Wearable Technology as a Moderator Between Health Consciousness and Health-Related Quality of Life

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Abstract

This study investigated the relationship between health consciousness (HC) and health-related quality of life (HRQoL), with health technology use as a potential moderator. Data was collected in the city of Groningen, the Netherlands. N=72 participants aged between 17 and 87 ($M_{Age}(SD) = 40.96(20.85)$) completed a questionnaire. Health consciousness was measured using a reduced version of the Dutta-Bergman scale, HRQoL was assessed using the SF-12, and health technology use was operationalized as a binary variable and frequency of use. Multiple linear regressions revealed a positive but non-significant directional relationship between HC and HRQoL. The moderating effect of health technology use on this relationship was also non-significant, suggesting that HRQoL, as a stable construct, is less influenced by short-term behavioral changes or health interventions like wearables. These findings challenge assumptions about the direct impact of HC on HRQoL and highlight the need for nuanced theoretical frameworks that account for psychosocial factors, such as health anxiety, and potential confounders like socioeconomic status. Limitations include the small sample size, binary classification of technology use, and the insensitivity of HRQoL instruments to subtle changes. Future research should employ diverse samples, refine operationalizations of health technology use, and adopt longitudinal designs to better capture long-term effects on HRQoL.

Keywords: Self-monitoring, Moderation analysis, Behavior change, Feedback loops, Health outcomes, Health anxiety.

Wearable Technology as a Moderator Between Health Consciousness and Health-Related Quality of Life

In recent years, wearable health technology has revolutionized personal health management by enabling individuals to track and monitor various aspects of their health in real-time (Lenouvel et al., 2019). From fitness trackers to smartwatches, wearables provide continuous feedback on physical activity and metrics such as sleep patterns and heart rate, fostering greater awareness of one's health (Michie et al., 2013). This enhanced awareness ties closely to the concept of Health Consciousness (HC), which refers to an individual's level of health awareness and motivation to engage in health-promoting behaviors (Schwartz, 2012). Health-conscious individuals are more likely to adopt healthy lifestyles and maintain it, which can positively impact their health-related quality of life (HRQoL; De Wit, 2006).

Wearables and Health Consciousness

Emerging research underscores the positive impacts of health consciousness on HRQoL, reinforced by advanced monitoring technologies. For instance, studies have shown that health literacy and awareness significantly contribute to improved well-being and lifestyle choices among university students, indicating that increased awareness can lead to healthier behavior patterns and better health outcomes (Rashid et al., 2023). Further supporting this, Zhang et al. (2024) highlighted the mediating roles of self-esteem and social support in enhancing HRQoL through health awareness. Additionally, Richards et al. (2010) detailed how self-care practices among mental health professionals, as a component of health consciousness, are directly linked to enhanced well-being through self-awareness and mindfulness, mediated by routine self-monitoring.

Self-monitoring involves the process of tracking one's behaviors or physiological states and receiving feedback to adjust behavior accordingly (De Wit, 2006). Wearables have made self-monitoring more accessible and effective by providing continuous data that users can act on in real time. Research shows that feedback loops—where users receive real-time information on their behavior—play a crucial role in supporting self-regulation and motivating behavior change (Lenouvel et al., 2019; Vega, 2013). As mentioned, progress monitoring and consistent feedback can reinforce one's health consciousness by means of higher engagement with behavior change or attainment (Michie et al., 2013). For example, users of activity trackers like Fitbit and Apple Watch are encouraged to reach daily activity goals, which not only increases their physical activity but also fosters a greater sense of control over, and awareness of, their health (Dunn et al., 2018; Mercer et al., 2016).

Wearables in Healthcare

Furthermore, wearable technology has proven to be an effective tool in improving chronic disease management and predicting health outcomes. Adeghe et al. (2024) discuss how wearable devices have become instrumental in monitoring patient health, facilitating early interventions that are personalized and proactive, significantly reducing hospital readmissions. Tarakci et al. (2018) illustrate the integration of wearables with performance-based payment systems in healthcare, showcasing their role in improving patient management and supporting financial incentives for healthcare providers. Additionally, Burnham et al. (2018) found that wearables could effectively predict critical health outcomes such as mortality and readmissions, enhancing the predictive power of health monitoring systems.

Research Objectives and Hypotheses

Health literacy, a key aspect of health consciousness, plays a crucial role in promoting subjective well-being among university students, providing a foundation for exploring its broader impact on health outcomes (Rashid et al., 2023). The extent to which this relationship is strengthened or weakened by the use of wearable devices has not been fully explored. This study investigates whether the use of wearable health technology as a moderator can enhance the impact of health consciousness on subjective health outcomes, thereby contributing to research on its effectiveness in promoting health behavior change. Furthermore, the findings will provide insights into how wearables can be leveraged to improve health. Specifically, this research aims to test the following hypotheses:

H1a: Health consciousness is positively associated with HRQoL.

H1b: The use of wearable health technology moderates the relationship between HC and HRQoL.

Methods

Design and Participants

This study used a cross-sectional correlational design to assess the moderating effect of health technology usage on the relationship between health consciousness (HC) and HRQoL. Cross-sectional designs, ideal for observing variable associations at a single point, offer a snapshot of exposures and outcomes in the population (Wang & Cheng, 2020). The primary benefit of utilizing a cross-sectional design in our study is its efficiency. It enables quick and cost-effective data collection, ideal for examining the moderating effects of wearable technology on the relationship between health consciousness and health outcomes. This method provides a timely snapshot of these associations, helping to estimate their prevalence and generate hypotheses for further investigation.

To collect the necessary data, a custom questionnaire on Qualtrics (2024) was utilized, available in Dutch and English for accessibility reasons. Participants were recruited through random sampling at various public locations in Groningen, including Forum, Vinkhuizen, Paddepoel, and the Groningen Train Station. Inclusion criteria required participants to be 16 years or older and able to provide informed consent, as well as being capable of filling out the questionnaire either in Dutch or English. A total of 72 participants (M_{age} (SD) = 40.96 (20.85); 44% Female, 54% Male, 1% No answer) were recruited. Out of 84 initial participants, 12 were excluded due to incompletion of the questionnaire.

Procedure

Potential participants were approached by researchers who provided a brief explanation of the study's purpose and participation requirements. Those who expressed interest were offered refreshments as compensation and given the option to complete the survey either immediately on a tablet provided or at their convenience via a QR code link. The survey took approximately 15 minutes to complete. After completion, participants had the option to partake in a raffle containing a 5€ prize. Participant answers were only considered if informed consent was given both at the start and end of the Questionnaire. The EC-BSS at the University of Groningen developed a checklist; On the basis of that list the study was exempt from full ethical review (EC code: PSY-2425-S-0063).

Measurements

The study utilized a questionnaire collaboratively developed by a group of six bachelor thesis students, consisting of self-developed items and published scales. It comprised a total of 69 items, with sections tailored to address each student's research variables alongside shared demographic questions. These questions covered participants' age, gender, annual net income, and highest completed degree.

Health Consciousness

The independent variable was measured using a shorter version of the Dutta-Bergman Health Consciousness Scale as adapted by Hong (2012). Eight items were selected based on their contribution to the overall reliability ($\alpha > .7$) in the pilot test. They utilized a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) and assess participants' health awareness and concern (e.g., "I'm very self-conscious about my health"). A back translation procedure was adopted to translate the original version into Dutch. The sample has a cronbach's alpha of 0.59 for this scale.

HRQoL

The dependent variable was measured using an adapted version of the 12-Item Short Form Survey (SF-12; Ware et al., 1996). This measure evaluates physical and mental health domains through items addressing physical functioning, pain, general health, energy, and social functioning (e.g. "During the past 4 weeks, how much of the time has your physical health or emotional problems interfered with your social activities (like visiting friends, relatives, etc.)?"). Two pairs of items were adapted to a yes/no format for simplicity: one assessing limitation due to emotional problems and the other addressing limitation from physical health. Both Dutch and English versions of the SF-12 were included in the questionnaire. In this sample, the scale proves internally consistent ($\alpha = 0.79$).

Use of Technology

The moderator was assessed through a binary question asking whether participants currently use health technology (e.g., wearable fitness trackers or health apps). The answer was then coded binarily; “yes” and “no”.

Statistical Analysis

Data Preparation and Processing

The final dataset, reduced to 72 participants, included only complete responses for key variables and was limited to demographic information, consent verification, and the main measurement scales.

For the independent variable Health Consciousness, an average score of all eight items was calculated into a single variable. This approach enhanced the interpretability of the result corresponding to the context within a five-point Likert scale.

The dependent variable HRQoL was similarly computed as a single score. Each item's score was standardized by dividing it by the total number of possible response options. To maintain consistency in interpretation, three items (1, 8, and 9) were inversely coded so that higher scores uniformly reflected higher levels of HRQoL. The final HRQoL score was calculated as the mean of all standardized items.

Statistical Analysis

All statistical analyses were conducted using IBM SPSS Statistics (IBM Corporation, 2024). A hierarchical multiple regression was performed with HRQoL as the dependent variable. In the first step, Health Consciousness (HC) was entered to test the direct association (H1a). In the second step, Use of Health Technology (UoHT) and the interaction term (HC ×

UoHT) were added to investigate the moderation effect (H1b). Continuous variables were mean-centered prior to creating interaction terms, and significant level was set at $\alpha = .05$. Prior to hypothesis testing, all relevant assumptions for multiple linear regression were examined and met; further elaboration in results section.

Power analysis

Prior to data collection, a power analysis was conducted using G*Power 3.1 (Faul et al., 2007) to determine the required sample size. For detecting a small to medium effect size ($f^2 = 0.15$; Cohen, 1988), with $\alpha = 0.05$ and desired power of 0.80, the analysis indicated a minimum required sample size of 92 participants. Our final sample size of 72 participants approached but fell slightly short of this target.

Results

Sample Characteristics

A total of 72 participants provided complete data for this analysis. Of these, approximately 44% self-identified as female, 54% as male, and 1% chose not to answer (Appendix, Table 1). The mean age of the sample was 40.96 years (SD = 20.85), ranging from 17 to 87 years (Appendix, Table 1). Participants' scores on HC and HRQoL were normally distributed with no outliers identified under visual inspection. All relevant assumptions for multiple linear regression were examined. Scatterplots suggested no major violations of linearity, and visual inspection of Q-Q plots and histograms of the standardized residuals did not indicate severe departures from normality. (Appendix, Graph 1 and 2). A residuals-versus-predicted scatterplot likewise showed no clear evidence of heteroscedasticity, and the Variance Inflation Factors (VIF) were all below 2.0, suggesting that multicollinearity was not a concern (Tabachnick et al., 2019).

Health Consciousness and HRQoL

A simple linear regression model was used to test the association between health consciousness and health-related quality of life. The centered HC variable (HCCentered; $M_{HCCentered}(SD) = 0.002(0.4)$) is the sole predictor of HRQoL ($M_{HRQoL}(SD) = 8.8(1.31)$). The model was not statistically significant ($F(1,70) = 1.991$, $p = .163$, $R^2=0.028$), accounting for only about 2.8% of the variance in HRQoL. The unstandardized coefficient for HCCentered was B=0.539 (SE = 0.382), and the standardized coefficient (β) was .166. Although the direction of the effect was positive, indicating that an increase in HC was associated with a slight increase in HRQoL, the relationship failed to reach conventional levels of statistical significance ($p > .05$). Hence, Hypothesis 1 was not supported.

The Moderation Effect of the Use of Technology

Hypothesis 1b stated that use of health technology (UoHT; $M_{UoHT}(SD) = 0.4(0.49)$) would moderate the effect of HC on HRQoL. To test this, a second multiple regression model was conducted by adding UoHT (coded 0 = "no," 1 = "yes"). In this model, HRQoL was again the outcome, with HCCentered, UoHT, and HCCentered × UoHT entered simultaneously as predictors. The overall model was also non-significant ($F(3,68) = 0.959$, $p = .417$). As a result, neither the main effects nor the interaction made a statistically reliable contribution to explaining variations in HRQoL. Thus, there was no evidence to support Hypothesis 2.

Taken together, these findings suggest that, within this particular sample, health consciousness alone did not significantly predict health-related quality of life, nor did the use of health technology moderate the strength of this relationship. While the direction of coefficients for HC was consistently positive, the effects were too small to be distinguished from random variation.

Discussion

This study investigated the relationship between HC and HRQoL, with health technology use as a potential moderator. The results indicated no statistically significant associations between these variables, suggesting that the hypothesized relationships may not hold in the current context. These findings challenge assumptions of direct, straightforward associations between HC and HRQoL and highlight the complexity of these interactions. The findings suggest that HRQoL, as a long-term construct, may not be significantly influenced by short-term interventions like wearable technology. Additionally, individual differences in health perception, such as heightened awareness in highly health-conscious individuals, could have confounded the results.

Comparison with Previous Studies

The first hypothesis, H1a, posited a positive association between health consciousness (HC) and health-related quality of life (HRQoL). However, the results of this study indicated that this relationship was non-significant. This aligns with other research indicating that subjective health outcomes such as HRQoL may remain relatively stable over time and are not easily influenced by health awareness alone (Karimi & Brazier, 2016). Evidence from related studies further support these findings.

For example, Li et al. (2022) found that despite the use of motivational interventions and instant messaging support, the long-term impact on smoking cessation behavior among patients with non-communicable diseases was not significant. The study highlighted that while short-term changes were observed, sustained behavioral change was limited, partly due to intrinsic behavioral resistance and declining user engagement over time. Similarly, Holmen et al. (2014) reported that a mobile health self-management system for individuals with type 2 diabetes had limited effects on long-term health outcomes such as glycated hemoglobin levels and HRQoL. This underlines the difficulty in translating short-term engagement with technology into meaningful, lasting improvements in health.

Additionally, Timmermans & Kaufman (2020) emphasized that digital health technologies often fail to address the broader psychosocial and environmental factors influencing health outcomes. Their work suggests that the inequities and limitations in the design and implementation of these technologies contribute to their limited effectiveness in promoting stable long-term improvements.

In regards to the moderator effect, non-significant findings in this study align with research showing limited or no long-term effects of wearable health technology on health outcomes or behavior change. For instance, Fadhil (2021) highlights behavioral barriers such as boredom and unmet user expectations as primary reasons for the abandonment of wearables, which often fail to provide sustained value beyond their novelty. Similarly, Nelson et al. (2020) observed fluctuating user engagement, where initial enthusiasm often waned due to inadequate integration into daily routines and counterintuitive feedback mechanisms. Additionally, Huhn et al. (2022) reported that while wearable technologies show promise in short-term interventions, their long-term impact remains limited by declining user engagement and the failure to meet evolving user needs.

Another potential explanation for the non-significant findings between HC and HRQoL in this study is the role of health anxiety as a confounding variable. Research has shown that heightened health consciousness can sometimes lead to increased health-related worries, which negatively impact HRQoL (Lee, 2019). Similarly, Strine et al. (2005) demonstrated that individuals with frequent anxiety symptoms tend to report lower HRQoL, highlighting the pervasive influence of psychosocial factors on subjective health outcomes.

Theoretical Implications

The findings suggest that health anxiety may act as a mediating factor in the relationship between HC and HRQoL. While HC reflects attentiveness to health-related behaviors, this heightened awareness can sometimes amplify worries about health, leading to overly critical self-assessments of quality of life. Conversely, individuals with lower HC may report higher HRQoL due to a lack of awareness or concern about potential health issues. This dynamic highlights the importance of considering subjective psychological factors, such as health anxiety, in theoretical models that aim to explain the relationship between HC and HRQoL. By incorporating these mediating factors, future theoretical frameworks could better account for the complexities of how HC interacts with psychosocial variables to shape subjective health outcomes.

Regarding the non-significance of wearables on HRQoL; it is a long-term, relatively stable construct that may not be significantly influenced by short-term interventions, such as wearable technology use. Karimi and Brazier (2016) suggest that HRQoL often reflects self-perceived health status rather than a dynamic quality of life, limiting its responsiveness to transient or situational changes. This stability highlights the challenges of achieving measurable improvements in HRQoL through interventions focused on short-term behaviors or technologies.

Behavior change models, including the Health Behavior Goal Model (De Wit, 2006) and the Transtheoretical Model (Maes & Gebhardt, 2000), suggest that consistent feedback and engagement are crucial for maintaining long-term behavioral change. While wearable devices have the potential to enable personalized interventions, they often fall short in practice. For example, many wearable technologies provide generic recommendations (e.g., step counts or calorie goals) that fail to account for individual health conditions, preferences, or lifestyles. This lack of personalization can lead to disengagement, as users may feel that the feedback does not align with their specific needs or goals.

To improve personalization, wearable devices could incorporate adaptive algorithms that adjust feedback based on user behavior patterns and preferences. For instance, instead of static daily step goals, a wearable could suggest tailored activity plans that consider the user's physical condition, daily schedule, or motivation level. Furthermore, integrating contextual data, such as stress levels or sleep patterns, could enhance the relevance of feedback, fostering sustained engagement and adherence. By addressing these shortcomings, wearable devices could better support the mechanisms identified in behavior change models, increasing their effectiveness in driving long-term health improvements.

Practical Importance

The results of this study offer valuable insights into the practical implications of wearable health technology, despite the lack of significant findings. The limited long-term impact of wearable devices suggests a need to reevaluate their design and implementation. As noted by Fadhil (2021), addressing user engagement through gamification and personalized incentives could mitigate abandonment and improve long-term adherence to health goals. Nelson and his colleagues (2020) also emphasized the importance of fostering sustained user motivation by designing wearables that seamlessly integrate into diverse lifestyles. Huhn and his colleagues (2022) further advocates for incorporating adaptive feedback mechanisms to ensure that users perceive ongoing value in their devices.

Additionally, the findings challenge assumptions about the relationship between HC and HRQoL, highlighting the need for context-sensitive interventions. For instance, health consciousness may fail to improve HRQoL in cases where heightened awareness leads to health-related worries or stress, particularly among individuals prone to health anxiety. Practical strategies to address this include designing interventions that balance increasing health awareness with fostering emotional resilience, such as integrating stress management techniques into health promotion programs.

Furthermore, the relationship between HC and HRQoL may be mediated by access to resources, such as socioeconomic status (SES) or availability of healthcare. Practical applications should account for these disparities by tailoring interventions to an individual's circumstances. For example, providing cost-effective health resources and actionable, realistic health goals can mitigate frustration among individuals with high HC but limited means to act on their awareness. These approaches ensure that health interventions promote well-being without inadvertently reducing HRQoL.

Limitations

This study faced several limitations that should be addressed in future research. First, the sample size was insufficient to detect small or subtle effects, limiting the study's statistical power and the ability to draw definitive conclusions. Second, the recruitment strategy, which relied on specific public locations, resulted in a relatively homogeneous participant pool, reducing the generalizability of the findings. A more diverse sample would provide insights into how variables like SES and cultural factors influence the relationships between HC, HRQoL, and technology use.

The binary classification of health technology use also oversimplified its role as a moderator. While frequency of use was measured, a more comprehensive approach—including measures of device type, intensity, and purpose of use—could provide a richer understanding of how wearable technology impacts health outcomes.

Finally, the cross-sectional design, while well-suited for the hypotheses, limits the ability to capture changes over time that are crucial for understanding long-term behavioral changes and their impact on HRQoL. As Wang and Cheng (2020) highlight, this design cannot establish causality due to the simultaneous measurement of exposures and outcomes. Furthermore, it is susceptible to biases such as recall bias, where participants may inaccurately report past behaviors, and selection bias, which can impact the representativeness of the sample.

Additionally, as Hernández-Segura et al. (2022) note, HRQoL instruments like the SF-36 are effective at assessing broad multidimensional constructs of health but are often not sensitive enough to detect short-term or incremental changes. These methodological constraints reinforce the need for longitudinal research designs, which are better suited for exploring temporal dynamics and causal pathways influencing HRQoL and health behavior adoption.

Future Research Directions

Future studies should address these limitations by employing larger, more diverse samples to improve statistical power and generalizability. Expanding the operationalization of health technology use to include engagement levels, device types, and usage purposes could provide deeper insights into its role as a moderator. Additionally, longitudinal designs are essential for capturing changes in HC, HRQoL, and health technology use over time, allowing for stronger causal inferences and a better understanding of long-term effects.

Future research should also investigate the potential role of psychosocial factors, such as health anxiety, as confounders in the relationship between HC and HRQoL. Health anxiety may bias self-reported HRQoL scores, with highly health-conscious individuals over-reporting health concerns and less health-conscious individuals under-reporting them. Incorporating objective health metrics, such as biometric or clinical health indicators, could help mitigate these biases and provide a more accurate understanding of the HC-HRQoL relationship. Additionally, exploring how health anxiety interacts with other potential moderators, such as socioeconomic status (SES) and health literacy, could uncover further complexities in the dynamics between HC and HRQoL.

The role of wearable technology in improving health outcomes also warrants further exploration. While this study highlighted its limited long-term impact, future research could examine how wearable devices influence short-term behaviors, such as adherence rates and physical activity levels, and whether these effects translate into measurable long-term improvements in HRQoL. Research should also address the potential mismatch between the short-term feedback mechanisms of wearables and the stable, long-term nature of HRQoL. Adaptive feedback systems that account for contextual factors such as stress levels, sleep patterns, and user preferences may enhance the sustained engagement required for meaningful changes in subjective health outcomes.

Conclusions

This study highlights the complexity of the relationship between HC, HRQoL, and wearable health technology. The non-significant findings challenge the assumption of a direct, linear relationship between HC and HRQoL, suggesting that health awareness alone may not directly improve subjective health outcomes. Additionally, the results question the moderating role of wearable technologies, emphasizing the misalignment between their short-term feedback mechanisms and the long-term, multidimensional nature of HRQoL.

These findings underscore the need for research methodologies that account for psychosocial confounders, such as health anxiety, and incorporate objective health measures to reduce biases in self-reported outcomes. By addressing these limitations, future research can advance understanding of how health awareness and technology influence long-term health and well-being across physical and psychosocial dimensions.

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Appendix

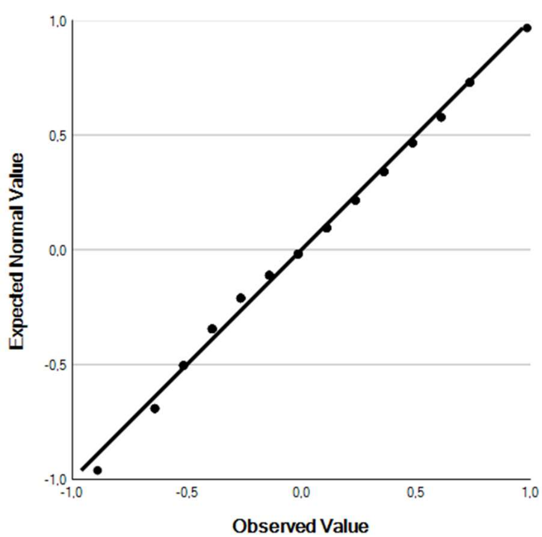
Table 1

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	72	17	87	40,96	20,849
Gender					
Feale	32				
Male	39				
No Answer	1				

Graph 1

Normal Q-Q Plot of HCCentered



Graph 2

Normal Q-Q Plot of HRQoL