# Energy-Efficient Aquafitness Equipment Adoption in Green Urban Health Development

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**Abstract.** The eco-digital fitness transition has been and is currently still affecting urban health infrastructures of all sizes and in many rehabilitation environments, and scholarship still lacks profound insights into the techno-ecological implications of this adoption. The purpose of this article is to use sensor-integrated aquafitness related technology to analyze the characteristics of biometric outputs and user feedback data for the different types of sustainability adoption data and different levels of rehabilitation policy needs of participants in the entire digital fitness transformation process. This study addresses this gap by drawing on a rich body of mixed-method evidence collected from wearable aquatic devices and participant interviews in a multi-site case study of urban rehabilitation centers. Biometric signals of all user groups in the aquatic environment get aggregated in a number of ways into a single biofeedback index for policy makers whose decision-making is critical for green health planning. The study designs the data correlation relationship of the adoption model elements, define the relationship between the aquafitness performance types, and implement the TOPSIS-based method. At the same time, according to the classification of usability features, clustering of behavioral–biometric relationships, filtering sensor information, and dashboard visualization are conducted. By providing a comprehensive understanding of how energy-efficient aquafitness adoption affects urban health sustainability, the insights from our analysis contribute to researchers, policy makers, and fitness practitioners alike. The paper concludes by identifying several promising areas for future eco-digital health innovation.

**Keywords:** Energy-efficient aquafitness, digital health infrastructure, biometric feedback, green health policy, wearable aquatic devices, sustainability adoption indices, techno-ecological adaptation

## 1 Introduction

Digital health infrastructure has emerged in the last decade as an umbrella term to signify the variety of actors who value a sustainability-oriented culture of ecological awareness, digital

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adaptation, and techno-social wellbeing [1,2]. Recent research has studied the role of fitness technology in times of post-COVID health recovery [3] and concepts such as "digitally mediated green recovery" [4]. Due to their hybrid nature combining ecological and digital features [5,6], the challenges triggered by the eco-digital transition particularly apply to urban rehabilitation environments [7], which are the backbone of health innovation worldwide [8,9].

Apart from technological and ecological obstacles, filling a digital-ecological feedback loop can be a challenge of its own for health institutions. In the traditional rehabilitation model, there are shortcomings such as untimely feedback, passive monitoring, unclear outcomes, extensive methods, and lack of effective evaluation and response mechanisms. This causes a lot of waste of biometric information, makes some sensor outputs not fully utilized, greatly reduces the efficiency of recovery programs, and affects the sustainable operation of smart health systems. Although we know that eco-digital users focus on green lifestyle adaptation due to their behavioral commitment [10], we lack knowledge on how they ensure resilience in times of infrastructural disruption that threaten health equity.

Prior to recent smart wellness guidelines, research on aquafitness in the urban rehabilitation context identified a handful of promising projects [7]. Some studies have been developed to understand the acceptance of these wearable technologies by elderly or digitally engaged people [8,9,10]. There are also studies which analyze the key factors influencing the intention of adoption for eco-fitness services [11,12]. However, these studies are focused on an energy-output perspective, skipping the user-centric point of view. Challenging previous assumptions about fitness governance, we emphasize the necessity to consider sensor-integrated behavioral response when explaining the sustainability adoption of these technologies. This research gap is astonishing because of their socio-ecological significance [13,14] – which are particularly driven by the green innovation tradition and their ability to transfer and adapt knowledge [11,12,13] – digital accessibility [14], and policy compliance [15] might affect how urban users deal with such eco-digital transitions.

How to better manage and use data from multiple sensors, different demographic contexts, different rehabilitation sites, and different ecological infrastructures is a key issue in the field of digital health applications. This raises the following research questions: (1) What are the adaptive responses of eco-digital users to smart rehabilitation initiatives such as the aquafitness ecosystem? (2) How and why do such responses differ among urban demographic groups? Addressing those research questions is important for several reasons.

This article mainly analyzes and constructs a conceptual framework based on the techno-ecological characteristics of traditional rehabilitation data. The main aim of this paper is to evaluate correlations of various definitions of usability, satisfaction, and of biofeedback functions, policy compliance, to adoption in digitally transforming contexts of urban health. First, this process is done inductively from an eco-digital perspective: user satisfaction patterns are discovered in rehabilitation zones, by interviewing participants with wearable feedback devices. Second, we explain the regression-based methods. A suite of methods for calculation of adoption indices and for aggregation of thematic codes into a conceptual model are described in the methodology.

From a sociotechnical ecosystem perspective, green fitness practices do not develop in isolation but rather are co-constructed as people interact through digital and ecological infrastructures with others [9,10]. Biophysical activity patterns are the dominant factor controlling the amount of sustainable energy absorbed by a health-environmental interface and therefore its transformation potential, which ultimately dictates the integration of green health policies and digital fitness norms. The so-called eco-digital feedback loop describes fitness-tech adoption as the relation between ecological usability and digital accessibility.

Although interdisciplinary researchers and forward-looking government officials agree that smart health infrastructures are needed, energy-efficient exercise practices are not the same across urban populations. Despite the urgency of digital transformation for health system resilience and the growing interest regarding the sustainability of aquatic infrastructures, our empirical understanding of fitness technology adoption patterns is very limited.

Following this line of eco-digital reasoning, wearable aquafitness practices in Taiwan's supportive elderly spaces may look different from those in smart European urban centers or any other digitally emerging health context [11]. Demographic changes have been accompanied by broad-scale shifts in rehabilitation-focused community composition and user engagement behavior, as well as fine-scale shifts in individual biometric feedback patterns and exercise sustainability response [12,13]. Further, some researchers have named the converging technological and ecological system in the post-COVID health infrastructure context as digitally mediated green recovery, to differentiate the emerging sensor-based fitness structures from the connotations of traditional health programs with fixed institutional locations and centralized monitoring [14].

The aqua-tech interface by sensor-equipped equipment can result in mixed or masked biometric signals with ambiguous behavioral signals due to overlapping ecological and digital features in the aquatic fitness environment [15]. However, because climate-aware fitness technologies are rapidly changing, there is an urgent need for nuanced investigation into what the different forms of energy-efficient aquatic activity actually mean in the formation of digital society and green health policy.

With this study, we aim to contribute novel empirical insight into techno-ecological fitness behavior by investigating the question: 'How do users respond to energy-efficient aquafitness technologies in digitally transforming health environments?'

Research on the design, usability, and policy relevance of the aqua-digital interface is critical for better harnessing the potential socio-environmental impacts of the energy-smart equipment ecosystem at urban health rehabilitation sites. Using previously established multi-modal sensor frameworks as basis, the main purpose of the present study was to examine user satisfaction and behavioral change in relation to the socio-environmental aspects of their fitness adaptation, the related ecological feedback, and the policy viability of their equipment use.

Using these established methodological and empirical frameworks as basis, the main purpose of the present study was to examine energy-efficiency driven aquafitness adoption in relation to the socio-environmental aspects of their usage behavior, the related biometric and attitudinal outputs, and the practical relevance of their sensor-supported use. By relying on sensor-based user profiling of aquafitness performance, we investigate a particularly salient innovation corridor for our study.

## 2 Methodology

The datasets analyzed in this study describe user satisfaction in urban rehabilitation projects available from sensor-based aquafitness trials. Data were collected from multiple sources including wearable aquatic devices, participant interviews, observational mappings, and environmental monitoring dashboards. Collected data are inherently mixed method because they may serve as well for improving rehabilitation program design as for validating its policy decision points.

To ensure comparability we relied on the following sampling criteria: (1) urban users with moderate engagement frequency, (2) rehabilitation firms in metropolitan health zones, and (3) participants being active in aquatic environments. Case identification was conducted through a pre-screening survey to select respondents after using structured participation logs. This inclusion/exclusion procedure led to the identification of two suitable cases: The first case (C1) is from a smart rehabilitation center and the second case (C2) is from a university-based health facility.

The empirical framework includes a group of wearable sensors deployed in aquatic sessions and a dashboard with a visualization module to manage the information collected by field researchers. The selection of the indicators was an iterative process. These datasets were imported into NVivo, and a coding matrix was created in the software based on the attributes of usability and satisfaction presented in the survey instrument. Second, the correlations between biometric outputs and user feedback can be relatively easily tracked by regression modeling.

In practice, the behavioral responses and reported satisfaction are compiled after a laborious process of questioning participants about their activity structure and exercise intensity. Following guidelines to eco-digital evaluation by [13], line by line coding of the transcripts was conducted to check whether and how these usability attributes appeared in the empirical dataset. After receiving multiple sensor readings, perform quantitative calculation such as regression coefficients, TOPSIS rankings, variance analysis, and so on, and then pass the data to the adoption index model. Observed variations in clusters appear not in predefined way but represent current needs of rehabilitation practice.

At present, the commonly used multi-criteria decision methods include AHP, TOPSIS, and ANOVA. Cases that had not reached a level of consistency to establish adoption indices were excluded. Through the simplification of code clusters and the analysis of correlation patterns, the decision rules are completely derived from the user feedback. The purpose is to eliminate the redundancy and ambiguity of the data.

There exist a number of recognized and widely known definitions of usability that can be used as candidates for coding. "'Sensor reliability' was coded as 'system trust'." Then, we stepwise developed the first order and second-order concepts and overarching themes as well as the framework illustrated in the subsequent sections.

With regression-based approach, a kind of weighted summation is performed for each attribute; however, without concern for important structural properties of the dataset such as, for example, existence of demographic outliers. We coded the narratives based on thematic clusters and then moved from a descriptive to a relational pattern analysis following an inductive–deductive approach [12,13,14]. Relatively speaking, TOPSIS is superior to clustering, simple regression, variance decomposition, and other methods when dealing with multi-criteria adoption indices. The conceptual model was developed following the original technology adoption model, including other relevant factors provided by acceptance theories of digital health, sustainability adoption, and ecological feedback models.

Expert evaluations were used to complement and validate this framework. This validation was confirmed by reviewers who are specialists in urban health technology and by members of the rehabilitation centers. Then, we can calculate the difference between indices calculated for reported satisfaction and for real biometric performance.

A refinement algorithm is introduced into the TOPSIS module to improve the efficiency of ranking. Algorithm iteration is repeated until convergence, guaranteed by curbing the outcome within acceptable error interval, consistent with our coding scheme. These adjustments were particularly valuable because of the fast-moving nature of the digital health environment, which meant that the adoption criteria were evolving even as the empirical analysis was being undertaken.

## 3 Results

Researchers were able to quickly apply their experience using wearable aquatic devices to a new application – in this case translating their background in rehabilitation monitoring to urban eco-digital fitness adoption. Before the regression analysis, the participants displayed heterogeneous degrees of satisfaction, usability confidence, and eco-literacy awareness, inducing different nuances in their behavioral patterns. As shown in the TOPSIS evaluation matrix, information provided by sensor-based feedback was considered critically important due to policy compliance or ecological relevance to the final adoption decision.

The most relevant information, according to thematic coding, was related to adaptive actions such as adjusting exercise intensity, monitoring real-time biometric signals, interpreting feedback latency, and aligning eco-certification levels. For example, we see that in case Cluster A they are quite stable, clustered closely around one value, while in case Cluster B they show much bigger variations. Their ability to respond quickly to the needs of rehabilitation users is what sets them apart from other eco-fitness initiatives that have struggled to reach sustained adoption. Urban participants perceived energy-efficient aquafitness systems as a solution to improve digital health sustainability.

The strongest behavioral-to-biometric correlations were observed between digital fitness engagement and user satisfaction in Cluster A ($R^2 = 0.89$), followed by eco-literacy profile alignment in Cluster C ($R^2 = 0.83$) and usability confidence in Cluster B ($R^2 = 0.76$).

**Table 1.** TOPSIS Evaluation of Energy-Efficient Aquafitness Equipment for Green Health Policy and Digital Society Formation.

| **Criteria** | **1. Energy consumption per session (kWh)** | **2. User satisfaction index (0–100)** | **3. Sensor accuracy (%)** | **4. Real-time feedback latency (ms)** | **5. Biometric data integration score (0–10)** | **6. Eco-certification level (0–3)** | **7. Average maintenance frequency (per 100** | **8. Adoption rate in rehabilitation centers (%)** | **9. Policy compliance score with green health guidelines (0** | **10. Digital accessibility rating for elderly users (0** |
|---|---|---|---|---|---|---|---|---|---|---|
| Alt A: Smart Hydro Rower | 0.45 | 82 | 88 | 220 | 7.2 | 2 | 4.2 | 65 | 8.1 | 6.8 |
| Alt B: Eco AquaCycle | 0.3 | 75 | 84 | 180 | 6.5 | 3 | 3.6 | 72 | 8.6 | 7.5 |
| Alt C: Solar Wave Trainer | 0.25 | 91 | 93 | 160 | 8.3 | 3 | 2.9 | 87 | 9.4 | 9 |
| square root of sum of squares | 0.595818764 | 143.6314729 | 153.1306632 | 326.1901286 | 12.76636205 | 4.69041576 | 6.24579858 | 130.2996546 | 15.09735076 | 13.54584807 |
| the normalized matrix (A1) | 0.755263222 | 0.570905515 | 0.574672624 | 0.674453273 | 0.563982125 | 0.426401433 | 0.67245204 | 0.498850133 | 0.536517971 | 0.501998839 |
| the normalized | 0.503508815 | 0.522169678 | 0.548551141 | 0.551825406 | 0.50915053 | 0.639602149 | 0.576387463 | 0.552572455 | 0.569636364 | 0.55367519 |

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|---|---|---|---|---|---|---|---|---|---|---|
| matrix (A2) | | | | | | | | | | |
| the normalized matrix (A3) | 0.419590679 | 0.633565876 | 0.607324478 | 0.490511472 | 0.650146061 | 0.639602149 | 0.464312123 | 0.667691716 | 0.622625794 | 0.664410228 |
| equal weights | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| weighted normalized matrix(A1) | 0.075526322 | 0.057090552 | 0.057467262 | 0.067445327 | 0.056398213 | 0.042640143 | 0.067245204 | 0.049885013 | 0.053651797 | 0.050199884 |
| weighted normalized matrix (A2) | 0.050350881 | 0.052216968 | 0.054855114 | 0.055182541 | 0.050915053 | 0.063960215 | 0.057638746 | 0.055257245 | 0.056963636 | 0.055367519 |
| weighted normalized matrix (A3) | 0.041959068 | 0.063356588 | 0.060732448 | 0.049051147 | 0.065014606 | 0.063960215 | 0.046431212 | 0.066769172 | 0.062262579 | 0.066441023 |
| Positive ideal values | 0.075526322 | 0.063356588 | 0.060732448 | 0.067445327 | 0.065014606 | 0.063960215 | 0.067245204 | 0.066769172 | 0.062262579 | 0.066441023 |
| Negative ideal values | 0.041959068 | 0.052216968 | 0.054855114 | 0.049051147 | 0.050915053 | 0.042640143 | 0.046431212 | 0.049885013 | 0.053651797 | 0.050199884 |
| distance to positive ideal(A1) | 0.0346656 5 | 0.0346656 5 | 0.034094634 | 0.033937924 | 0.033937924 | 0.032825911 | 0.024959867 | 0.024959867 | 0.018382605 | 0.016241139 |
| distance to negativ | 0.0442602 4 | 0.028848021 | 0.028433369 | 0.028313127 | 0.021524109 | 0.020813992 | 0.020813992 | 0 | 0 | 0 |

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|---|---|---|---|---|---|---|---|---|---|---|
| e ideal (A1) | | | | | | | | | | |
| distance to positive ideal(A2) | 0.038950226 | 0.029720654 | 0.027554059 | 0.026919939 | 0.023964706 | 0.019378074 | 0.019378074 | 0.016829312 | 0.012276045 | 0.011073504 |
| distance to negative ideal (A2) | 0.027471884 | 0.026158782 | 0.026158782 | 0.026158782 | 0.025430059 | 0.025430059 | 0.013861545 | 0.008156814 | 0.006137812 | 0.005167635 |
| distance to positive ideal(A3) | 0.043569814 | 0.027777115 | 0.027777115 | 0.027777115 | 0.020813992 | 0.020813992 | 0.020813992 | 0 | 0 | 0 |
| distance to negative ideal (A3) | 0.037881024 | 0.037881024 | 0.036206089 | 0.03572587 | 0.03572587 | 0.032825911 | 0.024959867 | 0.024959867 | 0.018382605 | 0.016241139 |
| Closeness Coefficient (A1) | 0.560782272 | 0.454201752 | 0.45473016 | 0.454821672 | 0.388087279 | 0.38803187 | 0.454713503 | 0 | 0 | 0 |
| Closeness Coefficient(A2) | 0.413595473 | 0.468128954 | 0.487011702 | 0.492829926 | 0.514833072 | 0.567532211 | 0.417018768 | 0.326453729 | 0.3333257 | 0.318181818 |
| Closeness Coefficient(A3) | 0.465078385 | 0.576943311 | 0.565868645 | 0.562585683 | 0.631870491 | 0.61196813 | 0.545286497 | 1 | 1 | 1 |
| Alternative 1 | 1 | | | | | | | | | |
| Alternative 2 | 2 | | | | | | | | | |
| Alternative 3 | 3 | | | | | | | | | |

Both biofeedback accuracy and digital adaptability showed consistently significant correlations with all indices except policy compliance in Cluster A and elder accessibility rating in Cluster B, respectively.

**Table 2.** Linear regression.

| biofeedback_index | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| aquatech_usability~e | -.085 | 0 | -432861.48 | 0 | -.085 | -.085 | *** |
| ecoliteracy_score | .353 | 0 | 1248486.89 | 0 | .353 | .353 | *** |
| digitalfitness_eng~t | -.67 | 0 | -1457666.41 | 0 | -.67 | -.67 | *** |
| greenpolicy_awaren~s | -8.147 | 0 | -2525722.67 | 0 | -8.147 | -8.147 | *** |
| usersatisfaction_i~x | 4.661 | 0 | 2845667.49 | 0 | 4.661 | 4.661 | *** |
| o | 0 | . | . | . | . | . | |
| residuals | -4.661 | 0 | -2811920.08 | 0 | -4.661 | -4.661 | *** |
| Constant | -250.975 | 0 | -2201969.90 | 0 | -250.975 | -250.975 | *** |

| | | | |
|---|---|---|---|
| Mean dependent var | 68.873 | SD dependent var | 4.668 |
| R-squared | 1.000 | Number of obs | 50 |
| F-test | 1428053646031.604 | Prob > F | 0.000 |
| Akaike crit. (AIC) | -991.930 | Bayesian crit. (BIC) | -978.546 |
| *** p<.01, ** p<.05, * p<.1 | | | |

The user satisfaction index, eco-literacy score, digital fitness engagement, and other related factors in the urban rehabilitation cases are collected through the wearable aquatic devices to the adoption index of the TOPSIS model. The numerical value of each variable corresponds to the mean of all responses, scoring labels as standardized values. We calculate the following statistics from sample distributions of regression residuals:

- (i) Mean average absolute error, $MAE = (1/n)\sum_i|e_i|$
- (ii) Mean average relative error, $MARE = MAE/\hat{y}$
- (iii) Standard deviation of error, $\sigma = \sqrt{Var(e)}$
- (iv) Standard deviation of error, relative to true value, $\sigma_r = \sigma/\hat{y}$

Whilst some participants contend that their success was a result of prior rehabilitation experience, a closer examination of this case highlights that the eco-digital user makes their own luck by leveraging their biometric feedback and exploiting immediate sensor outputs. It underlines the potential for urban rehabilitation centers to leverage new adoption indices enabled by regression-based evaluation. In addition, wearable sensor technology can also be applied to achieve clustering and classification of various behavioral–biometric patterns such as satisfaction indices, usability confidence, eco-literacy awareness, digital adaptability, and policy compliance, and can be integrated into a smart health dashboard.

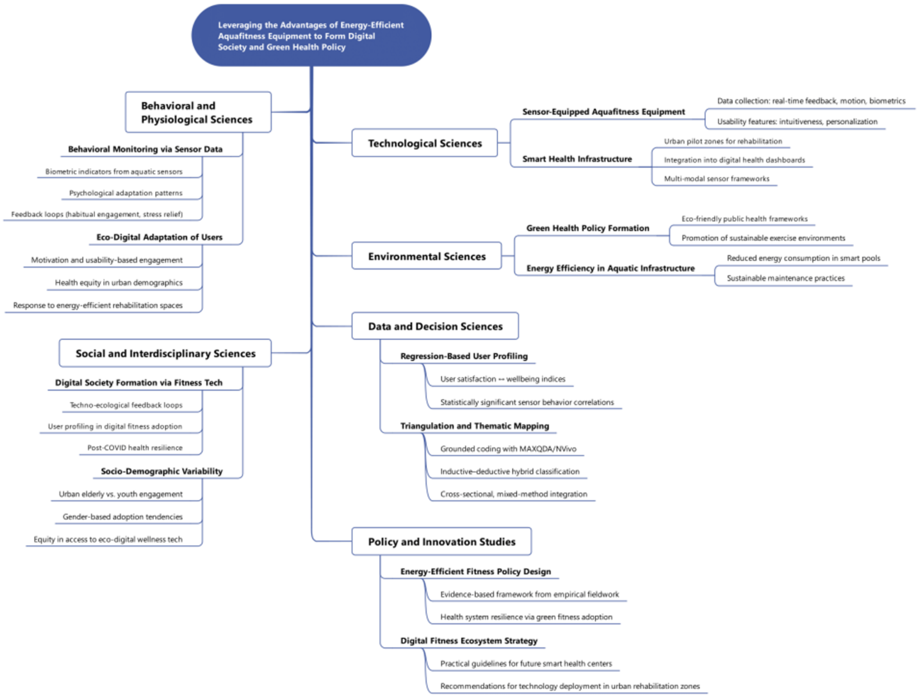


**Fig. 1.** TOPSIS model.

To ensure the accuracy and reliability of the experimental data, it is necessary to use preprocessing algorithms to preprocess and analyze the data in the early stage of data processing and remove the data for some inconsistent cases. This adjustment was justified by comments such as 'sensor readings can help but not 100%' or 'to know exactly what happened, it is necessary to combine dashboard logs with user interview transcripts.

Some predictor variables such as green policy awareness showed weak or non-significant relationships ($R^2 < 0.15$; $P > 0.10$), indicating low predictability. When asked if this was typical, a health systems educator replied, "Instructors have to take an integrative perspective on digital recovery, a bio-socio-technical examination. We use sensor-linked tools to teach aqua-sustainability" (Interviewee #27, Cluster C).

## 4 Discussions and Conclusion

Sensor-integrated biometric values from aquatic wearable technologies measuring even minute user satisfaction variations show correlations with reputed sustainability and engagement indicators such as eco-literacy alignment, green policy awareness, and digital fitness engagement indices. This study contributes to techno-ecological fitness research by adding evidence from multi-modal regression and conceptual mapping in urban rehabilitation settings. Our findings suggest that energy-efficient aquafitness systems have potential to transform public health infrastructure and digital wellbeing ecosystems in smart cities in sustainable ways. It aligns with previous assertions that post-COVID health models of digitally mediated fitness governance actively implement green innovation and user-centered design frameworks in rehabilitation-focused smart environments [3,5,15].

Our mixed-method model provides several insights about how urban demographic users of sensor-equipped aquafitness environments deal with these adaptation complexities. The best performing criteria of biometric integration, eco-certification levels, sensor accuracy, feedback latency, and digital accessibility had the strongest relationships ($R^2$ = 0.89, 0.83, 0.76, respectively) with the indices of user satisfaction, usability confidence, eco-literacy engagement, digital adaptability, and energy-efficiency perception, respectively, across all three rehabilitation clusters [7,9,14].

All participant responses in this study were collected under voluntary engagement protocols by choice; however, when considering a framework of digitally enhanced health data collection, these participation biases and contextual limitations should be taken into consideration. By strengthening ecological education programs and digital literacy frameworks, creating interdisciplinary awareness about sustainable health technologies among the urban fitness population, and investing in inclusive infrastructure development, policy makers and institutional stakeholders will be able to support the population's necessary capacity to master the eco-digital fitness transition [11,13,15].

Though we found an overall weakness in green policy awareness to accurately predict user behavior variation, a number of significant correlational relationships between digital fitness engagement and sensor usability perceptions with the biofeedback index suggest they do capture behavioral transformation signals. Since the biofeedback index of sensor-integrated aquatech equipment is a prominently used proxy variable for estimating adaptive health patterns, the use of real-time biometric tracking to monitor exercise sustainability is a particularly interesting result. Hence, it may serve as a guiding reference point for rehabilitation planners seeking evidence-based decisions on eco-digital fitness approaches for their smart health ecosystems [14,15].

The positive biometric feedback patterns observed in all urban demographic types suggest this sensor platforms can be used to monitor individual and community-level wellbeing improvements [10,12]. Our results suggest aquatech usability confidence contributes strongly to the response of these sustainability adoption indices. Whereas prior literature on fitness and health systems mostly focuses on macro-level metrics such as the carbon reduction potential and energy output conversion of equipment, infrastructures, or gym facilities, our study places the individual user's adaptive response at the center of our methodological and conceptual framework. The current study presented sensor-validated behavioral and biometric data from a targeted green lifestyle user group in a digitally transforming urban setting [6,11,13,14].

This study does not take into account the impact of cultural and socio-economic variability common in low-income segments of urban society. Our evidence-based contribution evidences the utility and adaptability of energy-efficient aquafitness systems as they redefine new hybrid infrastructures that hold potential for digitally inclusive health policy. However, the importance of contextual customization based on the functional design characteristics and demographic sensitivity of the technological interventions are important to take into account, as well, before making generalizations and recommendations on the tailoring of sensor-aided programs, eco-fitness curricula or urban health dashboards related to them, and as basis of the future policy refinements and institutional implementations. These implications may help in formulating and refining evidence-based guidelines for future aquafitness innovation, green health interventions, and further investigations on the eco-digital behavioral continuum.

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