Neuropods:

User Acceptance and Market Fit of a Visible Behind-the-Ear Closed-Loop Wearable for Stress Reduction

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Abstract

Yet the acceptance of visible, closed-loop devices remains underexplored. This study examines user acceptance and perceived market fit of Neuropods, a behind-the-ear wearable that combines HRV-based stress detection with on-device tVNS. Guided by TAM/UTAUT/HBM and the stigma literature, a theory-driven, cross-sectional online survey (N = 148) operationalized willingness to wear, perceived stigma/visibility, design and wearability, and market fit. Hypotheses and analyses were pre-specified; inference relied on robust regression alongside targeted majority tests.

Findings show that willingness to wear a visible BTE device is above the scale midpoint but context-sensitive—lower in work/formal settings than in private/social contexts—so an unequivocal "clear-majority" threshold is not uniformly met. In contrast, the combined tracking-plus-stimulation proposition is evaluated favorably on market fit. Multivariate results identify design/wearability as a strong positive determinant of willingness, stigma/visibility as a comparably strong negative determinant, and current wearable ownership as an independent positive factor. Conditional on design and willingness, stigma shows little additional effect on market-fit judgments.

The thesis delivers the first empirical evidence on acceptance of visible BTE closed-loop wearables and extends technology-acceptance accounts with an explicit visibility/stigma pathway alongside design/wearability. Managerially, the results prioritize comfort and professional, minimalist aesthetics, discreet form-language to lower visibility costs, and clear validation/privacy messaging—especially for professional settings and non-owners—when positioning combination devices such as Neuropods.

Keywords: *Wearable technology; Digital health; User acceptance; Stigma and visibility; Market fit*

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Sumário

Contudo, a aceitação de dispositivos visíveis e em circuito fechado é pouco conhecida. Este estudo avalia a aceitação do utilizador e a adequação ao mercado do Neuropods, um vestível retroauricular que combina deteção de stresse pela VFC e tVNS. Com base em TAM/UTAUT/HBM, um inquérito online (N = 148) mediu disposição para usar, estigma/visibilidade, design/usabilidade e adequação ao mercado.

A disposição para usar um BTE visível fica acima do ponto médio, mas depende do contexto: é menor em ambientes de trabalho/formais do que em contextos privados/sociais, pelo que um limiar de "maioria clara" não se verifica de modo uniforme. A proposta de monitorização mais estimulação recebe avaliações favoráveis de adequação ao mercado. Nos modelos multivariados, design/usabilidade é determinante positivo forte; estigma/visibilidade é determinante negativo de magnitude semelhante; e a posse atual de vestíveis é efeito positivo independente. Controlando por design e disposição, o estigma acrescenta pouco às avaliações de mercado.

A tese fornece evidência inicial sobre a aceitação de vestíveis BTE de circuito fechado e estende modelos de aceitação com uma via explícita de visibilidade/estigma em paralelo ao design/usabilidade. Implicações: priorizar conforto, estética minimalista/profissional e mensagens claras de validação e privacidade, sobretudo em contextos profissionais e para não utilizadores.

Palavras-chave: *Tecnologias vestíveis; Saúde digital; Aceitação do utilizador; Estigma e visibilidade; Adequação ao mercado*

Title: Neuropods: Aceitação do Utilizador e Adequação ao Mercado de um Dispositivo Vestível Atrás da Orelha, em Circuito Fechado, para Redução do Stresse

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List of Abbreviations

AI — Artificial Intelligence

BTE — Behind-the-Ear

BP — Breusch–Pagan (Test)

CES — Cranial Electrotherapy Stimulation

CI — Confidence Interval

CSV — Comma-Separated Values

DV — Dependent Variable

EDA — Electrodermal Activity

EEG — Electroencephalography

GDPR — General Data Protection Regulation

HBM — Health Belief Model

HC3 — Heteroskedasticity-Consistent (Type 3) Robust Standard Errors

H_1 — Hypothesis 1

H_2 — Hypothesis 2

HR — Heart Rate

HRV — Heart Rate Variability

IP — Internet Protocol (Address)

IS — Information Systems

IV — Independent Variable

KPI — Key Performance Indicator

LM — Linear Model (R)

ML — Machine Learning

MLR — Multiple Linear Regression

mHealth — Mobile Health

M — Mean

N — Sample Size

NA — Not Available / Missing Value (R)

OLS — Ordinary Least Squares

PPG — Photoplethysmography

Q–Q — Quantile–Quantile (Plot/Test)

RCT — Randomized Controlled Trial

R — R (Statistical Computing Language)

R^2 — Coefficient of Determination (R-squared)

RQ_1 — Research Question 1

RQ_2 — Research Question 2

SD — Standard Deviation

SE — Standard Error

SEM — Structural Equation Modeling

TAM — Technology Acceptance Model

tVNS — transcutaneous Vagus Nerve Stimulation

UTAUT — Unified Theory of Acceptance and Use of Technology

UTAUT2 — Unified Theory of Acceptance and Use of Technology 2

VFC — Variabilidade da Frequência Cardíaca *(PT; Heart Rate Variability)*

VIF — Variance Inflation Factor

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1 Introduction

Stress-related disorders are a widespread societal challenge – They contribute significantly to the global disease burden and affect mental health, physical well-being, and economic productivity across populations (Demir et al., 2025; González Ramírez et al., 2023). Chronic stress increases the risk of cardiovascular diseases, impairs cognitive functioning, and reduces workplace performance. This underscores the need for prevention and intervention strategies that are both accessible and acceptable to end users (Piwek et al., 2016). Advances in wearable health technologies create new opportunities to address these challenges. They enable continuous physiological monitoring, personalized feedback, and, in some cases, direct therapeutic intervention (Canali et al., 2022; Panicker & Gayathri, 2019).

Within the stress-reduction wearable market, three principal categories can be distinguished: devices designed exclusively for tracking physiological parameters such as heart rate variability (HRV), devices delivering stimulation-based interventions such as neurostimulation, and combination devices that integrate both modalities in a single platform (Canali et al., 2022). While tracking-only devices provide valuable insights into stress patterns, they typically require the user to take subsequent action, whereas stimulation-only devices intervene directly but often lack personalized, data-driven targeting (Sellers et al., 2023; Topalovic et al. 2023). Combination devices, in contrast, employ continuous sensing to trigger targeted interventions in real time, potentially increasing therapeutic efficacy and user engagement (Demir et al., 2025). Neuropods is positioned in this third category, combining HRV-based stress detection with behind-the-ear (BTE) transcutaneous vagus nerve stimulation (tVNS) in a discreet form factor, thereby functioning as a closed-loop system that monitors, interprets, and responds to physiological signals without active user input.

Despite the market's growth and the technical potential of integrated solutions, existing academic research has largely concentrated on acceptance factors for tracking-only or stimulation-only devices, leaving the combined category underexplored (Canali et al., 2022; González Ramírez et al., 2023). Studies consistently show that acceptance of wear-able health technologies depends on comfort, aesthetics, perceived accuracy, and the degree of intrusiveness, as well as on trust in algorithmic decision-making, transparency of data handling, and perceived benefits relative to possible risks (Dinev & Hart, 2006). However, it remains unclear whether these determinants apply in the same way to combination devices, particularly those that are visibly worn in socially exposed locations such as behind-the-ear. Visibility can influence social identity and stigma, which in turn may affect adoption even if the device delivers superior functionality (Demir et al., 2025). This knowledge and literature gap is particularly relevant for closed-loop devices that not only detect but also intervene automatically, as their real-world success depends on both technical performance and sustained user acceptance in daily life.

This study investigates consumer acceptance of combined stress-reduction wearables, focusing on visible, behind-the-ear designs that integrate physiological tracking and stimulation. The research addresses two questions: **RQ$_1$** – Will users accept wearing a visible, behind-the-ear stress-reduction device in daily life? **RQ$_2$** – Does a combined tracking + stimulation wearable as a daily companion have a clear market fit? The hypotheses are developed at the end of the Literature review (Section 2.6) based on prior evidence.

This thesis is structured as follows: After this introduction, Chapter 2 reviews relevant literature with the required conceptual background, including an overview of the stress-reduction wearable market, theoretical models of user acceptance, societal perceptions of visible health devices, determinants of consumer acceptance, and user perspectives on algorithmic stress detection and predictive analytics. Chapter 3 outlines the research methodology, detailing the quantitative survey design, sampling strategy, measurement instruments, data collection procedures, and analysis methods. Chapter 4 presents the results, followed by Chapter 5, which discusses the findings in the context of prior research, identifies implications for product development and marketing, and outlines study limitations and directions for future research. Chapter 6 concludes with a summary of the answers to the research questions and the contributions of the study to both academic literature and market practice.

2 Literature review

2.1 Market overview for stress-reduction wearables

In recent years, consumer and healthcare markets for stress-related wearables have expanded alongside advances in biosensors and mobile integration, even as evidence and usage patterns remain heterogeneous (Bardhan et al., 2025; Piwek et al., 2016; Wu & Ye, 2020). Stress-reduction wearables can be differentiated threefold into (i) monitoring-only devices (e.g., HRV/EDA/respiration trackers), (ii) stimulation-only devices (e.g., CES or haptic breathing coaches), and (iii) combined systems that couple sensing with on-device feedback, approximating closed-loop use cases (Peake et al., 2018; Wu & Ye, 2020). This tripartite segmentation provides a useful analytical frame-work for understanding market structure, consumer adoption patterns, and the technological trajectories shaping product development (Peake et al., 2018; Yoo et al, 2010).

Monitoring-only wearables typically use non-invasive sensors to derive HRV, EDA, respiration and sometimes EEG; HRV remains the most common stress-related surrogate in commercial devices despite known limitations (Peake et al., 2018). Devices in this category include smartwatches, fitness trackers, and chest straps, often integrated with smartphone applications to provide analytics and long-term trend visualization (Peake et al., 2018; Wu & Ye, 2020). Adoption of HRV features has benefited from PPG and inertial sensing, yet motion artifacts, noisy signals and limited independent validation constrain the clinical utility of many consumer-grade implementations (Peake et al., 2018; Wu & Ye, 2020). While tracking-only devices have achieved mass-market penetration, their functionality is limited to passive monitoring, requiring users to initiate separate behavioral or therapeutic interventions (Piwek et al., 2016).

Stimulation-only devices typically use cranial electrotherapy stimulation (CES) or tactile/respiratory biofeedback to influence arousal and stress appraisals (Okano et al., 2025; Peake et al., 2018). Evidence for acute stress reduction is mixed; a recent pre-registered RCT found no reliable CES effects on physiological or cognitive responses to an acute stressor, underscoring the need for integrated monitoring to personalize dosing (Okano et al., 2025).

Combination wearables that fuse sensing with on-device stimulation have emerged to enable data-driven, quasi-closed-loop stress management and could capture share from both predecessors (Peake et al., 2018; Wu & Ye, 2020). By continuously screening HRV/EDA/respiration and triggering feedback when thresholds are crossed, such systems enable context-aware interventions and invite ML-based personalization (Fallon et al., 2025; Peake et al., 2018). These trajectories mirror broader digital-health and digital-innovation trends toward multi-sensor fusion and ML pipelines embedded in wearables and apps (Kohli & Melville, 2019; Nambisan et al., 2017; Wu & Ye, 2020; Yoo et al., 2010). Market positioning of such devices emphasizes their role as comprehensive stress management solutions, particularly in professional and high-performance contexts, where both prevention and rapid mitigation of stress are critical. This is consistent with IS reviews showing how data and analytics reconfigure product offerings and categories (Kohli & Melville, 2019).

Adoption is shaped by perceived usefulness/enjoyment, social influence and trust as well as rising self-care awareness—determinants consistently supported across countries in a meta-analysis and acceptance studies (Peng et al., 2021; Pfeiffer et al., 2016; Piwek et al., 2016). Miniaturization and lower costs have broadened access, and tighter integration with mobile/cloud health services supports personalized feedback and remote-monitoring workflows (Kohli & Melville, 2019; Peake et al., 2018; Wu & Ye, 2020). Nonetheless, accuracy varies widely between consumer- and research-grade devices; standards for signals/features remain heterogeneous, and there is no universally accepted protocol for la-belling and quantifying 'stress' in the wild (Peake et al., 2018; Wu & Ye, 2020).

To sum up, the market for stress-reduction wearables includes a mature tracking-only segment, a smaller stimulation-only segment with mixed evidence, and a nascent but strategically positioned combination segment (Okano et al., 2025; Peake et al., 2018). The shift toward closed-loop, personalized care is promising but constrained by sensing/validation limits, ecosystem alignment and platform governance requirements, and evidentiary gaps (Adner, 2017; Nambisan et al., 2017; Peake et al., 2018; Sanner et al., 2025; Wu & Ye, 2020). These dynamics underscore a research gap in robust multimodal integration and reliable stress labeling for adaptive intervention (Fallon et al., 2025).

The presented market segmentation highlights that combination devices occupy a unique but underexplored position. The integration of tracking and stimulation aligns with **RQ$_2$**, which asks whether such systems have a higher market fit. However, among the existent sources, no empirical assessment of user acceptance for visible, behind-the-ear designs could be identified, leaving **RQ1** unaddressed. Hence, these gaps justify the focus on combination devices as the basis for examining acceptance and market potential in the following sections.

2.2 User acceptance theory

The theoretical frameworks most commonly applied to explain the adoption of stress- and mental health-related wearable technologies include the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2), and the Health Belief Model (HBM), each offering distinct but complementary perspectives on user acceptance (Davis, 1989; Kim et al., 2021; Rosenstock, 1974; Venkatesh et al., 2003; Venkatesh et al., 2012). TAM centers on perceived usefulness and perceived ease of use as primary predictors of intention and use; in wearable healthcare, health information accuracy and health beliefs increase perceived usefulness and thereby intention, while privacy protection did not significantly predict perceived usefulness in Cheung et al. (2019)'s work (Davis, 1989; Venkatesh & Davis, 2000). This pattern is consistent with privacy-calculus theory, in which individuals weigh disclosure risks against perceived benefits when deciding to adopt (Acquisti et al., 2015; Dinev & Hart, 2006). UTAUT extends this with performance expectancy, effort expectancy, social influence, and facilitating conditions; in healthcare wearables, social influence, effort expectancy, and facilitating conditions affect intention and actual use (Dai et al., 2019; Larnyo et al., 2022; Venkatesh et al., 2003). Furthermore, UTAUT specifies moderators—age, gender, experience, voluntariness—and UTAUT2 adds hedonic motivation, price value, and habit for consumer technologies (Venkatesh et al., 2003; Venkatesh et al., 2012). The expanded theory aims to explain more diverse contexts.

HBM, in contrast, adopts a health psychology perspective, positing that acceptance and sustained use of wearables are influenced by perceived susceptibility to and perceived severity of a health condition, as well as perceived benefits and barriers (Rosenstock, 1974). In the context of activity trackers, individuals with higher health-risk perceptions and clear benefit recognition are more likely to use trackers; health information accuracy increases perceived usefulness, whereas privacy protection did not significantly predict perceived usefulness in Cheung et al. (2019) (Cheung et al., 2019; Kim et al., 2021). Self-efficacy also plays a critical role; higher confidence in managing health goals predicts information seeking and wearable use (Kim et al., 2021).

When comparing these models in relation to predictive analytics and intervention functionalities—such as algorithm-driven stress detection triggering automated interventions—TAM and UTAUT primarily emphasize technological performance and user expectations, whereas HBM focuses on personal health motivation and risk perception. Empirical findings indicate that acceptance of automated or feedback-driven wearables is shaped by anticipated efficacy and effort (TAM/UTAUT) and by experienced usability; privacy is a salient consideration, but its direct effect on perceived usefulness was non-significant in Cheung et al. (2019)'s work (Dai et al., 2019; de Looff et al., 2021). In this study, these frameworks are applied in combination. TAM and UTAUT capture technology-related and social determinants relevant to performance and usability, while HBM addresses health-specific motivations and perceived barriers (Davis, 1989; Kim et al., 2021; Rosenstock, 1974; Venkatesh et al., 2003). Using only one model would omit adoption factors unique to this use case. The combined application of these frameworks thus provides a comprehensive analytical basis for understanding and fostering the adoption of stress-reduction wearables in healthcare contexts.

Theoretical models such as TAM, UTAUT, and HBM offer complementary perspectives for analyzing user acceptance. Their combined application allows examination of both functional performance and health-related behavioral drivers, directly supporting **RQ$_1$** and **RQ$_2$**. To our knowledge, empirical applications of TAM, UTAUT/UTAUT2, or HBM to visible, behind-the-ear stress-reduction wearables remain underexplored; this study aims to fill that gap.

2.3 Societal perception of visible health devices

The Societal perception of visible health devices reflects both functional purpose and social meaning: lifestyle tracking devices tend to be viewed as everyday electronics, whereas medical-looking devices (e.g., hearing aids) are more often linked to impairment and may attract stigma or embarrassment in public use (Li et al., 2022; Madara & Bhowmik, 2024). While consumer wearables have become mainstream, devices perceived as medical still face persistent image barriers despite technical improvements, which can dampen willing-ness to wear them in public (Li et al., 2022; Madara & Bhowmik, 2024). Such image- and privacy-related concerns act as adoption barriers consistent with privacy-calculus theory—individuals trade off disclosure risks against expected benefits—which, alongside social influence, shapes intentions to adopt (Dinev & Hart, 2006; Venkatesh et al., 2003).

These dynamics are evident in hearing aids: added features like streaming have increased utility, yet stigma and concealment strategies persist in social settings. In practice, users still try to hide the device or avoid public use because its visible form continues to signal impairment rather than a lifestyle technology (Madara & Bhowmik, 2024).

Device visibility can shape self-presentation: users may hide or limit public use to avoid negative judgment, a pattern noted for visible medical devices and echoed in stress-wearable use (Li et al., 2022; Madara & Bhowmik, 2024). In stress-related contexts, public visibility can trigger embarrassment and reluctance to use the device when others might notice it, reinforcing avoidance behaviors (Li et al., 2022). These reactions align with the UTAUT 'social influence' construct: expected responses of peers or the public can materially affect intention to use (Venkatesh et al., 2003). For example, participants using a stress management wearable reported embarrassment when they thought others might see the device, which curtailed use in everyday contexts (Li et al., 2022). Similarly, reviews note that designs blending with consumer electronics aesthetics can mitigate stigma for visible medical devices (Madara & Bhowmik, 2024).

Public responses vary with familiarity and context: familiar categories tend to be accepted, while less familiar, health-signaling designs can elicit hesitation or distancing (Li et al., 2022; Madara & Bhowmik, 2024). These reactions can amplify discomfort and encourage concealment, which undermines consistent use over time (Madara & Bhowmik, 2024). Evidence suggests social acceptance improves with non-medical aesthetics and multipurpose functions that downplay a purely medical signal (Madara & Bhowmik, 2024).

In this context, the Societal perception of visible health devices is not solely determined by their medical efficacy or technological sophistication but is deeply embedded within broader cultural, social, and psychological frameworks that shape the acceptability of health-related self-disclosure in public. For behind-the-ear devices, discreet placement and consumer-electronics-style, multipurpose functionality are design levers to minimize stigma and support adoption (Madara & Bhowmik, 2024).
Overall, visibility and medical associations shape acceptance and can pose barriers for behind-the-ear wearables (Li et al., 2022; Madara & Bhowmik, 2024). These findings directly relate to **RQ_1**, as social perception may determine willingness to wear such devices. Existing work documents stigma, concealment, and aesthetics as levers, but does not test acceptance of visible, behind-the-ear stress devices—leaving a gap this study addresses (Li et al., 2022; Madara & Bhowmik, 2024).

2.4 Consumer acceptance of wearables

Consumer acceptance of wearable devices is shaped by an intricate combination of ergonomic, aesthetic, and psychological determinants, each exerting a measurable influence on both the initial adoption decision and the likelihood of sustained use over time. Ergonomic comfort is a primary determinant of willingness to wear and maximum wear time; in a controlled mobile-EEG study, flexible comfortable electrodes achieved the highest comfort, rigid/heavy headsets reduced comfort, and participants were unwilling to trade comfort for a more attractive design (Radüntz & Meffert, 2019). For head-mounted form factors, rigid/heavy designs and pin-type electrodes significantly lower comfort and limit long-duration wear, even when functional benefits are clear (Radüntz & Meffert, 2019).

Aesthetic and participatory design—treating assistive/health wearables as body adornments with jeweler-like, colorful or gender-appropriate forms—can increase social acceptability and mitigate perceived stigma in public use (Marti & Recupero, 2022). Conversely, conspicuous, medical-looking designs that fail to align with users' style norms risk deterring public use due to perceived stigma (Marti & Recupero, 2022).

Perceived usefulness is a strong predictor of intention to adopt wearable healthcare; in a structural model, perceived usefulness had the largest effect on adoption intention, alongside significant effects of consumer innovativeness and reference-group influence (Cheung et al., 2019). Beyond device-specific evidence, UTAUT identifies performance expectancy, effort expectancy, social influence and facilitating conditions as core determinants of behavioral intention and use (Venkatesh et al., 2003). Trust complements TAM by influencing intention directly and via perceived usefulness in online service contexts (Gefen et al., 2003). In consumer settings, habit, hedonic motivation and price value (in addition to performance/effort expectations) shape continued acceptance and use (Rha et al., 2022; Venkatesh et al., 2012).
Acceptance barriers are accentuated for head-mounted or ear-adjacent placements: comfort constraints documented for mobile-EEG headsets (e.g., reduced comfort with rigid/heavy hardware or pin electrodes) and lower social acceptability at certain body locations/activities (e.g., running vs. walking) have been observed (Radüntz & Meffert, 2019; Sehrt et al., 2022). Co-design frameworks ("co-design domino") formalize iterative user involvement to align technical and social requirements for wearables, helping to pre-empt acceptance barriers (Morcillo et al., 2020). Applying such methods—capturing feedback on size, materials, aesthetics and

interaction—has been used to increase perceived ownership and social acceptability of assistive/health wearables (Marti & Recupero, 2022; Morcillo et al., 2020).

To achieve market penetration and long-term adherence, behind-the-ear combination devices must pair demonstrable functional benefit with high comfort and socially acceptable, style-congruent design. This aligns with digital-innovation guidance on coupling data, design, and iterative improvement to shape product acceptance (Kohli & Melville, 2019).

2.5 Algorithmic stress detection and predictive analytics

Algorithmic stress detection in wearables commonly combines physiological biomarkers (e.g., HRV, EDA, HR) with machine-learning pipelines to identify elevated stress in everyday settings (González Ramírez et al., 2023; Nambisan et al., 2017; Vos et al., 2023). Wearable AI provides objective, continuous, non-invasive monitoring that addresses limitations of self-report and is used for stress detection/prediction in mHealth contexts (González Ramírez et al., 2023). User-oriented evidence reports value when systems support self-regulation during stress episodes, long-term goals, and stress awareness—typically via unobtrusive wearables plus actionable feedback (González Ramírez et al., 2023).

Trust and acceptance rely on accuracy/validation and generalization; a meta-analysis reports pooled *M* accuracy 0.856 (95% CI 0.70–0.93) with variable sensitivity/specificity and recommends use alongside established assessments (Vos et al., 2023). Evidence quality matters: the meta-analysis shows moderate performance with heterogeneity and advises use alongside clinical questionnaires; complementary reviews emphasize data quality, interoperability, and fairness as core requirements (Canali et al., 2022; Kohli & Melville, 2019). Conversely, inconsistent outputs and limited out-of-sample generalization undermine usefulness—prompting calls for consistent pipelines and rigorous validation (Vos et al., 2023).

Privacy and data protection constitute central determinants of user acceptance. Continuous physiological monitoring raises concerns about privacy, data sharing, and misuse, discussed as barriers in digital-health wearables (Canali et al., 2022). This follows a privacy-calculus logic in which adoption depends on whether perceived benefits outweigh disclosure risks and whether trust is established (Dinev & Hart, 2006). Recommended mitigations include data-quality and interoperability standards and attention to access/representativeness (Canali et al., 2022); in consumer health, privacy protection and data accuracy can raise perceived usefulness and intention (Cheung et al., 2019).

Closed-loop designs—where real-time detection triggers immediate intervention—are a plausible development path for wearables that couple sensing with on-device action. Studies indicate that tVNS can acutely increase HRV and modulate parasympathetic activity without invasive procedures, which supports its application in wearable-mediated closed-loop designs (Wolf et al., 2021).

Forecasting is active research, but models must balance sensitivity and specificity and demonstrate generalization; current evidence shows moderate sensitivity/specificity and limited cross-dataset robustness (Vos et al., 2023). Person-specific models often outperform generic ones in reviewed studies, indicating potential benefits of personalization (Vos et al., 2023).

In sum, the literature indicates that from a user perspective, algorithmic stress detection and predictive analytics in wearables are most likely to achieve sustained acceptance when they combine physiological validity, interpretability, privacy protection, and adaptive closed-loop interventions. These elements collectively address the intertwined issues of trust, usability, and perceived value, forming the basis for integrating HRV-driven detection with responsive stimulation technologies in next-generation consumer health devices.

HRV-based closed-loop systems combining detection and stimulation represent a technically feasible path to higher market fit, aligning with **RQ_2**. User trust depends on accuracy, privacy, and seamless integration, which are also essential for visible, behind-the-ear devices as in **RQ_1**. Existing studies do not evaluate these acceptance factors in combination, which defines the core contribution of this research.

2.6 Literature gap and research contribution

Recent work spans market structure and device typologies (tracking, stimulation, and emerging combinations) (Peake et al., 2018; Wu & Ye, 2020), user-acceptance frameworks (TAM/UTAUT/UTAUT2/HBM) (Cheung et al., 2019; Davis, 1989; Rosenstock, 1974; Venkatesh et al., 2003; Venkatesh et al., 2012), societal perception and stigma for visible, medical-looking devices (Li et al., 2022; Madara & Bhowmik, 2024), and algorithmic stress detection in wearables (Vos et al., 2023). Physiologically, tVNS can acutely modulate HRV/parasympathetic activity (Wolf et al., 2021), whereas evidence for CES effects is mixed (Okano et al., 2025). Across these literatures, no empirical assessment of user acceptance of a visible, BTE combination device was identified.

Most acceptance research applies models such as TAM, UTAUT, or HBM to health-related wearables (Binyamin & Hoque, 2020; Kim et al., 2021; Larnyo et al., 2022). While these frameworks identify determinants such as performance/effort expectancy, social influence, facilitating conditions, health beliefs and barriers (Cheung et al., 2019; Davis, 1989; Kim et al., 2021; Rosenstock, 1974; Venkatesh et al., 2003; Venkatesh et al., 2012), evidence on visible wearables shows that medical-looking designs are linked to stigma and concealment in public use (Li et al., 2022; Madara & Bhowmik, 2024).

Combination wearables that fuse sensing with on-device feedback are positioned as an emerging segment in digital health (Peake et al., 2018; Wu & Ye, 2020), aligning with digital-innovation views on how data and analytics reshape product offerings and trajectories (Kohli & Melville, 2019; Nambisan et al., 2017). Yet, existing market research does not explicitly link segment-level adoption trends to the comparative market fit of combination versus single-function devices. Evidence on consumer willingness to adopt behind-the-ear devices that integrate both tracking and stimulation is missing.

Societal perception studies demonstrate that medical-looking devices are more prone to stigma than lifestyle-oriented wearables (Li et al., 2022; Madara & Bhowmik, 2024). Design and positioning that blend with consumer-electronics aesthetics can mitigate stigma for visible medical devices (Madara & Bhowmik, 2024), but the acceptance of such strategies for visible, behind-the-ear stress-reduction devices has not been tested among the reviewed studies.

Algorithmic detection shows moderate performance with heterogeneity and is recommended alongside established assessments, with reviews emphasizing data quality, interoperability and fairness as core requirements (Canali et al., 2022). Still, there is no empirical evidence on how the integration of detection and stimulation in a visible form affects trust, adherence, or usage.

This gap is significant for both theory and practice. From a theoretical perspective, the lack of research on visible, behind-the-ear combination wearables prevents a full under-standing of how technology acceptance models interact with social stigma and market segmentation. From a practical perspective, companies lack evidence-based guidance on whether integrating tracking and stimulation in a visible device will improve market penetration and sustained use.

Taken together, the literature suggests two testable expectations that map onto the research questions. First, TAM/UTAUT/HBM link intention to perceived usefulness/effort and social influence, while the stigma literature shows visibility can suppress public use and consumer-electronics aesthetics can offset image costs (Cheung et al., 2019; Venkatesh et al., 2003; Li et al., 2022; Madara & Bhowmik, 2024). For a BTE device with minimalist, professionally suitable aesthetics and comfort emphasis, this implies a positive majority willingness despite context-dependent hesitation. Hence, **H_1**: A visible behind-the-ear stress-reduction device will be accepted by the majority of potential users (operationalized via two thresholds: soft majority >3 and clear majority ≥ 4 on a 1–5 scale). Second, work on market structure and digital innovation argues that integrating sensing with on-device intervention yields comparative value through timeliness, convenience, and personalization (Peake et al., 2018; Wu & Ye, 2020; Kohli & Melville, 2019), and users value actionable feedback when validity and governance are addressed (Canali et al., 2022). Hence, **H_2**: The perceived market fit (MF) of a combined tracking + stimulation wearable is above neutrality ($\mu\_MF > 3$ on a 1–5 scale).

This study addresses these gaps by focusing on a closed-loop, HRV-based stress-reduction device with tVNS, worn visibly behind-the-ear. It examines whether users are willing to wear such a device openly (tests **H_1**; aligns with **RQ_1**) and whether the combined tracking + stimulation concept is evaluated above neutrality on market fit (tests **H_2**; aligns with **RQ_2**). The study integrates TAM/UTAUT/UTAUT2 and HBM with evidence on societal perception (Li et al., 2022; Madara & Bhowmik, 2024), privacy-calculus (Cheung et al., 2019; Dinev & Hart, 2006), and algorithmic performance/governance (Canali et al., 2022), situating the inquiry within digital-innovation perspectives (Kohli & Melville, 2019; Nambisan et al., 2017). Physiological feasibility of tVNS effects on HRV informs the closed-loop use case (Wolf et al., 2021).

3 Methodology

3.1 Research design

This thesis adopted a quantitative, cross-sectional survey to assess user acceptance of a visible, behind-the-ear wearable that combines stress tracking via heart rate variability (HRV) with tVNS. The design is purpose-built to test the study's two hypotheses in a management context: **H_1/RQ_1** evaluates situational willingness to wear a visible device in everyday settings; **H_2/RQ_2** evaluates whether the market-fit score for the combined (tracking + stimulation) concept is above the neutral midpoint (= 3). A cross-sectional, self-administered format is appropriate because it captures attitudes and intentions at one point in time from a heterogeneous pool, supports group comparisons and multivariate modeling central to managerial inference, and minimizes researcher influence on responses.

Pre-specified, statistically testable hypotheses

Let *will_overall_score* denote the respondent's overall willingness composite on a 1–5 scale, and let *MF_score* denote the perceived market-fit composite on a 1–5 scale.

- **H_{1a} (soft majority):** $p_{soft} = P\,\mathrm{r}\left(will_{overall_{score}} > 3\right)$.
  - $H0: p_{soft} = 0.50\ vs. H1: p_{soft} \neq 0.50.$
- **H_{1b} (clear majority):** $p_{hard} = \mathrm{P\,r}\left(will_{overall_{score}} \geq 4\right)$.
  - $H0: p_{hard} = 0.50\ vs. H1: p_{hard} \neq 0.50.$
- **H_2 (market fit above neutrality):** $\mu_{MF} = E[MF_{score}]$.
  - $H0: \mu_{MF} = 3\ vs. H1: \mu_{MF} \neq 3.$

Planned subgroup contrasts (owners vs. non-owners) compare proportions for **H_{1a}/H_{1b}** via

$$\Delta p = p_{owners} - p_{non} \text{ with } H0: \Delta p = 0;\ H1: \Delta p \neq 0.$$

The full testing and modeling plan is detailed in Section 3.5; hypothesis tests are reported with two-sided p-values and 95% confidence intervals; decisions are based on two-sided tests ($\alpha = 0.05$); thresholds (>3 / ≥4, 50%) guide interpretation.

3.2 Data collection

Empirical data were collected via a self-administered online Qualtrics survey in English; after cleaning (Section 3.5), $N = 148$ complete responses remained for analysis. The instrument contained 32 items organized in a fixed flow: (i) a brief screener and usage history, (ii) core constructs—situational willingness to wear a visible behind-the-ear device; perceived stigma/visibility; comfort/design acceptance referencing an Apple-like minimalist, modern, timeless aesthetic; and two parsimonious behavioral determinants (privacy concern; preference for manual vs. automation); and (iii) demographics/controls (age group, gender, employment status, education, average daily stress). The 'weight' item in Block E was collected but excluded from the Design Acceptance composite (see Section 3.3). Recruitment was conducted over a period of approximately two weeks using various informal social and interest-based networks, including student cohorts, sports and hobby groups, as well as broader online communities. To enhance diversity, participants were also reached through personal contacts and a snowball sampling approach, which extended the survey's reach across different regions and demographic backgrounds. The survey order moved from neutral context (screener/usage) to focal perceptions (willingness, stigma, design) and ended with demographics to minimize priming and fatigue. Items were shown in fixed order within each block; blocks were separated by page breaks. No within-block randomization or force-response settings were used. Expected completion time was ~5–7 minutes, balancing construct coverage with respondent engagement. Under the ≥50% non-missing rule, all composite scores (Willingness – overall/work/private, Stigma, Design Acceptance, Market Fit) were computable for the full analyzed sample ($N = 148$).

Data quality and handling followed standard management-research practice. Only finished cases were retained; partial responses were fully excluded. Details on consent, anonymity and GDPR handling are reported in Section 3.6; data processing choices and control variables are described in Section 3.5.

3.3 Constructs and variables

This study specifies a compact, theory-informed set of constructs mapped directly to the research questions and to the finalized 32-item Qualtrics instrument. Two dependent constructs capture the core outcomes. Willingness to wear **(RQ_1/H_1)** reflects situational readiness to use a visible, behind-the-ear device in daily life and is operationalized as the respondent-level *M* of

Block C items (public transport, work, formal meetings, sports, restaurants/cafés, social gatherings, at home around family, meeting new people), each on a five-point Likert scale (1 = not at all willing … 5 = very willing). For hypothesis testing, H1a is evaluated on will_overall_score >3, whereas H1b uses the binary indicator accept_overall = 1{will_overall_score ≥4} computed from the same Block-C items. Perceived market fit of a combination device **(RQ_2/H_2)** reflects perceived comparative advantage of tracking + stimulation over tracking-only and is operationalized as the *M* of seven Block-F items covering comparative value and effectiveness, price premium, choice at equal price, choice if clinically validated, and two adoption-proximal items ('switch within 12 months', 'adopt as primary today'); all items use five-point agreement scales (1 = strongly disagree … 5 = strongly agree), and scores use a ≥4/7 non-missing rule. Higher values on both composites indicate stronger willingness and stronger perceived market fit, respectively. As a secondary outcome used for robustness and practical interpretation, adoption intention is captured via Block H (purchase consideration within 12 months; recommendation to others) and may be analyzed separately or as an outcome downstream of willingness/market-fit.

Explanatory constructs mirror the survey blocks that capture social perception and design. Perceived stigma & social perception (IV; Block D) measures the extent to which visibility may elicit negative judgment or self-consciousness. The stigma composite is formed from items indicating that others may think the wearer is ill or stressed, that the respondent would feel self-conscious, would avoid wearing around strangers, and that negative comments would reduce willingness (all coded so that higher = more stigma). The positive appearance item ("a tech-like appearance would make me feel more confident") was reversely scored and included in the stigma composite so that higher values consistently indicate more stigma. Design Acceptance uses a three-item core (minimalism, long-wear comfort behind-the-ear, professional suitability); the weight item is excluded from the Design Acceptance score. All core Block-E items (aesthetic, comfort, professional suitability) are coded so that higher values represent greater design acceptance; the weight item is coded but excluded from the composite. Two parsimonious psychological/behavioral determinants (IVs; Block G) are included as single indicators: privacy concern ("I am concerned about privacy with health wearables") and preference for manual vs. automation. These variables capture well-documented barriers in digital-health adoption while keeping the instrument concise.

Context and experience variables are used as controls to improve model specification and reduce omitted-variable bias. Wearable experience comprises frequency of current use (Block B) and a checklist of main purposes of use (fitness/health/stress/sleep/fashion/other) to describe the sample and support subgroup contrasts; familiarity with stress-related wearables (Block B) is retained as a continuous control (higher = more familiar). Demographics include age group bands, gender, employment status (student, employed, self-employed, retired, unemployed, other), and education level, all captured as categorical controls; average daily stress level (single five-point item) is included because baseline stress can shift acceptance independently of stigma or design. In line with the analysis plan, these controls enter regressions as dummy-coded sets (for multi-category factors) and continuous covariates (for Likert-type controls), allowing us to partial out background differences when estimating links central to $\mathbf{H_1}/\mathbf{H_2}$.

All attitudinal items use harmonized five-point Likert scales with fully labeled anchors, and numeric direction is standardized so that higher values always indicate “more” of the construct (more willingness, more market fit, more stigma, more design acceptance, more concern). The single reverse-polarity item (“a tech-like appearance would make me feel more confident”) is reverse-scored before aggregation so that higher values consistently indicate more stigma; other items are aligned in the ‘higher = more’ direction at coding time. For multi-item constructs (Willingness to Wear, Market Fit, Stigma, Design Acceptance) respondent-level scores are calculated as means using a ≥50% non-missing rule. Single-item variables (privacy concern, preference for manual vs. automation, daily stress) are analyzed as observed. A brief item-level coherence check (item–total relations) and, if warranted, a minimal exploratory factor check will be reported in the results to show that stigma and design items behave as theorized; full psychometric validation is beyond scope.

To situate the measurement choices, the instrument’s scales were derived from established theory and empirical evidence: Item content for technology-acceptance determinants followed established frameworks (TAM/UTAUT/UTAUT2/HBM) and predictors reported for health/wearable contexts; social perception/stigma items were informed by research on visible health devices and stigma (e.g., Li et al., 2022), and comfort/wearability reflected ergonomic findings for head/ear form factors (e.g., Radüntz & Meffert, 2019).

3.4 Survey design

The survey instrument was purpose-built to generate reliable, comparable evidence on user acceptance of a visible, behind-the-ear closed-loop wearable (HRV detection + tVNS) with an Apple-like minimalist, modern, timeless design. A cross-sectional online format was selected to reach a heterogeneous sample within the available timeframe and to maximize standardization of administration. The survey was implemented in Qualtrics with mobile-optimized layout, a progress indicator, page breaks between logical sections to reduce fatigue, and direct CSV export for R. The first page presented a short, neutral scenario describing Neuropods (form factor, HRV detection, non-invasive stimulation, purpose), followed by informed consent (purpose, voluntary participation, 18+ eligibility, anonymity, right to withdraw). Participation was anonymous; see Section 3.6 for consent and GDPR details.

The instrument contained 32 items (excluding consent), organized into blocks aligned with the constructs for **RQ_1/H_1** and **RQ_2/H_2**. Content, anchors, coding direction, and composite rules are specified in Section 3.3. Counting convention: the 32 items comprise 8 willingness items; 6 stigma items (including the reverse-scored tech-appearance item); 4 design/comfort items (with the weight item collected but excluded from the Design Acceptance composite); 7 market-fit items; 2 privacy/automation items; 2 adoption items; and 1 item each for familiarity with stress wearables, wearable-use frequency, and average daily stress. Screeners (Q1–Q2), the multi-select usage checklist (Q3), and demographics (Q13–Q16) are not part of the item count.

3.5 Analytical methodology

The analysis follows a five-stage, fully reproducible pipeline in R and is explicitly mapped to **H_1** (situational willingness to wear a visible behind-the-ear device) and **H_2** (perceived market fit of a tracking and stimulation device versus tracking-only). No results are reported here; this section documents procedures only.

Assumptions

Independence of observations was assumed at the respondent level (one person = one record). A simple random sampling design was not assumed (convenience sampling). Inference therefore relied on HC3-robust standard errors; heteroskedasticity tests and residual diagnostics were reported.

(1) Setup and cleaning

The Qualtrics CSV is imported with read_csv(). If the first two rows contain Qualtrics header artifacts (pattern check on *StartDate*/*EndDate*), they are removed; only Finished cases are retained. Submissions with implausibly short durations (<120s) are excluded. Entries with missing duration are retained. Empty strings are converted to NA, fully empty columns are dropped. Rows with >10% missing across non-meta survey items are removed. Exact duplicate rows across all columns are removed; then the latest record per *ResponseId* is kept based on a parsed timestamp (*RecordedDate* > *EndDate* > *StartDate*). Within 10-minute IP clusters, the last submission is retained. Binary indicators are normalized to 0/1. All Likert items are recoded to 1–5 with "higher = more" semantics (more agreement, willingness, familiarity, frequency, stress). The positive tech-confidence stigma item is reverse-scored so that higher values reflect more stigma and is included in the stigma composite. Respondent-level *M* composites use these item-count thresholds: Willingness overall (≥4/8), Work (≥1/2), Private-social (≥3/6); Market Fit (≥4/7); Stigma (≥3/6, including the reversed tech-confidence item); Design Acceptance (core, ≥2/3). Design Acceptance uses the 3-item core (minimalism, comfort, professional suitability); the weight-effect item is excluded. A hard acceptance indicator is defined for proportions testing (*accept_overall* = 1 if overall willingness ≥4, else 0/NA). Single-item variables are recoded to 1–5 where applicable (*privacy_concern*, *manual_vs_automation*, *stress_level*). Sanity checks confirm composite ranges [1,5]; the stigma block additionally records the non-missing item count (*stigma_n*).

(2) Descriptive and exploratory analysis

Sample composition is summarized by demographics (age group, gender, education, employment) and ownership status (current wearable owner vs. non-owner) as counts and percentages. For each demographic dimension and for ownership status, compact split tables report, per category/group: *n*, Has wearable % (where applicable), Willingness (overall, *M*), Accept ≥4%, Stigma (*M*), Design Acceptance (*M*), and Market Fit (*M*). Missing labels are retained as "NA/Unknown"; these summaries provide descriptive context only and are not used for inference.

No inferential tests across demographic categories are conducted; values are descriptive only. Exception: the pre-specified ownership contrast (current wearable owner vs. non-owner) is tested as outlined in stage (3).

Continuous/Likert constructs are summarized by *N*, *M* and *SD* (with additional plots showing 95% CIs where relevant). 95% CIs are shown for Market Fit in plots and for proportions in acceptance analyses.

A GGpairs plot reports Pearson correlations among four core variables (willingness overall, stigma, design acceptance, market fit).

Exploratory visuals include: scatter-with-smoother for willingness vs. stigma (faceted: Work/Private/Overall), distribution and *M*±95% CI plots for Market Fit (overall and by ownership), and acceptance rates (≥4) by stigma tertiles and wearable ownership.

(3) Hypothesis tests

H_{1a}/H_{1b} were evaluated using two-sided alternatives at α = 0.05 (soft majority: $p_{\text{soft}} > 0.50$; clear majority: $p_{\text{hard}} > 0.50$, with $\text{accept\_overall} = 1\{\text{will\_overall\_score} \geq 4\}$).

$$\widehat{p_{\text{soft}}} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\,\{\text{will\_overall\_score}_{\text{i}} > 3\}$$

$$\widehat{p_{\text{hard}}} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\,\{\text{will\_overall\_score}_{\text{i}} \geq 4\}$$

H_2 was tested with a one-sample t-test of *MF_score* against the neutral midpoint (= 3) using a two-sided alternative at α = 0.05.

$$t = \frac{\overline{\text{MF\_score}} - 3}{s_{\text{MF\_score}}/\sqrt{N}} \quad \text{with df} = N - 1$$

Two-sided p-values and 95% confidence intervals are reported. Planned subgroup contrasts (owners vs. non-owners) use two-sample tests of proportions without continuity correction (two-sided).

(4) Regression models

Factor setup: gender, age_group, education, employment are converted to factors with an explicit "Unknown" level (fct_explicit_na) and fixed reference categories via fct_relevel (Male, 25–34, Bachelor, Employed).

Demographic factors are included only in the “+Demographics” specifications (M1, M2), not in the focused models (M1.1, M2.1).

Estimated models (reported):

M1.1 (focused): $\text{will\_overall\_score}_\text{i} = \beta_0 + \beta_1\,\text{stigma\_score}_\text{i} + \beta_2\,\text{design\_accept\_score}_\text{i} + \beta_3\,\text{has\_wearable}_\text{i} + \beta_4\,\text{stress\_level}_\text{i} + \varepsilon_i$

M2.1 (focused): $\text{MF\_score}_\text{i} = \gamma_0 + \gamma_1\,\text{will\_overall\_score}_\text{i} + \gamma_2\,\text{design\_accept\_score}_\text{i} + \gamma_3\,\text{has\_wearable}_\text{i} + \gamma_4\,\text{stigma\_score}_\text{i} + u_i$

M1 (+ demographics): same as M1.1 plus gender_f + age_group_f + education_f + employment_f

M2 (+ demographics): same as M2.1 plus gender_f + age_group_f + education_f + employment_f

All models are estimated by OLS and reported with HC3 heteroskedasticity-robust standard errors.

(5) Diagnostics and sensitivity

Standard diagnostic panels (plot(lm, which = c(1,2,3,5))) are run for the focused models (m1.1, m2.1): Residuals vs Fitted, Normal Q-Q, Scale-Location, Residuals vs Leverage.

Influential points: Cook's distance is computed; a **4/n threshold** is applied, and indices above threshold plus the top 10 values are listed.

Collinearity checks: VIF and predictor correlations are reported for the model covariates.

Homoskedasticity: Breusch–Pagan tests are run; **HC3-robust *SE*** are reported regardless.

Normality: Q-Q plots of standardized residuals and Shapiro–Wilk tests are executed for m1.1 and m2.1.

Stages (1)–(2) establish data integrity and context; stage (3) provides construct-level tests of $\mathbf{H_1}$ (majority willingness) and $\mathbf{H_2}$ (market-fit above neutrality); stage (4) links the regression set-up (focused and demography-adjusted) to $\mathbf{H_1}/\mathbf{H_2}$; stage (5) documents diagnostics underpinning credible inference.

3.6 Ethical considerations

This study follows the research ethics policy of Católica Lisbon School of Business & Economics and internationally accepted principles of respect, beneficence, and justice, and is implemented to be minimal risk. Participation is voluntary and limited to adults (18+); the Qualtrics landing page presents plain-language informed consent (purpose, procedures, expected duration, risks/benefits, eligibility, right to refuse/withdraw at any time without penalty, data use, contacts for questions/withdrawal). The survey concerns perceptions and acceptance of a hypothetical visible, behind-the-ear stress-reduction wearable and does not collect sensitive medical data or ask for clinical histories; there is no deception. The study applies data minimization under the GDPR: the legal basis is consent (Art. 6(1)(a)); no special-category data are processed (Art. 9 not engaged); no direct identifiers (name, email, phone, address) are collected; IP addresses are present in the raw Qualtrics export and are used only for short-window deduplication (10-minute clusters). They are not used for analysis beyond deduplication; only aggregate results are reported. Data are hosted in Qualtrics with transport and at-rest encryption, then exported to R for analysis; the export is pseudonymized, access is restricted to the author and academic supervisor, and data are not shared with third parties. Participants may skip non-essential items and can request erasure of their response using the contact provided on the consent page until the dataset is irreversibly anonymized for analysis. To further protect participants, inclusion/exclusion criteria and data-quality rules are pre-specified; results are analyzed and presented transparently with acknowledgement of limitations, and no claims of clinical efficacy are made. The anonymized dataset and code will be retained only for the period required for grading and examination and then securely deleted in line with faculty policy, while the thesis may include summary tables and figures that cannot identify any individual respondent.

3.7 Summary of methodology

The analysis follows a transparent, staged pipeline in R mapped to $\mathbf{H_1}$ (situational willingness to wear) and $\mathbf{H_2}$ (perceived market fit of a tracking+stimulation device). After importing the Qualtrics export, header rows and non-consenting or incomplete cases are removed, implausibly short durations (<120 s) are excluded, duplicates are deduplicated (including 10-minute IP clusters), Likert items are harmonized to 1–5 with consistent direction, reverse-polarity items are aligned, and composite means for Willingness (overall/work/private), Stigma (including the reverse-coded tech-appearance item), Design Acceptance (3-item core, excluding weight), and Market Fit (7 items) are computed with a ≥50% non-missing rule.

Descriptives cover sample composition and core constructs; ownership splits are shown for key scores; a GGpairs plot previews correlations among Willingness, Stigma, Design Acceptance and Market Fit.

Hypothesis tests: for $\mathbf{H_1}$, two one-sample proportion tests with two-sided alternatives (majority thresholds >0.50 / ≥4 retained for interpretation); for $\mathbf{H_2}$, a one-sample t-test against the neutral midpoint (= 3) with a two-sided alternative. Planned binary contrasts compare ownership groups via two-sample tests of proportions without continuity correction (two-sided).

Multivariate evidence: two OLS models are estimated with HC3-robust SEs — M1.1 (Willingness ~ Stigma + Design + Ownership + Stress) and M2.1 (Market Fit ~ Willingness + Design + Ownership + Stigma); +Demographics versions (M1/M2) add gender, age group, education and employment.

Diagnostics include standard LM panels, Cook's distance (with 4/*n* threshold), VIF and predictor correlations, Breusch–Pagan tests, and QQ/Shapiro–Wilk on standardized residuals for the focused models. Diagnostics were conducted for the two focused OLS models (m1.1 and m2.1) as the primary inference specifications; the +Demographics variants (M1/M2) were estimated as robustness checks and were not separately diagnosed beyond spot checks. Substantive conclusions were unchanged.

4 Results

4.1 Descriptive and exploratory analysis

Sample and measurement

Table 4.1.1 Sample characteristics (N = 148): counts and percentages by gender, age group, education, and employment

Percentages are within-dimension shares; totals may not sum to 100% due to rounding. Missing values are labeled "NA/Unknown". Source: Author's analysis (R).

Table: Sample characteristics (counts and %). Sample characteristics by gender, age group, education and employment (counts and %). Values sum to N = 148; missing shown as 'NA/Unknown' where applicable.

Dimension	Category	n	%
Gender	Female	68	45.9
	Male	75	50.7
	Other/NA	5	3.4
Age group	18–24	20	13.5
	25–34	59	39.9
	35–44	29	19.6
	45–54	20	13.5
	55–64	16	10.8
	65+	4	2.7
Education	Bachelor	67	45.3
	Doctorate	8	5.4
	High school	22	14.9
	Master	48	32.4
	Other	3	2.0
Employment	Employed	106	71.6
	Retired	5	3.4
	Self-employed	18	12.2
	Student	14	9.5
	Unemployed	5	3.4

After cleaning, the analytic dataset comprised $N = 148$ respondents. All attitudinal items were harmonized to $1 - 5$ Likert scales (higher = more). Multi-item constructs were computed as respondent-level means with a $\geq 50\%$ non-missing rule; single-item indicators were analyzed as observed. Full variable statistics appear in Tables 4.1–4.3 and the Appendix.

Core constructs (overview)

Table 4.1.2 Core construct scores (1–5): overall (M, SD, n) and means by ownership (Has wearable / No wearable)

All scales are 1–5 (higher = more). Multi-item scores are respondent-level means (≥50% non-missing). Design Acceptance excludes the weight item; Willingness – Overall requires ≥4/8 items. Source: Author's analysis (R).

Table: Table: Core Scores (1–5) – Overall (M, SD, n) and means by ownership (HasNoWearable / HasWearable)

Variable	n	M	SD	HasNoWearable	HasWearable
Willingness – Work/Formal	148	3.50	1.19	3.07	3.71
Willingness – Private/Social	148	3.84	0.97	3.41	4.06
Stigma	148	2.79	0.69	2.81	2.78
Design Acceptance	148	3.85	0.68	3.64	3.95
Market Fit	148	3.87	0.74	3.56	4.03
Willingness – Overall	148	3.76	0.98	3.33	3.97

Willingness to wear sits above the scale midpoint overall ($M = 3.76, SD = 0.98$) and is context-sensitive: lower in work/formal settings ($M = 3.50, SD = 1.19$) than in private/social contexts (M = 3.84, SD = 0.97). Item means range from 3.22 (formal meetings) to 4.15 (sports); public-facing settings cluster around 3.5–4.1. Using the pre-specified threshold ≥4, the acceptance rate on the overall index is 48% (Table 4.1.3).
The stigma/visibility composite lies below neutrality (M = 2.79, SD = 0.69). The reverse-scored tech-appearance item is higher (M = 3.46), while the other stigma indicators fall between 2.54–2.73. Design acceptance is high (M = 3.85, SD = 0.68): the minimalist "Apple-like" aesthetic scores strongest (M = 4.14), with long-wear comfort (M = 3.71) and professional suitability (M = 3.72) rated solidly. Perceived market fit is clearly above midpoint (M = 3.87, SD = 0.74); the highest items are "choose if clinically validated" (M = 4.17) and "prefer a single combination device" (M = 4.03).

Context and experience

Wearable ownership is 65.3% (Table 4.1.2). Additional context indicators provide orientation: privacy concern is moderate (M = 3.44), manual-vs-automation leans toward automation (M = 2.79), 12-month purchase consideration is slightly positive (M = 3.41), as is recommendation (M = 3.53). Daily stress sits near the midpoint (M = 3.02).

Ownership—first look at RQ_1/RQ_2

Table 4.1.3 Acceptance at thresholds (>3; ≥4): overall and by ownership (%, 95% CI)

Soft majority: share with will_overall_score >3; clear majority: accept_overall = 1{will_overall_score ≥4}. CIs are two-sided binomial; totals based on N = 148 (group Ns shown in table). Source: Author's analysis (R).

Table: Ownership split: key scores (compact)

Ownership	n	Willingness Overall (M)	Accept ≥4 %	Stigma (M)	Design Acceptance (M)	Market Fit (M)
Has wearable	96	3.97	58.3	2.78	3.95	4.03
No wearable	51	3.33	27.5	2.81	3.64	3.56
NA/Unknown	1	4.86	100.0	3.00	5.00	4.86

Descriptively, owners report higher willingness (M = 3.97 vs. 3.33) and market fit (M = 4.03 vs. 3.56) than non-owners, with similar stigma (M = 2.78 vs. 2.81). Consistent with this pattern, acceptance (≥4) is 58.3% among owners versus 27.5% among non-owners (Table 4.3). These descriptive gaps motivate the pre- specified inferential tests in Sections 4.2–4.3.

Exploratory overview

Visual inspection of the exploratory panels suggests coherent structure among the core constructs (Appendix Figure A.1). Willingness to wear declines as perceived stigma increases, with an approximately linear negative trend; conversely, higher design acceptance aligns with higher willingness (Pearson r ≈ −.42 and .52, respectively; see Appendix Figure A.1). Distributions show no material floor or ceiling effects: willingness and design acceptance are roughly symmetric, whereas market fit is mildly right-skewed with a M above the neutral point. Ownership appears to shift the distributions upward for willingness and market fit, consistent with the descriptive gaps reported in Tables 4.2–4.3. These patterns are descriptive and motivate the pre-specified inferential tests reported in Sections 4.2–4.3.

4.2 Hypothesis tests

All tests follow the pre-specified plan (Section 3.5) with two-sided p-values at $\alpha = .05$. Where proportions are analyzed, one-sample and two-sample tests are reported without continuity correction. Visual summaries accompany the tests as compact panels:

Figure 4.2.1 Willingness vs. stigma by context (Overall, Private/Social, Work)

Points = individual respondents; blue line = linear fit with 95% CI (shaded). Axes scaled 1–5 (higher = more). N = 148. Source: Author's analysis (R).

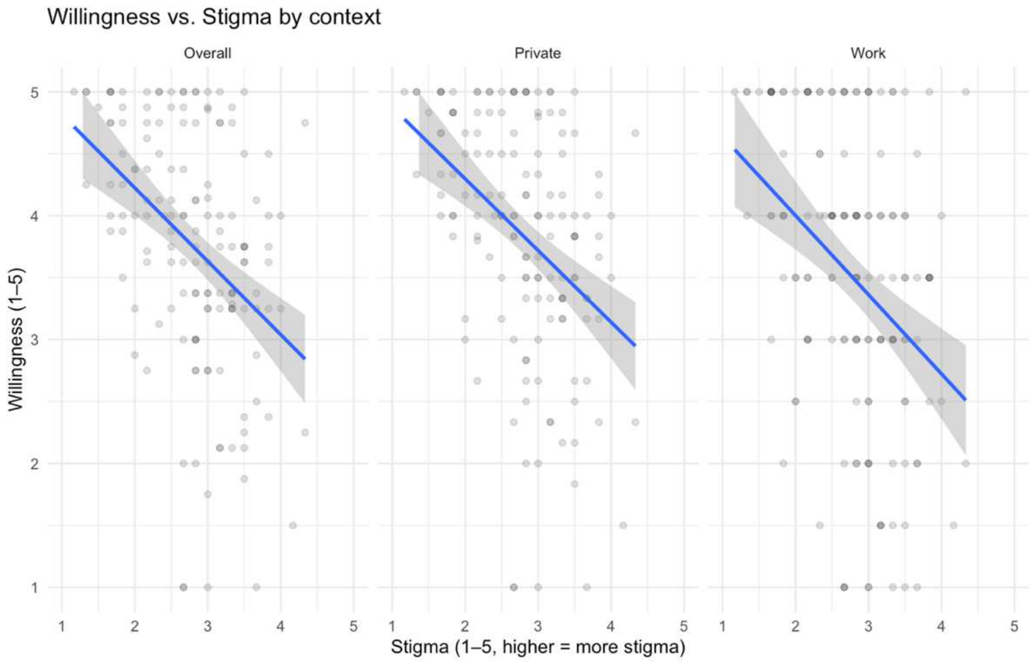


Figure 4.2.2 Acceptance (≥4) by stigma level and wearable ownership

Points show the share of respondents with overall willingness ≥4; whiskers = 95% binomial CIs. Dashed line marks the 50% majority threshold. "n=" labels are group sizes. Stigma levels are tertiles of the stigma composite. N = 148. Source: Author's analysis (R).

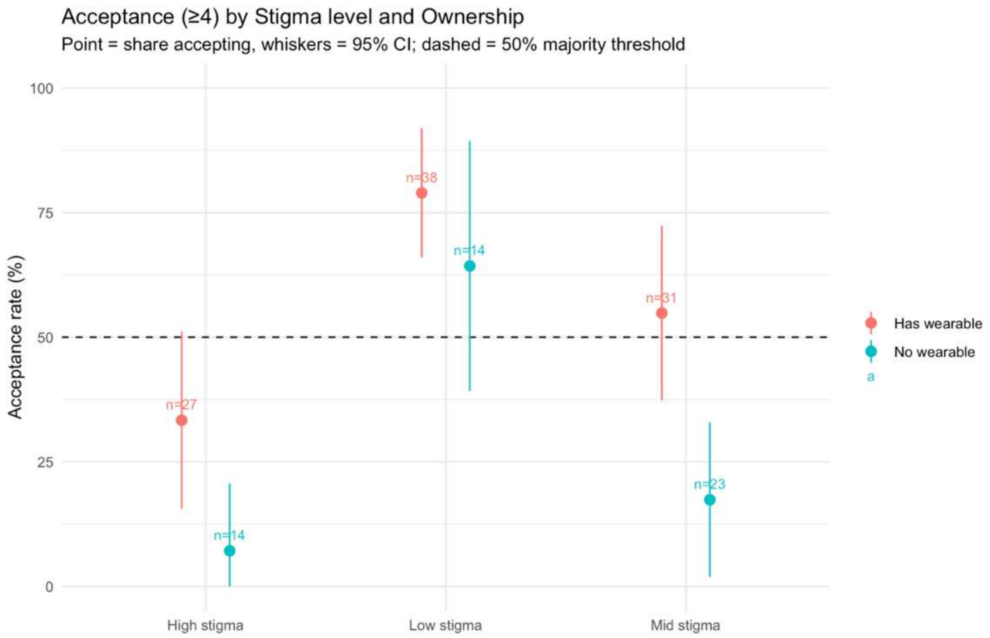


Figure 4.2.3 Market-fit (1–5) distribution vs. neutral point (3)

Violin + box plot; dot marks the mean. Dashed vertical line at the neutral midpoint (= 3). N = 148. Source: Author's analysis (R).

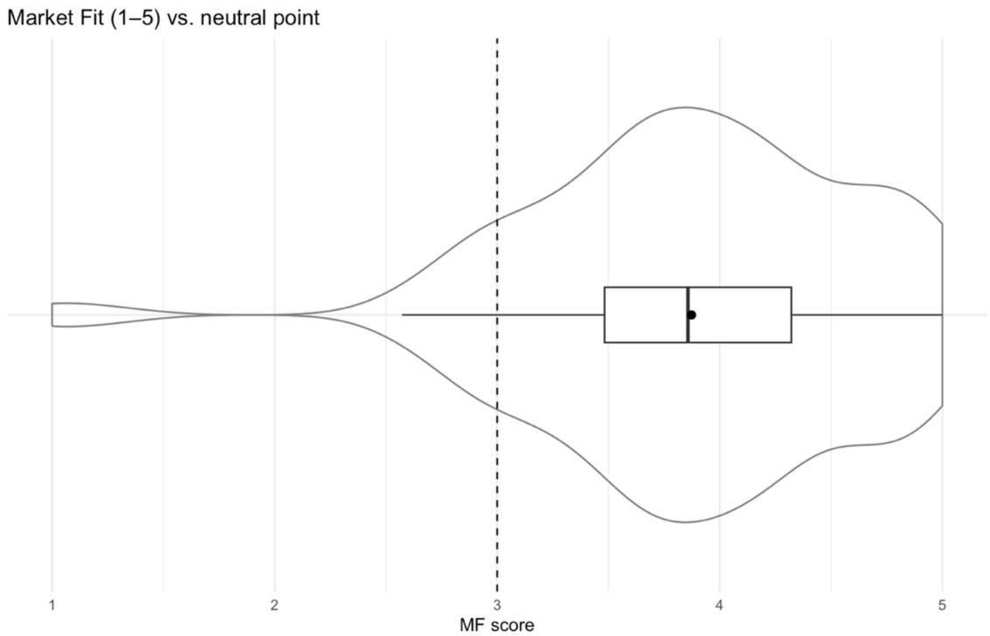
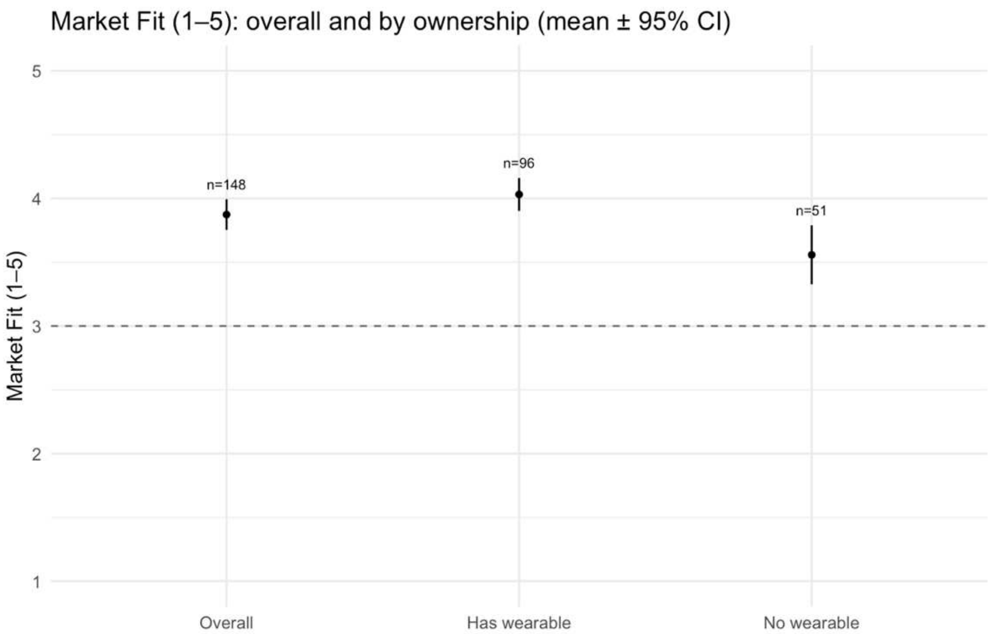


Figure 4.2.4 Market-fit (1–5): overall and by ownership (mean ± 95% CI)

Points = means with 95% CIs; dashed line = neutral midpoint (= 3). Both groups sit above 3 (descriptive). N = 148 (Has wearable: n = 96; No wearable: n = 51). Source: Author's analysis (R).



A correlations/distributions overview is provided for reference in Appendix Figure A.1.

4.2.1 H_1 — Situational willingness to wear a visible behind-the-ear device

The analysis tests whether a majority of respondents exceed (i) a positive threshold (>3 on the 1–5 scale) and (ii) a clear threshold (≥4).

- **Majority (>3):** One-sample proportion test vs 0.50: proportion = 0.797, 95% CI [0.725, 0.854], $\chi^2(1) = 52.324$, $p = 4.705 \times 10^{-13}$. Thus, a soft majority comfortably exceeds >3. Accordingly, H_0: $p_{soft} = 0.50$ is rejected in favor of the two-sided alterntive at $\alpha = .05$.
- **Majority (≥4):** One-sample proportion test vs 0.50: proportion = 0.480, 95% CI [0.401, 0.560], $\chi^2(1) = 0.243$, $p = .622$. The clear-majority criterion is not met. Accordingly, H_0: $p_{hard} = 0.50$ is not rejected at $\alpha = .05$.

Planned ownership contrast (pre-registered)

Dichotomizing acceptance and comparing current wearable owners with non-owners:

- **Positive threshold (>3):** non-owners = 0.667 vs. owners = 0.865; $\chi^2(1) = 8.032$, p = .0046. The gap favors owners by Δ = +0.198 (95% CI [+0.052, +0.344]); equivalently, the CI for (non-owners − owners) is [−0.344, −0.052]. Thus, H_0: $\Delta p = 0$ is rejected (two-sample test of proportions, two-sided) at α = .05.
- **Clear threshold (≥4):** non-owners = 0.275 vs. owners = 0.583; $\chi^2(1) = 12.735$, p = .00036. The owner advantage is Δ = +0.309 (95% CI [+0.152, +0.466]). Thus, H_0: $\Delta p = 0$ is rejected (two-sample test of proportions, two-sided) at α = .05.

Figure links

Figure 4.2.1 shows a monotonic negative relation between stigma and willingness across contexts (strongest slope in work/formal settings). Figure 4.2.2 visualizes acceptance rates (points with binomial 95% CIs) by stigma tertiles and ownership; the dashed line marks the 50% majority threshold.

4.2.2 H_2 — Perceived market fit of a combination (tracking + stimulation) device

One-sample t-test (two-sided) against the neutral midpoint (= 3): M = 3.873, 95% CI [3.753, 3.993], $t(147) = 14.329$, p $<2.2 \times 10^{-16}$. Market fit is clearly above neutrality. Accordingly, H_0: $\mu_{MF} = 3$ is rejected (two-sided) at α = .05.

Figure links

Figure 4.2.3 displays the distribution relative to the neutral line at 3 with *M* ± 95% CI; Figure 4.2.4 shows means (± 95% CI) by ownership—both groups sit above 3, with a higher *M* for owners (descriptive; no additional test was pre-specified).

Brief summary vis-à-vis hypotheses

— **H_1:** Supported for the **soft majority** (>3), **not** supported for the **clear majority** (≥4). Owners are significantly more accepting than non-owners at both thresholds. (Decision: reject H_0 for $p_{soft} = 0.50$; fail to reject H_0 for $p_{hard} = 0.50$, α = .05).

— **H_2:** Supported; perceived market fit exceeds the neutral point. (Decision: reject H_0: $\mu_{MF} = 3$ at α = .05).

These results motivate the multivariate models in Section 4.3, which assess whether the $\mathbf{H_1/H_2}$ patterns persist when jointly accounting for stigma, design acceptance, ownership, and controls.

4.3 Regression models

Four OLS specifications were estimated according to the pre-specified plan (Section 3.5). Models (1)–(2) explain Willingness to wear; Models (3)–(4) explain Perceived market fit. Coefficients are unstandardized; HC3-robust standard errors are reported in parentheses. Reference categories: male (gender), 25–34 (age), Bachelor (education), employed (employment). Model (1)/(3) add demographics; Model (2)/(4) are focused specifications. Full results appear in Table 4.3.1.

Table 4.3.1 Determinants of Willingness and Market Fit (OLS with HC3-robust standard errors)

Unstandardized OLS coefficients; HC3-robust standard errors in parentheses. Dependent variables: columns (1)–(2) Willingness – Overall (1–5); columns (3)–(4) Market Fit (1–5). Predictors are 1–5 composites unless stated; has_wearable coded 1 = current owner. Reference categories: male (gender), 25–34 (age), Bachelor (education), employed (employment). N, R², adjusted R², and F-tests shown at the bottom. Significance: p <.10, p <.05, p <.01. All composites computed with a ≥50% non-missing rule; higher values = "more" of the construct. Source: Author's analysis (R).

Determinants of Willingness and Market Fit

	Dependent variable:			
	will_overall_score		MF_score	
	(1)	(2)	(3)	(4)
will_overall_score			0.179**	0.147**
			(0.072)	(0.068)
stigma_score	-0.577***	-0.517***	-0.031	-0.094
	(0.097)	(0.091)	(0.088)	(0.080)
design_accept_score	0.581***	0.598***	0.372***	0.406***
	(0.094)	(0.095)	(0.087)	(0.087)
has_wearable	0.280*	0.430***	0.261**	0.248**
	(0.155)	(0.134)	(0.125)	(0.111)
stress_level	0.018	0.016		
	(0.078)	(0.076)		
gender_fFemale	0.091		-0.149	
	(0.128)		(0.104)	
gender_fOther	0.826		0.290	
	(0.767)		(0.624)	
gender_fUnknown	0.211		-0.261	
	(0.382)		(0.310)	
age_group_f18-24	0.355		-0.148	
	(0.224)		(0.182)	
age_group_f35-44	-0.159		0.280*	
	(0.181)		(0.142)	
age_group_f45-54	-0.256		0.143	
	(0.207)		(0.168)	
age_group_f55-64	-0.488**		0.484***	
	(0.224)		(0.185)	
age_group_f65+	-0.121		0.669	
	(0.527)		(0.427)	
education_fDoctorate	-0.297		0.032	
	(0.297)		(0.240)	
education_fHigh school	0.063		-0.147	
	(0.197)		(0.156)	
education_fMaster	-0.233		-0.209*	
	(0.147)		(0.120)	
education_fOther	-0.290		0.550	
	(0.449)		(0.364)	
employment_fRetired	-0.174		-0.323	
	(0.469)		(0.376)	
employment_fSelf-employed	-0.431**		-0.297*	
	(0.205)		(0.169)	
employment_fStudent	-0.541**		0.556***	
	(0.246)		(0.202)	
employment_fUnemployed	-0.205		0.121	
	(0.357)		(0.289)	
Constant	3.107***	2.555***	1.696***	1.855***
	(0.551)	(0.521)	(0.459)	(0.416)
Observations	146	146	147	147
R2	0.540	0.435	0.466	0.353
Adjusted R2	0.466	0.419	0.382	0.335
Residual Std. Error	0.717 (df = 125)	0.748 (df = 141)	0.581 (df = 126)	0.603 (df = 142)
F Statistic	7.334*** (df = 20; 125)	27.173*** (df = 4; 141)	5.508*** (df = 20; 126)	19.362*** (df = 4; 142)
Note:				*p<0.1; **p<0.05; ***p<0.01

$$(1)\ \boldsymbol{Will}_{\boldsymbol{overall}_{\boldsymbol{score}_i}} = \beta 0 + \beta 1\, Stigma_i + \beta 2\, DesignAcceptance_i + \beta 3\, HasWearable_i + \beta 4\, StressLevel_i + \beta 5\, Gender_i + \beta 6\, AgeGroups_i + \beta 7\, Education_i + \beta 8\, Employment_i + \varepsilon_i$$

$$(2)\ \boldsymbol{Will}_{\boldsymbol{overall}_{\boldsymbol{score}_i}} = \beta 0 + \beta 1\, Stigma_i + \beta 2\, DesignAcceptance_i + \beta 3\, HasWearable_i + \varepsilon_i$$

$$(3)\ \boldsymbol{MF}_{\boldsymbol{score}_i} = \beta 0 + \beta 1\, Will_{overall_{score_i}} + \beta 2\, Stigma_i + \beta 3\, DesignAcceptance_i + \beta 4\, HasWearable_i + \beta 5\, Gender_i + \beta 6\, AgeGroups_i + \beta 7\, Education_i + \beta 8\, Employment_i + \varepsilon_i$$

$$(4)\ \boldsymbol{MF}_{\boldsymbol{score}_i} = \beta 0 + \beta 1\, Will_{overall_{score_i}} + \beta 2\, Stigma_i + \beta 3\, DesignAcceptance_i + \beta 4\, HasWearable_i + \varepsilon_i$$

Willingness to wear (RQ$_1$)

Model (1) with controls (N = 146, R^2 = .540; adj. R^2 = .466) shows a strong negative association of **stigma** with **willingness** (β = −0.577, ***), and a positive association of **design acceptance** (β = 0.581, ***). **Current ownership** is also positive (β = 0.280, *). Stress and gender are not significant.

Among demographics, **age 55–64** *(*β = *−0.488, **)* and being **self-employed** *(*β = *−0.431, *)* or a **student** *(*β = *−0.541, **)* are lower than the **employed** reference group.

The focused Model (2) *(N = 146, R^2 = .435;* adj. *R^2 = .419)* replicates the core pattern with virtually unchanged magnitudes—**stigma** −0.517, **design** +0.598—and a larger **ownership** coefficient (+0.430).

Interpreting magnitudes, a one-point increase in **stigma** corresponds to roughly a 0.5–0.6 point lower **willingness** on the 1–5 scale, while a one-point increase in **design acceptance** corresponds to a ≈ 0.6 point higher **willingness**.

Perceived Market Fit (RQ$_2$)

Model (3) with controls (N = 147, R^2 = .466; adj. R^2 = .382) indicates that **willingness** is positively associated with **market fit** (β = 0.179, **), as is **design acceptance** (β = 0.372, ***) and **ownership** (β = 0.261, **). **Stigma** is small and not significant (β = −0.031, n.s.).

Among controls, **age 55–64** is higher (β = 0.484, **), **Master's education** is lower (β = −0.209, *), and **student** employment is higher (β = 0.556, **).

The focused Model (4) (N = 147, R^2 = .353; adj. R^2 = .335) confirms the pattern: **willingness** +0.147 (**),* **design** *+0.406*, **ownership** +0.248 (**), with **stigma** remaining non-significant (β = −0.094).

Model fit and robustness

All four models are statistically significant overall; accordingly, we reject H_0 (all slope coefficients = 0) for each model at $\alpha = .05$ (see F-tests in Table 4.3.1). Results are consistent across focused and full specifications. Inference relies on HC3-robust standard errors; diagnostics and sensitivity checks are reported in Section 4.4.

4.4 Diagnostics and sensitivity

Model assumptions were evaluated for the focused OLS specifications—m1.1 (DV: Willingness overall) and m2.1 (DV: Market Fit)—using the standard MLR1–MLR6 checks. Inference for the focused OLS models is reported with HC3-robust standard errors; substantive conclusions are unchanged relative to conventional SEs. Linearity and functional form (MLR1) were inspected via *Residuals vs. Fitted* plots for both models; the loess lines were close to horizontal with only slight curvature at the extremes, indicating no material non-linearity. Influential observations (MLR2) were screened with Cook's distance; independence is assumed at the respondent level (one person = one record); the sample is convenience-based. 10 observations in m1.1 and 8 in m2.1 exceeded the conventional $4/n$ threshold (largest Cook's D ≈ 0.081 in m1.1; ≈ 0.143 in m2.1). Sensitivity re-estimation excluding those cases left coefficient signs and significance patterns unchanged and produced similar R^2, suggesting no single case drives the results. Multicollinearity (MLR3) was assessed with VIF and pairwise predictor correlations. VIFs were low throughout—m1.1: 1.03–1.08; m2.1: 1.13–1.76—well below the conservative threshold of 5. Predictor correlations were modest (e.g., Willingness–Design Acceptance ≈ .52; Willingness–Stigma ≈ -.42), indicating adequate separability of constructs. The zero-conditional-mean assumption (MLR4) showed no systematic structure in the residuals versus fitted plots, supporting correct *M* specification given the included controls.

Figure 4.4.1 OLS diagnostic panels for model m1.1 (DV: Willingness overall)

Panels show Residuals vs Fitted (linearity), Normal Q–Q (normality), Scale–Location (homoskedasticity), and Residuals vs Leverage with Cook's distance contours (influence). Loess smooths are shown; labeled points mark the most extreme Cook's-D cases. N = 146. Source: Author's analysis (R).

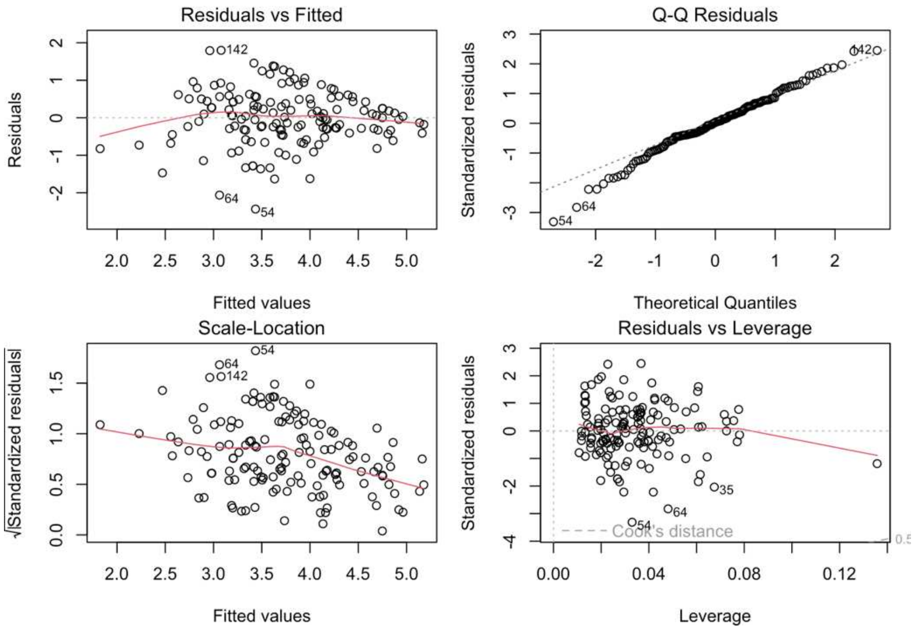
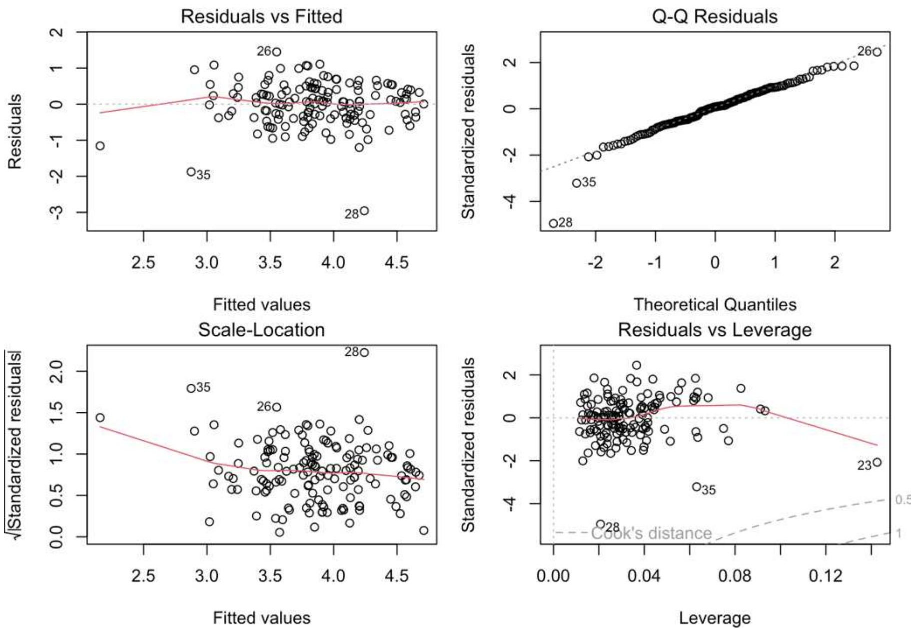


Figure 4.4.2 OLS diagnostic panels for model m2.1 (DV: Market Fit)

Panels show Residuals vs Fitted (linearity), Normal Q–Q (normality), Scale–Location (homoskedasticity), and Residuals vs Leverage with Cook's distance contours (influence). Loess smooths are shown; labeled points mark the most extreme Cook's-D cases. N = 147. Source: Author's analysis (R).



Homoskedasticity (MLR5) was examined via Scale–Location plots and Breusch–Pagan (BP) tests. Evidence of heteroskedasticity appears for m1.1 (BP = 13.316, p = .0098), but not for m2.1 (BP = 1.967, p = .742); therefore, HC3-robust standard errors are reported for inference. Normality of residuals (MLR6) was screened with Q–Q plots and Shapiro–Wilk (W) tests on standardized residuals. For m1.1 the test did not reject normality (W = 0.989, p = .301), while for m2.1 tail deviations led to rejection (W = 0.955, p <.001); the Q–Q plots show that non-normality is confined to the extremes. Because OLS coefficients remain unbiased under non-normality and HC3 controls size distortions, the main inferences are robust. Additional sensitivity checks—HC3-robust re-estimation, and refits excluding the 8–10 high-Cook's-D cases—left coefficient signs and significance patterns unchanged, with only marginal changes in adjusted R^2.

Taken together, diagnostics indicate that (i) linearity and model specification are adequate, (ii) multicollinearity is negligible, (iii) a small number of moderately influential cases does not alter results, (iv) mild heteroskedasticity and non-normal tails are addressed by HC3-robust inference, and (v) the findings are firm to standard sensitivity analyses.

5 Discussion

5.1 Interpretation of quantitative findings

The results provide a consistent account of how respondents evaluate a visible, BTE stress-reduction wearable and the combined "tracking + stimulation" proposition. On the 1–5 scale, overall willingness to wear is above the neutral midpoint (*M* = 3.76, *SD* = 0.98; *N* = 148), yet it is clearly context-sensitive. Willingness is lower in work/formal settings (*M* = 3.50, *SD* = 1.19) than in private/social contexts (*M* = 3.84, *SD* = 0.97). At the item level, formal meetings mark the local minimum (*M* = 3.22), whereas sports (*M* = 4.15) and family (*M* = 4.09) are highest. This gradient is consistent with higher perceived social exposure in professional settings suppressing stated willingness relative to private domains.

The majority tests clarify this pattern. A large "soft" majority exceeds the positive threshold (>3): $\hat{p} = 0.797$, 95% CI [0.725; 0.854], $\chi^2(1) = 52.324$, $p \approx 4.7 \times 10^{-13}$. By contrast, the "clear" majority criterion (≥4) is not met: $\hat{p} = 0.480$, 95% CI [0.401; 0.560], $\chi^2(1) = 0.243$, *p*=0.622. Substantively, respondents are positively disposed toward a visible BTE device, but unambiguous "clear-accept" responses are not yet dominant—especially in more exposed contexts. Quantitatively, the *M* shortfall from the clear-accept benchmark (4.00) is 0.24 points. Given the focused OLS estimates for willingness, this gap is of plausible magnitude to close with modest shifts in perceptions: an average +0.40 increase on the design-acceptance scale (0.40 × 0.598 ≈ +0.24) or a −0.46 decrease in perceived stigma (0.46 × 0.517 ≈ +0.24), holding other covariates constant.

Ownership of any wearable consistently separates respondents. At the ≥4 threshold, owners show 58.3% acceptance versus 27.5% among non-owners ($\chi^2(1) = 12.735$, *p*=0.00036; Δ ≈ +0.309). For the >3 threshold, owners reach 86.5% versus 66.7% ($\chi^2(1) = 8.032$, *p*=0.0046; Δ ≈ +0.198). *M* levels mirror these contrasts (overall willingness: 3.97 for owners vs. 3.33 for non-owners; work/formal: 3.71 vs. 3.07; private/social: 4.06 vs. 3.41). Notably, stigma means are similar across ownership (2.78 vs. 2.81), while design acceptance is higher among owners (3.95 vs. 3.64). The focused regression confirms that ownership exerts a positive association with willingness independent of design and stigma (β_*has_wearable* = +0.430, ***), consistent with a familiarity/experience channel rather than simple differences in perceived visibility costs.

The determinants of willingness are sharply identified. In the focused model (HC3-robust *SE*), design acceptance is positively associated (β = +0.598, ***), stigma is negatively associated (β = −0.517, ***), and ownership is positively associated (β = +0.430, ***), while self-reported daily stress is not associated (β = +0.016, n.s.). Together with the observed context gradient, these coefficients indicate that the wearing decision is governed primarily by evaluations of design/comfort and anticipated social perception, not by momentary stress levels in this non-clinical sample. The bivariate structure is aligned with these partial effects (Pearson r: willingness–design ≈ +0.52; willingness–stigma ≈ −0.42).

Perceived market fit for the combined "tracking + stimulation" concept is clearly above neutral: M = 3.873, 95% CI [3.753; 3.993], $t(147) = 14.329, p < 2.2 \times 10^{-16}$. Both owners and non-owners evaluate the proposition above the midpoint (4.03 vs. 3.56, respectively). In the focused market-fit model (HC3), willingness (β = +0.147, *), design acceptance (β = +0.406, ***), and ownership (β = +0.248, **) are positively associated, while stigma is not significant once these variables are held constant (β = −0.094, n.s.). This conditional separation indicates that visibility-related concerns primarily depress declared willingness to wear; they do not materially diminish the perceived value of the integrated functionality when design evaluations and readiness to wear are accounted for. Consistency with the item profile—"choose if clinically validated" scoring highest (M = 4.17)—suggests that respondents anchor value judgments in perceived efficacy/credibility and design rather than visibility.

Descriptive heterogeneity provides orientation only. Women report higher overall willingness than men (M = 3.91 vs. 3.63) and a higher share at ≥4 (55.9% vs. 42.7). Market-fit means are above 3 across all age bands, with values around 4.0 in the 35–44 and 55–64 groups. No inferential claims are drawn for these splits; they are consistent with the primary role of design, stigma, and ownership identified above.

Taken together, the evidence answers the research questions with precision. For **RQ_1/H_1**, willingness to wear a visible BTE device is broadly positive but remains context-contingent; clear-majority endorsement is not yet achieved, and the shortfall is attributable to visibility costs in socially exposed settings. For **RQ_2/H_2**, the combined "tracking + stimulation" proposition exhibits convincing market fit above neutrality. The models quantify practical levers: incremental improvements in perceived design quality and incremental reductions in perceived stigma—each on the order of roughly half a response category—are, on average, sufficient to move the

M willingness into the ≥4 band, with existing wearable experience providing an additional, independent lift. No causal claims are made; interpretations are confined to the observed descriptive patterns and the reported associations.

5.2 Theoretical implications

As shown in the findings, willingness to wear a visible BTE device is above midpoint but does not reach the ≥4 clear-majority threshold; owners are more accepting (**RQ_1/H_1**). The tracking-plus-stimulation concept is above neutral on market fit, with focused models emphasizing design/wearability and ownership, and only a minimal added role for stigma once design and willingness are held constant (**RQ_2/H_2**).
The evidence positions acceptance of a visible, BTE stress-reduction wearable as a joint function of technology-evaluation and social-exposure mechanisms, linking established adoption models with the stigma literature on visible health devices. In terms of TAM and UTAUT, design acceptance operates as a performance/effort expectancy construct with unusually large practical weight: in the focused model for willingness, a one-point increase on the design scale is associated with a ~0.60-point increase in willingness ($\beta = +0.598$, HC3). This magnitude indicates that aesthetic/ergonomic fit is not merely a hygiene factor in this form factor; it is a primary determinant of stated use in everyday settings. At the same time, the visibility/stigma composite aligns with the social influence/image pathway in UTAUT and with perceived barriers in health-behavior models: higher perceived stigma is associated with a ~0.52-point decrease in willingness ($\beta = -0.517$, HC3), and willingness is systematically lower in work/formal contexts than in private/social settings. Together, these patterns substantiate a dual-path explanation in which device-internal qualities (comfort, aesthetics, professional suitability) and device-external social evaluations (anticipated judgment, self-consciousness) exert independent, additive associations with the intention to wear. As presented in the findings for RQ2/H2 (Sections 4.2.2 and 4.3), the tracking-plus-stimulation concept attains market fit above the neutral midpoint; in the focused models market fit is positively associated with willingness and design/wearability and with current ownership, while stigma adds little once design and willingness are controlled.

The separation between willingness to wear and perceived market fit refines this theoretical picture. Market fit is clearly above neutrality at the construct level ($M = 3.87$), and—conditional on design evaluations and ownership—stigma is not associated with market fit in the focused model ($\beta = -0.094$, n.s.), whereas willingness and design remain positive correlates. This conditional pattern is consistent with the view that visibility concerns primarily depress the behavioral intention to wear in public rather than the value assigned to the combined "tracking + stimulation" proposition. In other words, beliefs about comparative advantage and efficacy can be favorable even when public wearing remains hesitant; once design acceptance and readiness to wear are accounted for, stigma does not further erode perceived fit. For theory, this suggests a useful distinction between proposition valuation and public-use intention in visible health technologies; classical acceptance models that treat intention as a direct function of usefulness and ease may devalue the role of context-dependent image costs when devices are conspicuous.

Ownership of any wearable emerges as an enabling condition that aligns with the "experience/habit/facilitating conditions" family in UTAUT2. Owners report higher willingness and higher market-fit evaluations than non-owners, and ownership retains a positive association with both willingness ($\beta = +0.430$, HC3) and market fit ($\beta = +0.248$, HC3) after accounting for design and stigma. Theoretically, this supports the interpretation that prior experience with wearables shifts the baseline of adoption-relevant beliefs upward—plausibly by normalizing on-body technology and lowering perceived effort or social image risk—rather than merely reflecting differences in perceived visibility costs, which are similar across groups at the composite level.

The majority-threshold results add nuance to intention modeling. A large soft majority exceeds the positive threshold (>3), while a clear-majority criterion (≥4) is not met overall. This divergence indicates that, for visible devices, intention may cluster just above neutrality but remain sensitive to social context. In theoretical terms, it underscores that contextual exposure functions as a boundary condition on standard acceptance relationships: positive usefulness/effort beliefs translate into unambiguous endorsement only when anticipated image costs are sufficiently low or design acceptance is sufficiently high. The quantitative deltas in the willingness model imply that relatively modest shifts—on the order of half a response category in design or stigma perceptions—are, on average, enough to move the *M* into the ≥4 band, reinforcing the interpretation that the constraint is not fundamental to the value proposition but contingent on visibility and design evaluations.

Finally, the absence of an association between self-reported daily stress and willingness in the focused specification ($\beta = +0.016$, n.s.) suggests that, in a non-clinical population, intention to wear a visible BTE device is not primarily need-driven by baseline stress. This aligns theoretical emphasis with evaluative and social mechanisms rather than with immediate health status as the dominant driver of stated adoption in everyday use.

Overall, the results support an extension of mainstream acceptance theory for visible health wearables: models should explicitly incorporate (i) a design/wearability block capturing aesthetic and ergonomic acceptance as a first-order predictor, and (ii) a visibility/stigma block capturing social-exposure costs that act directly on willingness and only indirectly—if at all—on perceived value of the technological proposition. These elements jointly explain why a combined "tracking + stimulation" system can achieve strong evaluative fit while clear-majority public-wear intention remains context-contingent. No causal claims are made; implications are confined to the observed associations and pre-specified tests.

5.3 Practical implications

As presented in the findings (**RQ_1/H_1**), overall willingness to wear a visible BTE device is above midpoint but does not reach the ≥4 clear-majority; owners are more accepting.
As indicated by the findings (**RQ_2/H_2**), the tracking-plus-stimulation concept shows market fit above 3; focused models underline design/wearability (+), stigma/visibility (−), and ownership (+), with stigma adding little to market-fit once design and willingness are controlled.
The findings yield action-oriented guidance for a visible, BTE device that combines tracking and stimulation. All implications remain within the scope of the reported associations and hypothesis tests and do not assert causality.

Design and wearability are primary levers for increasing stated intention to wear. In the focused willingness model, a one-point improvement on the design-acceptance scale is associated with a ~0.60-point increase in willingness ($\beta = +0.598$, HC3). From the sample M (3.76) to the clear-accept benchmark (4.00) the shortfall is 0.24 points; ceteris paribus, this can be closed by an improvement of roughly 0.4 response points on design acceptance. Product development should therefore prioritize the attributes embedded in that construct—long-wear comfort behind-the-ear, professional suitability, and a minimalist, consumer-electronics aesthetic—because they map directly onto the largest observed effect on willingness.

Visibility management should be treated as a parallel design objective. The stigma/visibility composite carries a similarly sized but negative association with willingness (β = −0.517, HC3), and willingness is systematically lower in work/formal contexts than in private/social settings. This pattern supports emphasis on discreet geometry and finishes, accessory-like styling, and context-aware communication that normalizes public wearing in more exposed situations. Given the context gradient, early usage narratives and demonstrations are likely to be most consistent with stated preferences when anchored in settings with higher baseline willingness (e.g., sports and family activities), while design and messaging explicitly address concerns in professional and formal environments.

The value proposition of "tracking + stimulation" is evaluatively strong, but translating that valuation into public-wear intention depends on design and visibility perceptions. Market fit is clearly above neutrality ($M = 3.87$), and—conditional on design, willingness, and ownership—stigma is not associated with market fit (β = −0.094, n.s.). This indicates that evidence for efficacy and integration can be persuasive without necessarily resolving public-use hesitation. Consequently, product communication should separate (i) proposition validation from (ii) public-use reassurance: the former establishes comparative advantage, while the latter depends on design and visibility management to shift willingness toward the ≥4 band.

Evidence signaling is a salient component of market-fit communication. The "choose if clinically validated" item attains the highest M (4.17), suggesting that clear, accessible validation (study summaries, third-party assessments, transparent claims) is aligned with how respondents form value judgments about the combined system. While no clinical efficacy is claimed here, consistently presenting validation artifacts is likely to support the already positive market-fit evaluations observed across owners and non-owners.

User experience with wearables is an enabling condition for acceptance and market fit. Ownership is positively associated with willingness (β = +0.430, HC3) and with market fit (β = +0.248, HC3); acceptance rates at the ≥4 threshold are 58.3% for owners versus 27.5% for non-owners. Roll-out and partnership strategies that reach existing wearable users first—where familiarity is higher—are therefore consistent with the response pattern in the data. At the same time, messaging for non-owners should directly address visibility and design concerns, as stigma levels are comparable across groups at the composite level while willingness differs.

Pricing and portfolio signals should reflect the comparative-advantage frame inherent in the market-fit construct. Item means indicate preference for a single combination device over separate devices and a willingness to choose the combination device at equal price, with moderate support for a price premium. Within the limits of the present data, this pattern supports positioning the combination device as a consolidated alternative to "tracker + separate intervention," while treating premium claims as contingent on concurrently strong design and validation signaling.

Operational monitoring can align with the study's acceptance thresholds. For product evaluation, the share of users at or above the ≥4 willingness threshold is a clear, interpretable KPI that mirrors $\mathbf{H_{1b}}$; tracking this KPI by context (work/formal vs. private/social) and by ownership segment will allow teams to assess whether design iterations and visibility-management measures move the distribution in the intended direction. Complementary monitoring of the design-acceptance and stigma composites provides a diagnostic view on which lever (aesthetic/ergonomic vs. visibility) explains changes in willingness over time.

Finally, governance and reassurance should be explicit but proportionate. Privacy concern sits at a moderate level (M = 3.44), and the sample leans toward automation over manual control (M = 2.79 on a scale where lower reflects greater comfort with automation). Clear statements on data handling, on-device processing where feasible, and user-level control options support these sensitivities without detracting from the closed-loop proposition. These measures function as enablers rather than primary drivers, complementing the core levers identified above: design acceptance and the reduction of visibility-related image costs.

5.4 Conclusion

This thesis examined user acceptance of a visible, BTE wearable that integrates physiological tracking with stimulation in a closed-loop configuration. It addressed two questions: whether such a device would be accepted for everyday use **($\mathbf{RQ_1/H_1}$)** and whether the combined "tracking + stimulation" proposition shows market fit beyond neutrality **($\mathbf{RQ_2/H_2}$)**.

The quantitative evidence indicates that willingness to wear is clearly above the scale midpoint but context-sensitive: public and formal settings depress stated willingness relative to private and social contexts. Majority tests show broad support above >3 but do not reach a ≥4 "clear-majority" benchmark. Multivariate estimates identify design/wearability as a strong positive correlate and perceived visibility/stigma as a comparably strong negative correlate of willingness; current wearable ownership contributes an independent positive association, while self-reported daily stress is not associated. Given the estimated magnitudes, modest improvements in perceived design or modest reductions in perceived stigma are, on average, sufficient to close the *M* shortfall to the ≥4 band.

Perceived market fit for the combined proposition lies convincingly above neutrality for the full sample and within both ownership segments. In focused models, willingness, design acceptance, and ownership are positively associated with market fit; stigma shows no residual association once these variables are held constant. This pattern supports a useful separation: valuation of the integrated functionality is anchored in perceived efficacy/credibility and design, whereas visibility primarily constrains public-wear intention.

The findings extend acceptance theory for visible health wearables by clarifying a dual-path structure. A design/wearability block (comfort, aesthetics, professional suitability) operates as a first-order predictor of intention; a visibility/stigma block (anticipated social evaluation) exerts a direct, adverse effect on willingness but little additional effect on market-fit judgments after conditioning on design and willingness. Ownership acts as an enabling condition consistent with experience/habit mechanisms in UTAUT2. These elements refine how classical usefulness/effort constructs translate into intention when conspicuity introduces image costs.

Managerially, priorities follow directly. Improving wearability and aesthetics is the main lever to shift willingness toward clear-majority acceptance, complemented by visibility management (discreet geometry and finishes, accessory-like styling, context-aware communication) for work/formal situations where willingness is lowest. Communication should separate proposition validation (transparent, accessible evidence) from public-use reassurance. Roll-out via segments with higher familiarity (current wearable users) is consistent with the ownership gradient, while messaging for non-owners should address visibility and design concerns explicitly. Tracking the share of users at or above the ≥4 threshold—by context and ownership—provides an operational KPI aligned with the hypothesis framework; monitoring design-acceptance and stigma composites offers diagnostic insight.

In sum, this study contributes empirical evidence for a visible BTE combination device—a segment largely absent from prior acceptance research—clarifies how design and visibility jointly structure intention, and provides a transparent analytic pipeline from construct-level tests to focused models and diagnostics. Within these bounds, integrated tracking-plus-stimulation systems can achieve strong evaluative fit; moving from broad acceptance to clear-majority public-wear intention is primarily a function of advancements in wearability and reductions in visibility-related image costs.

6 Limitations and future research

The study's scope and inferences are bounded by several limitations that also define priorities for subsequent work. First, evidence derives from a cross-sectional, intention-based survey: outcomes capture stated willingness and perceived market fit at one point in time rather than realized behavior or durability of use. Second, sampling via academic and professional networks produced a heterogeneous but non-probability sample; population-level generalizability is limited and self-selection on technology affinity cannot be excluded. Third, acceptance was elicited for a briefly described concept rather than for a production prototype in situ, so real-world frictions—fit, micro-interactions, battery life, notification burden—were not observed. Fourth, to preserve respondent burden, two governance determinants (privacy concern and automation preference) were single-item measures and the instrument used a fixed within-block order; full psychometric validation, randomization checks, and common-method diagnostics lie beyond scope. Fifth, analyses relied on OLS with HC3-robust errors applied to Likert-type composites; while diagnostics address heteroskedasticity and tail non-normality, omitted variables remain possible. Sixth, acceptance thresholds (>3 for "soft majority"; ≥4 for "clear majority") are substantively motivated conventions; alternative cut-points would shift pass/fail rates. Seventh, context coverage was intentionally parsimonious (work/formal versus private/social) and does not capture finer distinctions such as dress codes, stakeholder proximity, or visibility distance. Finally, the sample is non-clinical and includes a single-item stress indicator; transferability to clinical populations and high-stakes use cases is therefore limited.

These constraints suggest a focused research agenda. Field and longitudinal studies should link stated acceptance to actual wear behavior—especially in professional and formal settings—using telemetry (wear time, context detection) and, where appropriate, physiological endpoints.

Prototype experiments ought to manipulate visibility-relevant design features (geometry, finishes, accessory-like styling) to estimate the causal contribution of wearability and stigma reduction to intention and use. Measurement work should extend governance constructs to multi-item scales with confirmatory factor analysis, reliability testing, and cross-language validation. Sampling should broaden to probability-based or stratified frames, include under-represented groups and cultural replications, and incorporate clinical cohorts with richer stress measures. Modeling can separate direct and indirect pathways via design and stigma (e.g., SEM), and test alternative acceptance thresholds and distributional targets as robustness checks. Finally, governance interventions—privacy assurances, on-device processing, and transparent validation artifacts—should be evaluated experimentally to distinguish effects on market-fit judgments from effects on public-wear intention. Together, these steps would translate context-sensitive willingness into verified patterns of use and clarify how improvements in wearability and visibility management can shift acceptance from broad support toward clear-majority adoption in everyday life.

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Appendices

Survey

Introduction

Hello, and thanks for taking the time to help. I'm Patrick Herrmann, a master's student at Católica Lisbon School of Business & Economics. As part of my master's thesis and my startup project, I am evaluating perceptions of **Neuropods**, a visible, behind-the-ear, lightweight wearable with a minimalist, modern design. Neuropods detect stress via heart rate variability (HRV) and can automatically deliver non-invasive stimulation (tVNS) to reduce stress in real time.
Purpose: This survey will inform academic research and test the market fit of the startup concept.
Time: ~5–7 minutes.
Participation: Voluntary and anonymous.
Thank you for your time and honest feedback.

Screener

Q1. Do you currently use any wearable device? *(e.g., Apple Watch, Fitbit, Garmin, Oura Ring)*
( ) Yes
( ) No

Q2. Have you ever used a wearable for health or stress management? *(e.g., HR chest strap, fitness tracker)*
( ) Yes
( ) No

Usage History & Context

Q3. What are the main purposes for which you use your wearable device(s)? **(Select all that apply)**
[ ] Fitness *(e.g., Fitbit, Polar)*
[ ] Health *(e.g., Apple Watch ECG, blood oxygen)*
[ ] Stress management *(e.g., Muse headband, Whoop)*
[ ] Fashion
[ ] Other: ________

Q4. Familiarity *(5-point scale)*
How familiar are you with stress-related wearable technology?

1 = Not at all familiar | 2 = Slightly familiar | 3 = Moderately familiar | 4 = Very familiar | 5 = Extremely familiar

Q5. Frequency *(5-point scale)*
How often do you use your current wearable(s)?
1 = Never | 2 = Rarely | 3 = Sometimes | 4 = Often | 5 = Daily

---

Situational Willingness to Wear

Instruction: Assume **Neuropods** is visible behind your ear with an *Apple-like* design.
Scale (all items): 1 = Very unwilling | 2 = Unwilling | 3 = Neither willing nor unwilling | 4 = Willing | 5 = Very willing

Q6. Willing to wear…

- in public transport
- at work
- in formal meetings
- during sports
- in restaurants/cafés
- during social gatherings
- at home around family
- when meeting new people

Perceived Stigma & Social Perception

Scale (all items): 1 = Strongly disagree | 2 = Disagree | 3 = Neither agree nor disagree | 4 = Agree | 5 = Strongly agree

Q7. A tech-like appearance would make me feel more confident. *(single item)*

Q8. Please indicate your agreement:

- People might think I am ill if they see me wearing Neuropods.
- People might think I am stressed if they see me wearing Neuropods.
- I would feel self-conscious wearing Neuropods in public.
- I would avoid wearing Neuropods in situations with strangers.
- Negative comments from others would decrease my willingness to wear.

Comfort & Design Acceptance

Scale (all items): 1 = Strongly disagree | 2 = Disagree | 3 = Neither agree nor disagree | 4 = Agree | 5 = Strongly agree

Q9. Please indicate your agreement:

- The minimalist, Apple-like design of Neuropods increases my acceptance of the device.
- The behind-the-ear position of Neuropods feels comfortable for long-term wear.
- The design of Neuropods makes the device suitable for professional environments.
- The weight of the device affects my acceptance of it.

Perceived Market Fit of Combination Device

Scale (all items): 1 = Strongly disagree | 2 = Disagree | 3 = Neither agree nor disagree | 4 = Agree | 5 = Strongly agree

Q10. Please indicate your agreement:

- I see more value in **tracking + stimulation** than tracking alone.
- A combination device would be more effective for stress management.
- I would be willing to pay more for combination vs. tracking-only.
- Even at the same price, I would choose a combination device over tracking-only.
- I would choose a combination device if clinically validated.
- I would switch from my current tracking-only solution to a combination device within the next 12 months.
- If both were available today, I would adopt a combination device as my primary stress solution.

Psychological & Behavioural Factors

Scale (all items): 1 = Strongly disagree | 2 = Disagree | 3 = Neither agree nor disagree | 4 = Agree | 5 = Strongly agree

Q11. Please indicate your agreement:

- I am concerned about privacy with health wearables.
- I prefer manual over automation.

Purchase Intent & Adoption

Scale (all items): 1 = Strongly disagree | 2 = Disagree | 3 = Neither agree nor disagree | 4 = Agree | 5 = Strongly agree

Q12. Please indicate your agreement:

- I would consider buying Neuropods within the next 12 months.
- I would recommend Neuropods to friends/family.

Demographics & Control Variables

Q13. Age group

( ) 18–24 ( ) 25–34 ( ) 35–44 ( ) 45–54 ( ) 55–64 ( ) 65+

Q14. Gender

( ) Male ( ) Female ( ) Other

Q15. Employment status

( ) Student ( ) Employed ( ) Self-employed ( ) Retired ( ) Unemployed ( ) Other

Q16. Education level

( ) High school ( ) Bachelor ( ) Master ( ) Doctorate ( ) Other

Q17. Average daily stress level *(5-point scale)*

1 = Very low | 2 = Low | 3 = Moderate | 4 = High | 5 = Very high

---

End of Survey (Completion Message)

Thank you for participating in this survey.
Your response has been recorded.

Data

De-identified survey data are available on request.

Additional Tables

Table A.0.1 Dataset structure (skimr data summary)

Cleaned Qualtrics export with N = 148 rows and 64 columns. The table summarizes variable types (character, factor, numeric) and missingness. Used to document the analysis-ready dataset structure (no identifiers). Values reflect the post-cleaning dataset described in Section 3.1. Source: Author's analysis (R).

```
> skim(data.thesis)
── Data Summary ────────────────────────
                           Values
Name                       data.thesis
Number of rows             148
Number of columns          64
_______________________
Column type frequency:
  character                18
  factor                   4
  numeric                  42
________________________
Group variables            None

── Variable type: character ────────────────────────────────────────────────
   skim_variable         n_missing complete_rate min max empty n_unique whitespace
 1 StartDate                     0         1      19  19     0      141          0
 2 EndDate                       0         1      19  19     0      145          0
 3 Status                        0         1      10  10     0        1          0
 4 IPAddress                     0         1      10  15     0      146          0
 5 Progress                      0         1       3   3     0        1          0
 6 Duration (in seconds)         0         1       3   4     0      125          0
 7 Finished                      0         1       4   4     0        1          0
 8 RecordedDate                  0         1      19  19     0      142          0
 9 ResponseId                    0         1      17  17     0      148          0
10 LocationLatitude              0         1       5   8     0      116          0
11 LocationLongitude             0         1       5   9     0      116          0
12 DistributionChannel           0         1       9   9     0        1          0
13 UserLanguage                  0         1       2   2     0        1          0
14 usage_purposes                5         0.966   5 129     0       17          0
15 age_group                     0         1       3   5     0        6          0
16 gender                        4         0.973   4   6     0        3          0
17 employment                    0         1       7  13     0        5          0
18 education                     0         1       5  11     0        5          0

── Variable type: factor ───────────────────────────────────────────────────
  skim_variable n_missing complete_rate ordered n_unique top_counts
1 gender_f              0             1 FALSE          4 Mal: 75, Fem: 68, Unk: 4, Oth: 1
2 age_group_f           0             1 FALSE          6 25-: 59, 35-: 29, 18-: 20, 45-: 20
3 education_f           0             1 FALSE          5 Bac: 67, Mas: 48, Hig: 22, Doc: 8
4 employment_f          0             1 FALSE          5 Emp: 106, Sel: 18, Stu: 14, Ret: 5

── Variable type: numeric ──────────────────────────────────────────────────
   skim_variable                n_missing complete_rate  mean     sd   p0  p25  p50  p75 p100 hist
 1 will_work_score                      0         1     3.50  1.19   1    3    3.5  4.5  5
 2 will_private_score                   0         1     3.84  0.971  1    3.33 4    4.67 5
 3 stigma_score                         0         1     2.79  0.690  1.17 2.33 2.83 3.33 4.33
 4 design_accept_score                  0         1     3.85  0.678  1    3.33 4    4.33 5
 5 MF_score                             0         1     3.87  0.741  1    3.48 3.86 4.32 5
 6 will_overall_score                   0         1     3.76  0.981  1    3.25 3.88 4.66 5
 7 accept_overall                       0         1     0.480 0.501  0    0    0    1    1
 8 has_wearable                         1         0.993 0.653 0.478  0    0    1    1    1
 9 used_for_health_stress               0         1     0.649 0.479  0    0    1    1    1
10 fam_stress_wearables                 1         0.993 2.62  1.21   1    2    3    3.5  5
11 use_freq_wearable                    1         0.993 3.43  1.48   1    2    4    5    5
12 will_transit                         0         1     4.05  0.988  1    4    4    5    5
13 will_work                            2         0.986 3.79  1.16   1    3    4    5    5
14 will_formal                          0         1     3.22  1.37   1    2    3    4    5
15 will_sport                           1         0.993 4.15  1.11   1    4    4    5    5
16 will_cafes                           1         0.993 3.71  1.23   1    3    4    5    5
17 will_social                          0         1     3.53  1.24   1    2.75 4    5    5
18 will_family                          0         1     4.09  1.12   1    4    4    5    5
19 will_newpeople                       0         1     3.51  1.29   1    3    4    5    5
20 stig_tech_look_conf                  0         1     3.46  1.09   1    3    4    4    5
21 stig_seen_ill                        1         0.993 2.73  1.19   1    2    3    4    5
22 stig_seen_stressed                   0         1     2.72  1.11   1    2    3    4    5
23 stig_selfconscious                   0         1     2.65  1.09   1    2    3    3.25 5
24 stig_avoid_strangers                 0         1     2.54  1.15   1    2    2    3    5
25 stig_neg_comments                    0         1     2.65  1.32   1    1.75 2    4    5
26 design_accept_minimal                1         0.993 4.14  0.782  1    4    4    5    5
27 design_comfort_long                  1         0.993 3.71  0.891  1    3    4    4    5
28 design_prof_suitable                 0         1     3.72  0.857  1    3    4    4    5
29 design_weight_effect                 0         1     3.81  1.10   1    3    4    5    5
30 MF_value_combo_vs_single             0         1     3.88  0.840  1    3    4    4    5
31 MF_effective_combo_vs_single         0         1     4.01  0.816  1    4    4    5    5
32 MF_paymore_combo_vs_single           1         0.993 3.78  1.05   1    3    4    5    5
33 MF_choose_combo_vs_single            1         0.993 4.03  0.982  1    4    4    5    5
34 MF_choose_combo_if_validated         0         1     4.17  0.958  1    4    4    5    5
35 MF_switch_to_combo_12m               1         0.993 3.53  0.974  1    3    3    4    5
36 MF_adopt_combo_primary_today         0         1     3.73  1.01   1    3    4    4    5
37 privacy_concern                      1         0.993 3.44  1.22   1    2    4    4    5
38 manual_vs_automation                 2         0.986 2.79  1.00   1    2    3    3    5
39 Purchase_buy_12                      0         1     3.41  1.19   1    3    4    4    5
40 Purchase_recommend                   1         0.993 3.53  1.04   1    3    3    4    5
41 stress_level                         1         0.993 3.02  0.831  1    3    3    4    5
42 stigma_n                             0         1     5.99  0.0822 5    6    6    6    6
```

Table A.0.2 Summary statistics for all variables (N, Mean, SD, Min, Median, Max)

Statistics produced with stargazer in R for the full variable set. Likert constructs are coded 1–5 with "higher = more". Binary indicators are 0/1 (e.g., has_wearable). Sample sizes may vary by variable due to item nonresponse. See Section 3.1 for construct definitions and coding. Source: Author's analysis (R).

```
> stargazer(data.frame(data.thesis), type = "text"
+           , median = TRUE, no.space = TRUE
+           , title = "Summary Statistics")

Summary Statistics
==================================================================
Statistic                     N  Mean  St. Dev.  Min  Median  Max
------------------------------------------------------------------
will_work_score              148 3.497  1.193   1.000 3.500  5.000
will_private_score           148 3.841  0.971   1.000 4.000  5.000
stigma_score                 148 2.790  0.690   1.167 2.833  4.333
design_accept_score          148 3.852  0.678   1.000 4.000  5.000
MF_score                     148 3.873  0.741   1.000 3.857  5.000
will_overall_score           148 3.757  0.981   1.000 3.875  5.000
accept_overall               148 0.480  0.501     0     0      1
has_wearable                 147 0.653  0.478     0     1      1
used_for_health_stress       148 0.649  0.479     0     1      1
fam_stress_wearables         147 2.619  1.207     1     3      5
use_freq_wearable            147 3.429  1.476     1     4      5
will_transit                 148 4.054  0.988     1     4      5
will_work                    146 3.788  1.164     1     4      5
will_formal                  148 3.223  1.369     1     3      5
will_sport                   147 4.150  1.113     1     4      5
will_cafes                   147 3.707  1.229     1     4      5
will_social                  148 3.527  1.242     1     4      5
will_family                  148 4.088  1.118     1     4      5
will_newpeople               148 3.514  1.291     1     4      5
stig_tech_look_conf          148 3.459  1.090     1     4      5
stig_seen_ill                147 2.728  1.191     1     3      5
stig_seen_stressed           148 2.716  1.113     1     3      5
stig_selfconscious           148 2.649  1.093     1     3      5
stig_avoid_strangers         148 2.541  1.145     1     2      5
stig_neg_comments            148 2.649  1.319     1     2      5
design_accept_minimal        147 4.136  0.782     1     4      5
design_comfort_long          147 3.714  0.891     1     4      5
design_prof_suitable         148 3.716  0.857     1     4      5
design_weight_effect         148 3.811  1.096     1     4      5
MF_value_combo_vs_single     148 3.878  0.840     1     4      5
MF_effective_combo_vs_single 148 4.014  0.816     1     4      5
MF_paymore_combo_vs_single   147 3.776  1.046     1     4      5
MF_choose_combo_vs_single    147 4.034  0.982     1     4      5
MF_choose_combo_if_validated 148 4.169  0.958     1     4      5
MF_switch_to_combo_12m       147 3.531  0.974     1     3      5
MF_adopt_combo_primary_today 148 3.730  1.014     1     4      5
privacy_concern              147 3.442  1.223     1     4      5
manual_vs_automation         146 2.795  1.003     1     3      5
Purchase_buy_12              148 3.412  1.195     1     4      5
Purchase_recommend           147 3.531  1.036     1     3      5
stress_level                 147 3.020  0.831     1     3      5
stigma_n                     148 5.993  0.082     5     6      6
------------------------------------------------------------------
```

Table A.0.3 Gender split: ownership and key scores (compact)

Groups: Female, Male, Other/NA. Columns: Has wearable (%), Willingness – Overall (M), Accept ≥4 (%), Stigma (M), Design Acceptance (M), Market Fit (M). Means (M) on 1–5 Likert scales (higher = more). Percentages are within-group shares. Values are descriptive only (no inference). NA/Unknown retained where applicable. Total sample N = 148. Source: Author's analysis (R).

Table: Gender split: ownership and key scores (compact)

Gender	n	Has wearable %	Willingness Overall (M)	Accept ≥4 %	Stigma (M)	Design Acceptance (M)	Market Fit (M)
Male	75	62.2	3.63	42.7	2.87	3.86	3.87
Female	68	67.6	3.91	55.9	2.66	3.88	3.90
Other/NA	5	80.0	3.62	20.0	3.37	3.47	3.57

Table A.0.4 Age-group split: ownership and key scores (compact)

Groups: 18–24, 25–34, 35–44, 45–54, 55–64, 65+ (plus Unknown if present). Columns: Has wearable (%), Willingness – Overall (M), Accept ≥4 (%), Stigma (M), Design Acceptance (M), Market Fit (M). Means (M) on 1–5 Likert scales (higher = more). Percentages are within-group shares. Descriptive only; NA/Unknown retained. N = 148. Source: Author's analysis (R).

Table: Age group split: ownership and key scores (compact)

AgeGroup	n	Has wearable %	Willingness Overall (M)	Accept ≥4 %	Stigma (M)	Design Acceptance (M)	Market Fit (M)
18–24	20	80.0	3.99	50.0	3.10	3.92	3.97
25–34	59	57.6	3.68	47.5	2.85	3.76	3.68
35–44	29	89.7	3.89	55.2	2.80	3.93	4.12
45–54	20	36.8	3.67	35.0	2.62	3.85	3.74
55–64	16	75.0	3.57	50.0	2.49	4.00	4.17
65+	4	25.0	3.83	50.0	2.29	3.75	4.00

Table A.0.5 Education split: ownership and key scores (compact)

Groups: High school, Bachelor, Master, Doctorate, Other/Unknown. Columns: Has wearable (%), Willingness – Overall (M), Accept ≥4 (%), Stigma (M), Design Acceptance (M), Market Fit (M). Means (M) on 1–5 Likert scales (higher = more). Percentages are within-group shares. Descriptive only; NA/Unknown retained. N = 148. Source: Author's analysis (R).

Table: Education split: ownership and key scores (compact)

Education	n	Has wearable %	Willingness Overall (M)	Accept ≥4 %	Stigma (M)	Design Acceptance (M)	Market Fit (M)
High school	22	50.0	3.81	54.5	2.74	3.86	3.85
Bachelor	67	74.6	3.90	53.7	2.87	3.85	3.96
Master	48	62.5	3.52	35.4	2.78	3.82	3.68
Doctorate	8	71.4	4.11	62.5	2.38	4.21	4.30
Other	3	0.0	3.00	33.3	2.61	3.33	4.00

Table A.0.6 Employment split: ownership and key scores (compact)

Groups: Employed, Self-employed, Student, Retired, Unemployed, Other/Unknown. Columns: Has wearable (%), Willingness – Overall (M), Accept ≥4 (%), Stigma (M), Design Acceptance (M), Market Fit (M). Means (M) on 1–5 Likert scales (higher = more). Percentages are within-group shares. Descriptive only; NA/Unknown retained. N = 148. Source: Author's analysis (R).

Table: Employment split: ownership and key scores (compact)

Employment	n	Has wearable %	Willingness Overall (M)	Accept ≥4 %	Stigma (M)	Design Acceptance (M)	Market Fit (M)
Employed	106	75.2	3.98	58.5	2.72	3.93	3.96
Self-employed	18	38.9	2.93	16.7	2.97	3.54	3.33
Student	14	50.0	3.40	14.3	2.95	3.76	4.04
Unemployed	5	0.0	3.02	20.0	3.23	3.53	3.40
Retired	5	60.0	3.67	60.0	2.67	4.00	4.03

Table A.0.7 Ownership split: key scores (compact)

Groups: Has wearable vs No wearable. Columns: n (group size), Willingness – Overall (M), Accept ≥4 (%), Stigma (M), Design Acceptance (M), Market Fit (M). Means (M) on 1–5 Likert scales (higher = more). Percentages are within-group shares where shown. Descriptive only; NA/Unknown retained. N = 148. Source: Author's analysis (R).

Table: Ownership split: key scores (compact)

Ownership	n	Willingness Overall (M)	Accept ≥4 %	Stigma (M)	Design Acceptance (M)	Market Fit (M)
Has wearable	96	3.97	58.3	2.78	3.95	4.03
No wearable	51	3.33	27.5	2.81	3.64	3.56
NA/Unknown	1	4.86	100.0	3.00	5.00	4.86

Additional Figure

Figure A.1 Correlations and distributions (GGpairs) of willingness, stigma, design acceptance, and market fit

*Upper triangle shows Pearson correlations (r) with two-tailed significance (*** p <.001, ** p <.01, * p <.05). Diagonal panels display kernel density estimates for each variable; lower triangle shows jittered scatterplots. All constructs are measured on 1–5 Likert scales (higher = more). N = 148. Source: Author's analysis (R).*

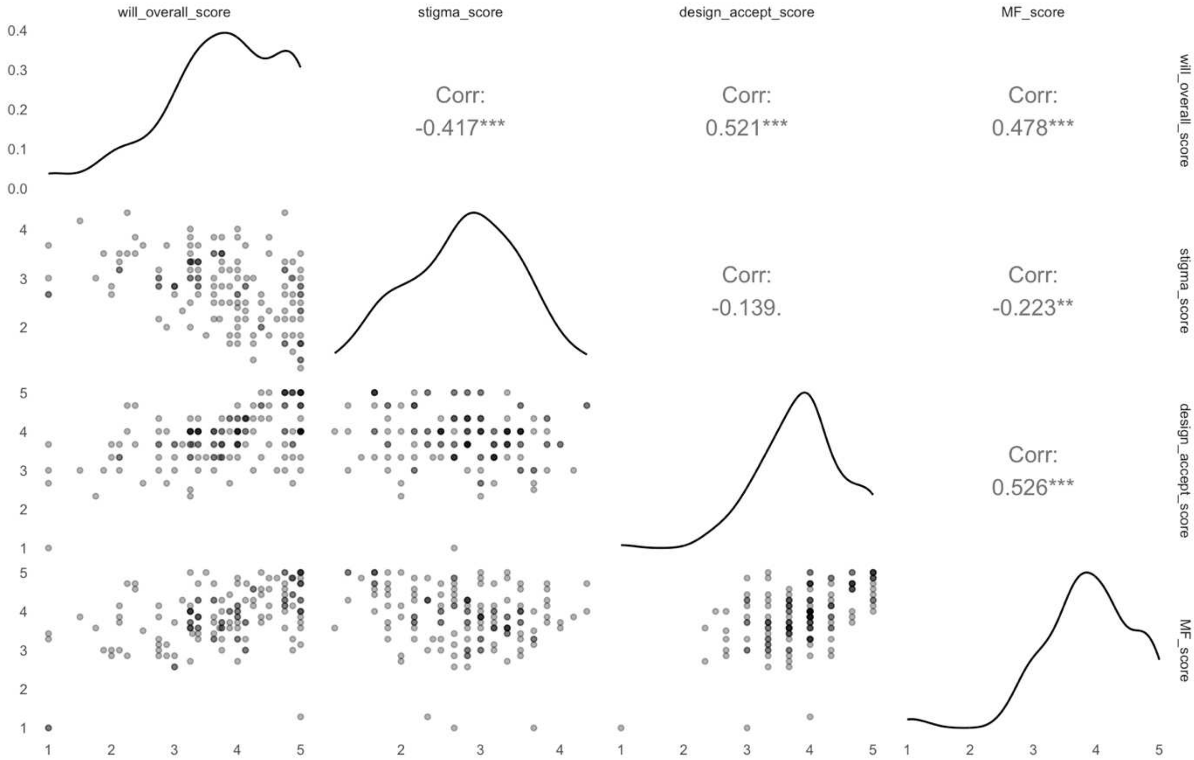


Table A.2 MLR1/MLR4: Residuals vs Fitted (linearity & zero-mean)

Scatter of standardized residuals against fitted values; red curve is a LOESS smoother; dashed line at 0. Left: m1.1 (DV = Willingness, overall). Right: m2.1 (DV = Market Fit). Approximate horizontality and lack of systematic structure indicate acceptable functional form (MLR1) and support $E[u \mid X] = 0$ *(MLR4). Source: Author's analysis (R).*

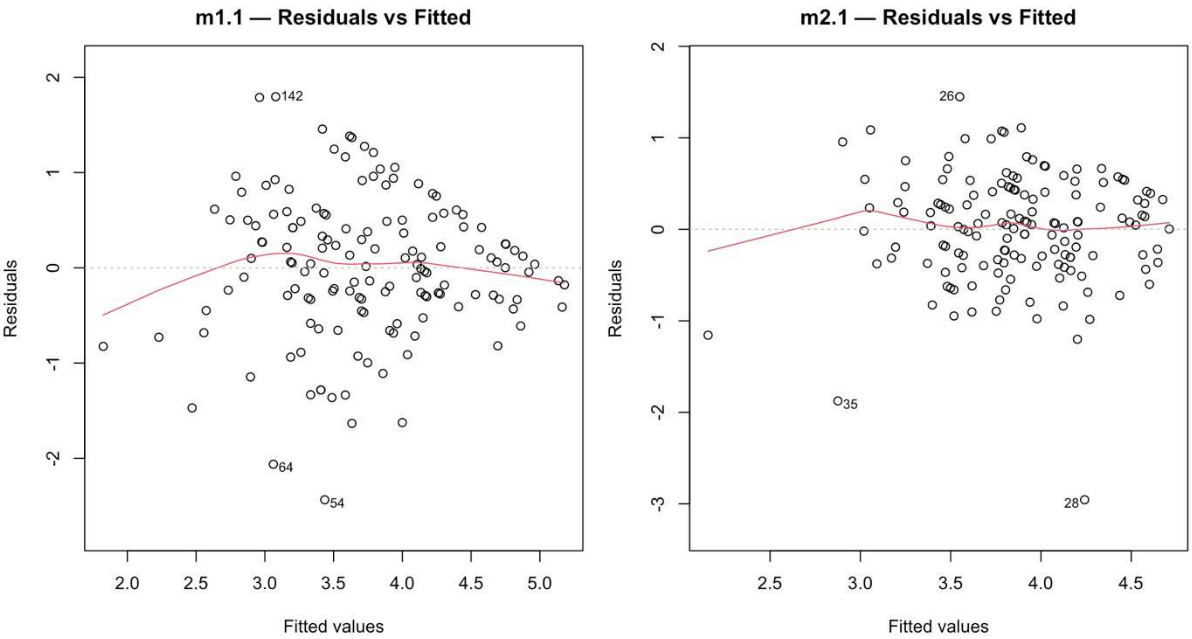
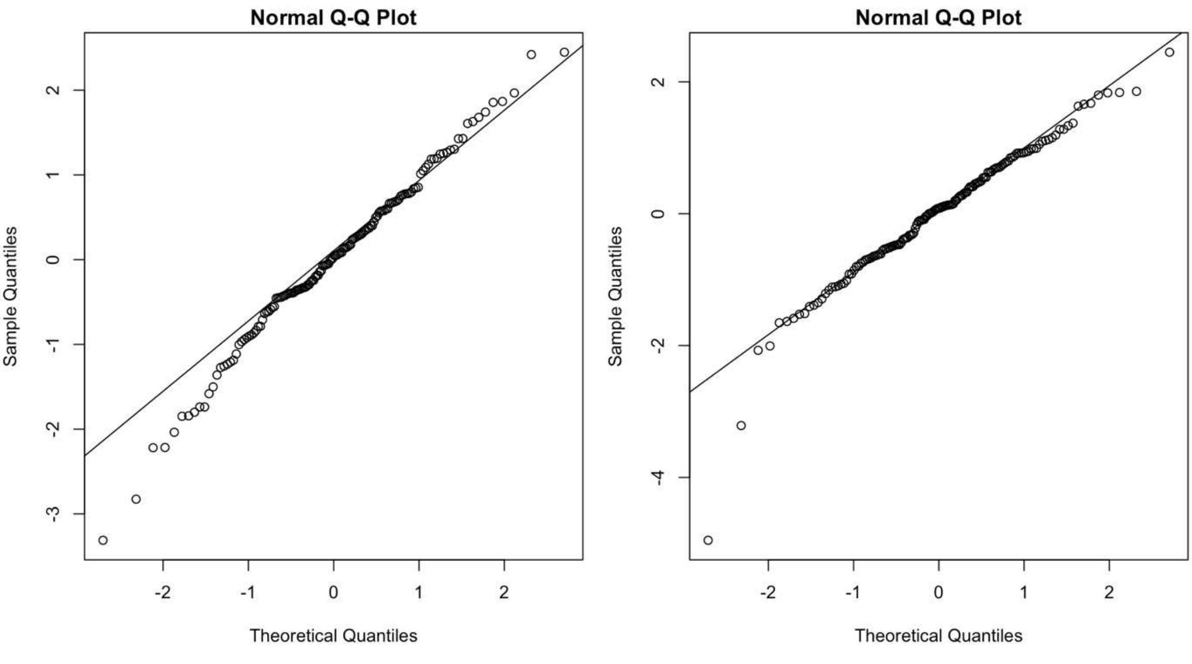


Table A.3 Normality of residuals (Q–Q plots)

m1.1 (DV = Willingness, overall). Right: m2.1 (DV = Market Fit). Shapiro–Wilk tests: m1.1 W = 0.989, p = .301 — fail to reject normality; m2.1 W = 0.955, p <.001 — reject normality due to tail deviations. Inference in the main text uses HC3-robust standard errors. Source: Author's analysis (R).



Additional R Output

R scripts used for data cleaning, analysis, and figure generation are available on request.

MLR 2

```
> cook_m1.1 <- cooks.distance(m1.1); cut_m1.1 <- 4 / nobs(m1.1)

> cat("\n[MLR2] m1.1: Cook's D > 4/n at indices:\n"); print(which(cook_m1.1
> cut_m1.1))


[MLR2] m1.1: Cook's D > 4/n at indices:

 23  35  36  46  54  64  78  81 123 142

 22  34  35  45  53  63  76  79 121 140

> cat("[MLR2] m1.1: Top 10 Cook's D:\n"); print(sort(cook_m1.1, decreasing
= TRUE)[1:min(10, length(cook_m1.1))])

[MLR2] m1.1: Top 10 Cook's D:

        64         54         35        142         23         46
81         78        123         36

0.08068173 0.07480121 0.06000606 0.04569914 0.04420337 0.04393108
0.04304673 0.03340980 0.03281969 0.02985181

>

> cook_m2.1 <- cooks.distance(m2.1); cut_m2.1 <- 4 / nobs(m2.1)

> cat("\n[MLR2] m2.1: Cook's D > 4/n at indices:\n"); print(which(cook_m2.1
> cut_m2.1))


[MLR2] m2.1: Cook's D > 4/n at indices:

10 19 23 26 28 35 46 86

10 19 23 26 28 35 46 85

> cat("[MLR2] m2.1: Top 10 Cook's D:\n"); print(sort(cook_m2.1, decreasing
= TRUE)[1:min(10, length(cook_m2.1))])

[MLR2] m2.1: Top 10 Cook's D:

        23         35         28         26         86         46
10         19        108         68

0.14281704 0.13905972 0.10405450 0.04565376 0.04513167 0.03395967
0.03181330 0.02964372 0.02364289 0.02141795
```

MLR 3

```
> cat("\n[MLR3] VIF m1.1:\n"); print(car::vif(m1.1))


[MLR3] VIF m1.1:

       stigma_score design_accept_score        has_wearable
stress_level

           1.026373            1.075453            1.069609
1.025598

> cat("\n[MLR3] VIF m2.1:\n"); print(car::vif(m2.1))


[MLR3] VIF m2.1:

 will_overall_score design_accept_score        has_wearable
stigma_score

           1.761666            1.378879            1.133057
1.244351

>

> pred_m1.1 <- c("stigma_score","design_accept_score","has_weara-
ble","stress_level")

> pred_m2.1 <- c("will_overall_score","design_accept_score","has_weara-
ble","stigma_score")

>

> cat("\n[MLR3] Predictor correlations (m1.1):\n")


[MLR3] Predictor correlations (m1.1):

> print(data.thesis %>% dplyr::select(dplyr::all_of(pred_m1.1)) %>%
corrr::correlate(diagonal = 1) %>% corrr::fashion(decimals = 3))

Correlation computed with

• Method: 'pearson'

• Missing treated using: 'pairwise.complete.obs'

                 term stigma_score design_accept_score has_wearable
stress_level

1        stigma_score        1.000                -.139        -.025
-.059
```

```
2 design_accept_score        -.139                1.000         .222
.054

3        has_wearable        -.025                 .222        1.000
.146

4        stress_level        -.059                 .054         .146
1.000

> cat("\n[MLR3] Predictor correlations (m2.1):\n")


[MLR3] Predictor correlations (m2.1):

> print(data.thesis %>% dplyr::select(dplyr::all_of(pred_m2.1)) %>%
corrr::correlate(diagonal = 1) %>% corrr::fashion(decimals = 3))

Correlation computed with

• Method: 'pearson'

• Missing treated using: 'pairwise.complete.obs'

                 term will_overall_score design_accept_score has_wearable
stigma_score

1  will_overall_score              1.000                .521         .316
-.417

2 design_accept_score               .521               1.000         .222
-.139

3        has_wearable               .316                .222        1.000
-.025

4        stigma_score              -.417               -.139        -.025
1.000

>
```

MLR5

```
> cat("\n[MLR5] Breusch–Pagan tests:\n"); print(lmtest::bptest(m1.1));
print(lmtest::bptest(m2.1))


[MLR5] Breusch–Pagan tests:


      studentized Breusch–Pagan test
```

```
data:  m1.1
BP = 13.316, df = 4, p-value = 0.009829


      studentized Breusch-Pagan test

data:  m2.1
BP = 1.9674, df = 4, p-value = 0.7418

>
> se_m1.1_hc3 <- sqrt(diag(sandwich::vcovHC(m1.1, type = "HC3")))
> se_m2.1_hc3 <- sqrt(diag(sandwich::vcovHC(m2.1, type = "HC3")))
> cat("\n[MLR5] Breusch-Pagan tests:\n"); print(lmtest::bptest(m1.1));
print(lmtest::bptest(m2.1))

[MLR5] Breusch-Pagan tests:

      studentized Breusch-Pagan test

data:  m1.1
BP = 13.316, df = 4, p-value = 0.009829


      studentized Breusch-Pagan test

data:  m2.1
BP = 1.9674, df = 4, p-value = 0.7418

>
> se_m1.1_hc3 <- sqrt(diag(sandwich::vcovHC(m1.1, type = "HC3")))
```

```
> se_m2.1_hc3 <- sqrt(diag(sandwich::vcovHC(m2.1, type = "HC3")))
>
> stargazer::stargazer(
+   m1.1, m2.1,
+   type = "text", no.space = TRUE,
+   title = "Determinants (Focused Models) — HC3 Robust SE",
+   dep.var.caption = "",
+   column.labels = c("Willingness (overall)", "Market Fit"),
+   se = list(se_m1.1_hc3, se_m2.1_hc3)
+ )

Determinants (Focused Models) — HC3 Robust SE
===================================================================
                      will_overall_score          MF_score
                     Willingness (overall)       Market Fit
                              (1)                    (2)
-------------------------------------------------------------------
will_overall_score                                 0.147*
                                                  (0.078)
stigma_score               -0.517***               -0.094
                            (0.087)               (0.071)
design_accept_score        0.598***               0.406***
                            (0.108)               (0.097)
has_wearable               0.430***                0.248**
                            (0.145)               (0.103)
stress_level                 0.016
                            (0.082)
Constant                   2.555***               1.855***
                            (0.566)               (0.476)
-------------------------------------------------------------------
```

```
Observations                    146                      147
R2                             0.435                    0.353
Adjusted R2                    0.419                    0.335
Residual Std. Error    0.748 (df = 141)        0.603 (df = 142)
F Statistic         27.173*** (df = 4; 141) 19.362*** (df = 4; 142)
===================================================================
Note:                                  *p<0.1; **p<0.05; ***p<0.01
```

MLR6

```
> cat("\n[MLR6] Shapiro–Wilk (std. residuals):\n")


[MLR6] Shapiro–Wilk (std. residuals):
> print(shapiro.test(rstandard(m1.1)))


      Shapiro–Wilk normality test


data:  rstandard(m1.1)
W = 0.98893, p–value = 0.3012


> print(shapiro.test(rstandard(m2.1)))


      Shapiro–Wilk normality test


data:  rstandard(m2.1)
W = 0.95483, p–value = 0.0001001
```