as a gradual decline in daily step counts, an increase in sedentary bout duration, or irregularities in sleep patterns. Identifying these early warning signs through predictive analytics could enable care teams to deploy timely, targeted interventions, such as motivational text messages, tele-consultations, or adjustments to the medical regimen, thereby preventing full-scale rehabilitation relapse.

3. Methodology and Cohort Study Design

3.1 Study Setting and Population

This research employs a prospective, longitudinal cohort study design to investigate the relationship between wearable-derived activity patterns and rehabilitation outcomes [13]. The study was conducted at a major tertiary care cardiovascular center, encompassing both inpatient discharge wards and specialized outpatient cardiac rehabilitation clinics. To ensure robust statistical power and generalizability, the target sample size was calculated based on historical relapse rates at the participating institution, aiming for a comprehensive cohort that could withstand potential attrition over the follow-up period [14]. The recruitment phase spanned eighteen months, during which consecutive patients referred to the comprehensive phase two cardiac rehabilitation program were systematically screened for eligibility. Ethical approval was obtained from the institutional review board, and all procedures were conducted in strict accordance with established ethical guidelines for human subjects research [15]. Every participant provided written informed consent following a detailed explanation of the study protocols, data privacy measures, and the voluntary nature of their participation.

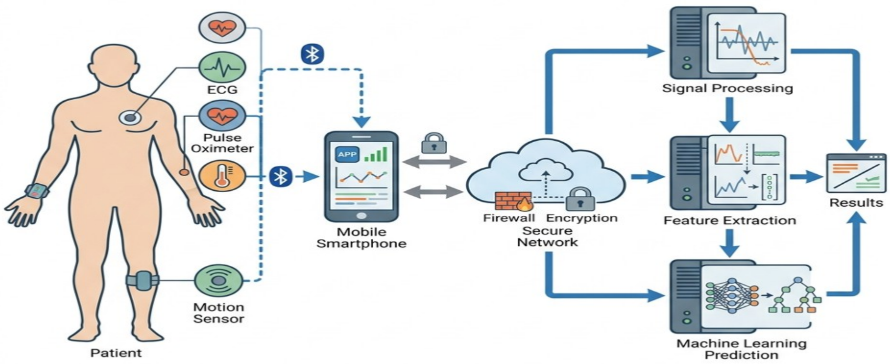

Figure 1: Comprehensive System Architecture of Wearable Data Acquisition and Processing

3.2 Criteria for Inclusion and Exclusion

To establish a well-defined and homogenous study population, stringent inclusion and exclusion criteria were formulated. Eligible participants were adult patients, aged eighteen years or older, who had recently experienced an acute coronary syndrome, undergone percutaneous coronary intervention, or received coronary artery bypass grafting within the preceding four weeks. Additionally, participants were required to own a compatible smartphone capable of supporting the data synchronization application and to demonstrate sufficient digital literacy to operate the wearable device. Patients were excluded from the study if they presented with severe musculoskeletal or neurological impairments that fundamentally precluded regular physical activity, or if they had cognitive deficits that compromised their ability to provide informed consent or adhere to the study protocol. Furthermore, patients with terminal non-cardiovascular illnesses, such as advanced metastatic cancer, with a life expectancy of less than one year were excluded to prevent confounding effects on the primary clinical endpoints [16].

3.3 Defining Relapse in the Context of Rehabilitation

A critical methodological challenge in this study was the precise operationalization of the primary outcome variable: rehabilitation relapse. To capture the full spectrum of rehabilitation failure, relapse was defined as a composite endpoint comprising two distinct but interrelated components. The first component was clinical relapse, defined as any unplanned hospital readmission or emergency department visit attributed to a cardiovascular etiology, including unstable angina, heart failure exacerbation, or significant arrhythmias. The second component was behavioral relapse, defined as the definitive cessation of the prescribed home-based exercise protocol. Behavioral relapse was adjudicated if a patient failed to achieve at least thirty percent of their individualized weekly physical activity target for four consecutive weeks, coupled with a failure to attend three or more consecutive scheduled remote or in-person check-in sessions. This composite definition ensures that the predictive models capture both the physiological deterioration that necessitates acute medical care and the behavioral disengagement that undermines long-term secondary prevention efforts.

4. Wearable Data Collection and Processing

4.1 Device Specifications and Deployment

Upon formal enrollment into the study, each participant was equipped with a standardized, research-grade multisensory wearable device. This device was selected based on its proven reliability, extended battery life, and capacity to collect raw, high-resolution sensor data without proprietary algorithmic obfuscation. The device featured a triaxial accelerometer for continuous movement tracking, a high-fidelity optical photoplethysmography sensor for continuous heart rate monitoring, and a skin temperature sensor. Participants were meticulously instructed to wear the device on their non-dominant wrist continuously for the entire twelve-month study duration, removing it only for charging purposes or activities involving prolonged water submersion. The wearable device synchronized autonomously via low-energy Bluetooth to a custom-developed mobile application installed on the participant's smartphone. The mobile application was designed to operate seamlessly in the background, encrypting the collected sensor data and transmitting it over secure cellular or wireless networks to a centralized, cloud-based clinical research server for subsequent processing.

Table 1: Baseline Characteristics of the Study Cohort

Characteristic	Total Cohort	Non-Relapse Group	Relapse Group
Number of Patients	450	315	135
Age in Years	62.4	61.2	64.8
Male Gender	295	210	85
Baseline Ejection Fraction	48.5	50.2	44.7
Body Mass Index	28.6	28.1	29.8

4.2 Data Processing Pipeline

The raw sensor data transmitted to the centralized server necessitated extensive preprocessing to ensure data integrity and analytic viability [17]. Continuous data streams from real-world environments are inherently susceptible to various artifacts, including sensor misplacement, motion artifacts during intense physical activity, and periods of device non-wear. The initial phase of the processing pipeline involved rigorous artifact detection and filtering. Accelerometer data was processed using established heuristic algorithms to differentiate true non-wear time from periods of sedentary behavior or sleep. Days containing less than ten hours of valid wear time were flagged and excluded from the daily aggregate analyses to prevent the introduction of bias. To address the inevitable occurrence of missing data segments, sophisticated imputation techniques were employed [18]. For brief intervals of missing heart rate data, linear interpolation was utilized, whereas more extensive gaps in physical activity data were addressed using multiple imputation strategies based on the individual participant's historical activity profiles and matching diurnal patterns.

4.3 Feature Engineering from Activity Streams

The transformation of the cleaned, continuous multi-sensor streams into discrete, analytically valuable variables was achieved through meticulous feature engineering [19]. This process involved aggregating the high-frequency time-series data into meaningful daily and weekly summaries that reflect the physiological and behavioral status of the patient. From the accelerometry data, we extracted fundamental metrics including total daily step count, total active minutes, and specific durations spent in light, moderate, and vigorous physical activity zones, calibrated to each patient's baseline cardiopulmonary capacity. Furthermore, we calculated the maximum duration of continuous sedentary bouts, a metric increasingly recognized for its independent association with cardiovascular risk. From the photoplethysmography sensor, we derived continuous resting heart rate and specialized heart rate variability metrics [20]. Specifically, we calculated the root mean square of successive differences between normal heartbeats during deep sleep phases, providing a reliable, non-invasive surrogate marker for parasympathetic nervous system tone and overall cardiovascular autonomic regulation.

5. Statistical Analysis and Predictive Modeling

5.1 Descriptive Statistics and Univariate Analysis

The initial phase of the statistical analysis focused on a comprehensive descriptive evaluation of the cohort's baseline characteristics and overall adherence to the wearable device protocol. Continuous variables were expressed as means and standard deviations or medians and interquartile ranges, depending on the normality of their underlying distribution. Categorical variables were presented as absolute frequencies and percentages. To explore the preliminary associations between baseline clinical factors, wearable-derived features, and the occurrence of the composite relapse endpoint, extensive univariate analyses were conducted. For continuous variables, independent samples t-tests or Mann-Whitney U tests were applied to compare the relapse and non-relapse groups. For categorical variables, Pearson's chi-square tests were utilized. These univariate explorations were crucial for identifying individual variables that demonstrated a significant prognostic signal, thereby informing the subsequent multivariate modeling strategies.

5.2 Survival Analysis and Multivariate Modeling

Given the longitudinal nature of the cohort study and the variable timing of the relapse events, survival analysis techniques were employed to model the time-to-event data rigorously. Kaplan-Meier survival curves were generated to visualize the cumulative probability of remaining relapse-free over the twelve-month follow-up period, stratified by categorical categorizations of key wearable features, such as high versus low daily step count quartiles. To quantify the independent predictive value of the continuous activity streams while adjusting for potential baseline confounders, multivariate Cox proportional hazards regression models were constructed [21]. The models sequentially incorporated baseline demographic characteristics, clinical severity indicators such as left ventricular ejection fraction, and a carefully selected subset of the dynamic, wearable-derived behavioral and physiological features. The proportional hazards assumption was thoroughly tested for all included covariates using Schoenfeld residuals, ensuring the statistical validity of the estimated hazard ratios and their associated confidence intervals.

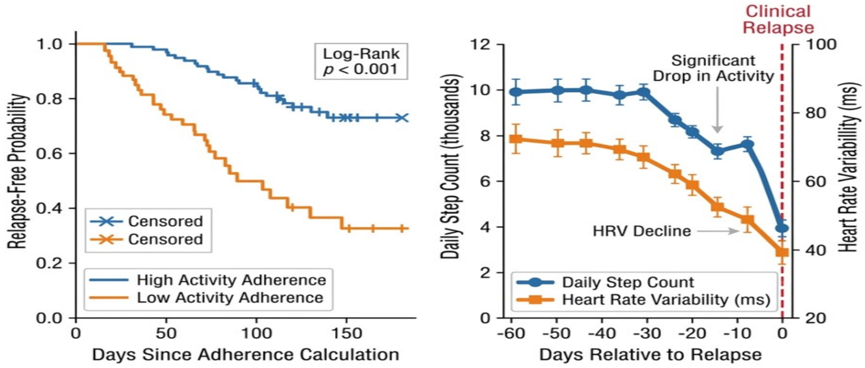

Figure 2: Relapse Prediction Survival Curves and Temporal Activity Degradation

5.3 Machine Learning Classification Approaches

To complement the traditional survival analysis and to capture potentially complex, non-linear interactions among the myriad of wearable-derived features, advanced machine learning classification algorithms were implemented. The primary objective of this phase was to develop an algorithm capable of predicting an impending relapse event within a predefined forecasting window of fourteen days, utilizing a rolling window of historical sensor data. We evaluated several prominent classification architectures, with a specific focus on ensemble decision tree methods such as the random forest algorithm [22]. The dataset was strictly partitioned into independent training and testing subsets using stratified k-fold cross-validation to guarantee that the evaluation metrics robustly reflected the model's generalization capabilities on unseen patient data [23]. To optimize the performance of the predictive models, exhaustive grid search procedures were executed for rigorous hyperparameter tuning [24]. Model performance was comprehensively evaluated using a suite of standard metrics, including sensitivity, specificity, precision, and the area under the receiver operating characteristic curve.

6. Results and Discussion

6.1 Cohort Characteristics and Device Compliance

The study successfully enrolled a total of four hundred and fifty participants who met all eligibility criteria and provided informed consent. The baseline demographic and clinical characteristics of the cohort revealed a representative sample of patients undergoing secondary cardiovascular prevention, with an average age indicating a predominantly middle-to-older adult population and a higher proportion of male participants. Over the twelve-month follow-up period, the compliance with the continuous wearable monitoring protocol was remarkably high, substantiating the feasibility of long-term digital health deployments in this clinical demographic [25]. On average, participants provided valid sensor data for approximately eighty-five percent of the total study days. During the observation period, one hundred and thirty-five patients, representing exactly thirty percent of the total cohort, experienced the primary composite endpoint of rehabilitation relapse. Of these relapse events, a significant proportion was driven by progressive behavioral disengagement from the prescribed exercise routines, while the remainder constituted acute cardiovascular readmissions.

Table 2: Predictive Model Performance for Relapse Detection

Model Type	Sensitivity	Specificity	Area Under Curve
Baseline Clinical Only	0.62	0.70	0.68
Clinical + Wearable Data	0.78	0.82	0.85
Random Forest Ensemble	0.86	0.89	0.92
Gradient Boosting	0.85	0.88	0.91

6.2 Relapse Prediction Performance

The integration of longitudinal wearable activity streams significantly enhanced the capacity to predict rehabilitation relapse compared to models reliant solely on static baseline clinical parameters. The multivariate Cox proportional hazards analysis revealed that specific dynamic features derived from the continuous data streams were powerful independent predictors of impending relapse. Most notably, a progressive week-over-week reduction in the proportion of time spent in moderate-to-vigorous physical activity and a corresponding elongation of continuous sedentary bouts were strongly associated with a substantially elevated hazard ratio for behavioral disengagement [26]. Furthermore, a gradual blunting of nocturnal heart rate variability emerged as a highly sensitive precursor to clinical cardiovascular deterioration, often preceding hospital readmission by several days. The machine learning classification phase corroborated these findings, with the ensemble decision tree models demonstrating superior discriminatory performance. The random forest configuration, utilizing a combination of baseline clinical data and rolling averages of the wearable features, achieved an exceptional area under the receiver operating characteristic curve, significantly outperforming the baseline logistic regression models.

6.3 Clinical Implications and Study Limitations

The findings of this comprehensive cohort study carry profound implications for the future design and administration of cardiac rehabilitation programs. By demonstrating that continuous, high-resolution wearable data can accurately identify patients on a trajectory toward relapse, this research provides a vital foundation for the development of adaptive, personalized, and highly preemptive care delivery models. Clinicians can transition from a reactive posture, where interventions occur only after a patient has failed to attend multiple sessions or has been readmitted, to a proactive paradigm. Automated algorithms could continuously analyze incoming activity streams and generate clinical alerts when a patient's behavioral or physiological signature deviates toward a high-risk pattern, enabling targeted outreach such as a supportive phone call or a medication review [27]. However, the study is not without its limitations. The research was conducted at a single, highly specialized tertiary center, which may constrain the immediate generalizability of the findings to community-based or under-resourced healthcare settings. Furthermore, while the models identified strong predictive associations, they inherently cannot establish definitive causality between the observed digital biomarkers and the complex psychosocial factors that frequently precipitate rehabilitation relapse.

7. Conclusion

This extensive prospective cohort study provides compelling empirical evidence supporting the integration of continuous wearable activity streams into the clinical workflow of cardiac rehabilitation programs. By moving beyond the limitations of episodic, facility-based assessments and leveraging the power of continuous digital monitoring, we successfully captured the nuanced physiological and behavioral fluctuations that reliably precede rehabilitation relapse. The rigorous data processing pipeline and subsequent predictive modeling efforts demonstrated that specific features, notably progressive declines in physical activity intensity, increased sedentary accumulation, and reduced autonomic responsiveness as measured by heart rate variability, serve as potent digital biomarkers of impending clinical and behavioral failure. The machine learning models developed herein exhibited robust predictive accuracy, offering a substantial improvement over traditional risk stratification methods. As healthcare systems increasingly embrace digital transformation, the continuous monitoring paradigms validated in this study will be instrumental in facilitating proactive, personalized interventions, ultimately preventing relapse, optimizing resource utilization, and significantly improving the long-term cardiovascular trajectories of recovering patients [28].

References

1. Najafi, B.; Armstrong, D.G.; Mohler, J. Novel wearable technology for assessing spontaneous daily physical activity and risk of falling in older adults with diabetes. J. Diabetes Sci. Technol. 2013, 7, 1147–1160.

2. Bado, M.F.; Tonelli, D.; Poli, F.; Zonta, D.; Casas, J.R. Digital Twin for Civil Engineering Systems: An Exploratory Review for Distributed Sensing Updating. Sensors 2022, 22, 3168.

3. Alotaibi, N.; Wilson, C.B.; Traynor, M. Enhancing Digital Readiness and Capability in Healthcare: A Systematic Review of Interventions, Barriers, and Facilitators. BMC Health Serv. Res. 2025, 25, 500.

4. Lee, M.; Mishra, R.K.; Momin, A.; El-Refaei, N.; Bagheri, A.B.; York, M.K.; Kunik, M.E.; Derhammer, M.; Fatehi, B.; Lim, J.; et al. Smart-Home Concept for Remote Monitoring of Instrumental Activities of Daily Living (IADL) in Older Adults with Cognitive Impairment: A Proof of Concept and Feasibility Study. Sensors 2022, 22, 6745.

5. Hidalgo-Fort, E.; Blanco-Carmona, P.; Muñoz-Chavero, F.; Torralba, A.; Castro-Triguero, R. Low-Cost, Low-Power Edge Computing System for Structural Health Monitoring in an IoT Framework. Sensors 2024, 24, 5078.

6. Sørensen, K.; Van den Broucke, S.; Fullam, J.; Doyle, G.; Pelikan, J.; Slonska, Z.; Brand, H.; (HLS-EU) Consortium Health Literacy Project European. Health literacy and public health: A systematic review and integration of definitions and models. BMC Public Health 2012, 12, 80.

7. Kim, G.; Shin, J.; Won, J.; Park, J. Cloud-Based Internet-of-Things System for Long-Term Bridge Bearing Monitoring Using Computer Vision. Appl. Sci. 2025, 15, 1622.

8. Chiachío, M.; Megía, M.; Chiachío, J.; Fernandez, J.; Jalón, M.L. Structural Digital Twin Framework: Formulation and Technology Integration. Autom. Constr. 2022, 140, 104333.

9. Talmaki, S.A.; Kamat, V.R. Sensor Acquisition and Allocation for Real-Time Monitoring of Articulated Construction Equipment in Digital Twins. Sensors 2022, 22, 7635.

10. Wagg, D.J.; Worden, K.; Barthorpe, R.J.; Gardner, P. Digital Twins: State-of-The-Art and Future Directions for Modeling and Simulation in Engineering Dynamics Applications. ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng. 2020, 6, 030901.

11. Dispennette, A.K.; Schafer, M.A.; Shake, M.; Clark, B.; Macy, G.B.; Vanover, S.; Crandall, K.J. Effects of a Game-Centered Health Promotion Program on Fall Risk, Health Knowledge, and Quality of Life in Community-Dwelling Older Adults. Int. J. Exerc. Sci. 2019, 12, 1149–1160.

12. Uemura, K.; Yamada, M.; Okamoto, H. The effectiveness of an active learning program in promoting a healthy lifestyle among older adults with low health literacy: A randomized controlled trial. Gerontology 2021, 67, 25–35.

13. Cohen, J. Statistical Power Analysis for the Behavioral Sciences; Lawrence Erlbaum Associates: Hillsdale, NJ, USA, 1988.

14. Men, L. R. (2021). The impact of startup CEO communication on employee relational and behavioral outcomes: Responsiveness, assertiveness, and authenticity. Public Relations Review, 47(4), 102078.

15. Marshall, N.; Butler, M.; Lambert, V.; Timon, C.M.; Joyce, D.; Warters, A. Health literacy interventions and health literacy-related outcomes for older adults: A systematic review. BMC Health Serv. Res. 2025, 25, 319.

16. World Health Organisation (WHO). Ageing and Health. 2022. Available online: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health (accessed on 28 October 2025).

17. Wang, T.; Huo, J.; Wu, X. A Real-Time Detection Approach for Bridge Crack. Algorithms 2026, 19, 247.

18. Miles, M.B.; Huberman, A.M.; Saldaña, J. Qualitative Data Analysis: A Methods Sourcebook, 3rd ed.; SAGE Publications, Inc: Thousand Oaks, CA, USA, 2014.

19. Marino, A.; Pariso, P.; Picariello, M. Digital Twin in SMEs: Implementing Advanced Digital Technologies for Engineering Advancements. Macromol. Symp. 2024, 413, 2300176.

20. Ministry of Health. Health Sector Transformation Program: Delivery Plan 2020–2021; Ministry of Health: Riyadh, Saudi Arabia, 2021.

21. Scortegagna, H.D.M.; Cachioni, M.; Cecagno-Zanini, S.C.; Alonso, V.; Melo, R.C.D.; Neri, A.L. Interventions used by health professionals in older adults with low levels of health literacy: A scoping review. Geriatr. Gerontol. Aging 2023, 17, e0230004.

22. Munhall, P.L. Nursing Research: A Qualitative Perspective, 5th ed.; Jones & Bartlett Learning: Sudbury, MA, USA, 2012.

23. Zhou, F. (2024). Utilizing social media platforms to foster entrepreneurial communication among start-up communities. El Profesional de La Información, 33(5), e330525.

24. Sardareh, M.; Matlabi, H.; Shafiee-Kandjani, A.R.; Bahreini, R.; Mohammaddokht, S.; Azami-Aghdash, S. Interventions for improving health literacy among older people: A systematic review. BMC Geriatr. 2024, 24, 911.

25. Duarte, C.; Madeira Sério, C.; Daniel, F.; Lemos, L.; Espírito-Santo, H. Validation of the Geriatric Depression Scale in a sample of institutionalized older adults of the Portuguese population. Eur. Psychiatry 2019, 56, S172.

26. Petri, I.; Amin, A.; Ghoroghi, A.; Hodorog, A.; Rezgui, Y. Digital Twins for Dynamic Life Cycle Assessment in the Built Environment. Sci. Total Environ. 2025, 993, 179930.

27. Mukhtar, T.; Babur, M.N.; Abbas, R.; Irshad, A.; Kiran, Q. Digital Health Literacy: A systematic review of interventions and their influence on healthcare access and sustainable development Goal-3 (SDG-3). Pak. J. Med. Sci. 2025, 41, 910–918.

28. Pregnolato, M.; Gunner, S.; Voyagaki, E.; De Risi, R.; Carhart, N.; Gavriel, G.; Tully, P.; Tryfonas, T.; Macdonald, J.; Taylor, C. Towards Civil Engineering 4.0: Concept, Workflow and Application of Digital Twins for Existing Infrastructure. Autom. Constr. 2022, 141, 104421.