The Digitalized Triathlon: How Tech is Transforming a Popular Sport

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Dissertation written under the supervision of Professor Peter V. Rajsingh

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Abstract

Title: The Digitalized Triathlon: How Tech is Transforming a Popular Sport

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This thesis examines how technology adoption is transforming digital triathlon experiences, focusing on behavioral drivers, adoption barriers, commercialization dynamics, and future expectations. A mixed-methods approach was employed, combining 13 expert interviews with a survey of 257 triathletes. The Digital Sports Technology Adoption Model (D-STAM) was developed and empirically validated, integrating the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the Expectation-Confirmation Model (ECM). Adoption patterns varied across user segments: Performance Expectancy was a primary driver for both elite and recreational athletes, while Effort Expectancy and Facilitating Conditions significantly influenced only recreational users. Among coaches, Social Influence demonstrated a marginal effect. Across all segments, prior experience with digital tools predicted habitual usage.

In the post-adoption phase, habitual use significantly influenced satisfaction, continued usage, and perceived return on investment, which subsequently increased openness to commercial platforms. However, satisfaction and continued engagement were negatively affected by technostress, data overload, and perceived misalignment between digital feedback and personal intuition. Recreational athletes reported greater sensitivity to these factors. While complexity and cost inhibited adoption, privacy concerns were minimal. Freemium access was broadly expected, and commercial receptiveness was more strongly associated with perceived value than with sponsorship appeal.

Participants expressed demand for more intuitive, integrated, and actionable digital solutions, while expressing skepticism toward virtual racing as a credible competitive format. This research advances sport-specific technology adoption theory and offers practical insights for platform developers, endurance brands, and coaches aiming to foster sustainable digital engagement in triathlon.

Keywords: Triathlon, digital sports technology, technology adoption, athlete engagement, commercialization, D-STAM

Resumo

Título: O Triatlo Digitalizado: Como a Tecnologia Está Transformando um Esporte Popular
Autora: Melissa Fritsch

Esta dissertação investiga como a adoção de tecnologias está transformando as experiências digitais no triatlo, por meio da análise de fatores comportamentais, barreiras à adoção, dinâmicas de comercialização e expectativas futuras. Foi utilizada uma abordagem de métodos mistos, combinando 13 entrevistas com especialistas e uma pesquisa com 257 triatletas. O Modelo de Adoção de Tecnologia Esportiva Digital (D-STAM) foi desenvolvido e validado empiricamente, integrando o Modelo de Aceitação de Tecnologia (TAM), a Teoria Unificada de Aceitação e Uso de Tecnologia 2 (UTAUT2) e o Modelo de Expectativa-Confirmação (ECM). Os padrões de adoção variaram por segmento: a Expectativa de Desempenho foi central para atletas de elite e recreativos, enquanto a Expectativa de Esforço e as Condições Facilitadoras influenciaram apenas usuários recreativos. Entre treinadores, a influência social teve efeito marginal. Em todos os grupos, a experiência previu o uso habitual.

Na fase pós-adoção, o uso habitual influenciou a satisfação, a continuidade e o retorno percebido sobre o investimento, promovendo abertura a plataformas comerciais. No entanto, tecnodistresse, sobrecarga de dados e conflitos entre feedback digital e intuição afetaram negativamente o engajamento. Usuários recreativos mostraram maior sensibilidade. Complexidade e custo dificultaram a adoção, enquanto preocupações com privacidade foram mínimas. O acesso gratuito foi amplamente esperado, e a aceitação comercial esteve mais ligada ao valor percebido do que ao patrocínio.

Participantes pediram soluções mais intuitivas, integradas e úteis, mantendo ceticismo quanto às corridas virtuais. Este estudo contribui para a teoria da adoção tecnológica no esporte e oferece recomendações práticas para desenvolvedores, marcas e treinadores.

Palavras-chave: Triatlo, tecnologia digital, adoção de tecnologia, engajamento de atletas, comercialização, D-STAM

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I would also like to acknowledge that selected AI tools were used to support the efficiency and accuracy of this research. ChatGPT was employed for language refinement, specifically for grammar and stylistic suggestions, and to help structure content more clearly. Summaries of expert interview transcripts were also AI-assisted before being manually reviewed and revised by the author. At no point did AI replace the core analytical tasks of conceptual development, critical interpretation, or hypothesis formation as all intellectual contributions and data evaluations were carried out independently. I recognize the limitations of AI systems, including the potential for inaccuracies and bias, and took care to verify all outputs used. Full responsibility for the content, findings, and conclusions of this dissertation remains with the author.

Finally, I want to thank my Mum, whose unwavering support and belief in me carried me through every stage of this journey. Her presence, both emotional and practical, made all the difference.

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List of Abbreviations

AGT	Arena Games Triathlon
AI	Artificial Intelligence
AR	Augmented Reality
ANOVA	Analysis of Variance
DCF	Dynamic Capabilities Framework
DOI	Diffusion of Innovation Model
D-STAM	Digital Sports Technology Adoption Model
ECM	Expectation-Confirmation Model
GDPR	General Data Protection Regulation
HRV	Heart Rate Variability
PU	Perceived Usefulness
PEOU	Perceived Ease of Use
ROI	Return on Investment
TAM	Technology Adoption Model
UCI	Union Cycliste Internationale
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
VIF	Variance Inflation Factor
VO2 max	Maximum Volume of Oxygen
VR	Virtual Reality

1. Introduction

Digital transformation is reshaping sports by altering how athletes train, compete, and connect. Within endurance sports, particularly triathlon, the convergence of wearable technology, virtual training platforms, and data-driven performance analysis is now essential to athletic preparation. Companies such as Zwift, Wahoo, and TrainingPeaks offer innovations that provide athletes with personalized insights, immersive training experiences, and digital community engagement (Westmattelmann et al., 2021). This paradigm shift reflects a broader industry trend within global sports technology, valued at $18.85 billion in 2024 and projected to grow at a CAGR of 21.9% from 2025 to 2030 (Grand View Research, 2024).

COVID-19 accelerated virtual training and competition, prompting behavioral shifts among athletes. Participation in virtual events surged by over 200% in various regions (Stapley et al., 2024; Strava, 2021). Elite and recreational triathletes adopted digital technologies as supplements to traditional training (Seçkin et al., 2023). Accelerated adoption was facilitated by strategic collaborations between sports brands and technology enterprises (Elo et al., 2023). However, while virtual races gained momentum during the pandemic, participation dropped sharply post-pandemic, only 2.4% of race entries were virtual in 2024 compared to 33.4% in 2020 (RunSignup, 2025).

While wearable technology has become widely adopted among athletes, with up to 91% of Olympic athletes integrating it into their training, engagement with virtual training platforms remains low (Lee, 2025). Some athletes appreciate the benefits of personalized data analytics and virtual competition. However, others cite concerns about data privacy, costs, and the potential erosion of traditional triathlon culture (Mertala & Palsa, 2024; Seçkin et al., 2023). Moreover, platforms like Zwift face retention challenges, with 30% of users quitting within three months (Canvasbusinessmodel.com, 2023).

Strategic alliances (Murthy et al., 2016) are instrumental in expanding market reach and optimizing service delivery. But their efficacy within niche sports, such as triathlon, remains underexplored (Elo et al., 2023). Additionally, the literature emphasizes training efficacy and performance metrics, with less focus on the strategic and commercial implications of digital innovation (Westmattelmann et al., 2021).

Research Gap and Contribution

This study seeks to address the following research question:

RQ: **How is technology adoption transforming digital triathlon experiences?**

We examined the current endurance sports landscape and the dimensions of digital transformation, emphasizing key technologies, prevailing market trends, and athlete behaviors. We sought to identify critical enablers and barriers to digital adoption in triathlon to determine whether digital endurance is a paradigm shift or a transient trend.

2. Literature Review

2.1 The Digital Transformation of the Triathlon Industry

The following chapter offers an overview of triathlon and highlights key technological advancements that are reshaping training.

2.1.1 Triathlon as an Endurance Sport and Its Evolution

Triathlon has evolved from a niche pursuit into a globally recognized sport combining swimming, cycling, and running. Since the 1970s, the growth of the sport has been fueled by significant international events like the IRONMAN World Championship and the Olympic triathlon (Adelfinsky, 2023). These competitions have encouraged global participation and brought in sponsorships and media attention. Recent data indicate that triathlon participation in Europe has reached unprecedented levels, with a 24% increase in registrations among 18–35-year-olds for IRONMAN events in 2024 and over 15,000 first-time finishers, reflecting a 12% year-on-year growth (Endurance Sportswire, 2024).

Triathlon training has evolved from periodized coaching and in-person sessions to utilizing digital technologies. Coaches now use quantitative performance assessments and real-time physiological monitoring rather than relying solely on athlete feedback and observations (Wells et al., 2022).

2.1.2 The Growing Impact of Digitalization on Training, Competition, and Engagement

Digitalization has reshaped how triathletes train, compete, and interact with the endurance community. Wearable technologies, cloud analytics, and virtual platforms support the use of GPS watches, heart rate monitors, and power meters, which now play a central role in data-driven performance management across swim, bike, and run (Dovgan, 2023). For a detailed device overview, see Appendix A.

COVID-19 accelerated the adoption of virtual training and competition formats, with platforms like Zwift, TrainerRoad, and Rouvy enabling triathletes to train and race remotely (Strava, 2021). Mixed-reality competitions, such as the Arena Games Triathlon (AGT), further illustrate digitalization. AGT combines real-world swimming with virtual cycling and running via Zwift-connected smart trainers and treadmills, enabling hybrid competition with real-time monitoring (Stapley et al., 2024). These experiences extend competitive opportunities to athletes without access to traditional race settings.

2.2 Consumer Adoption of Digital Sports Technologies

Digital platforms, wearable technology, and virtual training impact depends on how athletes and coaches adopt and interact with these tools.

2.2.1 Theoretical Frameworks on Consumer Behavior and Technology Adoption

Consumer adoption of technology is shaped by behavioral, psychological, and commercial factors. Frameworks such as the Technology Adoption Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012), and the Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001) provide insights about user acceptance and continued use. Additionally, Rogers' Diffusion of Innovation (DOI) Model (2003) shows how technological innovations disseminate over time.

TAM (Davis, 1989) posits that user acceptance is determined by two dimensions: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU reflects how much a given technology is perceived to enhance performance or effectiveness. In digital sports, PU implicates factors such as performance enhancement, health monitoring, injury prevention, training load management, and scientific validation (Guppy et al., 2023; Yousaf et al., 2021). In contrast, PEOU captures how effortless a technology is perceived to be. Devices that are intuitive, comfortable, and compatible with existing routines tend to have higher adoption (Kastoriano & Halkias, 2020).

Therefore, PU and PEOU describe how attitudes influence the behavioral intention to adopt, which in turn predicts actual usage. Attitude reflects users' overall evaluative response, whereas intention captures motivation and likelihood of engaging with the technology. In performance-driven environments, intention is often formed primarily through PU. Athletes may overlook usability issues if the technology offers measurable gains (Huang & Yongquan, 2025; Kastoriano & Halkias, 2020). Conversely, PEOU tends to be privileged for recreational athletes, as complex interfaces or unclear feedback can diminish use motivation (Mertala & Palsa, 2024). Coaches demonstrate unique adoption patterns, balancing PU and PEOU while also considering athlete autonomy, coaching philosophy, and data interpretation demands (Wells et al., 2022).

The diagram below illustrates the TAM framework:

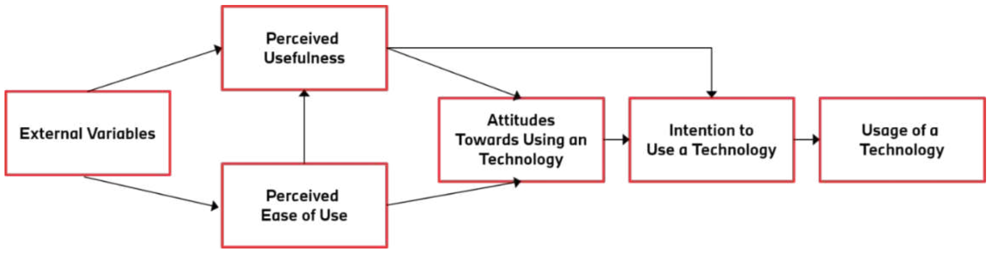

Figure 1: The Technology Acceptance Model (Davis, 1989)

UTAUT2 extends TAM, integrating additional determinants including Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit (Venkatesh et al., 2012). Social Influence impacts recreational athletes, particularly within virtual training communities such as Zwift and Strava (Westmattelmann et al., 2021). These platforms facilitate engagement, but their social comparison mechanisms, such as leaderboards and rankings, can deter people. They may also contribute to performance pressure and unrealistic benchmarks, which are detrimental to adoption and engagement (Westmattelmann et al., 2021). Facilitating Conditions, such as user support, platform integration, and institutional backing, are particularly relevant for coaches. Fragmented digital ecosystems and time constraints can limit engagement, even when usefulness is recognized. Coaches often rely on technology data, but structural barriers can hinder full adoption (Wells et al., 2022). Thus, Facilitating Conditions are a key enabler of coach-specific adoption patterns (Venkatesh et al., 2012).

Hedonic Motivation, defined as enjoyment derived from use, depends on the athlete's competitive level (Venkatesh et al., 2012). Recreational athletes often engage with interactive features that enhance enjoyment and social connection, making gamification a key factor (Westmattelmann et al., 2021). In contrast, elite athletes prioritize performance data, structured training methods, and physiological accuracy over entertainment-driven engagement (Werner & Bischof, 2024). While gamification may appeal to some competitive athletes when integrated with precise feedback, it is generally irrelevant to training priorities. A more detailed discussion on gamification is in Section 2.3.3. Additionally, Price Value is derived from user's perception of cost-benefits, meaning perceived value must outweigh costs (Qi et al., 2024).

ECM explains how continued use of technology (Habit) is influenced by how expectations align with actual experiences (Bhattacherjee, 2001). Users who experience 'neutral confirmation', where performance meets but does not exceed expectations, may be less likely to continue use, underscoring the importance of exceeding expectations to foster long-term retention (Yousaf et al., 2021). Trust in data security and privacy significantly impacts post-adoption behaviors, particularly for biometric wearables. Concerns over misuse of personal health data are a barrier (Guppy et al., 2023).

The DOI Model follows a diffusion S-curve to explain the adoption process. Adoption begins slowly with a small subset of Innovators, accelerates as Early Adopters and the Early Majority drive expansion, and eventually plateaus with the Late Majority and Laggards. The S-curve illustrates how initial resistance is gradually overcome as social proof, economic feasibility, and technological refinement encourage adoption (Rogers, 2003). *Figure 2* depicts the five distinct adopter categories, characterized by specific behavioral attributes.

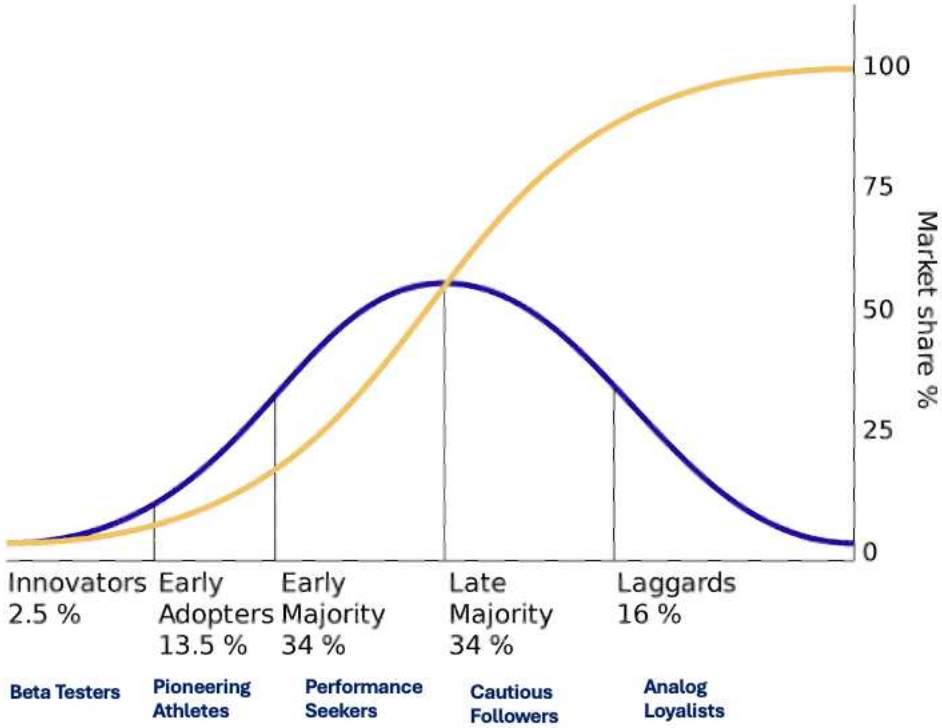

Figure 2: Diffusion of Innovation Model (Rogers, 1962)

Innovators experiment with emerging technologies, often beta testing a novel solution. Their risk tolerance and proclivity for experimentation serve as catalysts for subsequent waves of adoption.

Early Adopters are competitive triathletes and forward-thinking coaches who integrate validated technologies into training methodologies. These individuals function as influential nodes within the social ecosystem, shaping broader acceptance (Wells et al., 2022).

The Early Majority represents a point in technology adoption, reaching an inflection. At this stage, usability, economic viability, and demonstrated effectiveness are important (Kastoriano

& Halkias, 2020). This cohort relies on peer influence and observed benefits before full adoption.

The Late Majority only adopts technology when it becomes an industry standard. Economic barriers, technology skepticism, and resistance are adoption deterrents (Mertala & Palsa, 2024). Adoption is often contingent upon lower costs and overwhelming social validation.

Laggards are characterized by persistent resistance, stemming from inertia, perceived switching costs, financial constraints, or an aversion to digitalization (Qi et al., 2024). Adoption occurs primarily through necessity rather than voluntary engagement, typically when technologies become ubiquitous and indispensable (Rogers, 2003).

2.2.2 Barriers and Challenges to Adoption

Despite increasing availability of sports tech, adoption rates remain uneven due to economic, psychological, and ethical constraints (Westmattelmann et al., 2021). However, barriers vary by demographics, suggesting that adoption is context-dependent.

Economic Constraints and Behavioral Responses

Economic constraints mainly affect recreational athletes, due to high upfront hardware costs (e.g., power meters, multisport watches) and recurring expenses for digital training platforms (Seçkin et al., 2023). Adoption models, such as TAM and UTAUT2, suggest that the perceived price-value ratio impacts long-term engagement. Many athletes cite cost as a barrier to sustained use, as they perceive digital platforms as expensive in relation to the benefits (Qi et al., 2024).

Athletes are more likely to disengage from digital platforms when the perceived cost outweighs performance benefits, a behavioral response linked to expectancy constructs (Mertala & Palsa, 2024).

Technostress and Cognitive Overload

Technostress and cognitive overload are additional barriers. Coaches and recreational athletes report data fatigue from excessive performance tracking, leading to decision paralysis and reduced reliance on intuition (Michalik & Schermuly, 2023; Wells et al., 2022). For coaches, technostress is heightened by managing multiple data streams for different athletes (Michalik & Schermuly, 2023). Pressure to integrate new technologies and uncertainty about long-term efficacy contribute to resistance. In contrast, elite athletes actively seek more training data (Werner & Bischof, 2024).

Psychological Resistance to Digitalization

Older athletes are particularly resistant to digitalization (Woods et al., 2021), while concerns over data privacy and biometric surveillance extend even to elite competitors (Guppy et al., 2023). This challenges the assumption that performance-oriented athletes are universally receptive to digital innovations.

2.2.3 Gamification and Athlete Engagement

Recreational athletes vs elite athletes

Gamification aims to boost motivation and engagement by incorporating interactive elements, including leaderboards, virtual rewards, and milestone-based progression (Al-Zyoud, 2021). The effectiveness of gamified features depends on an athlete's competitive level and training goals, with notable disparities between recreational and elite cohorts (Habachi et al., 2024).

Recreational athletes are more receptive to gamification, as it strengthens intrinsic motivation, promotes social bonding, and facilitates structured training (Polo-Peña et al., 2020). Badges, rankings, and challenges support goal-setting and reinforce performance through quantifiable milestones (Habachi et al., 2024).

Elite athletes engage more selectively, prioritizing metrics, evidence-based training, and physiological optimization over gamified features (Westmattelmann et al., 2021). While some elite athletes use virtual race simulations and adaptive analytics, the extrinsic rewards of gamification remain secondary to data-driven performance (Uhm et al., 2023). Aligning gamification with high-performance training needs is essential (Habachi et al., 2024).

Short-Term vs. Long-Term Adoption

Recreational athletes' initial attraction to leaderboards, gamified training incentives, and digital competition diminishes if not aligned with training progress (Uhm et al., 2023). Gamified features lose appeal when seen as superficial or poorly tailored to performance improvement (Habachi et al., 2024).

When integrated with meaningful analytics, such as adaptive training and real-time feedback, gamification enhances athlete engagement, particularly as users progress in their training (Westmattelmann et al., 2021; Habachi et al., 2024).

2.3 Strategic Partnerships and Business Models in Digital Triathlon

This section examines how strategic partnerships and business model innovations jointly enable value creation and digital transformation in triathlon.

2.3.1 The Role of Strategic Alliances in Driving Innovation

Strategic alliances function as platforms for ongoing innovation and capability development (Ferrigno et al., 2024), particularly when complementary digital assets are integrated. Collaborations, like IRONMAN's partnership with ROUVY, facilitated the integration of performance analytics, AI-driven training protocols, and mixed-reality race simulations (IRONMAN, 2025; Westmattelmann et al., 2021). IRONMAN, a global long-distance triathlon series, leverages such partnerships to enhance its digital offerings. The Dynamic Capabilities Framework (Barreto, 2010; Eisenhardt & Martin, 2000; Teece et al., 1997) explains how alliances help firms sense opportunities, reconfigure resources, and sustain innovation. Teece's (2010) concept of complementary resources highlights how such collaborations transform business models, as seen in IRONMAN's expanded value proposition through ROUVY's augmented reality cycling platform.

Eisenhardt and Martin (2000) conceptualize dynamic capabilities as structured, learnable routines that foster adaptation in volatile settings. The iterative refinement of virtual race features based on user data exemplifies learning-based capability building (Rouvy, 2025). Barreto (2010) defines dynamic capabilities as the ability to sense and seize opportunities in a timely manner. IRONMAN sensed growing demand for immersive home training, partnered with a tech innovator, and redirected strategic focus toward hybrid experiences. Feedback loops between the firms optimized technological performance and athlete satisfaction (IRONMAN, 2025).

2.3.2 Business Models and Commercialization Strategies

Digital triathlon platforms employ diverse business models to drive commercialization.

<u>Freemium Models and Trial-Based Conversion</u>

Freemium models blend free access with premium upgrades (Mäntymäki et al., 2020). They lower adoption barriers by showing platform value before requiring financial commitment (Mäntymäki et al., 2020). Platforms like TrainingPeaks use free tracking tools to foster engagement while monetizing premium coaching plans (SportsPro, 2024). This converts users from exploration to commitment, consistent with adoption theories that stress reducing uncertainty (Venkatesh et al., 2012).

Subscription Models and Retention through Habit Formation

Subscription-based platforms foster habitual user engagement, promoting retention. Unlike transactional revenue models, subscriptions depend on user retention (Mäntymäki et al., 2019). Retention dynamics relate to habit formation theory, which posits that repeated exposure to behavioral reinforcements encourages continued use (Dam et al., 2018).

The habit loop is a cognitive construct composed of cues (triggers), routines (behavior execution), and rewards (positive reinforcement), which constitute a feedback loop (Eyal, 2014). For digital endurance platforms, cues occur through workout reminders and performance notifications, prompting user engagement. The routine consists of structured training sessions, biometric data logging, and participation in interactive challenges, while rewards emerge through personalized analytics and gamified progress incentives (Westmattelmann et al., 2021).

Expectation-confirmation theory posits that continued engagement is based on fulfilling initial user expectations through persistent reinforcement of perceived value (Bhattacherjee, 2001). Digital fitness ecosystems demonstrate how habitual engagement attenuates churn rates, with platforms such as TrainingPeaks and TrainerRoad leveraging structured training plans and adaptive performance feedback (Westmattelmann et al., 2021; Qi et al., 2024). Similarly, Zwift's gamification architecture, characterized by virtual races and competitive leaderboards, drives sustained participation (Westmattelmann et al., 2021).

Habitual platform use enhances retention and supports premium-tier services, such as advanced analytics and personalized coaching (Qi et al., 2024). Through behavioral reinforcement, subscription-based platforms aim to acquire lifelong users.

Co-Branding Strategies and Value Co-Creation

Effective co-branding partnerships strategically leverage brand equity to deliver tangible performance benefits while fostering symbolic associations aligned with consumer aspirations (Yu et al., 2021).

Integrating TrainingPeaks' performance tracking tools into IRONMAN's athlete preparation programs improved training personalization and accessibility. Merging a technology-driven platform with one of the most prestigious triathlon brands elevated the brand equity of both entities (SportsPro, 2024).

Co-branding hinges on brand fit, the degree to which partners share complementary values, target audiences, and market positioning. A strong brand fit makes collaborations feel authentic rather than opportunistic, boosting consumer trust and purchase intent. The TrainingPeaks–IRONMAN partnership enhanced functional value while reinforcing IRONMAN's symbolic status as the pinnacle of endurance sport. This high-image congruence created a unified consumer perception (Yu et al., 2021).

2.3.3 Challenges in Commercializing Digital Triathlon Experiences

Digital partnerships have expanded access to immersive training and performance analytics, but barriers persist. One key challenge is market fragmentation. Incompatible data standards across platforms like Zwift, TrainingPeaks, and Rouvy hinder seamless metric sharing, resulting in inefficiencies for athletes, coaches, and brands (Bădescu et al., 2022; Qi et al., 2024).

Data security and privacy concerns further complicate adoption. Platforms like Garmin Connect and Strava aggregate sensitive biometric and geolocation data, prompting questions about ownership, third-party access, and unauthorized monetization (Seçkin et al., 2023). Jurisdictional differences in data protection laws also impede universal governance protocols (Qi et al., 2024).

Finally, user-level resistance remains a persistent obstacle. Despite evidence of training efficacy, many, especially elite athletes, still prefer traditional outdoor training tailored to race-specific conditions. Surveys indicate that a significant proportion of users continue to view digital tools as supplementary rather than essential, which slows mainstream adoption (Westmattelmann et al., 2021; Qi et al., 2024).

2.4 Future Strategic Considerations for Digital Triathlon

The next phase of digital triathlon raises critical questions about oversight, equity, and sustainable innovation. These developments can be interpreted through the lenses of Institutional Theory and Open Innovation, which help frame the regulatory and collaborative dynamics shaping the sport's digital trajectory.

Institutional Theory (Dimaggio & Powell, 1983) highlights how governing bodies and formal structures influence the adoption of emerging technologies. As AI-assisted coaching and biometric tracking become more prevalent, compliance with data privacy laws, competition fairness standards, and algorithmic accountability grows increasingly important. Sports federations such as World Athletics and the UCI have imposed limits on real-time biometric monitoring and AI-based performance tools. While some permit heart rate and power data, others prohibit metabolic feedback due to fairness concerns (Guppy et al., 2023). Standardized policies are necessary to govern AI use and ensure regulatory coherence across disciplines. Blockchain-based solutions offer a potential safeguard by allowing athletes to control, encrypt, and selectively share their data, minimizing exploitation risks (Berkani et al., 2024).

In parallel, Open Innovation Theory (Chesbrough, 2003) emphasizes the role of cross-organizational collaboration in driving athlete-centered innovation. Strategic alliances between triathlon brands and technology firms increasingly enable co-developed platforms that integrate AI, performance analytics, and immersive environments. AR and VR tools offer realistic race simulations with real-time biomechanical feedback, enhancing training fidelity (Westmattelmann et al., 2021). AI-based models optimize workload distribution, monitor fatigue, and predict injury risks using biometric and historical data (Huang & Yongquan, 2025). However, these systems cannot replicate psychological readiness, race-day unpredictability, or emotional resilience, qualities essential for peak performance (Qi et al., 2024). For elite athletes, intuition, adaptability, and strategic autonomy remain indispensable alongside data-driven guidance (Michalik & Schermuly, 2023).

As digital triathlon continues to evolve, balancing technological innovation with ethical governance, athlete autonomy, and cross-sector collaboration will be central to its sustainable development.

3. Methodology

The research methodology employed quantitative and qualitative data collection and analysis protocols.

3.1 Research Design

The framework in *Figure 3* illustrates our mixed-methods approach. Triangulation enhanced the validity of findings by corroborating insights across data sources (Jack & Raturi, 2006).

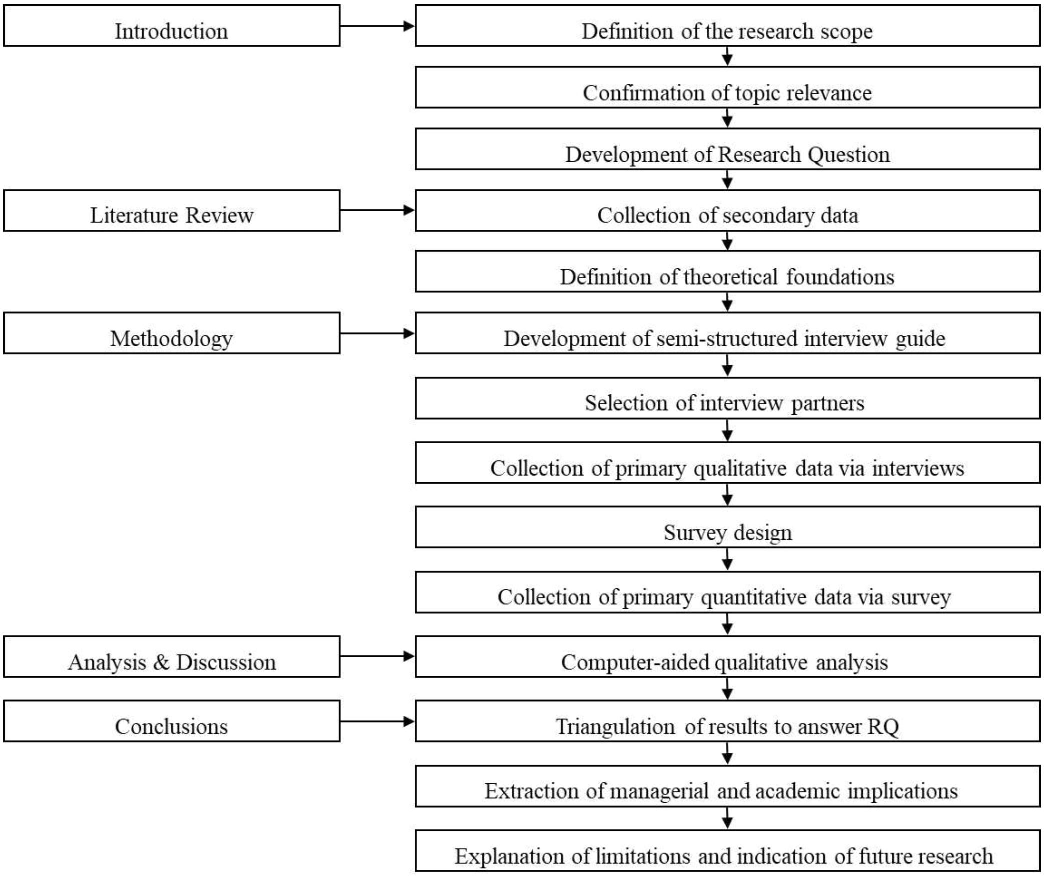

Figure 3: Research Design

Semi-structured interviews with professional athletes, coaches, and age-group triathletes captured industry-specific insights, identifying trends that may not be discernible through quantitative measures (Gioia et al., 2013).

A survey distributed among triathletes provided empirical data on the drivers of athlete technology adoption and impediments. The structure of the survey allowed for statistical analysis of behavioral trends across different athlete demographics (Mayring, 2014).

Finally, findings were triangulated to strengthen the validity of the research outcomes. Integrating qualitative and quantitative insights enhanced the explanatory power of the study (Jack & Raturi, 2006).

3.2 Theoretical Foundation: Digital Sports Technology Adoption Model (D-STAM)

We employed a tailored conceptual framework: the Digital Sports Technology Adoption Model (D-STAM). D-STAM was built upon the Technology Adoption Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012), and the Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001), adapting them to endurance sports and athlete-brand-technology interaction.

Prior models provide heuristics for understanding general technology adoption behavior, whereas D-STAM seeks to capture unique dynamics of sports-specific platforms, such as wearables, training ecosystems, or virtual racing technologies. This framework shaped the semi-structured interview guide and survey. In the interview analysis phase, D-STAM also guided the initial coding.

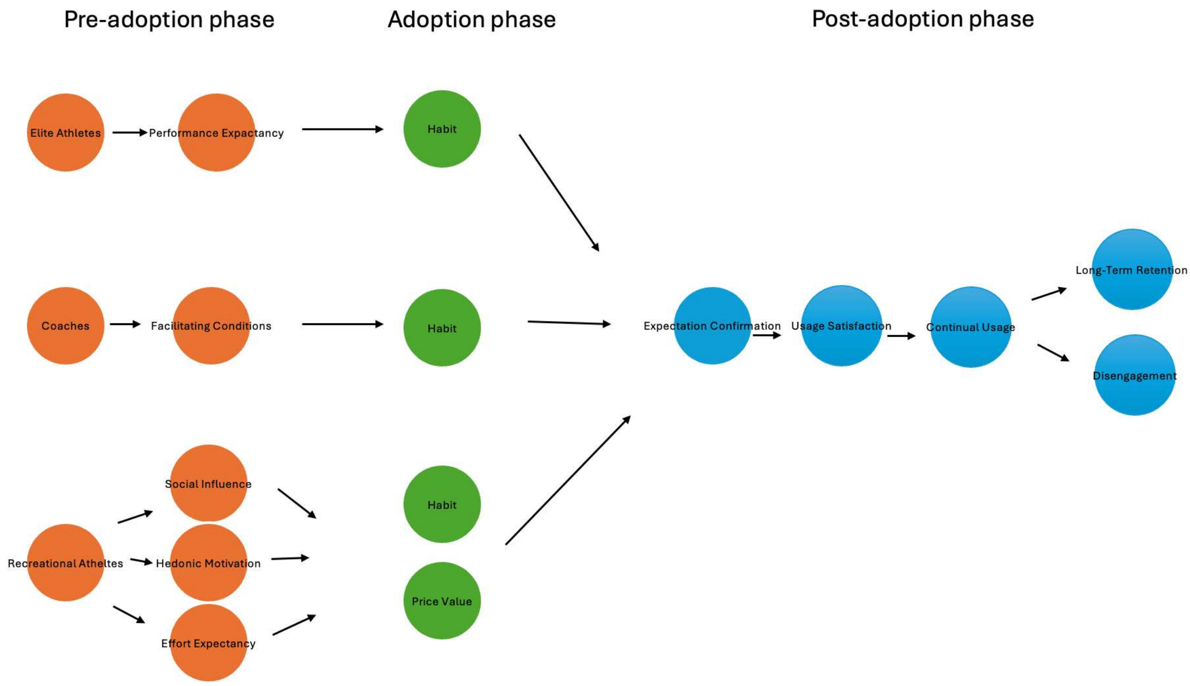

Figure 4: Digital Sports Technology Adoption Model (D-STAM)

Figure 4 illustrates D-STAM, which maps constructs onto distinct user segments and adoption trajectories in triathlon.

In the pre-adoption phase, elite athletes are primarily influenced by Performance Expectancy, reflecting their focus on performance enhancement and data precision. Recreational athletes are driven by Effort Expectancy, Hedonic Motivation, and Social Influence as they prefer intuitive, enjoyable, and socially engaging platforms. Coaches evaluate Facilitating Conditions, including technical support and infrastructure compatibility, as prerequisites for adoption.

During the adoption and usage phase, Habit plays a central role in long-term usage across all user types. Conversely, Price Value may limit sustained engagement, especially among recreational athletes who perceive costs outweighing perceived benefits. In the post-adoption phase, athletes experiencing usage satisfaction are more likely to continue using digital sports technologies, whereas unmet expectations cause disengagement.

D-STAM thus offers a differentiated perspective on technology adoption in triathlon, linking user motivations and contextual conditions to actual usage behavior across the sport's key actor groups.
The following hypotheses were proposed based on mapping to D-STAM elements:

- **H1 (Performance Expectancy):** Performance Expectancy positively influences digital platform adoption among elite athletes.
- **H2 (Effort Expectancy):** Effort Expectancy positively influences digital platform adoption among recreational athletes.
- **H3 (Social Influence):** Social Influence positively impacts digital platform engagement among recreational athletes.
- **H4 (Facilitating Conditions):** Facilitating Conditions positively impact coaches' adoption of digital performance tracking tools.
- **H5 (Hedonic Motivation):** Hedonic Motivation (e.g., gamification) increases digital platform engagement among recreational athletes.
- **H6 (Price Value):** Perceived price value negatively influences platform adoption among recreational athletes.
- **H7 (Habit):** Habit positively predicts long-term usage of digital platforms across all user segments.

3.3 Data collection

The subsequent paragraphs discuss the data collection used in *Chapter 4*.

3.3.1 Primary Data Collection - Expert Interviews

As previously stated, semi-structured interviews were the primary qualitative data collection method used to examine stakeholder experiences and enabled the exploration of emergent themes (Barriball & While, 1994; Cohen & Crabtree, 2006; Rowley, 2012).

An interview guide provided structure while allowing for questions tailored to the interviewee's expertise and responses (Rowley, 2012). Select questions were adapted to three stakeholder groups: professional athletes, coaches, and age-group triathletes. This aligned with best practices in qualitative research to maintain contextual relevance while preserving cross-group comparability (Turner, 2010).

The 27 core questions are outlined in the Appendix. Each session lasted approximately 30 minutes. Some questions included Likert scales to introduce an ordinal measurement within the qualitative framework (Joshi et al., 2015).

The sample of thirteen elite athletes, coaches, and recreational triathletes ensured diverse stakeholder representation. Recruitment was conducted through multiple channels, including direct outreach via email and social media, personal networks, and referrals. Data adequacy was achieved by sampling diverse stakeholders, and after 13 interviews, no new themes emerged, indicating saturation where further interviews were unlikely to yield additional insights (Guest et al., 2006).

All interviews were conducted via video conferencing, recorded with participant consent, and transcribed verbatim for thematic analysis. To maintain participant confidentiality, interviewees are anonymized.

3.3.2 Primary Data Collection – Consumer Survey

To complement the qualitative insights, we conducted a survey examining consumer adoption, engagement, and perceptions. This allowed for comparative analyses and validation of key themes identified in the qualitative phase (Fowler, 2013). The questionnaire targeted triathletes across different experience levels and was distributed online through endurance sports forums, social media platforms, and email outreach.

The survey design included key topics, utilizing Likert scales and categorical questions, tailored to the experts' perspectives. It was administered in English and German and designed and hosted on Qualtrics. The digital format minimized researcher influence, allowing respondents to provide candid, anonymous feedback (Fowler, 2013).

The questionnaire was divided into six sections to assess athlete engagement with digital sports technologies: (1) athletic background; (2) usage patterns of digital training tools and virtual platforms; (3) consumer adoption; (4) perceptions of brand partnerships between technology companies and triathlon brands; (5) expectations for the future of digital triathlon; and (6) demographic information.

A total of 282 participants initiated the survey. Responses were screened based on: completion status, eligibility (Q1: triathlon experience), and attentiveness (Q19: quality control question). After excluding incomplete responses and those failing the qualifying or control questions, a final sample size of n = 257 was retained. The sample included 42 professional athletes, 42 coaches, and 173 recreational triathletes. As is typical for the triathlon population at large, the sample was skewed towards recreational athletes (in 2024, USA Triathlon reported 302,000 total participants compared to only 462 American-registered elites (Gary, 2025; O'Mara, 2024)). Nevertheless, the sample composition had sufficient representation from all three user groups. This sample size aligned with established guidelines, where 200 to 400 responses are typically considered adequate to ensure a 5–10% margin of error at a 95% confidence level (Krejcie & Morgan, 1970). The survey design and analysis adhered to methodological guidelines to support valid statistical interpretation (Dillman et al., 2014).

3.4 Data analysis

3.4.1 Primary Data – Expert Interviews

Thematic content analysis of the interviews was conducted using MAXQDA24 (Kuckartz & Rädiker, 2019). The initial coding framework was developed deductively, informed by the theoretical foundation (e.g., TAM, UTAUT2, ECM, and the D-STAM model proposed in Section 3.2.2). It was iteratively refined through inductive coding to incorporate emerging themes (Fereday & Muir-Cochrane, 2006). The frequency distributions and code relations are described in Chapter 4.1. Qualitative findings were later mapped against the D-STAM hypotheses in Section 4.1.5. The final coding system and interview summaries are in the Appendix.

3.4.2 Primary Data – Survey

The survey data ($n = 257$) were analyzed using IBM SPSS Statistics to test D-STAM hypotheses and explore adoption patterns across athlete roles. Variables were cleaned, coded, and scaled. Composite indices (e.g., DevicesUsed, MetricsUsed) were computed, multiple-response items were dummy-coded, and open-text responses were thematically categorized.

We employed descriptive statistics, chi-square tests, one-way ANOVAs with post hoc Tukey tests, Levene's test for variance homogeneity, and ordinal regressions. Likert-type items were analyzed using ordinal regression models following methodological guidance for ordinal data (Field, 2017). Interaction terms were used to test potential moderating effects (e.g., technostress, income, experience), and Spearman correlations were applied to examine non-parametric associations.

Model fit for ordinal regressions was assessed using Nagelkerke R^2. In line with behavioral research conventions, lower R^2 values were considered acceptable when models showed statistical significance and predictors were theoretically grounded (Newman & Newman, 2000).

Multicollinearity was assessed for all multivariate models using variance inflation factors (VIFs) and tolerance values. All VIFs were well below the critical threshold of 5 (maximum VIF < 2), indicating no collinearity concerns among predictors.

4. Analysis & Discussion

4.1 Expert Interviews

The following analysis delineates insights structured around four core themes: usage patterns, adoption behavior, commercialization dynamics, and future-oriented perspectives.

4.1.1 Technology Usage & Performance Tracking

Based on coded interview data, this section examines the devices employed, the most frequently tracked metrics, and the platforms used to consolidate and interpret training data.

<u>Devices Used</u>

Interviewees reported high technological penetration, with notable standardization across device categories. As shown in *Figure 5*, power meters (92%), chest straps (85%), and Garmin watches (77%) were the most commonly used. These tools provide metrics like power output, heart rate, and GPS, and are often used together. They were considered essential for performance-focused training across all user groups, including elite athletes, recreational athletes, and coaches. Nearly half also used bike computers. In contrast, foot pod sensors, body core temperature sensors, and lactate monitors were adopted more selectively, primarily among elite athletes and coaches. Coaches additionally deployed specialized tools such as communication systems and GPS sensors for open-water swimming, reflecting a broader scope of data capture.

While the overall device landscape was consistent, elite athletes and coaches tended to use multiple devices concurrently, indicating greater systemization and technical literacy. Recreational athletes typically used simpler setups centered around the Garmin ecosystem.

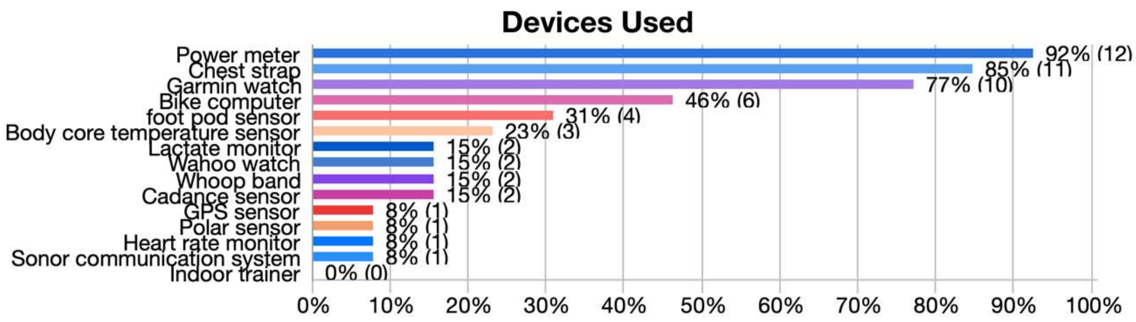

Figure 5: Most frequently used devices among interviewed triathletes

Metrics Tracked

As shown in *Figure 6,* all respondents tracked heart rate, followed by power (92%), pace (69%), and cadence (46%). Sleep (38%) and HRV (31%) were also common, reflecting growing attention to internal load and recovery.

Elite athletes and coaches tended to track a broader range of physiological and biomechanical parameters. Beyond standard metrics, resting heart rate, lactate, VO2 max, and stroke count were mentioned. These metrics are often integrated into structured performance diagnostics or used to guide the tapering and periodization process.

Recreational athletes prioritized metrics readily available through wrist-based devices or smart apps. Most participants reported tracking their heart rate and pace across all sessions, with a subset using HRV or recovery scores to inform their rest decisions. Deep physiological metrics (e.g., lactate or VO2 max) were generally absent from their training routines.

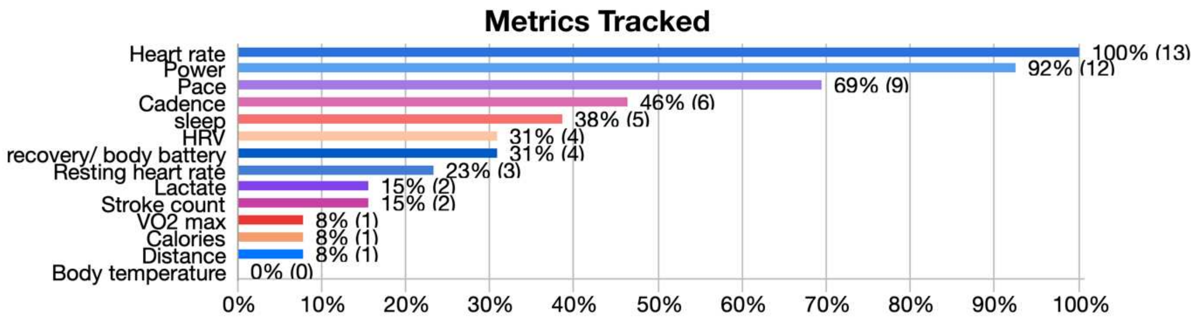

Figure 6: Performance metrics tracked by athletes and coaches

Platforms Used

As seen in *Figure 7,* three digital platforms dominated: TrainingPeaks (58%), Zwift (50%), and Garmin Connect (50%). TrainingPeaks was primarily used for structured training plans, Garmin Connect for continuous monitoring, and Zwift for indoor cycling simulations.

Elite athletes and coaches described structured integration of multiple platforms, often supported by federations or sponsors (e.g., national team access to TrainingPeaks). Coaches further employed WKO for detailed cycling analysis and AeroTune for aerodynamic modeling. Recreational athletes frequently used Garmin Connect as their primary data hub, supplementing it with Strava for motivational features and Zwift for winter training. Several interviewees noted frustrations with platform fragmentation, particularly when tools like MyWhoosh failed to sync with Garmin or Strava.

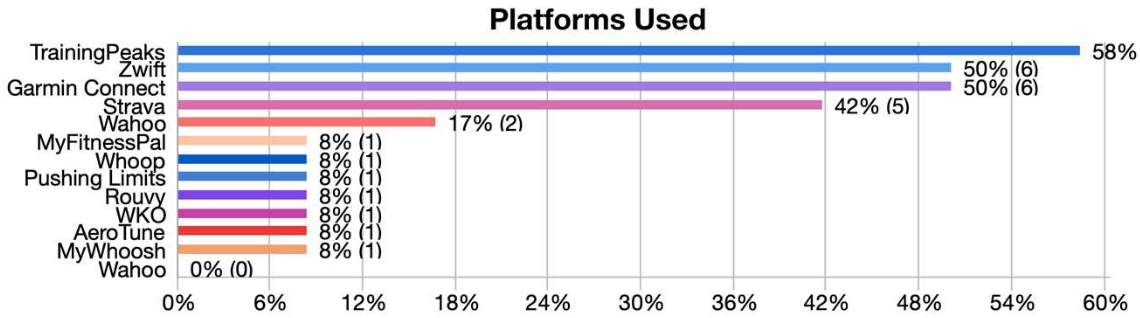

Figure 7: Platforms used for training planning and analysis

Technology usage was structured around a core set of devices and metrics, with variation in complexity and integration across user types. While elite athletes and coaches relied on multi-device ecosystems and high-resolution metrics, recreational athletes prioritized usability and automation. Platform preferences varied according to training needs and institutional support. However, integration challenges persist.

4.1.2 Athlete Technology Adoption

This section examines the psychological and cognitive factors that influence adoption decisions, including perceived usefulness, data trust, ease of use, technostress, motivation, and the balance between digital feedback and intuitive judgment.

Note: Quotations are used more extensively here to illustrate segment-specific adoption strategies, as numeric aggregation across roles (3–4 experts per group) was less informative.

<u>Perceived Usefulness and Trust in Data</u>

Perceived usefulness was a key adoption driver, although the rationale varied by segment. Several elite athletes emphasized diagnostic precision: "With lactate and VO_2 testing, I've finally trained correctly without guessing" (P2). Coaches echoed this utility for individualized planning: "It's a huge advancement, as I can assess an athlete's fitness in real-time and adjust immediately" (C2). Recreational athletes emphasized the importance of structure: "Without it, I wouldn't know what to do, how fast I am, or what values to train at" (R1). Trust in core metrics like power or heart rate was high, although some recreational athletes expressed skepticism about derived indicators: "I don't fully believe in the sleep scores since some mornings I feel great even if WHOOP tells me I'm in the red" (R4).

Ease of Use and Interpretability

Ease of use was essential for recreational athletes. “TrainingPeaks was too technical; I needed help” (R1), while others found the setup straightforward once guided. Among elites, digital tool use had become habitual: “It’s second nature, as these are my daily tools” (P1). Coaches focused on athlete comprehension: “Some athletes don’t know what the values mean and that’s where coaching becomes essential” (C1). Usability concerns were more pressing for recreational users, while coaches mitigated interpretability challenges.

Technostress and Psychological Responses

Recreational athletes more frequently reported technostress. “It stressed me out when I broke my Garmin sleep score streak” (R4), one noted, while another described skipping metrics to avoid pressure. Elite athletes generally minimized pre-race data: “I don’t even look since it would just make me nervous” (P2). Coaches acknowledged stress patterns among athletes and described filtering as part of their role: “I filter the data so they can focus on what matters” (C4). Psychological strain was rarely reported as a reason for complete discontinuation but contributed to temporary disengagement.

Balancing Intuition vs. Data

Most participants attempted to balance digital feedback with intuition. “We’re not machines, so you need to listen to your body” (P1) captured the sentiment among elite athletes. Coaches reinforced intuitive adjustments, especially under race stress. Recreational athletes were split, since some used tech as a reference, while others became overly dependent: “WHOOP started controlling how I felt about training, even when my legs felt fine” (R3). The data revealed no uniform segmental stance but a range of balancing strategies, often shaped by experience and confidence.

Social Influence and Coaching Resistance

Social influence affected recreational users: “I use Garmin and Strava because my friends do and recommended” (R2). Elite athletes occasionally referenced peer benchmarking: “I switched to Wahoo because it’s what they use in the pro peloton” (P3). Coaches rarely mentioned external influence and emphasized independent evaluation: “I don’t care what’s trendy, only what works technically” (C1). Several athletes and coaches described prior reliance on outdated systems (e.g., Excel plans), due to coaching history influencing exposure and timing of adoption.

Gamification and Motivation

Gamified features had mixed effects. Recreational athletes frequently mentioned Zwift badges or Strava challenges as motivational: “I go after Zwift badges as it keeps me engaged” (R4). Coaches used gamification strategically to drive specific efforts: “We sometimes race on Rouvy to see how far they can push” (C3). Elite athletes generally saw them as irrelevant: “It’s a nice extra, but not relevant for serious training” (P5). Thus, gamification appeared segment-specific in motivational impact, with greater relevance for recreational users.

Cost–Value Perception

Only recreational athletes raised cost concerns. “Zwift is too expensive now” (R4), one remarked, while another described canceling platforms based on perceived value: “I cancel when the value drops” (R3). Some still justified the investment: “I use it daily, so it’s fine” (R2). Elite athletes and coaches prioritized functionality: “I buy the best once as it lasts” (P4), and “If a product doesn’t clearly help, we don’t use it” (C2). Hardware cost was generally tolerated, but recurring platform fees were more contentious.

Privacy and Ethical Considerations

Privacy was rarely mentioned. Most athletes dismissed concerns when asked: “I don’t really care as data is being collected everywhere” (R1). Coaches held similar views. Anticipated concerns about AI-based prediction or surveillance surfaced occasionally but did not impact current adoption decisions.

Summary of Interconnected Factors

Patterns emerged, though views varied. Performance precision, usability, and motivational design shaped adoption differently across roles, yet individual variation was notable, especially among recreational athletes. Coaches played a role in mediating, reducing stress, and enhancing interpretability. Utility, emotional alignment, intuitive fit, and manageable complexity promoted long-term engagement.

4.1.3 Commercialization and Strategic Partnerships in Triathlon

This section examines platform loyalty, pricing strategies, and brand collaborations’ influence on stakeholder perceptions.

Platform Loyalty and Data Lock-In

Platform stickiness was a key barrier to switching, noted across all user groups. Five interviewees (38%) cited reluctance due to training history and platform familiarity. Expert R2 (recreational) emphasized emotional attachment to performance records, while Expert P1 (elite) described himself as someone who “doesn’t switch easily”. Coaches and experienced users similarly preferred consistency, primarily when data integration supports longitudinal performance tracking. Findings suggested platform loyalty is shaped by identity, habit, and analytic continuity, not just cost.

Freemium vs. Paid Models

Freemium and paid usage were mentioned equally by five interviewees, with each option being equally represented. Recreational athletes employed cost-saving strategies, such as rotating email addresses for trials (P4) or switching to free platforms like MyWhoosh (C3), who stated, “I just want to ride”. Conversely, users who paid for services typically justified the investment through specific platform features. Expert R3 subscribed to TrainingPeaks Premium to track fatigue trends, while Expert P2 considered ROUVY’s paid tier worthwhile for race-specific simulations. These examples highlighted that willingness to pay depends more on perceived functional value than on general pricing attitudes. Freemium usage demonstrated flexible strategies tailored to training needs and financial priorities.

Strategic Partnerships and Innovation Impact

Nine out of thirteen interviewees (69%) saw brand collaborations as major drivers of digital product innovation. Examples included Komoot syncing (P3), Wahoo–Zwift control features (P4), and Garmin’s pro-level updates, highlighting elite input shaping consumer tech. Coaches viewed real-world testing and feedback loops as integral to the development. Expert P1 described how oxygen sensors transitioned from lab-based diagnostics to wearable tech and predicted that lactate monitors would follow. Strategic alliances enabled faster feature rollout, stronger platform utility, and innovation cycles informed by elite users.

Critiques of Innovation and Market Saturation

While many praised innovation efforts, several interviewees raised concerns about functionality gaps and trend-driven development. Expert R3 criticized stagnant platforms that neglect user feedback, while Expert C2 noted that federations adopt tools only when proven effective. Critiques reflected a gap between innovation potential and athlete relevance, suggesting that not all commercial innovations translate into meaningful performance enhancements.

Sponsorships: Awareness vs. Authentic Adoption

Three interviewees (23%) acknowledged sponsor visibility, mainly at expos or races. For instance, Expert R2 mentioned using discount codes from race goodie bags. However, elite athletes and coaches stressed utility over branding. Expert P2 remarked, “I don’t promote everything I use,” and Expert C3 emphasized testing over trust. Expert C2 noted that federations’ loyalty is conditional. Overall, while sponsorships aid discovery, they rarely determine long-term usage.

Concerns Around Overcommercialization

Several participants, mainly coaches and elite athletes, expressed discomfort with the increasing commercialization of triathlon tech. Expert C1 pointed to marginal gains not justifying steep price increases, while P2 criticized races like Challenge Roth for excessive branding. C2 warned against adopting tools “just because they’re new”. These insights reveal discomfort with spectacle-driven commercialization and suggest that performance impact, not trendiness, should drive evaluation.

Commercialization and partnerships influence engagement through loyalty, pricing, and innovation. While brand collaborations accelerate product development, especially via elite input, adoption depended on functional value, not exposure alone. Sponsorships support visibility but rarely influence long-term use. Ultimately, adoption decisions reflected a balance between performance needs, cost, and personal utility.

4.1.4 The Future of Digital Triathlon

This final subchapter explores emerging trends in the triathlon ecosystem.

AI-Driven Training Complement, Not Replacement

Most interviewees (92%, n = 12) believed AI will enhance, but not replace, human coaching. Across all groups, participants emphasized the irreplaceable value of human intuition, interpersonal trust, and contextual decision-making. Elite athletes like Expert P2 explained, “With AI, you miss that trust and human adjustment”. P5 added that AI lacks the nuance to understand personality or emotional shifts. Recreational athletes R1 and R2 shared this concern, doubting AI’s ability to handle real-world complexity.

Nonetheless, 46% (n = 6) saw potential for AI in adaptive suggestions or data analysis. R4, for instance, viewed AI as a means to help coaches manage more athletes. Some recreational athletes also appreciated AI's efficiency in generating pre-structured plans. Still, negative perceptions were dominant (69%, n = 9), often linked to failed adjustments, overreliance on algorithms, or lack of contextual flexibility.

Virtual Racing: Contested Legitimacy and Niche Utility

Opinions on virtual racing were split. Five participants (38%) considered it a legitimate option, especially in cycling, while six (46%) questioned its fairness and realism. Concerns included device calibration differences and cheating risks. Expert P2 described Zwift drafting as "complete nonsense," while P1 highlighted treadmill variation as a significant limitation: "Smart trainers can have 1–2% variation, but treadmills have up to 5%, that's a massive difference".

Skepticism was most substantial among professional athletes and coaches, who saw virtual formats as lacking credibility for serious competition. However, a few participants, such as C3 (coach) and R3 (recreational athlete), acknowledged virtual racing's value for training and accessibility. Notably, only these two experts clearly differentiated between their value for training and their limits as a race substitute. Virtual formats thus remain supplementary tools rather than credible alternatives to physical competition.

Missing Innovations: Demands for Interpretability and Physiological Tracking

When asked about unmet needs, 46% (n = 6) mentioned the lack of interpretability tools. P3 and C3 called for systems that translate metrics into advice, such as AI-generated explanations like "This number means X, and you should adjust Y". Interpretive support was crucial for those with limited time or technical skills.

Physiological tracking was the second central theme. Continuous lactate monitoring was cited by 3 interviewees (23%), including elite athletes P1 and P5, who described current blood-testing methods as impractical and costly. Other suggestions included real-time glucose (n = 2), portable VO_2 tracking (n = 1), and wind resistance sensors (n = 1). These requests came primarily from elite athletes. Recreational users prioritized accessibility, integration, and affordability.

See *Figure 8* for a visual summary of innovation gaps.

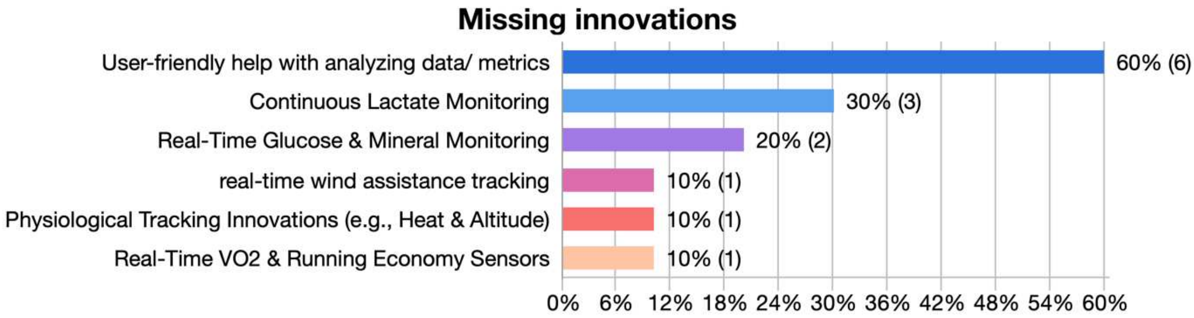

Figure 8: Missing Innovations

Interpretation Across Groups

All stakeholder groups acknowledged the promise of emerging technologies. Nevertheless, professionals emphasized emotional precision in coaching and were most critical of virtual racing. Recreational athletes expressed more enthusiasm for freemium AI tools and saw virtual formats as useful complements. Coaches supported hybrid approaches, employing AI for diagnostics while maintaining human oversight.

The future of digital triathlon appears less defined by radical disruption than by hybridization. Athletes and coaches seek tools that amplify, not replace, existing practices. Adoption depends on usability, fairness, and trust, so future innovation must be both technically and human-centered.

4.1.5 D-STAM Mapping Summary and Hypothesis Alignment

To consolidate the qualitative, this section maps key findings to the proposed hypotheses of the D-STAM framework.

Table 1: D-STAM Hypotheses: Qualitative Support by User Segment

Hypothesis	**Construct**	**Proposed for**	**Supported by Findings**	**Degree of Support**	**User Segment Relevance**
H1: Performance Expectancy influences adoption	Performance Expectancy	Elite Athletes	Strong motivation via training efficiency, recovery precision, and performance insights	Strong	Yes: Elites | Partially: Coaches, Recreational
H2: Effort Expectancy drives adoption	Effort Expectancy	Recreational Athletes	Adoption tied to ease of use, cognitive simplicity, and interface clarity	Strong	Yes: Recreational | Partially: Coaches, Elites
H3: Social Influence increases engagement	Social Influence	Recreational Athletes	Influential during early adoption; peer/friend influence and elite reference cues	Moderate	Yes: Recreational | Partially: Elites | No: Coaches

H4: Facilitating Conditions influence adoption	Facilitating Conditions	Coaches	Strong among coached athletes and coaches using structured platforms	Strong	Yes: Coaches, Elites | No: Recreational
H5: Gamification increases engagement	Hedonic Motivation	Recreational Athletes	Motivational for some recreational athletes, irrelevant or distracting for elites and coaches	Mixed	Yes: Recreational | No: Elites, Coaches
H6: Price–value perception hinders adoption	Price–Value	Recreational Athletes	Subscription fatigue cited; cost tolerable for hardware but not recurring platforms	Moderate	Yes: Recreational | Partially: Elites | No: Coaches
H7: Habit predicts long-term usage	Habit	All Segments	Daily routines formed; described as "second nature" by many elite and coached athletes	Strong	Yes: All Segments

Table 2: Emergent Constructs and Model Extension

New Hypothesis	**Construct**	**Observed Impact**	**Proposed Addition to D-STAM**
H8	Technostress & Cognitive Load	Undermines confidence and continuity, particularly with sleep/recovery data	New Moderator
H9	Economic Constraints	Price sensitivity affects retention and freemium conversion	New Moderator
H10	Coaching Resistance	Some coaches hesitant to fully adopt digitalization	Limiting Factor / Segment-Specific Barrier

These insights validate D-STAM's core constructs while highlighting psychological dimensions that warrant integration into endurance-sport-specific technology adoption models. They also provide a clear foundation for statistical testing following the survey analysis (Chapter 4.2).

4.2 Survey

This section presents the survey findings. The analysis examines patterns and tests hypotheses across athlete segments. A demographic overview is provided in Appendix C.2.

4.2.1 Usage Patterns of Digital Technologies

Table 3 summarizes device and metric usage across athlete roles. Professionals and coaches reported significantly higher adoption of advanced tools, including lactate meters ($\chi^2(2) = 158.08$, $p < .001$), core temperature sensors ($\chi^2(2) = 75.32$, $p < .001$), and smart trainers ($\chi^2(2) = 19.11$, $p < .001$). Wearables such as Whoop Bands were also more common among professionals (28.6%) than recreational athletes (2.9%) ($\chi^2(2) = 29.11$, $p < .001$). In terms of metrics, professionals and coaches were more likely to track HRV ($\chi^2(2) = 48.66$, $p < .001$), lactate thresholds ($\chi^2(2) = 53.28$, $p < .001$), and body temperature ($\chi^2(2) = 73.99$, $p < .001$).

Table 3: Usage Of Devices And Metrics By Role

Category	Item	Recreational (%)	Professional (%)	Coach (%)	χ²	p-value
Device	GPS watch	98.3	100.0	100.0	1.47	.479
Device	Heart rate monitor	88.4	97.6	100.0	8.26	.016
Device	Lactate Meter	2.9	90.5	54.8	158.08	<.001
Device	Core Temp Sensor	4.6	57.1	40.5	75.32	<.001
Device	Smart Trainer	75.7	97.6	97.6	19.11	<.001
Device	Whoop Band	2.9	28.6	14.3	29.11	<.001
Device	Power Meter	66.5	100.0	97.6	33.5	<.001
Device	Cadence sensor	41.6	90.5	92.0	58.18	<.001
Device	Digital training app	100.0	56.1	88.1	39.17	<.001
Device	Virtual training platforms	59.0	90.5	85.7	22.46	<.001
Device	Bike computer	74.6	97.6	90.5	14.60	<.001
Metric	Heart rate	89.6	97.6	97.6	5.07	.079
Metric	Pace	89.6	97.6	95.2	3.68	.159
Metric	VO2 max	59.0	66.7	71.4	2.65	.266
Metric	Recovery status	39.3	35.7	45.2	.828	.661
Metric	Predicted race time	23.7	4.8	9.5	10.69	.005
Metric	HRV	42.2	88.1	88.1	48.66	<.001
Metric	Lactate Threshold	27.2	78.6	71.4	53.28	<.001
Metric	Body Temperature	5.8	52.4	52.4	73.99	<.001
Metric	Training Stress Score	32.4	21.4	83.3	43.38	<.001
Metric	Sleep Metrics	41.6	78.6	76.2	29.10	<.001
Metric	Cadence	39.3	88.1	85.7	57.78	<.001
Metric	Power output	73.4	100.0	95.2	22.13	<.001

ANOVA tests confirmed these role-based differences. For device usage, a significant main effect was found ($F(2, 254) = 83.93$, $p < .001$, $\eta^2 = .398$), with professionals ($M = 9.57$) and coaches ($M = 8.69$) using significantly more devices than recreational athletes ($M = 5.74$). A similar pattern was observed for metric tracking ($F(2, 254) = 34.17$, $p < .001$, $\eta^2 = .212$), where coaches ($M = 8.71$) and professionals ($M = 8.10$) again reported higher engagement than recreational athletes ($M = 5.65$). These findings confirm role-based segmentation in digital adoption.

4.2.2 Adoption Drivers & D-STAM Hypotheses (H1–H7)

To test the D-STAM hypotheses (H1–H7), a series of analyses examined how key adoption constructs predicted usage behavior and varied by athlete role (Q2). The evaluation included ordinal regression, segmental models, and relevance comparisons (Q8–Q13), adoption stages (Q7), and actual usage (Q14), offering empirical support for D-STAM's segmentation logic.

4.2.2.1 Ordinal Regression for D-STAM Constructs (H1–H7)

An ordinal regression tested whether the six D-STAM predictors (Q8–Q13) explained variation in training metric usage frequency (Q14). The model was statistically significant ($\chi^2(6) = 63.544$, $p < 0.001$; Nagelkerke $R^2 = 0.259$), indicating moderate explanatory power.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	454.274			
Final	390.730	63.544	6	<.001

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	726.966	790	.947
Deviance	370.963	790	1.000

Link function: Logit.

Pseudo R-Square

Cox and Snell	.219
Nagelkerke	.259
McFadden	.133

Link function: Logit.

Three predictors were significant: Performance Expectancy (Q8; B = –0.767, p < 0.001), Effort Expectancy (Q9; B = –0.791, p < 0.001), and Facilitating Conditions (Q11; B = –0.346, p = 0.010). Given Q14's coding (lower values = higher frequency), negative coefficients indicate that stronger agreement with these constructs relates to more regular use of digital training tools, thus supporting H1, H2, and H6.

The model also indirectly supported H7, as habitual usage (Q14) was significantly influenced by its proposed antecedents. In contrast, Social Influence (Q10; p = 0.089) and Hedonic Motivation (Q12; p = 0.059) were not significant, and Price Value (Q13; p = 0.930) showed no effect. Together, these results leave H3, H4, and H5 unsupported in the full sample.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Q14 = 1]	-6.878	3.794	3.288	1	.070	-14.314	.557
	[Q14 = 2]	-4.922	3.783	1.693	1	.193	-12.338	2.493
	[Q14 = 3]	-3.956	3.786	1.092	1	.296	-11.377	3.465
	[Q14 = 4]	-2.381	3.818	.389	1	.533	-9.864	5.102
Location	Q8	-.767	.192	15.890	1	<.001	-1.144	-.390
	Q9	-.791	.187	17.833	1	<.001	-1.158	-.424
	Q10	.264	.155	2.884	1	.089	-.041	.568
	Q11	-.346	.133	6.715	1	.010	-.607	-.084
	Q12	-.247	.131	3.568	1	.059	-.502	.009
	Q13	.017	.193	.008	1	.930	-.361	.395

Link function: Logit.

4.2.2.2 Role-Specific Ordinal Regression Models and Perceived Construct Differences

Segment-specific ordinal regressions were conducted to test D-STAM hypotheses across athlete roles and identify distinct predictors of habitual engagement with training metrics (Q14).

For recreational athletes, the model was statistically significant ($\chi^2(6) = 37.336$, $p < 0.001$, Nagelkerke $R^2 = .220$). Effort Expectancy (Q9; $B = -0.750$, $p < 0.001$) supported H2. Performance Expectancy (Q8; $p = 0.003$) and Facilitating Conditions (Q11; $p = 0.036$) were also significant, though not originally hypothesized. Social Influence (Q10), Hedonic Motivation (Q12), and Price Value (Q13) were not significant, providing no support for H3, H5, or H6. This suggests recreational athletes respond to a mix of usability, utility, and system support rather than motivational incentives.

For coaches, the model was not significant ($\chi^2(6) = 6.547$, $p = 0.365$), and Facilitating Conditions (Q11; $p = 0.643$) did not support H4. Social Influence approached significance ($p = 0.059$), hinting at a potentially underestimated role in coaching technology use.

For professional athletes, the model could not be interpreted due to quasi-complete separation: 95.2% reported using metrics in every session, resulting in insufficient variance. Though the model appeared to fit perfectly ($\chi^2(6) = 16.081$, $p = 0.013$, Nagelkerke $R^2 = 1.000$), this is a statistical artifact. Nonetheless, the uniform engagement behavior provides strong descriptive support for H1, affirming that performance expectations drive adoption among elite users.

Habit (H7) was indirectly supported whenever predictors significantly influenced usage. Among recreational athletes, the combined effect of Q8, Q9, and Q11 indicates that habit formation is shaped by both motivational and structural factors. Overall, results validate D-STAM's segmentation logic and suggest a broader influence of Performance Expectancy and Facilitating Conditions than initially hypothesized.

Model Fitting Information

What is your primary role in triathlon?	Model	-2 Log Likelihood	Chi-Square	df	Sig.
Professional athlete	Intercept Only	16.081			
	Final	.000	16.081	6	.013
Recreational triathlete	Intercept Only	357.016			
	Final	319.680	37.336	6	<.001
Coach	Intercept Only	58.165			
	Final	51.618	6.547	6	.365

Link function: Logit.

Parameter Estimates

What is your primary role in triathlon?			Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Professional athlete	Threshold	[Q14 = 1]	-191.929	.000	.	1	.	-191.929	-191.929
	Location	Q8	-.403	33117.855	.000	1	1.000	-64910.207	64909.401
		Q9	-3.163	36726.657	.000	1	1.000	-71986.089	71979.763
		Q10	-.849	47023.823	.000	1	1.000	-92165.848	92164.150
		Q11	-40.478	46160.442	.000	1	.999	-90513.282	90432.326
		Q12	.279	25701.498	.000	1	1.000	-50373.731	50374.290
		Q13	-1.689	13229.467	.000	1	1.000	-25930.969	25927.590
Recreational triathlete	Threshold	[Q14 = 1]	-3.033	4.462	.462	1	.497	-11.779	5.713
		[Q14 = 2]	-1.146	4.458	.066	1	.797	-9.884	7.591
		[Q14 = 3]	-.263	4.460	.003	1	.953	-9.005	8.479
		[Q14 = 4]	1.321	4.485	.087	1	.768	-7.470	10.112
	Location	Q8	-.658	.218	9.089	1	.003	-1.085	-.230
		Q9	-.750	.209	12.863	1	<.001	-1.160	-.340
		Q10	.143	.170	.706	1	.401	-.191	.477
		Q11	-.296	.141	4.376	1	.036	-.573	-.019
		Q12	-.226	.140	2.613	1	.106	-.500	.048
		Q13	.190	.224	.722	1	.395	-.248	.628
Coach	Threshold	[Q14 = 1]	-9.411	11.116	.717	1	.397	-31.197	12.376
		[Q14 = 2]	-6.960	11.105	.393	1	.531	-28.725	14.805
	Location	Q8	-.456	.500	.833	1	.361	-1.436	.524
		Q9	-.567	.632	.803	1	.370	-1.806	.673
		Q10	.888	.471	3.552	1	.059	-.035	1.812
		Q11	-.290	.624	.215	1	.643	-1.513	.934
		Q12	-.242	.418	.335	1	.563	-1.062	.577
		Q13	-.311	.567	.301	1	.583	-1.422	.800

Link function: Logit.

Two ordinal regression models tested how athletes across roles perceived adoption constructs (Q8–Q13), using recreational athletes and coaches as alternating reference groups. When recreational athletes served as the reference, professionals rated Performance Expectancy ($B = 2.313$, $p < .001$), Effort Expectancy ($B = 1.941$, $p < .001$), Facilitating Conditions ($B = 0.826$, $p = .019$), and Price Value ($B = 1.747$, $p < .001$) significantly higher. Coaches also rated these four constructs significantly higher than recreational athletes ($p < .005$).

Using coaches as the reference group confirmed only one significant difference: professionals rated Effort Expectancy higher ($B = 0.968$, $p = .028$). No significant differences emerged between professionals and coaches for Performance Expectancy, Facilitating Conditions, or Price Value ($p > .10$). Across both models, Social Influence and Hedonic Motivation showed no significant differences between roles ($p > .45$).

These findings underscore D-STAM's segmentation logic: professionals and coaches perceive greater utility, usability, and value from digital training technologies than recreational athletes. Results are shown in *Figure 9*.

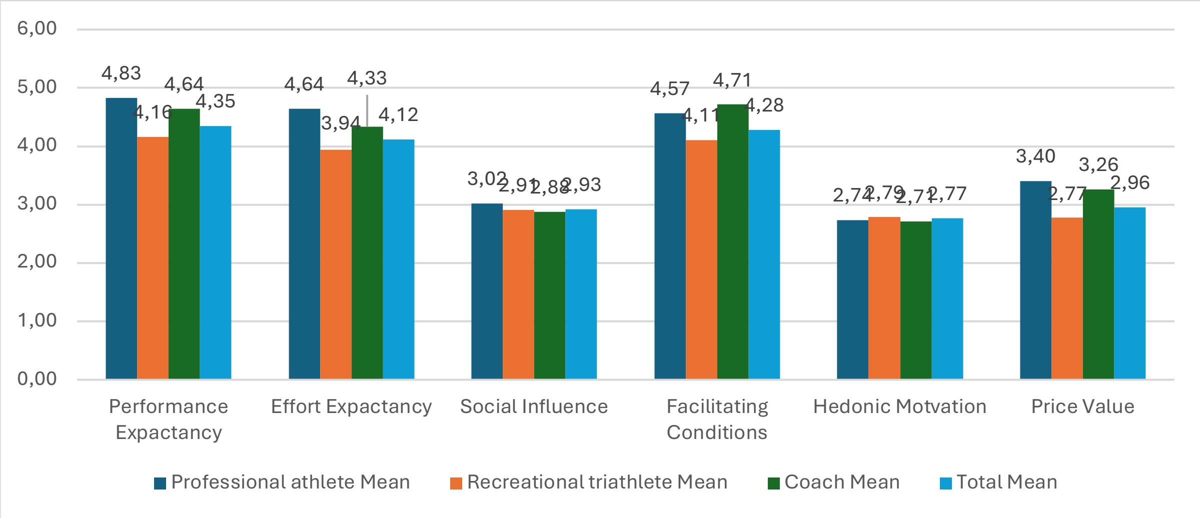

Figure 9: Mean Ratings of D-STAM Constructs by Athlete Role

4.2.2.3 Segment Differences in Adoption Stage (Q7)

To explore adoption timing and its variation by athlete role, adoption stage (Q7) was compared across segments using a chi-square test. The result was statistically significant ($\chi^2(8) = 67.642$, $p < 0.001$), with a moderate association (Cramer's V = 0.363). Professional athletes and coaches were more likely to classify themselves as Early Adopters, while recreational athletes were more evenly distributed across categories and disproportionately represented among Late Majority and Laggards. This supports the segmental logic of D-STAM and aligns with the Diffusion of Innovation theory.

As visualized in *Figure 10*, adoption stage distribution differed notably across roles. The overall response pattern deviated from Rogers' classic S-curve: a higher proportion of athletes identified as Innovators or Early Adopters than as members of the Early or Late Majority. This inverted curve likely reflects triathlon's strong performance ethos and a culture of technological openness, especially among professionals and coaches. It may also suggest that the digital triathlon sector remains expanding, with early adoption concentrated among highly engaged users.

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	67.642[a]	8	<.001
Likelihood Ratio	77.148	8	<.001
Linear-by-Linear Association	.999	1	.318
N of Valid Cases	257		

a. 4 cells (26.7%) have expected count less than 5. The minimum expected count is 1.31.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.513	<.001
	Cramer's V	.363	<.001
N of Valid Cases		257	

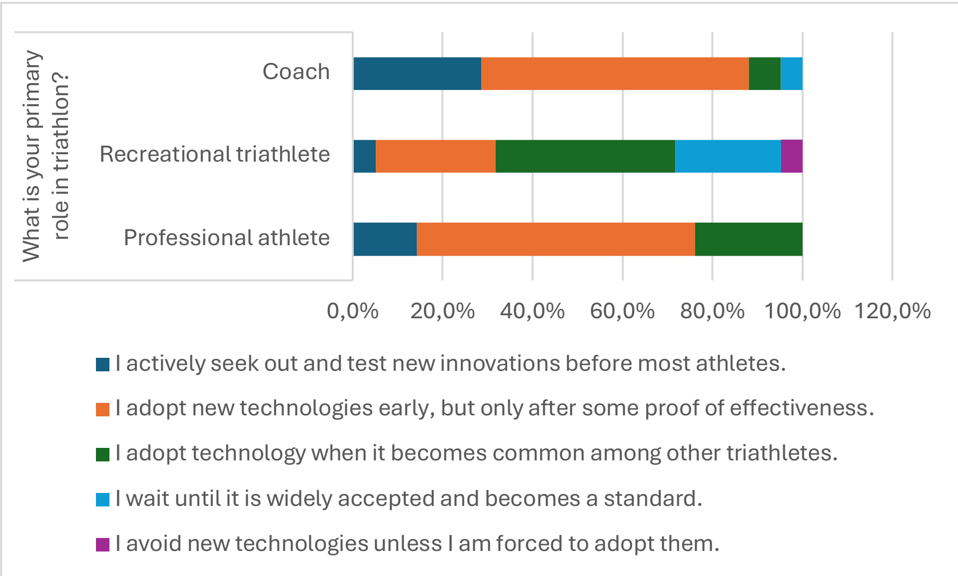

Figure 10: Adoption Stage Distribution by Athlete Role

What is your primary role in triathlon? * How do you usually adopt new sports technologies (e.g., power meters, AI coaching, virtual training)? Crosstabulation

			How do you usually adopt new sports technologies (e.g., power meters, AI coaching, virtual training)?					
			I actively seek out and test new innovations before most athletes.	I adopt new technologies early, but only after some proof of effectiveness.	I adopt technology when it becomes common among other triathletes.	I wait until it is widely accepted and becomes a standard.	I avoid new technologies unless I am forced to adopt them.	Total
What is your primary role in triathlon?	Professional athlete	Count	6	26	10	0	0	42
		Expected Count	4.4	15.9	13.4	7.0	1.3	42.0
		% within How do you usually adopt new sports technologies (e.g., power meters, AI coaching, virtual training)?	22.2%	26.8%	12.2%	0.0%	0.0%	16.3%
	Recreational triathlete	Count	9	46	69	41	8	173
		Expected Count	18.2	65.3	55.2	28.9	5.4	173.0
		% within How do you usually adopt new sports technologies (e.g., power meters, AI coaching, virtual training)?	33.3%	47.4%	84.1%	95.3%	100.0%	67.3%
	Coach	Count	12	25	3	2	0	42
		Expected Count	4.4	15.9	13.4	7.0	1.3	42.0
		% within How do you usually adopt new sports technologies (e.g., power meters, AI coaching, virtual training)?	44.4%	25.8%	3.7%	4.7%	0.0%	16.3%
Total		Count	27	97	82	43	8	257
		Expected Count	27.0	97.0	82.0	43.0	8.0	257.0
		% within How do you usually adopt new sports technologies (e.g., power meters, AI coaching, virtual training)?	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

4.2.2.4 Ordinal Regression: Segment Differences in Usage Behavior

An ordinal regression tested whether training metric usage (Q14) differed by athlete role. The model was significant ($\chi^2(2) = 27.720$, $p < .001$) and showed good fit (Pearson $\chi^2(6) = 2.443$, $p = .875$). Professionals tracked significantly more frequently than both recreational athletes ($B = –2.708$, $p < .001$) and coaches ($B = 2.157$, $p = .007$). No significant difference was found between recreational athletes and coaches ($B = –0.551$, $p = .131$). As shown in *Figure 11*, professionals reported the highest tracking engagement, supporting D-STAM's segmentation logic. Results are summarized in *Table 4*.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	57.340			
Final	29.620	27.720	2	<.001

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	2.443	6	.875
Deviance	4.152	6	.656

Link function: Logit.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	57.340			
Final	29.620	27.720	2	<.001

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	2.443	6	.875
Deviance	4.152	6	.656

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q14 = 1]	.848	.333	6.478	1	.011	.195	1.502
	[Q14 = 2]	2.546	.379	45.075	1	<.001	1.803	3.290
	[Q14 = 3]	3.395	.440	59.538	1	<.001	2.533	4.258
	[Q14 = 4]	4.736	.661	51.393	1	<.001	3.441	6.031
Location	[Q2=1]	-2.157	.800	7.264	1	.007	-3.725	-.588
	[Q2=2]	.551	.365	2.282	1	.131	-.164	1.267
	[Q2=3]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q8 = 2]	-4.425	.480	84.955	1	<.001	-5.366	-3.484
	[Q8 = 3]	-3.068	.387	62.800	1	<.001	-3.827	-2.310
	[Q8 = 4]	-.909	.339	7.205	1	.007	-1.573	-.245
Location	[Q2_recode_rec=.00]	-1.435	.371	14.982	1	<.001	-2.162	-.709
	[Q2_recode_rec=1.00]	.878	.555	2.503	1	.114	-.210	1.965
	[Q2_recode_rec=2.00]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

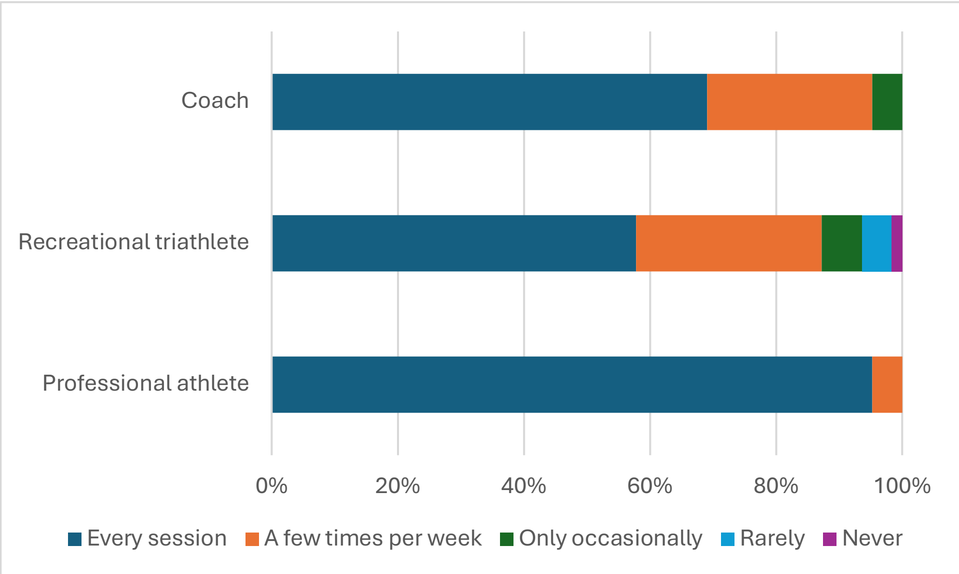

Figure 11: Frequency of Training Metric Usage by Athlete Role

Table 4: Segment-Specific D-STAM Hypotheses and Revealed Adoption Drivers

Segment	Hypothesized Predictors (H1–H6)	Supported Hypotheses	Additional Significant Predictors	Summary
Elite Athletes	H1: Performance Expectancy	Descriptively supported (H1)	—	Usage uniform (95.2% “every session”); formal testing not possible
Recreational Athletes	H2: Effort Expectancy H3: Social Influence H5: Hedonic	H2 (Effort Expectancy)	Performance Expectancy (p = 0.003) Facilitating Conditions (p = 0.036)	Multi-factor adoption logic; driven by ease of use, outcome value, and infrastructure

	Motivation H6: Price Value			
Coaches	H4: Facilitating Conditions	Not supported (H4)	Social Influence ($p = 0.059$, marginal)	Adoption logic less clearly explained by D-STAM; peer pressure may matter

4.2.3 D-STAM Model Extensions: Moderators & Barriers

Building on D-STAM, we tested whether adoption behavior was further influenced by psychological and contextual factors not captured in the original model. Specifically, we investigated perceived barriers (Q15), technostress (Q18), intuition (Q16–17), and experience (Q3) as potential inhibitors or moderators of usage.

4.2.3.1 Perceived Barriers to Adoption

Survey responses (Q15) revealed that high costs were the most commonly reported barrier, selected by 86.3% overall, consistently across coaches (95.0%), professionals (85.0%), and recreational athletes (84.4%). Compatibility issues (47.1%) and setup complexity (37.9%) followed, with significant role-based differences: 70.0% of coaches and pros cited compatibility challenges vs. 35.6% of recreational athletes; 70.0% of pros and 57.5% of coaches reported setup issues, compared to 25.0% of recreational athletes.

Chi-square tests confirmed these differences: setup complexity ($\chi^2(2) = 36.241$, $p < 0.001$, $V = 0.376$), compatibility ($\chi^2(2) = 26.095$, $p < 0.001$, $V = 0.319$), and preference for traditional methods ($\chi^2(2) = 10.492$, $p = 0.005$, $V = 0.202$). Cost barriers did not vary significantly across roles ($\chi^2(2) = 3.344$, $p = 0.188$), nor did privacy concerns ($\chi^2(2) = 4.200$, $p = 0.122$).

These results supported our qualitative findings: while cost was a shared concern, coaches and elite athletes faced higher usability and integration burdens when adopting digital tools.

$BarriersAdoption Frequencies

		Responses N	Responses Percent	Percent of Cases
Barriers Adoption[a]	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) High costs	207	45.4%	86.3%
	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) Complexity of setup and use	91	20.0%	37.9%
	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) Lack of compatibility with existing devices	113	24.8%	47.1%
	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) Privacy concerns (data security)	20	4.4%	8.3%
	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) Preference for traditional training methods	25	5.5%	10.4%
Total		456	100.0%	190.0%

a. Dichotomy group tabulated at value 1.

$BarriersAdoption*Q2 Crosstabulation

			What is your primary role in triathlon? Professional athlete	Recreational triathlete	Coach	Total
Barriers Adoption[a]	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) High costs	Count	34	135	38	207
		% within Q2	85.0%	84.4%	95.0%	
	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) Complexity of setup and use	Count	28	40	23	91
		% within Q2	70.0%	25.0%	57.5%	
	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) Lack of compatibility with existing devices	Count	28	57	28	113
		% within Q2	70.0%	35.6%	70.0%	
	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) Privacy concerns (data security)	Count	1	13	6	20
		% within Q2	2.5%	8.1%	15.0%	
	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply) Preference for traditional training methods	Count	1	24	0	25
		% within Q2	2.5%	15.0%	0.0%	
Total		Count	40	160	40	240

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

4.2.3.2 Technostress as a Cognitive Load Indicator (H(8))

Q18 responses (recoded from 1 = “Never” to 5 = “Always”) assessed perceived technostress. An ordinal regression confirmed significant role-based differences ($\chi^2(2) = 23.380$, $p < .001$).

Recreational athletes (B = 1.610, p < .001) and professionals (B = 1.287, p = .002) reported significantly more technostress than coaches. No significant difference was found between professionals and recreational athletes (B = –0.323, p = .309) (*Figure 12).*

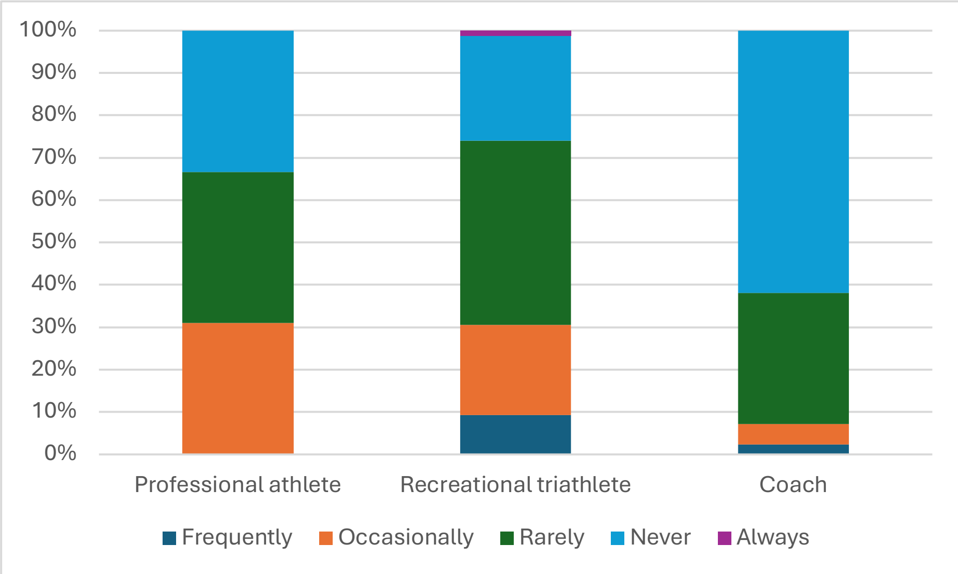

Figure 12: Technostress Levels by Athlete Role

Despite segmental variation, technostress did not correlate with usage frequency (Spearman ρ = 0.090, p = 0.152), suggesting it does not directly influence metric engagement.

Correlations

Correlations

		Technostress Recoded	How often do you track your training metrics (e.g., power, heart rate, HRV, cadence)?
Technostress Recoded	Pearson Correlation	1	.090
	Sig. (2-tailed)		.152
	N	257	257
How often do you track your training metrics (e.g., power, heart rate, HRV, cadence)?	Pearson Correlation	.090	1
	Sig. (2-tailed)	.152	
	N	257	257

To test moderation (H8), an ordinal regression assessed whether technostress weakened the link between Performance Expectancy (Q8) and digital usage (Q14). While the overall model was significant ($\chi^2(3) = 28.704$, p < 0.001), only Performance Expectancy predicted usage (B = –1.039, p = 0.007). Neither technostress (p = 0.725) nor the interaction term (p = 0.680) was significant. Thus, high cognitive load did not undermine performance-driven engagement.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	151.091			
Final	122.387	28.704	3	<.001

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q14 = 1]	-3.713	1.651	5.060	1	.024	-6.949	-.478
	[Q14 = 2]	-1.964	1.640	1.434	1	.231	-5.177	1.250
	[Q14 = 3]	-1.106	1.648	.451	1	.502	-4.335	2.123
	[Q14 = 4]	.274	1.711	.026	1	.873	-3.081	3.628
Location	Q8	-1.039	.388	7.153	1	.007	-1.800	-.277
	Q18_Recode	-.236	.672	.123	1	.725	-1.554	1.082
	PE_TechStress	.067	.163	.170	1	.680	-.252	.386

Link function: Logit.

4.2.3.3 Intuition Preferences and Discontinuation Behavior

Q16 measured training style preferences from entirely intuitive to fully digital. Most athletes (75.9%) reported a balanced approach, especially elite athletes (90.5%) and coaches (92.9%), whereas recreational athletes showed greater variation (68.2%). An ordinal regression confirmed no significant role-based differences ($\chi^2(2) = 2.336$, $p = .311$). Professionals did not differ significantly from coaches ($B = 0.696$, $p = .170$) or recreational athletes ($B = 0.191$, $p = .629$), nor did coaches differ significantly from recreational athletes ($B = –0.505$, $p = .208$). *Figure 13* illustrates segmental patterns.

To what extent do you prefer intuition-based performance assessment (e.g., listening to your body, perceived effort) over digital metrics and data analysis? * What is your primary role in triathlon? Crosstabulation

			What is your primary role in triathlon? Professional athlete	Recreational triathlete	Coach	Total
To what extent do you prefer intuition-based performance assessment (e.g., listening to your body, perceived effort) over digital metrics and data analysis?	Fully rely on digital metrics and technology 💻	Count	0	6	0	6
		Expected Count	1.0	4.0	1.0	6.0
		% within What is your primary role in triathlon?	0.0%	3.5%	0.0%	2.3%
	Somewhat rely on digital metrics	Count	0	18	3	21
		Expected Count	3.4	14.1	3.4	21.0
		% within What is your primary role in triathlon?	0.0%	10.4%	7.1%	8.2%
	A balanced mix of intuition and digital data ⚖□	Count	38	118	39	195
		Expected Count	31.9	131.3	31.9	195.0
		% within What is your primary role in triathlon?	90.5%	68.2%	92.9%	75.9%
	Somewhat rely on intuition	Count	4	22	0	26
		Expected Count	4.2	17.5	4.2	26.0
		% within What is your primary role in triathlon?	9.5%	12.7%	0.0%	10.1%
	Fully rely on intuition and subjective feeling 🫀	Count	0	9	0	9
		Expected Count	1.5	6.1	1.5	9.0
		% within What is your primary role in triathlon?	0.0%	5.2%	0.0%	3.5%
Total		Count	42	173	42	257
		Expected Count	42.0	173.0	42.0	257.0
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q16 = 1]	-3.306	.513	41.544	1	<.001	-4.312	-2.301
	[Q16 = 2]	-1.715	.369	21.615	1	<.001	-2.439	-.992
	[Q16 = 3]	2.314	.392	34.904	1	<.001	1.546	3.082
	[Q16 = 4]	3.789	.487	60.552	1	<.001	2.835	4.744
Location	[Q2=1]	.696	.508	1.882	1	.170	-.298	1.691
	[Q2=2]	.505	.401	1.584	1	.208	-.282	1.292
	[Q2=3]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q16 = 1]	-3.812	.430	78.680	1	<.001	-4.654	-2.969
	[Q16 = 2]	-2.221	.233	90.504	1	<.001	-2.678	-1.763
	[Q16 = 3]	1.809	.206	77.033	1	<.001	1.405	2.212
	[Q16 = 4]	3.284	.353	86.525	1	<.001	2.592	3.976
Location	[Q2_recode_rec=.00]	.191	.395	.233	1	.629	-.584	.966
	[Q2_recode_rec=1.00]	-.505	.401	1.584	1	.208	-1.292	.282
	[Q2_recode_rec=2.00]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

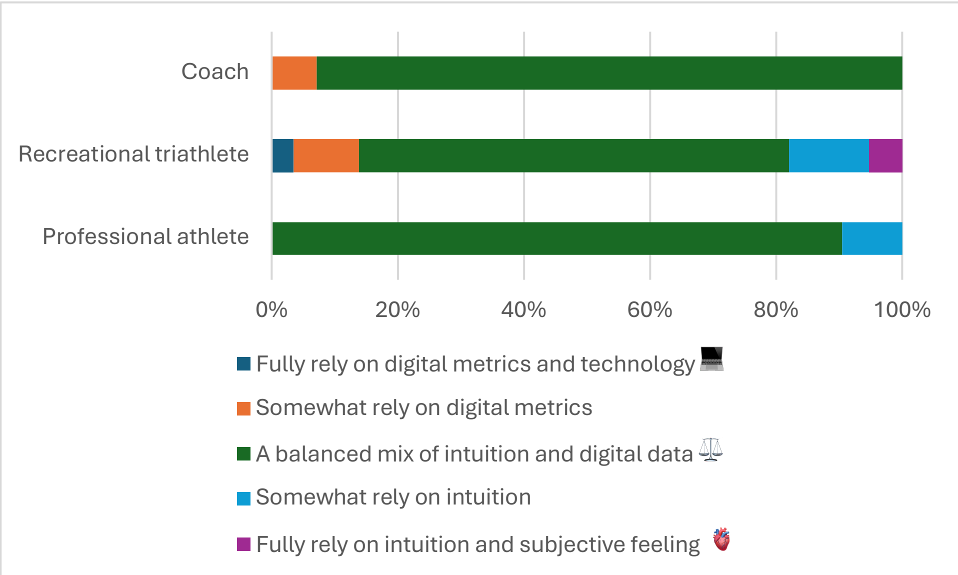

Figure 13: Intuition Preferences by Athlete Role

Q17 explored discontinuation due to conflicts with intuition. While 63.8% said digital tools complemented intuition, 28.8% reported partial avoidance, and only 5.1% rejected digital tools entirely. Coaches and professionals were most likely to report complementarity (76.2%), while 38.7% of recreational athletes reported some level of avoidance. A chi-square test was marginally non-significant ($\chi^2(6) = 11.529$, $p = 0.073$, $V = 0.150$), but revealed a trend: rejection was most common among recreational athletes and absent among coaches. *Figure 14* depicts this distribution.

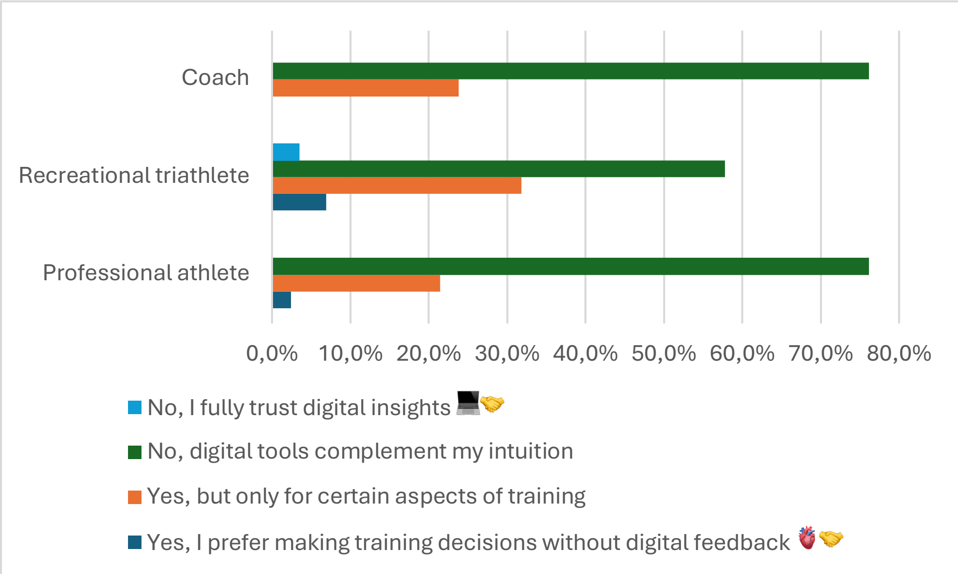

Figure 14: Discontinuation Behavior Based on Intuition Conflict by Athlete Role

Overall, athletes favored hybrid decision-making, combining experiential judgment with digital insights. Complete rejection or blind reliance was rare, underscoring the importance of integrating intuition and digital approaches for sustained engagement.

Have you ever avoided or discontinued using a digital training tool because you felt it interfered with your natural training intuition or decision-making? * What is your primary role in triathlon? Crosstabulation

			What is your primary role in triathlon?			
			Professional athlete	Recreational triathlete	Coach	Total
Have you ever avoided or discontinued using a digital training tool because you felt it interfered with your natural training intuition or decision-making?	Yes, I prefer making training decisions without digital feedback 🫀🤝	Count	1	12	0	13
		Expected Count	2.1	8.8	2.1	13.0
		% within What is your primary role in triathlon?	2.4%	6.9%	0.0%	5.1%
	Yes, but only for certain aspects of training	Count	9	55	10	74
		Expected Count	12.1	49.8	12.1	74.0
		% within What is your primary role in triathlon?	21.4%	31.8%	23.8%	28.8%
	No, digital tools complement my intuition	Count	32	100	32	164
		Expected Count	26.8	110.4	26.8	164.0
		% within What is your primary role in triathlon?	76.2%	57.8%	76.2%	63.8%
	No, I fully trust digital insights 💻🤝	Count	0	6	0	6
		Expected Count	1.0	4.0	1.0	6.0
		% within What is your primary role in triathlon?	0.0%	3.5%	0.0%	2.3%
Total		Count	42	173	42	257
		Expected Count	42.0	173.0	42.0	257.0
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	11.529[a]	6	.073
Likelihood Ratio	15.506	6	.017
Linear-by-Linear Association	.031	1	.860
N of Valid Cases	257		

a. 5 cells (41.7%) have expected count less than 5. The minimum expected count is .98.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.212	.073
	Cramer's V	.150	.073
N of Valid Cases		257	

4.2.3.4 Moderation Tests: Income and Coaching Status

This section tests D-STAM's moderation hypotheses H9 and H10. The first model examined whether income level (Q33) moderated the link between Price Value (Q13) and usage frequency (Q14). The ordinal regression model was not significant ($\chi^2(3) = 3.093$, $p = 0.377$), with no meaningful contribution from Price Value ($p = 0.835$), income levels (all $p > 0.05$), or the interaction term ($p = 0.726$). Thus, H9 was not supported.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	156.350			
Final	153.256	3.093	3	.377

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Q14 = 1]	-.625	1.168	.287	1	.592	-2.914	1.664
	[Q14 = 2]	1.051	1.175	.800	1	.371	-1.252	3.353
	[Q14 = 3]	1.844	1.194	2.386	1	.122	-.496	4.183
	[Q14 = 4]	3.178	1.290	6.065	1	.014	.649	5.707
Location	Q13	-.102	.491	.043	1	.835	-1.064	.860
	PV_Income	-.048	.136	.123	1	.726	-.314	.219
	[Q33=1]	-.763	1.896	.162	1	.687	-4.480	2.953
	[Q33=2]	-.465	1.562	.089	1	.766	-3.526	2.596
	[Q33=3]	-.771	1.214	.403	1	.525	-3.151	1.608
	[Q33=4]	-.264	.845	.097	1	.755	-1.921	1.393
	[Q33=5]	-.755	.696	1.177	1	.278	-2.118	.609
	[Q33=6]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

The second model tested whether coaching status moderates the effect of Facilitating Conditions (Q11) on usage. The model was statistically significant ($\chi^2(3) = 17.434$, $p < 0.001$), with

Facilitating Conditions emerging as a strong predictor ($B = -0.523$, $p < 0.001$). However, neither coaching status ($p = 0.711$) nor the interaction ($p = 0.694$) was significant, providing no support for H10.

These findings suggested that while core predictors, like Facilitating Conditions, remained important, income and coaching status did not moderate their influence on digital training engagement.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	96.391			
Final	78.957	17.434	3	<.001

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Q14 = 1]	-.613	2.501	.060	1	.806	-5.516	4.290
	[Q14 = 2]	1.091	2.505	.190	1	.663	-3.819	6.001
	[Q14 = 3]	1.944	2.514	.598	1	.439	-2.984	6.872
	[Q14 = 4]	3.306	2.561	1.666	1	.197	-1.714	8.326
Location	FC_Coach	.215	.545	.155	1	.694	-.854	1.284
	Q11	-.523	.128	16.825	1	<.001	-.773	-.273
	[isCoach=.00]	.948	2.556	.137	1	.711	-4.063	5.958
	[isCoach=1.00]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

4.2.3.5 Exploratory Moderation: Triathlon Experience

To explore whether experience shaped adoption behavior, triathlon experience (Q3) was recoded into a binary variable (0 = 1–3 years, 1 = 4+ years). Three ordinal regression models tested whether experience moderates the relationships between Effort Expectancy (Q9), Performance Expectancy (Q8), and Social Influence (Q10) with usage frequency (Q14).

In the Effort Expectancy model, experience showed a significant main effect ($B = 3.399$, $p = 0.040$), and the interaction term approached significance ($p = 0.079$). The model fit was strong ($\chi^2(3) = 38.253$, $p < 0.001$, $R^2 = 0.164$), suggesting that experienced athletes use digital metrics more consistently, somewhat independently of ease-of-use perceptions.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	117.859			
Final	79.605	38.253	3	<.001

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	32.679	25	.139
Deviance	33.546	25	.118

Link function: Logit.

Pseudo R-Square

Cox and Snell	.138
Nagelkerke	.164
McFadden	.080

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q14 = 1]	-4.641	.859	29.220	1	<.001	-6.323	-2.958
	[Q14 = 2]	-2.824	.822	11.796	1	<.001	-4.435	-1.212
	[Q14 = 3]	-1.874	.832	5.076	1	.024	-3.504	-.244
	[Q14 = 4]	-.421	.958	.193	1	.660	-2.298	1.456
Location	Q9	-.507	.382	1.758	1	.185	-1.257	.242
	EE_x_Exp	-.761	.434	3.081	1	.079	-1.611	.089
	[Q3_recode=.00]	-3.399	1.655	4.219	1	.040	-6.643	-.156
	[Q3_recode=1.00]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

For Performance Expectancy, the model was significant ($\chi^2(3) = 28.753$, $p < 0.001$), and Performance Expectancy remained a strong predictor ($B = -1.123$, $p = 0.022$), but experience ($p = 0.646$) and the interaction term ($p = 0.626$) were not. Thus, performance beliefs influence usage regardless of experience.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	104.755			
Final	76.002	28.753	3	<.001

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	26.432	21	.190
Deviance	26.901	21	.174

Link function: Logit.

Pseudo R-Square

Cox and Snell	.106
Nagelkerke	.125
McFadden	.060

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q14 = 1]	-3.104	.763	16.556	1	<.001	-4.600	-1.609
	[Q14 = 2]	-1.353	.739	3.354	1	.067	-2.802	.095
	[Q14 = 3]	-.497	.756	.432	1	.511	-1.979	.985
	[Q14 = 4]	.881	.887	.987	1	.321	-.858	2.621
Location	Q8	-1.123	.490	5.263	1	.022	-2.083	-.164
	PE_x_Exp	.252	.518	.238	1	.626	-.762	1.267
	[Q3_recode=.00]	1.009	2.196	.211	1	.646	-3.296	5.313
	[Q3_recode=1.00]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

The Social Influence model was not significant ($\chi^2(3) = 1.094$, $p = 0.779$), and neither main nor interaction effects reached significance.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	91.998			
Final	90.904	1.094	3	.779

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	30.046	33	.615
Deviance	31.290	33	.552

Link function: Logit.

Pseudo R-Square

Cox and Snell	.004
Nagelkerke	.005
McFadden	.002

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q14 = 1]	.298	.452	.434	1	.510	-.589	1.185
	[Q14 = 2]	1.922	.479	16.086	1	<.001	.983	2.861
	[Q14 = 3]	2.760	.527	27.408	1	<.001	1.727	3.793
	[Q14 = 4]	4.094	.721	32.245	1	<.001	2.681	5.507
Location	SI_x_Exp	-.314	.322	.952	1	.329	-.946	.317
	Q10	.191	.283	.457	1	.499	-.363	.745
	[Q3_recode=.00]	-1.029	1.116	.850	1	.356	-3.215	1.158
	[Q3_recode=1.00]	0^a	.	.	0	.	.	.

Link function: Logit.

Taken together, experience appears to independently predict digital engagement, especially in conjunction with usability beliefs, but it does not moderate most D-STAM relationships. *Table 5* summarizes moderator findings, while *Figure 15* visualizes key adoption pathways across Sections 4.2.2 and 4.2.3.

Table 5: Summary of Moderator Hypotheses and Exploratory Interaction Tests

Hypothesis	Moderator	Interaction Tested	Model Fit (χ^2, df, p)	Interaction p-value	Main Effect Significant	Supported
H8	Technostress (Q18)	PE × Technostress	$\chi^2(3) = 28.704$, $p < 0.001$	p = 0.680	PE: p = 0.007	No
H9	Income (Q33)	Price Value × Income	$\chi^2(3) = 3.093$, $p = 0.377$	p = 0.697	None	No
H10	Coaching Status (Q4)	FC × Coaching Status	$\chi^2(3) = 15.909$, $p = 0.001$	p = 0.694	FC: p < 0.001	No
—	Experience (Q3 recoded)	EE × Experience	$\chi^2(3) = 38.253$, $p < 0.001$	p = 0.079	Experience: p = 0.040	Partial (exploratory)

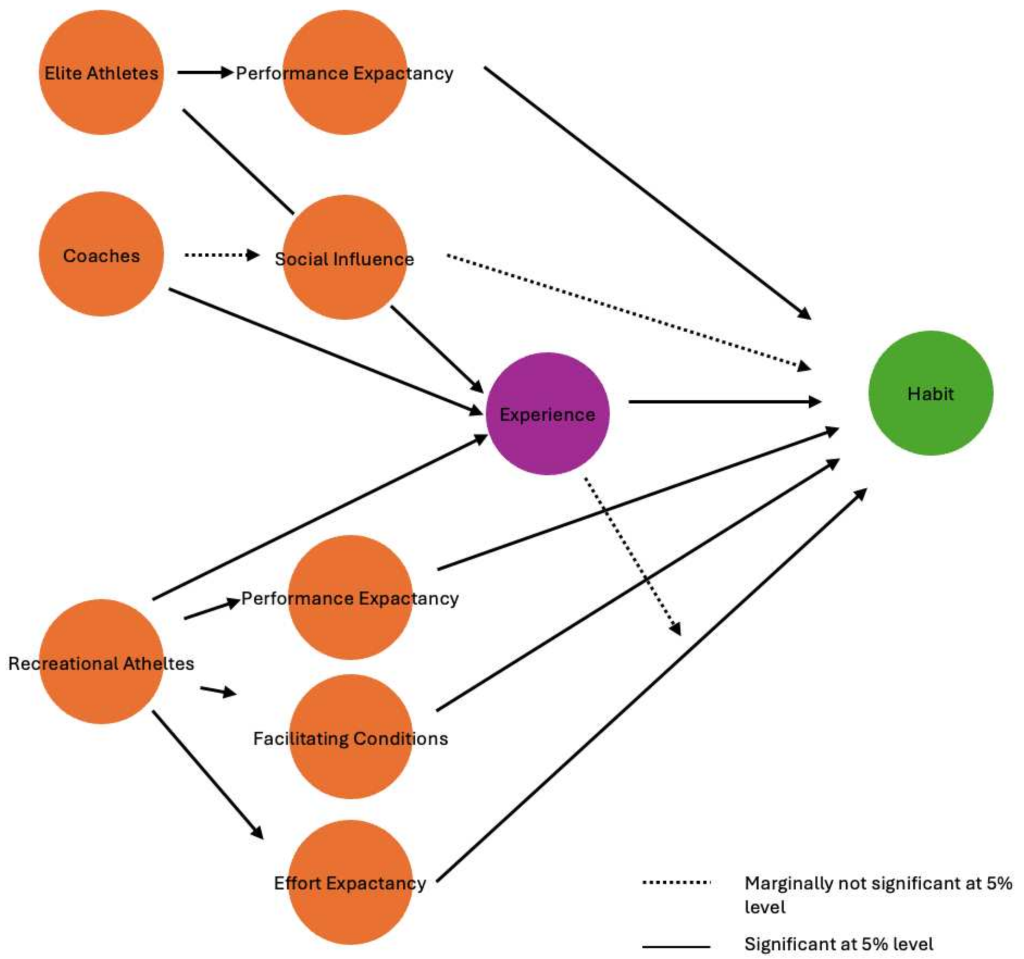

Figure 15: Visual Summary of Supported D-STAM Drivers and Relationships

4.2.4 Strategic Partnerships & Commercialization

Section 4.2.4 examines how various aspects of perceived and experienced value impact an athlete's openness to digital commercialization strategies. It draws on Q20–Q24 to explore how brand partnerships, freemium models, and platform loyalty relate to adoption behavior. While Q22 and Q23 captured conditions that might increase adoption, such as brand affiliation or free trials, Q24 reflected reasons athletes stay with platforms. Together, these variables offer insight into how commercial models align with what athletes value before and after adoption, addressing the role of strategic partnerships and commercialization in digital triathlon.

4.2.4.1 Perceptions of Brand–Tech Partnerships

Q20 assessed how athletes perceive brand–tech collaborations in driving digital training innovation. Overall responses showed moderate to high agreement (M = 3.39, SD = 0.80), with 36.2% selecting “a moderate amount” and 48.6% “a lot,” suggesting that such partnerships are widely seen as innovation enablers.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
To what extent do partnerships between triathlon brands and technology companies contribute to the development of digital training tools? (e.g., new virtual training options or improved data analytics)	257	1	5	3.39	.799
Valid N (listwise)	257				

To what extent do partnerships between triathlon brands and technology companies contribute to the development of digital training tools? (e.g., new virtual training options or improved data analytics)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None at all	6	2.3	2.3	2.3
	A little	26	10.1	10.1	12.5
	A moderate amount	93	36.2	36.2	48.6
	A lot	125	48.6	48.6	97.3
	A great deal	7	2.7	2.7	100.0
	Total	257	100.0	100.0	

An ordinal regression confirmed significant role-based differences ($\chi^2(2) = 10.511$, $p = .005$). Professionals rated these partnerships significantly more favorably than both recreational athletes ($B = 1.008$, $p = .004$) and coaches ($B = 1.203$, $p = .006$), while coaches and recreational athletes did not differ significantly ($B = –0.194$, $p = .547$). *Figure 16* illustrates the perception gradient by role.

Descriptives

To what extent do partnerships between triathlon brands and technology companies contribute to the development of digital training tools? (e.g., new virtual training options or improved data analytics)

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Professional athlete	42	3.71	.554	.085	3.54	3.89	2	4
Recreational triathlete	173	3.34	.871	.066	3.20	3.47	1	5
Coach	42	3.31	.604	.093	3.12	3.50	2	4
Total	257	3.39	.799	.050	3.29	3.49	1	5

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Q20 = 1]	−3.661	.420	75.834	1	<.001	−4.485	−2.837
	[Q20 = 2]	−1.871	.204	83.755	1	<.001	−2.272	−1.470
	[Q20 = 3]	.074	.150	.245	1	.620	−.219	.367
	[Q20 = 4]	3.809	.405	88.448	1	<.001	3.015	4.603
Location	[Q2_recode_rec=.00]	1.008	.355	8.071	1	.004	.313	1.704
	[Q2_recode_rec=1.00]	−.194	.322	.363	1	.547	−.826	.438
	[Q2_recode_rec=2.00]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

		Parameter Estimates						
							95% Confidence Interval	
		Estimate	Std. Error	Wald	df	Sig.	Lower Bound	Upper Bound
Threshold	[Q20 = 1]	-3.466	.486	50.961	1	<.001	-4.418	-2.515
	[Q20 = 2]	-1.677	.319	27.598	1	<.001	-2.302	-1.051
	[Q20 = 3]	.268	.293	.839	1	.360	-.306	.843
	[Q20 = 4]	4.003	.480	69.624	1	<.001	3.063	4.943
Location	[Q2=1]	1.203	.436	7.624	1	.006	.349	2.056
	[Q2=2]	.194	.322	.363	1	.547	-.438	.826
	[Q2=3]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

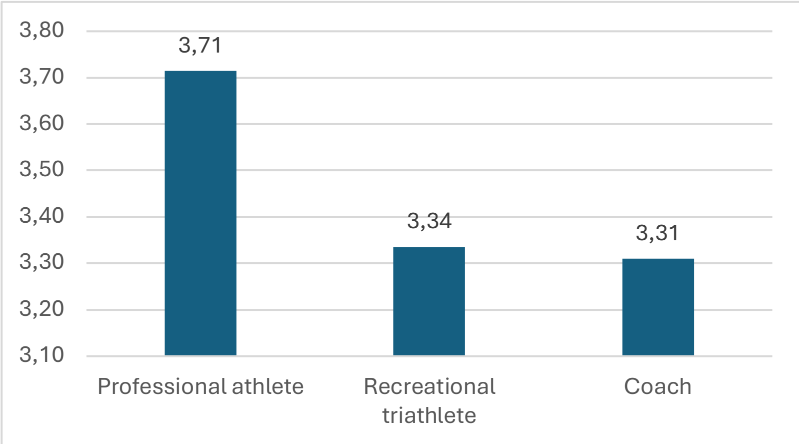

Figure 16: Perceived Partnership Contribution by Athlete Role

Q21 further examined perceived company orientation. While 44.0% believed companies pro-actively anticipate athlete needs, 35.0% saw them as commercially driven, and 21.0% viewed them as slow to adapt. A chi-square test confirmed significant differences by role ($\chi^2(4, N = 257) = 20.162$, $p < .001$): 71.4% of professionals saw companies as proactive, compared to 35.8% of recreational athletes and 50.0% of coaches. The latter two segments were more likely to describe companies as commercially focused.

Do triathlon brands and technology companies anticipate athlete needs, or do they respond too slowly to emerging trends? (e.g., in AI-based training, virtual racing, or new wearables)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	They are proactive and anticipate needs.	113	44.0	44.0	44.0
	They respond but often too slowly.	54	21.0	21.0	65.0
	They mostly focus on commercial interests.	90	35.0	35.0	100.0
	Total	257	100.0	100.0	

Do triathlon brands and technology companies anticipate athlete needs, or do they respond too slowly to emerging trends? (e.g., in AI-based training, virtual racing, or new wearables) * What is your primary role in triathlon? Crosstabulation

			What is your primary role in triathlon?			
			Professional athlete	Recreational triathlete	Coach	Total
Do triathlon brands and technology companies anticipate athlete needs, or do they respond too slowly to emerging trends? (e.g., in AI-based training, virtual racing, or new wearables)	They are proactive and anticipate needs.	Count	30	62	21	113
		% within What is your primary role in triathlon?	71.4%	35.8%	50.0%	44.0%
	They respond but often too slowly.	Count	4	45	5	54
		% within What is your primary role in triathlon?	9.5%	26.0%	11.9%	21.0%
	They mostly focus on commercial interests.	Count	8	66	16	90
		% within What is your primary role in triathlon?	19.0%	38.2%	38.1%	35.0%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	20.162[a]	4	<.001
Likelihood Ratio	20.611	4	<.001
Linear-by-Linear Association	4.383	1	.036
N of Valid Cases	257		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 8.82.

These findings suggested professionals tended to view brand–tech collaborations as performance-driven and innovation-oriented, while coaches and recreational athletes showed greater skepticism, possibly due to differing exposure levels or commercialization concerns.

4.2.4.2 Adoption Likelihood of Partnered Platforms

Q22 assessed the likelihood of athletes adopting a digital platform officially partnered with a major triathlon organization (e.g., IRONMAN, PTO). The overall mean was moderate (M = 2.62, SD = 1.08), with responses clustering around “neutral” (30.0%), “somewhat unlikely” (25.7%), and “somewhat likely” (24.5%). Only 0.8% selected “extremely likely,” indicating general ambivalence toward brand affiliation as a standalone adoption driver.

Statistics

Would you be more likely to adopt a new digital training platform if it was officially partnered with a well-known triathlon organization (e.g., IRONMAN, PTO, Challenge Family)?

N	Valid	257
	Missing	0
Mean		2.62
Std. Deviation		1.076

Would you be more likely to adopt a new digital training platform if it was officially partnered with a well-known triathlon organization (e.g., IRONMAN, PTO, Challenge Family)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Extremly unlikely	49	19.1	19.1	19.1
	Somewhat unlikely	66	25.7	25.7	44.7
	Neutral	77	30.0	30.0	74.7
	Somewhat likely	63	24.5	24.5	99.2
	Extremly likely	2	.8	.8	100.0
	Total	257	100.0	100.0	

An ordinal regression confirmed significant role-based differences ($\chi^2(2) = 29.930$, $p < .001$). Professionals were significantly more likely to adopt partnered platforms than both recreational athletes ($B = 1.864$, $p < .001$) and coaches ($B = 1.463$, $p < .001$), while no significant difference emerged between coaches and recreational athletes ($B = 0.401$, $p = .196$). *Figure 17* illustrates the likelihood of adoption across roles.

Descriptives

Would you be more likely to adopt a new digital training platform if it was officially partnered with a well-known triathlon organization (e.g., IRONMAN, PTO, Challenge Family)?

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Professional athlete	42	3.33	1.028	.159	3.01	3.65	1	4
Recreational triathlete	173	2.44	1.053	.080	2.28	2.60	1	5
Coach	42	2.67	.928	.143	2.38	2.96	1	4
Total	257	2.62	1.076	.067	2.49	2.75	1	5

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Q22 = 1]	-1.609	.304	28.028	1	<.001	-2.205	-1.013
	[Q22 = 2]	-.322	.284	1.285	1	.257	-.879	.235
	[Q22 = 3]	1.119	.294	14.469	1	<.001	.543	1.696
	[Q22 = 4]	5.130	.769	44.509	1	<.001	3.623	6.636
Location	[Q2=1]	1.463	.415	12.452	1	<.001	.650	2.275
	[Q2=2]	-.401	.310	1.674	1	.196	-1.009	.206
	[Q2=3]	0^a	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Q22 = 1]	-1.208	.172	49.353	1	<.001	-1.545	-.871
	[Q22 = 2]	.079	.148	.286	1	.593	-.211	.370
	[Q22 = 3]	1.521	.181	70.680	1	<.001	1.166	1.875
	[Q22 = 4]	5.531	.734	56.754	1	<.001	4.092	6.970
Location	[Q2_recode_rec=.00]	1.864	.342	29.691	1	<.001	1.194	2.535
	[Q2_recode_rec=1.00]	.401	.310	1.674	1	.196	-.206	1.009
	[Q2_recode_rec=2.00]	0^a	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

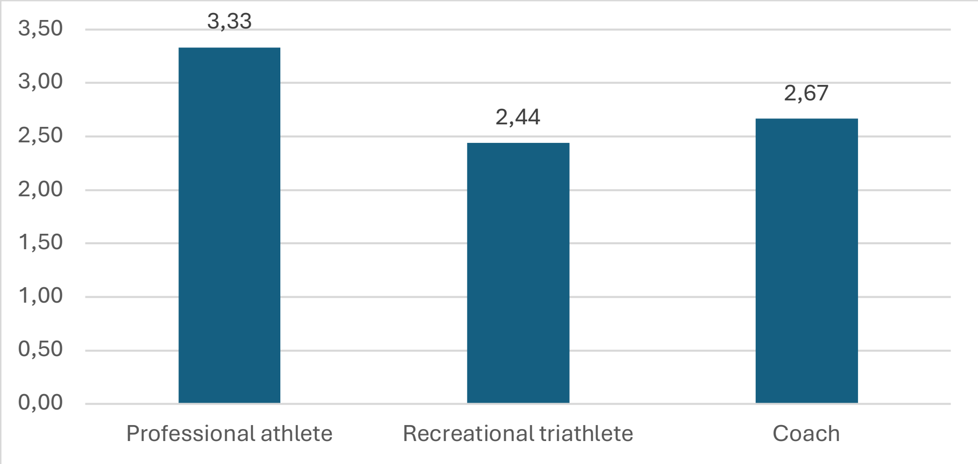

Figure 17: Adoption Likelihood of Partnered Platforms by Athlete Role

To test whether perceived ROI influenced this tendency, an ordinal regression was run with Q13 as the predictor and Q22 as the outcome. The model was significant ($\chi^2(1) = 20.784$, $p < .001$), and ROI perception positively predicted adoption likelihood ($B = 0.695$, $p < .001$), although the effect size was modest (Nagelkerke $R^2 = .083$).

Overall, professionals were more receptive to brand-affiliated platforms, likely due to stronger ties to sponsorship ecosystems. Recreational athletes were more hesitant, suggesting that affiliation alone does not drive adoption unless perceived value is high.

Pseudo R-Square

Cox and Snell	.078
Nagelkerke	.083
McFadden	.029

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Q22 = 1]	.529	.462	1.311	1	.252	-.376	1.434
	[Q22 = 2]	1.825	.471	15.000	1	<.001	.902	2.749
	[Q22 = 3]	3.200	.499	41.072	1	<.001	2.222	4.179
	[Q22 = 4]	7.040	.870	65.455	1	<.001	5.335	8.746
Location	Q13	.695	.155	20.118	1	<.001	.391	.998

Link function: Logit.

4.2.4.3 Importance of Freemium Access Models

Q23 examined the importance of athletes testing a digital platform before subscribing. Freemium access was rated highly ($M = 3.93$, $SD = 1.06$), with 49.4% selecting "very important" and 30.4% “extremely important.” Only 5.1% considered it unimportant, indicating that free trials are a widely expected baseline.

Statistics

How important is a free trial period in determining whether you commit to a paid subscription for a digital training platform?

N	Valid	257
	Missing	0
Mean		3.93
Std. Deviation		1.058

How important is a free trial period in determining whether you commit to a paid subscription for a digital training platform?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not at all important	13	5.1	5.1	5.1
	Slightly important	18	7.0	7.0	12.1
	Moderately important	21	8.2	8.2	20.2
	Very important	127	49.4	49.4	69.6
	Extremely important	78	30.4	30.4	100.0
	Total	257	100.0	100.0	

An ordinal regression revealed no significant differences across athlete roles ($\chi^2(2) = 1.963$, $p = .375$). Professionals ($B = –0.428$, $p = .186$) and coaches ($B = –0.107$, $p = .741$) did not differ significantly from recreational athletes. Additionally, professionals and coaches did not differ significantly from each other ($B = –0.321$, $p = .433$). These results confirmed the broad consensus across roles regarding the importance of freemium access.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q23 = 1]	-2.928	.390	56.485	1	<.001	-3.692	-2.165
	[Q23 = 2]	-1.988	.328	36.777	1	<.001	-2.630	-1.345
	[Q23 = 3]	-1.376	.308	19.993	1	<.001	-1.979	-.773
	[Q23 = 4]	.844	.298	7.999	1	.005	.259	1.428
Location	[Q2=1]	-.321	.410	.615	1	.433	-1.125	.482
	[Q2=2]	.107	.324	.109	1	.741	-.527	.741
	[Q2=3]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[Q23 = 1]	-3.035	.300	102.406	1	<.001	-3.623	-2.447
	[Q23 = 2]	-2.094	.213	96.777	1	<.001	-2.512	-1.677
	[Q23 = 3]	-1.483	.180	67.979	1	<.001	-1.835	-1.130
	[Q23 = 4]	.737	.156	22.243	1	<.001	.431	1.043
Location	[Q2_recode_rec=.00]	-.428	.324	1.751	1	.186	-1.062	.206
	[Q2_recode_rec=1.00]	-.107	.324	.109	1	.741	-.741	.527
	[Q2_recode_rec=2.00]	0[a]	.	.	0	.	.	.

Link function: Logit.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	67.308			
Final	65.344	1.963	2	.375

Link function: Logit.

An ordinal regression tested whether perceived ROI (Q13) predicted trial importance (Q23), but results were non-significant ($\chi^2(1) = 0.014$, $p = .904$; $B = 0.019$, $p = .903$), with a poor model fit (Nagelkerke $R^2 = .000$; Pearson $\chi^2(15) = 28.884$, $p = .017$).

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	28.884	15	.017
Deviance	25.375	15	.045

Link function: Logit.

Pseudo R-Square

Cox and Snell	.000
Nagelkerke	.000
McFadden	.000

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Q23 = 1]	-2.876	.539	28.470	1	<.001	-3.933	-1.820
	[Q23 = 2]	-1.930	.496	15.123	1	<.001	-2.903	-.957
	[Q23 = 3]	-1.315	.484	7.393	1	.007	-2.263	-.367
	[Q23 = 4]	.887	.479	3.431	1	.064	-.052	1.826
Location	Q13	.019	.155	.015	1	.903	-.285	.323

Link function: Logit.

Overall, freemium access emerged as a basic entry expectation rather than a differentiator, shaped by value perception or athlete role.

4.2.4.4 Platform Loyalty Motivations and Stickiness

Q24 explored post-adoption motivations to understand what sustains platform engagement. “Training improvement” (79.8%) and “data history” (52.2%) were the most cited reasons, with “social features” (17.0%) trailing behind (*Figure 18*). Other reasons, such as coach use, usability, and price, were rarely mentioned.

$Q24_Motivations Frequencies

		Responses		Percent of Cases
		N	Percent	
Q24_Motivations[a]	If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice My historical data is stored there	129	33.3%	52.2%
	If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training	197	50.9%	79.8%
	If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The social and interactive features keep me engaged	42	10.9%	17.0%
	Q24_coach_use	3	0.8%	1.2%
	Q24_price_issue	1	0.3%	0.4%
	Q24_habit	2	0.5%	0.8%
	Q24_training	3	0.8%	1.2%
	Q24_integration	1	0.3%	0.4%
	Q24_innovation	3	0.8%	1.2%
	Q24_usability	2	0.5%	0.8%
	Q24_perceived_value	4	1.0%	1.6%
otal		387	100.0%	156.7%

a. Dichotomy group tabulated at value 1.

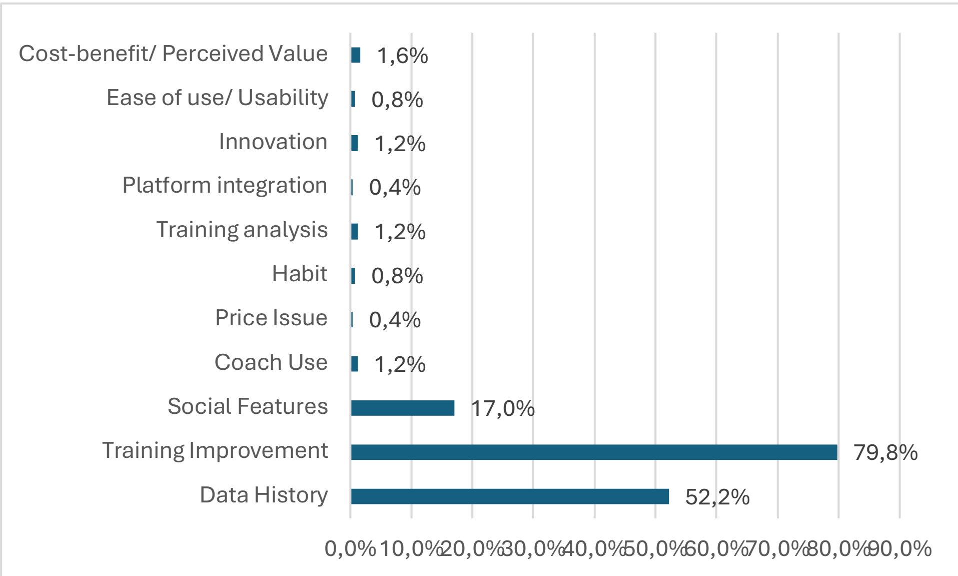

Figure 18: Platform Loyalty Motivations

A chi-square test showed that “training improvement” was cited more by professionals (88.1%) and coaches (83.3%) than by recreational athletes (72.3%) ($\chi^2(2) = 5.990$, $p = .050$). No significant differences were observed for “data history” or “social features.”

If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice My historical data is stored there * What is your primary role in triathlon?

Crosstab

			What is your primary role in triathlon?			
			Professional athlete	Recreational triathlete	Coach	Total
If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice My historical data is stored there	0	Count	16	93	19	128
		% within What is your primary role in triathlon?	38.1%	53.8%	45.2%	49.8%
	My historical data is stored there	Count	26	80	23	129
		% within What is your primary role in triathlon?	61.9%	46.2%	54.8%	50.2%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	3.735[a]	2	.155
Likelihood Ratio	3.759	2	.153
Linear-by-Linear Association	.427	1	.514
N of Valid Cases	257		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 20.92.

If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training * What is your primary role in triathlon?

Crosstab

			What is your primary role in triathlon?			
			Professional athlete	Recreational triathlete	Coach	Total
If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training	0	Count	5	48	7	60
		% within What is your primary role in triathlon?	11.9%	27.7%	16.7%	23.3%
	The regular use improves my training	Count	37	125	35	197
		% within What is your primary role in triathlon?	88.1%	72.3%	83.3%	76.7%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	5.990[a]	2	.050
Likelihood Ratio	6.487	2	.039
Linear-by-Linear Association	.265	1	.607
N of Valid Cases	257		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 9.81.

Further analysis linked loyalty motivations to receptiveness to commercialization. Athletes citing "training improvement" were more likely to adopt brand-affiliated platforms (Q22_binary) ($\chi^2(1) = 4.388$, $p = .036$; $M = 2.72$ vs. 2.30) and value freemium access (Q23_binary) ($\chi^2(1) = 8.323$, $p = .004$). "Data history" showed only a marginal association with adoption ($p = .067$), while "social features" showed no effect.

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	4.388[a]	1	.036		
Continuity Correction[b]	3.706	1	.054		
Likelihood Ratio	4.759	1	.029		
Fisher's Exact Test				.042	.024
Linear-by-Linear Association	4.371	1	.037		
N of Valid Cases	257				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 15.18.

b. Computed only for a 2x2 table

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	8.323[a]	1	.004		
Continuity Correction[b]	7.297	1	.007		
Likelihood Ratio	7.667	1	.006		
Fisher's Exact Test				.006	.004
Linear-by-Linear Association	8.290	1	.004		
N of Valid Cases	257				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 12.14.

b. Computed only for a 2x2 table

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.346[a]	1	.067		
Continuity Correction[b]	2.842	1	.092		
Likelihood Ratio	3.364	1	.067		
Fisher's Exact Test				.085	.046
Linear-by-Linear Association	3.333	1	.068		
N of Valid Cases	257				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 32.37.

b. Computed only for a 2x2 table

A logistic regression confirmed that ROI (Q13) was the only significant predictor of openness to partnered platforms ($\chi^2(4) = 23.532$, $p < .001$; $B = 0.728$, $p < .001$), rendering loyalty motivations non-significant. Mediation analysis supported this: "training improvement" predicted adoption initially ($p = .040$) but lost significance when ROI was included ($p = .205$), indicating complete mediation.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	23.532	4	<.001
	Block	23.532	4	<.001
	Model	23.532	4	<.001

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice My historical data is stored there	.483	.305	2.498	1	.114	1.620
	If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training	.468	.413	1.282	1	.257	1.596
	If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The social and interactive features keep me engaged	-.643	.486	1.750	1	.186	.526
	Do you feel digital sports technologies provide a good return on investment for your training?	.728	.216	11.343	1	<.001	2.071
	Constant	-3.866	.740	27.270	1	<.001	.021

a. Variable(s) entered on step 1: If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice My historical data is stored there, If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training, If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The social and interactive features keep me engaged, Do you feel digital sports technologies provide a good return on investment for your training?.

Classification Table[a]

Observed			Predicted Q22_binary .00	Predicted Q22_binary 1.00	Percentage Correct
Step 1	Q22_binary	.00	192	0	100.0
		1.00	65	0	.0
	Overall Percentage				74.7

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training	.811	.395	4.227	1	.040	2.251
	Constant	-1.735	.362	23.018	1	<.001	.176

a. Variable(s) entered on step 1: If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training	.519	.409	1.610	1	.205	1.681
	Do you feel digital sports technologies provide a good return on investment for your training?	.785	.214	13.389	1	<.001	2.192
	Constant	-3.909	.716	29.776	1	<.001	.020

a. Variable(s) entered on step 1: If you subscribe to a training platform, what is the primary reason for staying? - Selected Choice The regular use improves my training, Do you feel digital sports technologies provide a good return on investment for your training?.

In summary, loyalty to platforms was shaped by performance value, but commercialization receptiveness hinged on perceived ROI. Athletes stayed with platforms and adopted brand-affiliated ones when the offering aligned with their performance goals, supporting D-STAM's emphasis on post-adoption value alignment.

The segment-specific adoption dynamics, post-adoption behavior, and commercialization pathways identified in this study are visualized in the following figure, integrating all statistically supported drivers, tested moderators and mediators, and outcome variables.

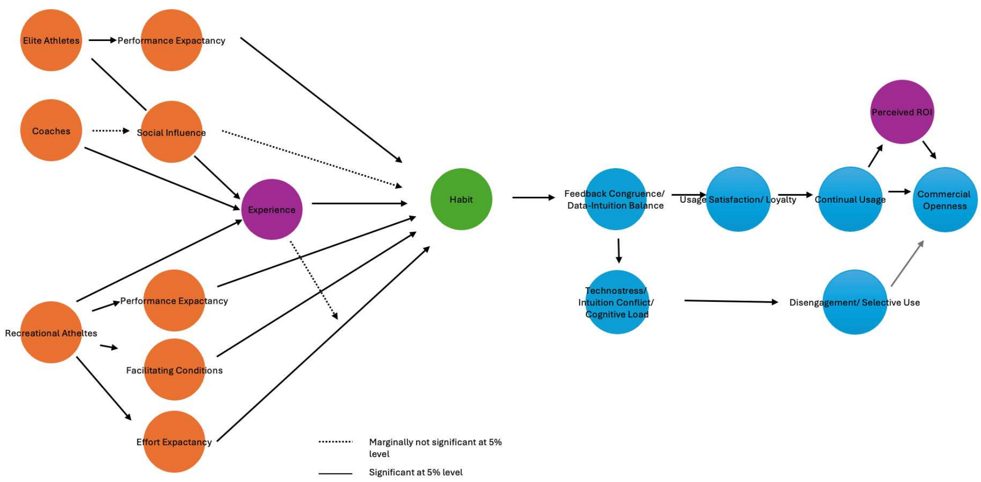

Figure 19: Final D-STAM framework: Segment-specific adoption drivers, post-adoption dynamics, and commercialization outcomes in digital triathlon.

4.2.5 Future of Digital Triathlon

This final analysis section investigates how athletes perceived the future of digital triathlon across four dimensions: legitimacy of virtual racing, perceived challenges, attitudes toward AI-based coaching, and anticipated innovation needs.

4.2.5.1 Virtual Racing Legitimacy

To evaluate how athletes evaluate virtual racing within triathlon, Q25 asked whether such formats should count toward official rankings. A large majority (79.8%) saw virtual races as training tools rather than competitive formats, while only 8.6% supported official recognition. Another 11.7% were undecided.

Do you believe virtual racing should be officially recognized in competitive triathlon rankings?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes, it is a legitimate race format	22	8.6	8.6	8.6
	No, it should remain a training tool	205	79.8	79.8	88.3
	Not sure	30	11.7	11.7	100.0
	Total	257	100.0	100.0	

Role-based differences emerged: 88.1% of professionals and 90.5% of coaches rejected virtual racing legitimacy, compared to 75.1% of recreational athletes. Recreational athletes were also more likely to be uncertain (16.2%). A chi-square test confirmed a significant association between role and perception ($\chi^2(4) = 10.809$, $p = .029$, $V = .145$), as shown in *Figure 20.*

Do you believe virtual racing should be officially recognized in competitive triathlon rankings? * What is your primary role in triathlon? Crosstabulation

			What is your primary role in triathlon?			
			Professional athlete	Recreational triathlete	Coach	Total
Do you believe virtual racing should be officially recognized in competitive triathlon rankings?	Yes, it is a legitimate race format	Count	4	15	3	22
		% within What is your primary role in triathlon?	9.5%	8.7%	7.1%	8.6%
	No, it should remain a training tool	Count	37	130	38	205
		% within What is your primary role in triathlon?	88.1%	75.1%	90.5%	79.8%
	Not sure	Count	1	28	1	30
		% within What is your primary role in triathlon?	2.4%	16.2%	2.4%	11.7%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	10.809[a]	4	.029
Likelihood Ratio	13.496	4	.009
Linear-by-Linear Association	.059	1	.808
N of Valid Cases	257		

a. 4 cells (44.4%) have expected count less than 5. The minimum expected count is 3.60.

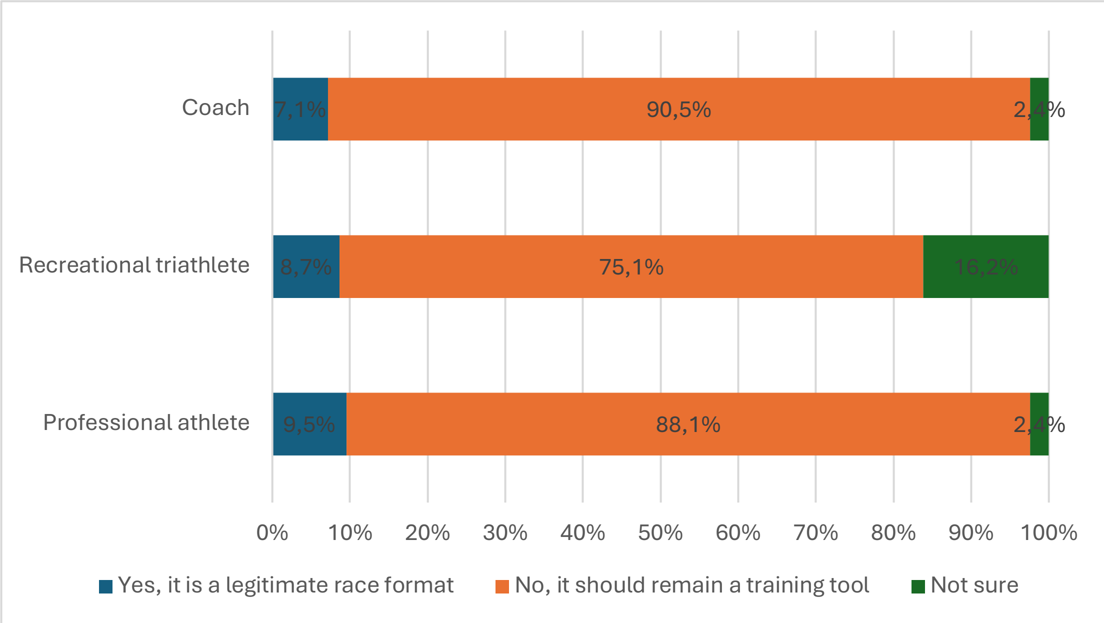

Figure 20: Virtual Racing Legitimacy Perceptions by Athlete Role

A second chi-square test examined experience-based variation (Q3_recode). Although support levels remained low overall, less experienced athletes were more likely to be uncertain (18.5%) than experienced ones (9.9%). However, this difference was not statistically significant ($\chi^2(2) = 4.662$, $p = .097$, $V = .135$).

Do you believe virtual racing should be officially recognized in competitive triathlon rankings? * Q3_recode Crosstabulation

			Q3_recode		
			.00	1.00	Total
Do you believe virtual racing should be officially recognized in competitive triathlon rankings?	Yes, it is a legitimate race format	Count	2	20	22
		% within Q3_recode	3.7%	9.9%	8.6%
	No, it should remain a training tool	Count	42	163	205
		% within Q3_recode	77.8%	80.3%	79.8%
	Not sure	Count	10	20	30
		% within Q3_recode	18.5%	9.9%	11.7%
Total		Count	54	203	257
		% within Q3_recode	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	4.662[a]	2	.097
Likelihood Ratio	4.751	2	.093
Linear-by-Linear Association	4.631	1	.031
N of Valid Cases	257		

a. 1 cells (16.7%) have expected count less than 5. The minimum expected count is 4.62.

The results underscored widespread skepticism toward virtual racing as a formal discipline, especially among experienced athletes, professionals, and coaches.

4.2.5.2 Future Challenges in Digital Triathlon

Q26 assessed what athletes see as the biggest challenges for digital triathlon's future. The most frequently cited concerns were high costs (73.8%), balancing digital tools with human expertise (61.3%), overcommercialization (55.1%), and data overload (45.7%). Other concerns included technology reliability (39.8%), privacy (39.5%), market saturation (28.1%), and limited access to smart setups (23.0%) *(Figure 21*).

$FutureChallenges Frequencies

		Responses		Percent of Cases
		N	Percent	
$FutureChallenges[a]	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) High costs of digital training tools and platforms	189	19.0%	73.8%
	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Technology reliability and accuracy	102	10.3%	39.8%
	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Privacy and data security	101	10.2%	39.5%
	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Over-commercialization of training tools	141	14.2%	55.1%
	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Skepticism from traditional athletes and coaches towards digital training methods	31	3.1%	12.1%
	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Limited access to high-speed internet and smart training setups in certain regions	59	5.9%	23.0%

	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Overload of training data leading to cognitive fatigue and mental stress	117	11.8%	45.7%
	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Balancing digital technologies with human expertise and intuition	157	15.8%	61.3%
	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Ensuring continued athlete engagement through gamification and personalization	24	2.4%	9.4%
	What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Market saturation and platform fatigue (e.g., too many digital training options, leading to declining long-term user engagement)	72	7.3%	28.1%
Total		993	100.0%	387.9%

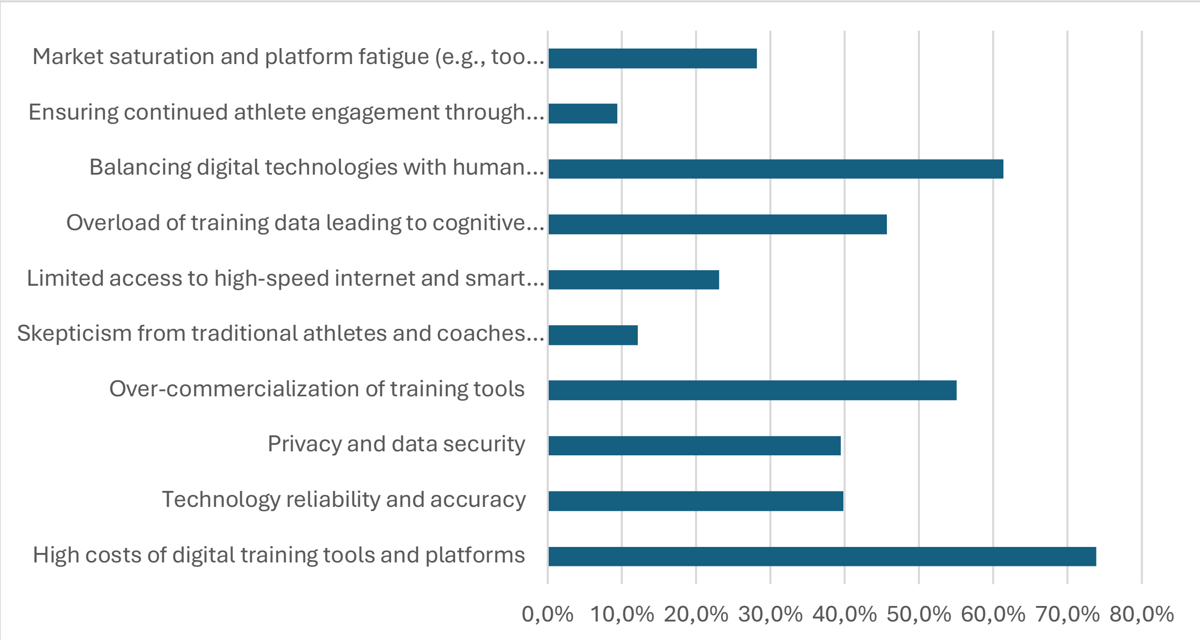

Figure 21: Future Challenges in Digital Triathlon

Role-based differences revealed diverging priorities. Professionals and coaches emphasized systemic concerns: high costs (88.1% professionals, 81.0% coaches vs. 68.2% recreational; $\chi^2(2) = 8.286$, $p = .016$), balancing tech and intuition (81.0% professionals, 73.8% coaches vs. 53.2% recreational; $\chi^2(2) = 14.384$, $p < .001$), privacy (59.5% professionals, 61.9% coaches vs. 28.9% recreational; $\chi^2(2) = 24.039$, $p < .001$), and tech reliability ($\chi^2(2) = 6.946$, $p = .031$).

Crosstab

			What is your primary role in triathlon? Professional athlete	Recreational triathlete	Coach	Total
What do you see as the biggest future challenge in digital triathlon? (Select all that apply) High costs of digital training tools and platforms	0	Count	5	55	8	68
		% within What is your primary role in triathlon?	11.9%	31.8%	19.0%	26.5%
	High costs of digital training tools and platforms	Count	37	118	34	189
		% within What is your primary role in triathlon?	88.1%	68.2%	81.0%	73.5%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	8.286[a]	2	.016
Likelihood Ratio	9.078	2	.011
Linear-by-Linear Association	.548	1	.459
N of Valid Cases	257		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.11.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.180	.016
	Cramer's V	.180	.016
N of Valid Cases		257	

Crosstab

			What is your primary role in triathlon? Professional athlete	Recreational triathlete	Coach	Total
What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Balancing digital technologies with human expertise and intuition	0	Count	8	81	11	100
		% within What is your primary role in triathlon?	19.0%	46.8%	26.2%	38.9%
	Balancing digital technologies with human expertise and intuition	Count	34	92	31	157
		% within What is your primary role in triathlon?	81.0%	53.2%	73.8%	61.1%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	14.384[a]	2	<.001
Likelihood Ratio	15.197	2	<.001
Linear-by-Linear Association	.449	1	.503
N of Valid Cases	257		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 16.34.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.237	<.001
	Cramer's V	.237	<.001
N of Valid Cases		257	

Crosstab

			What is your primary role in triathlon? Professional athlete	Recreational triathlete	Coach	Total
What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Privacy and data security	0	Count	17	123	16	156
		% within What is your primary role in triathlon?	40.5%	71.1%	38.1%	60.7%
	Privacy and data security	Count	25	50	26	101
		% within What is your primary role in triathlon?	59.5%	28.9%	61.9%	39.3%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	24.039[a]	2	<.001
Likelihood Ratio	23.865	2	<.001
Linear-by-Linear Association	.050	1	.824
N of Valid Cases	257		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 16.51.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.306	<.001
	Cramer's V	.306	<.001
N of Valid Cases		257	

Recreational athletes focused on accessibility: limited smart setup access (28.9% vs. 16.7% coaches, 4.8% professionals; $\chi^2(2) = 12.258$, $p = .002$) and platform fatigue (36.4% vs. 9.5% professionals, 11.9% coaches; $\chi^2(2) = 18.581$, $p < .001$).

Crosstab

			What is your primary role in triathlon? Professional athlete	Recreational triathlete	Coach	Total
What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Technology reliability and accuracy	0	Count	21	114	20	155
		% within What is your primary role in triathlon?	50.0%	65.9%	47.6%	60.3%
	Technology reliability and accuracy	Count	21	59	22	102
		% within What is your primary role in triathlon?	50.0%	34.1%	52.4%	39.7%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6.946[a]	2	.031
Likelihood Ratio	6.879	2	.032
Linear-by-Linear Association	.050	1	.824
N of Valid Cases	257		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 16.67.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.164	.031
	Cramer's V	.164	.031
N of Valid Cases		257	

Crosstab

			What is your primary role in triathlon?			
			Professional athlete	Recreational triathlete	Coach	Total
What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Limited access to high-speed internet and smart training setups in certain regions	0	Count	40	123	35	198
		% within What is your primary role in triathlon?	95.2%	71.1%	83.3%	77.0%
	Limited access to high-speed internet and smart training setups in certain regions	Count	2	50	7	59
		% within What is your primary role in triathlon?	4.8%	28.9%	16.7%	23.0%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	12.258[a]	2	.002
Likelihood Ratio	14.954	2	<.001
Linear-by-Linear Association	1.676	1	.195
N of Valid Cases	257		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.64.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.218	.002
	Cramer's V	.218	.002
N of Valid Cases		257	

Crosstab

			What is your primary role in triathlon? Professional athlete	Recreational triathlete	Coach	Total
What do you see as the biggest future challenge in digital triathlon? (Select all that apply) Market saturation and platform fatigue (e.g., too many digital training options, leading to declining long-term user engagement)	0	Count	38	110	37	185
		% within What is your primary role in triathlon?	90.5%	63.6%	88.1%	72.0%
	Market saturation and platform fatigue (e.g., too many digital training options, leading to declining long-term user engagement)	Count	4	63	5	72
		% within What is your primary role in triathlon?	9.5%	36.4%	11.9%	28.0%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	18.581[a]	2	<.001
Likelihood Ratio	20.876	2	<.001
Linear-by-Linear Association	.059	1	.808
N of Valid Cases	257		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.77.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.269	<.001
	Cramer's V	.269	<.001
N of Valid Cases		257	

In summary, professionals prioritized systemic and ethical concerns, while recreational athletes focused on cost, access, and platform fatigue. Coaches bridged both perspectives through their dual role as users and facilitators.

4.2.5.3 Perceptions of AI-Based Coaching

Q27 explored athletes' views on whether AI could replace human coaches in triathlon. Nearly half (47.5%) rejected the idea, emphasizing the value of intuition and experience. Another 44.7% supported AI as a complement, only 5.8% believed in complete AI replacement, and 1.9% were undecided.

Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes, AI will eventually be as effective or better than human coaches	15	5.8	5.8	5.8
	AI can be useful, but human coaches are still necessary for mental and strategic aspects	115	44.7	44.7	50.6
	No, AI lacks the human intuition and experience required for high-level coaching	122	47.5	47.5	98.1
	I do not know	5	1.9	1.9	100.0
	Total	257	100.0	100.0	

Perceptions varied significantly by role ($\chi^2(6) = 21.834$, $p = .001$, Cramer's V = .206). Professionals were most skeptical, 73.8% rejected full replacement, followed by coaches (59.5%). Recreational athletes were more open to hybrid models (51.4%) or full AI use (7.5%) (*Figure 22)*.

Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training? * What is your primary role in triathlon? Crosstabulation

			What is your primary role in triathlon?			
			Professional athlete	Recreational triathlete	Coach	Total
Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training?	Yes, AI will eventually be as effective or better than human coaches	Count	1	13	1	15
		% within What is your primary role in triathlon?	2.4%	7.5%	2.4%	5.8%
	AI can be useful, but human coaches are still necessary for mental and strategic aspects	Count	10	89	16	115
		% within What is your primary role in triathlon?	23.8%	51.4%	38.1%	44.7%
	No, AI lacks the human intuition and experience required for high-level coaching	Count	31	66	25	122
		% within What is your primary role in triathlon?	73.8%	38.2%	59.5%	47.5%
	I do not know	Count	0	5	0	5
		% within What is your primary role in triathlon?	0.0%	2.9%	0.0%	1.9%
Total		Count	42	173	42	257
		% within What is your primary role in triathlon?	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	21.834[a]	6	.001
Likelihood Ratio	23.827	6	<.001
Linear-by-Linear Association	1.058	1	.304
N of Valid Cases	257		

a. 5 cells (41.7%) have expected count less than 5. The minimum expected count is .82.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.291	.001
	Cramer's V	.206	.001
N of Valid Cases		257	

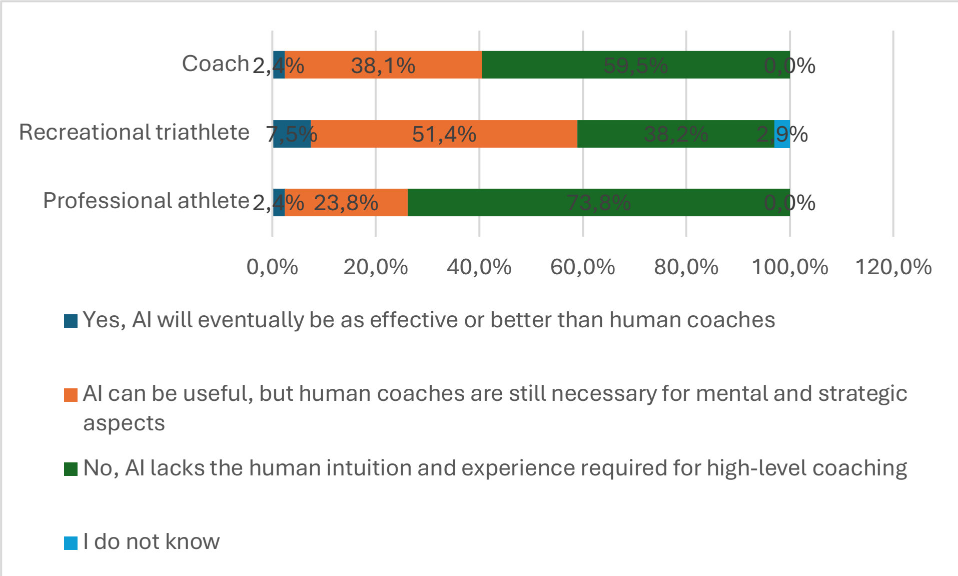

Figure 22: Attitudes Toward AI-Based Coaching by Athlete Role

A follow-up chi-square test between Q27 and training style preference (Q16) revealed a significant association ($\chi^2(12) = 31.414$, $p = .002$, $V = .202$). Athletes strongly favoring intuition were more likely to reject AI coaching, whereas those using digital metrics or balanced approaches were more open to hybrid support.

These findings highlighted the perceived limitations of AI in replacing the human element in coaching. While digital systems were broadly accepted for support and planning, many athletes, particularly professionals, still prioritized the experiential and adaptive qualities that human coaches provide.

To what extent do you prefer intuition-based performance assessment (e.g., listening to your body, perceived effort) over digital metrics and data analysis? * Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training? Crosstabulation

			Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training?				
			Yes, AI will eventually be as effective or better than human coaches	AI can be useful, but human coaches are still necessary for mental and strategic aspects	No, AI lacks the human intuition and experience required for high-level coaching	I do not know	Total
To what extent do you prefer intuition-based performance assessment (e.g., listening to your body, perceived effort) over digital metrics and data analysis?	Fully rely on digital metrics and technology 💻	Count	0	1	5	0	6
		% within Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training?	0.0%	0.9%	4.1%	0.0%	2.3%
	Somewhat rely on digital metrics	Count	5	10	5	1	21
		% within Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training?	33.3%	8.7%	4.1%	20.0%	8.2%
	A balanced mix of intuition and digital data ⚖️	Count	6	90	96	3	195
		% within Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training?	40.0%	78.3%	78.7%	60.0%	75.9%
	Somewhat rely on intuition	Count	2	10	14	0	26
		% within Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training?	13.3%	8.7%	11.5%	0.0%	10.1%
	Fully rely on intuition and subjective feeling 🫀	Count	2	4	2	1	9
		% within Do you think AI-based coaching (e.g., adaptive training	13.3%	3.5%	1.6%	20.0%	3.5%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	31.414[a]	12	.002
Likelihood Ratio	24.663	12	.017
Linear-by-Linear Association	.024	1	.878
N of Valid Cases	257		

a. 13 cells (65.0%) have expected count less than 5. The minimum expected count is .12.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.350	.002
	Cramer's V	.202	.002
N of Valid Cases		257	

4.2.5.4 Innovation Expectations

To capture athlete-driven innovation demands, Q28 invited athletes to suggest future enhancements for digital triathlon technologies. Thirty-six open responses were thematically coded and dummy-coded for analysis. The most common suggestions included real-time biometric tracking (27.8%), adaptive training and nutrition tools (16.7%), and simplified feedback systems (8.3%). Additional ideas mentioned swim-specific technologies, personalized features based on gender or age, improved platform integration, and enhanced fairness in virtual formats (*Figure 23*).

Multiple Response

[DataSet1]

Case Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
$DigitalInnovation[a]	36	14.0%	221	86.0%	257	100.0%

a. Dichotomy group tabulated at value 1.

$DigitalInnovation Frequencies

		Responses		Percent of Cases
		N	Percent	
$DigitalInnovation[a]	Q28_Biometrics	10	27.8%	27.8%
	Q28_SimplifiedUX	3	8.3%	8.3%
	Q28_AdaptiveTrain	6	16.7%	16.7%
	Q28_SwimTech	2	5.6%	5.6%
	Q28_GenderAge	3	8.3%	8.3%
	Q28_Integration	3	8.3%	8.3%
	Q28_Resistance	3	8.3%	8.3%
	Q28_Fairness	1	2.8%	2.8%
	Q28_AtHomeTest	3	8.3%	8.3%
	Q28_PlatformImproveme nt	2	5.6%	5.6%
Total		36	100.0%	100.0%

a. Dichotomy group tabulated at value 1.

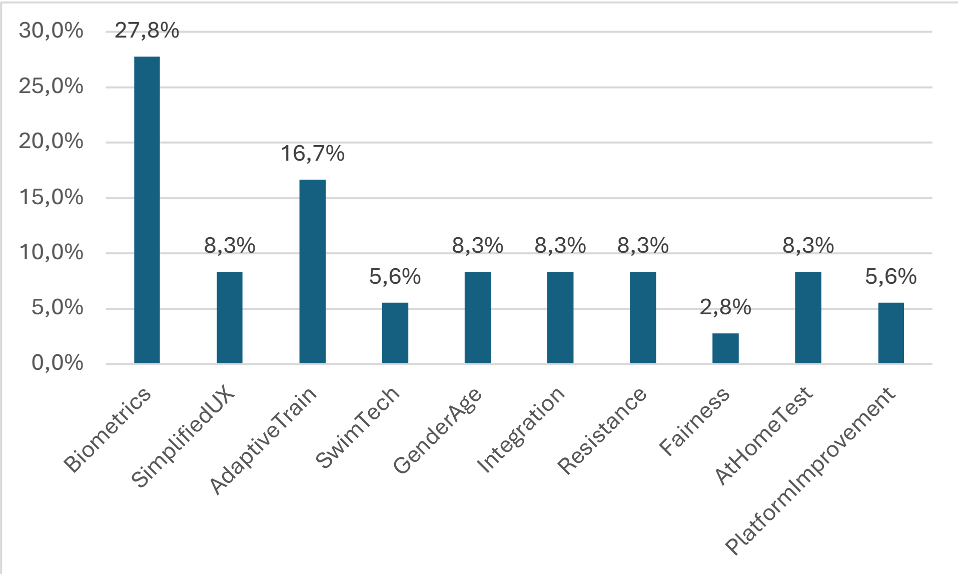

Figure 23: Athlete-Suggested Innovation Priorities

Chi-square tests revealed no significant differences in innovation preferences across athlete roles (all $p > .05$), indicating that professionals, recreational athletes, and coaches shared similar priorities. Despite the limited number of responses, the content suggests a collective emphasis on personalization, data usability, and integrated systems, highlighting practical needs not yet fully addressed by current digital solutions.

5. Conclusion

5.1 Summary of Key Findings

This study examined how technology adoption is transforming digital triathlon experiences by triangulating literature insights, 13 expert interviews, and a survey of 257 triathletes. The findings revealed that adoption behavior differed across user segments and was shaped by psychological, contextual, economic, and commercialization-related factors, as well as emerging digital expectations.

During the pre-adoption phase, survey results confirmed that Performance Expectancy and Effort Expectancy were central to adoption. Elite athletes prioritized tools that delivered tangible performance improvements, while recreational users emphasized usability and cognitive simplicity. Facilitating Conditions, like platform compatibility and device syncing, also influenced recreational users. While Hedonic Motivation and Social Influence were discussed in interviews, they did not reach statistical significance. However, Social Influence approached significance among coaches, indicating potential relevance for this subgroup. Adoption timing supported Rogers' diffusion model: professionals and coaches tended to identify as Early Adopters, while recreational athletes were more evenly spread across adopter categories.

During the adoption and use phase, digital tools became embedded in athlete routines to varying degrees. Survey data revealed that elite athletes and coaches used more devices and tracked more metrics than recreational athletes. Frequency of use correlated with performance orientation, platform usability, and daily routine integration. Although Habit was not measured directly, consistent use patterns, especially among elite users, suggest its influence. Continued use was most likely when platforms were seen as functional, easy to interpret, and well-aligned with training needs. While gamification and social features were noted in interviews, they did not significantly predict usage.

Contextual factors further influenced adoption. Recreational athletes reported the highest levels of technostress, particularly related to sleep tracking and conflicting recovery data, though this did not reduce usage. Coaches experienced significantly lower technostress than both recreational and elite athletes. Most respondents adopted a hybrid approach, balancing digital feedback with body intuition. While 76.2% of coaches and professionals viewed digital tools as complementary to intuition, recreational users were more likely to disengage when data contradicted their feelings. This suggests experienced users interpret data more confidently, while less experienced users respond more reactively. Triathlon experience significantly predicted usage and may moderate the effect of Effort Expectancy. In contrast, income and coaching status did not significantly moderate adoption. Economic constraints, platform complexity, and interoperability challenges, particularly for coaches, emerged as recurring adoption barriers. Privacy concerns were minimal.

Regarding commercialization, freemium access was widely expected and played a key role in initial engagement. Athletes were more likely to adopt platforms offering trial access and demonstrated functionality. While brand–tech partnerships were seen as innovation drivers, especially by professionals, they did not directly influence adoption. Openness to partnered platforms was explained by perceived return on investment (ROI), which fully mediated the effect of the "training improvement" loyalty motive. This suggested that athletes adopted brand-affiliated platforms not solely because of branding, but when the offering aligned with performance goals. Loyalty itself stemmed primarily from training benefits and data continuity, not branding or social features. Perceptions of brand strategies differed: professionals viewed platforms as proactive, whereas recreational athletes often perceived them as commercially motivated or slow to respond. Concerns about overcommercialization were particularly pronounced among elite users, reflecting discomfort with marketing saturation and diminishing value.

Looking ahead, most participants rejected virtual racing as a legitimate competitive format, citing concerns over fairness and device accuracy. AI-based coaching was widely welcomed as a helpful tool but not a replacement for human guidance. Across user groups, participants called for more intuitive platforms, actionable feedback, and seamless integration. Top innovation demands included real-time physiological tracking, adaptive planning, and simplified data interpretation. At the same time, concerns emerged around rising costs, overcommercialization, data fatigue, and platform overload, particularly among recreational users. Professionals and coaches highlighted infrastructure complexity, access disparities, and declining trust in overengineered features as potential barriers to broader adoption.

In sum, digital triathlon experiences are evolving by integrating performance-focused technologies. Adoption was driven by segment-specific needs and constrained by economic, psychological, and usability-related factors. Sustained engagement was most likely when digital tools are accessible, interpretable, and seamlessly embedded into athletes' daily routines.

5.2 Theoretical Implications

This study extends technology adoption theory by adapting and empirically testing the Digital Sports Technology Adoption Model (D-STAM) in the triathlon context. The model introduced a segment-specific structure differentiating adoption logics across elite athletes, recreational users, and coaches. Survey results confirmed Performance Expectancy, Effort Expectancy, and Facilitating Conditions are key adoption predictors, indicating that motivational and infrastructural factors shape habitual engagement. These findings underscored the value of role-based segmentation in explaining how digital technologies are adopted and sustained in endurance sports.

Beyond validating D-STAM, the study makes four key contributions to knowledge. First, it demonstrates that mainstream adoption constructs behave differently across user groups in high-performance sport, reinforcing the need for context-sensitive adaptations of existing models. Second, it incorporates commercialization dynamics, specifically perceived return on investment (ROI), into the adoption process. Mediation analysis demonstrated that ROI fully explained the relationship between platform loyalty and openness to brand-affiliated platforms, with training improvement emerging as the primary loyalty driver. This highlights how performance-based value perceptions, not branding or social features, govern commercialization receptiveness. Third, the study incorporates psychological factors often overlooked in traditional models. It offers evidence that technostress, data overload, and intuition conflict affect engagement, even if they do not always reduce usage frequency. Finally, by analyzing adoption timing across roles, the study offers new insights into how diffusion unfolds in niche, performance-driven communities, where early adoption is concentrated among elite athletes and coaches.

Thus, we have expanded the explanatory scope of adoption models, positioning D-STAM as a framework for understanding digital transformation in sport.

5.3 Managerial Implications

The findings provide actionable guidance for brands, tech providers, and coaches seeking to improve adoption, engagement, and retention in digital triathlon environments.

First, adoption is driven by role-specific needs. Elite athletes prioritize physiological precision and structured performance analytics, whereas recreational athletes respond more to usability, motivational support, and onboarding. Digital products should therefore be tailored in both complexity and interface design to match distinct user profiles.

Second, platforms must address cognitive and emotional barriers to sustained use. Technostress, data fatigue, and interpretability issues, particularly among recreational users, can be reduced through simplified dashboards, clear metric explanations, and customizable settings. Coaches play a central role in mediating digital feedback, equipping them with integrated tools that support hybrid coaching models can improve both athlete outcomes and platform loyalty.

Third, freemium access remains critical. Athletes expect to trial platforms before subscribing, and decisions are driven by perceived performance value. Communicating concrete ROI, such as improved training quality or reduced injury rates, is more effective than relying solely on brand prestige or sponsorships. Brand–tech partnerships are most effective when they result in co-developed features based on athlete input.

Finally, platforms must prioritize interoperability, personalization, and habit formation to maintain relevance and reduce churn. Seamless device integration, adaptive feedback aligned with user goals, and features that embed digital tools into daily routines are key to ensuring long-term engagement across user segments.

5.4 Limitations

This study has several limitations. The sample was skewed toward German-speaking triathletes, which limited the generalizability of the findings to broader geographic and cultural contexts. Data were self-reported, introducing potential for social desirability and recall bias, especially in how athletes described their technology use and attitudes. The sample likely overrepresents digitally literate users, potentially inflating adoption rates and underrepresenting more resistant perspectives. The cross-sectional design captured behavior at a single point in time. As platforms and user practices evolve rapidly, longitudinal research is needed to track behavioral change over time. Strong response consistency among elite athletes caused quasi-complete separation in one ordinal regression model, limiting its interpretive value. Despite these limitations, the study's mixed-methods approach and segment-specific analysis offer a solid foundation for understanding digital adoption in triathlon.

5.5 Directions for Future Research

Future research should build on this study by addressing several key gaps. First, longitudinal studies are necessary to capture the evolution of digital adoption and disengagement behaviors over time, particularly in relation to habit formation, perceived ROI, and technostress dynamics. Second, comparative analyses across endurance sports (e.g., cycling, rowing) and cultural settings could validate and extend the D-STAM framework, testing whether segment-specific adoption patterns are sport- or context-dependent. Third, organizational and federated dynamics deserve focused inquiry, particularly how collective adoption decisions, resource access, and institutional resistance influence technology integration at the team level. Finally, deeper psychological exploration of constructs like cognitive overload, trust in AI, and the conflict between data and intuition could benefit from experimental or longitudinal qualitative designs. Such studies would advance understanding of how athletes internalize, adapt to, or reject technological systems, informing both theory and the athlete-centered design of future digital ecosystems.

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Appendices

Appendix A: Overview of Common Triathlon Technologies

Category	Description	Common Examples
Wearables	Multi-sport GPS watches with integrated sensors	Garmin Forerunner, Polar Vantage, COROS Pace
Heart Rate Monitors	Track real-time heart rate via chest or optical sensors	Garmin HRM-Pro, Wahoo Tickr, Polar H10
Power Meters	Measure cycling or running power in watts	Favero Assioma, Garmin Vector, Stryd
Biomechanical Sensors	Provide data on gait, balance, body movement	Runscribe, Notch, Leomo Type-S
Virtual Training Platforms	Simulated environments for indoor workouts	Zwift, ROUVY, TrainerRoad
Apps & Software	Log and analyze performance metrics	TrainingPeaks, Strava, Final Surge
Smart Trainers	Indoor cycling trainers that simulate resistance and terrain	Wahoo KICKR, Tacx NEO, Elite Suito

This table is not exhaustive but illustrates the diversity of digital tools commonly used by triathletes for performance tracking, training adaptation, and virtual engagement.

Appendix B: Expert Interviews

.1 Interview Guide

Q#	Interview Question
1	What wearable devices do you (or your athletes) currently use (e.g., GPS watches, chest straps, power meters)?
2	Which performance metrics do you track most frequently (or monitor in your athletes)?
3	Do you (or your athletes) use digital training platforms (e.g., Zwift, TrainerRoad, TrainingPeaks)?
4	Do you use or integrate virtual training simulations (e.g., IRONMAN routes on Rouvy)? What are the advantages and disadvantages?
5	Do you believe digital technologies enhance your training or coaching quality? Rate the impact from 1–7.
6	How easy or difficult is it for you to use training technologies (e.g., Zwift, GPS, analytics)? Rate from 1–7.
7	How much does peer influence affect your adoption of sports tech? Rate from 1–7.
8	Do gamified features (e.g., badges, races) enhance motivation for you or your athletes?
9	How important is integration between wearables and platforms? Rate from 1–7.
10	Do you believe digital tools provide good value? Would a price increase affect your usage?
11	Do you use digital tools in every training session? How difficult would a switch be?
12	Have you felt overwhelmed by data? Can you give an example?
13	Do you second-guess decisions based on digital feedback or spend time interpreting data?
14	How much do you trust digital training data accuracy? Rate from 1–7.
15	How much do tech partnerships (e.g., IRONMAN-Rouvy) improve training tools?
16	Do you feel brands anticipate your needs or lag behind trends?
17	Would a partnership with a known triathlon brand increase your likelihood of adoption?
18	Have you used free trials of digital platforms? What influenced your conversion to paid plans?
19	Do you subscribe to digital platforms? Does historical data storage affect this decision?

20	Have you faced challenges in transferring or analyzing data across platforms?
21	Are you concerned about how platforms handle personal or athlete data?
22	Have you experienced tech issues (e.g., GPS errors, app crashes)? What was the impact?
23	Should digital training tools be officially recognized in triathlon competitions?
24	Have you had technical issues (e.g., lag, sync delays) with platforms?
25	Have you used AI-driven platforms (e.g., TrainerRoad)? What are the pros and cons?
26	How do AI-generated plans compare to human coaching?
27	If you could design the ideal digital triathlon ecosystem, what features would it include?

.2 Overview of interviewees

Interview ID	**Role of interviewee**	**Experience in triathlon (justification for this interviewee)**
Expert R1	age-group athlete	*training for his first long distance triathlon IRONMAN Hamburg *coached by former professional athlete
Expert R2	age-group athlete	*training for her first long distance triathlon Challenge Almere *coached by an experienced recreational athlete, but without trainer license *does triahtlon for 8 years
Expert R3	age-group athlete	*training for his first long distance triathlon *coached by licensed trainer
Expert R4	age-group athlete	*experienced recreational athlete *already participated various times at Challenge Roth, but trained for it without any coach
Expert P1	professional athlete	*athlete of the national German triathlon team *over 10 years of experience *2024: 1. place olympic games mixed relay, 21. place olympic games solo, 1. place world championship mixed relay Hamburg
Expert P2	professional athlete	*participant of the IRONMAN Pro Series *2021: 3rd place IRONMAN 70.3 Westfriesland 2024: German champion in the middle distance triathlon at the Ost-seeman/ finisher for the IRONMAN World Championship 2024
Expert P3	professional athlete	*athlete of the national German junior triathlon team *2023: Finisher World Triathlon Sprint & Relay Chamopinship Hamburg
Expert P4	professional athlete	*athlete of the national German triathlon team *2024: 6. place GER Sprint Triathlon National Championship
Expert P5	professional athlete	*athlete of the national German triathlon team *2023: 5th place at the U23 World Championships, 3rd place at the U23 European Championships, Winner of the Mixed Relay World Championship with her team. *2024: Debuted in IRONMAN 70.3 with a strong 2nd place at IRONMAN 70.3 Bahrain.
Expert C1	coach	*licensed coach for recreational and elite athletes *does triathlon over 15 years
Expert C2	coach	*coach of the German national triathlon team since 2024 *13 years national coach for German national young talent team
Expert C3	coach	*experienced recreational athlete *coach of various recreational athletes, without trainer license *Various podium places at the German Masters Swimming Cham-pionships
Expert C4	age-group athlete/ coach	*experienced recreational athlete and coach *already participated various times at IRONMAN Hawaii 98th over-all (2012), IM EC FFM 24th overall (2012)

.3 MAXQDA24 Code System

Codesystem					542
	Future of Digital Triathlon				2
		Virtual Racing			0
			Fairness & Regulation of Virtual Racing		5
			Virtual Racing for Training vs. Competition		2
			Legitimacy -		8
			Legitimacy +		7
		Missing innovations			2
			real-time wind assistance tracking		1
			User-friendly help with analyzing data/ metrics		7
			Physiological Tracking Innovations (e.g., Heat & Altitude)		1
			Real-Time VO2 & Running Economy Sensors		1
			Real-Time Glucose & Mineral Monitoring		2
			Continuous Lactate Monitoring		4
		AI-Driven Training			0
			Skepticism		4
			AI as a Coaching Tool vs. Full Replacement		14
			AI Coaching Adoption [-]		12
			AI Coaching Adoption [+]		9
	Commercialization & Strategic Partnerships in Triathlon				0
		Overcommercialization			3
		Platform Avoidance & Workarounds			3
		Pricing Justifications			6
		Platform Stickiness			8
		Reasons for Subscription Cancellations			1
		Brand Partnerships - Driving Innovation			0
			Impact on Innovation [-]		4
			Impact on Innovation [+]		15
		Brand Partnerships - Influence on Adoption			0
			Impact on Adoption [-]		7
			Impact on Adoption [+]		7
		Sponsorship Influence on Decision-Making			1
			Coach & Federation Influence vs. Sponsorships		1
			Sponsorship-Driven Product Awareness		3
		Freemium vs. Paid Models			0
			Freemium		8
			Paid Models		7
	Athlete Technology Adoption				0
		Privacy & Ethical Concerns			0
			Privacy & Data Security [-]		2
			Privacy & Data Security [+]		11
		Adoption Barriers vs. Facilitators			0
			Adoption Barriers		10
				Technical Barriers	3
				Data Fragmentation	2
			Adoption Facilitators		12
		Trust & Accuracy in Digital Tools			0
			Accuracy of Training Metrics [-]		7
			Accuracy of Training Metrics [+]		14
		Technostress & Cognitive Overload			0
			Balancing Intuition vs. Data		0
				Balancing Intuition vs. Data [+]	8
				Balancing Intuition vs. Data [-]	4

			Technostress - Psychological Burden		0
				Cognitive Load [-]	8
				Cognitive Load [+]	7
			Technostress - Overreliance on Data		0
				Psychological Impact of Recovery Metrics	3
				Psychological Impact of Missing Performance Streaks	1
				Psychological Impact of Pre-Race Data	3
		Price Value			1
			Cost & Subscription Value [-]		10
			Cost & Subscription Value [+]		13
		Facilitating Conditions			0
			Difficulties in analyzing metrics/ data		4
			Integration Across Platforms [-]		3
			Integration Across Platforms [+]		14
		Gamification & Engagement Factors			0
			Gamification & Motivation [-]		7
			Gamification & Motivation [+]		11
		Social vs. Independent Adoption			0
			Social Influence [-]		5
			Social Influence [+]		8
		Ease of Use			1
			Ease of Use [-]		7
			Ease of Use [+]		14
		Performance Expectancy			0
			Perceived Usefulness [-]		0
			Perceived Usefulness [+]		15
	Technology Usage & Performance Tracking				0
		Platforms Used			6
			Wahoo		2
			AeroTune		1
			WKO		1
			Pushing Limits		1
			Whoop		1
			MyFitnessPal		1
			Rouvy		1
			Strava		5
			Wahoo		0
			Garmin Connect		6
			TrainingPeaks		7
			MyWhoosh		1
			Zwift		6
		Metrics Tracked			0
			Stroke count		3
			Resting heart rate		3
			Distance		1
			recovery/ body battery		4
			sleep		5
			Power		14
			Calories		1
			Cadence		7
			Body temperature		0
			Lactate		2
			VO2 max		1
			HRV		4
			Heart rate		19
			Pace		13
		Devices Used			3

			Polar sensor	1
			Heart rate monitor	1
			Sonor communication system	1
			foot pod sensor	4
			GPS sensor	1
			Whoop band	2
			Indoor trainer	0
			Lactate monitor	2
			Body core temperature sensor	3
			Cadance sensor	2
			Bike computer	6
			Power meter	14
			Chest strap	11
			Wahoo watch	2
			Garmin watch	10

.4 Summary of Interview Expert R1

Technology Usage & Performance Tracking

Expert R1 used a Garmin ecosystem comprising a multisport watch, chest strap, and crank-based power meter. He consistently tracked heart rate and pace while running, and both power and heart rate while cycling. Swimming sessions were generally guided by feel, without reliance on data during the activity. His digital infrastructure included TrainingPeaks for planning, Garmin Connect and Strava for tracking, and Zwift for indoor cycling during winter months. Despite the functionality of virtual platforms, he preferred outdoor cycling for its motivational and experiential value.

Athlete Technology Adoption

He rated both data trust and ease of use at 7/7. He found digital tools highly intuitive and indispensable for structured training. At the same time, he experienced occasional technostress, particularly when HRV or resting heart rate values before sleep contradicted his subjective feeling of readiness. These discrepancies occasionally led to pre-sleep anxiety or second-guessing his training status. While he trained with a data-driven mindset, he emphasized the importance of listening to the body. He viewed AI-based coaching as potentially useful for beginners but did not consider it a substitute for experienced human coaches. His adoption decisions were based on individual assessment rather than peer influence.

Commercialization & Strategic Partnerships in Triathlon

Expert R1 was aware of brand partnerships such as Wahoo–Zwift and IRONMAN –Hoka but stated that these had no influence on his adoption behavior. While sponsorships increased visibility, he chose products based on functionality and performance benefit. He considered Zwift's subscription cost fair given its winter usage frequency and continued to use the free version of

TrainingPeaks. Marketing visibility might have initiated product awareness but was not sufficient for adoption.

Future of Digital Triathlon

He remained open to innovation, particularly if new tools could simplify workflows or improve insight generation. However, he remained sceptical about the increasing reliance on automation. He did not view AI coaching as suitable for experienced athletes due to its inability to adapt to context-specific variables. Similarly, while he acknowledged the training value of virtual racing formats, he did not perceive them as legitimate competitive alternatives to real-world triathlon events. He expressed greater interest in enhanced platform integration and smarter, context-aware feedback systems.

Important Quotes

"Without technology, I wouldn't know what to do, how fast I am, what values I should train at."
"If I were a complete beginner, I would trust AI coaching, but as an advanced athlete, I wouldn't."
"If a brand sponsors a race, I notice it, but it doesn't make me trust their product more."
"I wear my watch all the time, and if my HRV is off, I start wondering if something is wrong."
"Zwift's pricing is fair because I use it all the time in winter."
"I switched from Polar to Garmin, but not because of integration, there were other reasons."

.5 Summary of Interview Expert P1

Technology Usage & Performance Tracking

Expert P1 used a Garmin watch, chest strap, and crank-based power meter in daily training. He tracked heart rate and power output in cycling, pace and speed in running, and speed and lactate in swimming. For heat preparation and performance regulation, he occasionally used a core body temperature sensor. Lactate tests were performed manually but regularly in high-intensity training blocks. Training data were analyzed using TrainingPeaks, which served as his main planning and communication tool with his coach. He used Zwift for winter cycling but preferred outdoor sessions whenever possible.

Athlete Technology Adoption

He rated the ease of use of training technology at 7/7 and expressed strong trust in core performance metrics such as power and heart rate. However, he emphasized that athletes should critically assess data that feel inaccurate. Over time, he developed a balanced approach between objective data and subjective perception, stating, “We’re not machines.” He did not use AI-driven platforms and was skeptical of their applicability in elite sport, arguing that human coaches offered essential contextual awareness. Adoption was shaped by both his coach’s guidance and input from teammates, especially regarding brand and device selection.

Commercialization & Strategic Partnerships in Triathlon

Expert P1 did not let partnerships or sponsorships influence his platform or device choices. While aware of co-branding such as IRONMAN –Wahoo or Zwift–Wahoo, he prioritized long-term usability and seamless integration over marketing visibility. Although he did not pay for most devices due to sponsorship support, he evaluated pricing fairness based on product longevity and reliability. He used the premium version of TrainingPeaks and remained loyal to Zwift due to its large community and established functionality.

Future of Digital Triathlon

He considered elite sports an important driver of innovation, where technologies often transitioned from lab environments to mass-market applications. He cited the evolution of oxygen sensors as an example and expressed strong interest in real-time lactate measurement, potentially even via implant. He was highly critical of virtual racing as a competitive format, pointing to disparities in treadmill calibration and trainer resistance. While he saw digital racing as a temporary workaround, he did not consider it a viable alternative to in-person competition at the elite level.

Important Quotes

“At the highest level, training isn’t just about numbers and data, there’s also a human element.”
“We’re not machines, so some days, your wattage will be lower, and your heart rate will be higher.”
“You should always question accuracy. If a metric feels completely wrong, question the technology, not just your fitness.”
“Triathlon is all about more data, the more, the better. And that trend is spreading to amateur athletes.”
“A portable, real-time lactate monitor would be amazing.”
“Virtual racing isn’t truly fair as treadmills can have up to 5% variation.”

.6 Summary of Interview Expert R2

Technology Usage & Performance Tracking

Expert R2 used a Garmin Forerunner 955 paired with a Garmin chest strap and Wahoo cadence sensor for road cycling. She recently adopted power meter pedals for both her TT and road bikes. Her primary tracked metrics included heart rate, cadence, VO_2 max, running pace, and swim split times. She reported strong trust in Garmin's VO_2 max estimates, as they closely matched lab results. For indoor training, she used a smart trainer with built-in power meter and occasionally used MyWhoosh. Her core platforms were Garmin Connect and Strava, she previously used TrainingPeaks during an ultra-trail phase but later preferred manual plan input into Garmin.

Athlete Technology Adoption

She found Garmin tools intuitive and used them daily. Although her initial adoption was shaped by peer recommendations, she later maintained brand loyalty due to platform familiarity and long-term data visibility. She emphasized that she would not switch platforms if it meant losing her training history. While she was open to trying AI tools, she expressed doubts about their ability to account for individual schedules, fatigue, or illness. Her motivation was not driven by gamified features, since she described herself as intrinsically motivated and not competitive on social platforms.

Commercialization & Strategic Partnerships in Triathlon

Expert R2 stated that brand sponsorships had no influence on her adoption decisions. She ignored promotional content in platforms like Zwift or MyWhoosh but engaged with sponsor booths at physical races and used discount codes from race bags. She kept her Strava profile private and enabled location hiding to maintain privacy. While she accepted that companies collected her data, she was selective about who could view it publicly.

Future of Digital Triathlon

She believed virtual racing served a purpose during the pandemic but did not see it as a serious long-term alternative to physical events. The emotional, communal, and atmospheric components of live races were irreplaceable in her view. She called for improved integration between platforms, particularly expressing frustration that MyWhoosh did not sync with Garmin. She did not feel the need for new technologies and suggested that current tools were sufficient if they were better connected and more efficient.

Important Quotes

"Without data tracking, it's impossible to train with specific heart rate zones or intervals as these are crucial for improvement."

"If the numbers ever stressed me, I'd just run without my watch."

"I wouldn't switch if I lost my training history. I like seeing my progress over the years."

"I don't compare myself to others at all as I only track my own progress."

"It's essential to have seamless data transfer since athletes should be able to record data on one platform and instantly see it on another."

"Virtual races were great during COVID, but people prefer real races again."

.7 Summary of Interview Expert P2

Technology Usage & Performance Tracking

Expert P2 employed a highly structured digital training setup anchored around power output, heart rate, and recovery tracking. He used a crank-based power meter, chest strap, Garmin bike computer, and the Whoop band to monitor HRV and sleep data. He viewed power and lactate data as the most objective and actionable performance indicators. Indoor cycling was structured via Rouvy, chosen for its realistic IRONMAN course simulations. Although he used Zwift in the past, he considered Rouvy superior due to training specificity and stability. He regularly used Garmin Connect, Strava, and synced data across platforms. Resting heart rate and HRV trends informed recovery but were interpreted with caution.

Athlete Technology Adoption

He rated perceived usefulness of data at 7/7 and transitioned from FTP-based training to lab diagnostics (VO_2 max and lactate), which reshaped his training zones. He experienced mild technostress, particularly when recovery data conflicted with subjective readiness, occasionally avoiding Whoop metrics before races to prevent negative priming. He trusted data from power meters and lab protocols, while dismissing wrist-based heart rate. He found technology easy to use (7/7) but stated it should not override body awareness. He rejected AI-based coaching, citing its lack of situational judgment, emotional intelligence, and individualized feedback, especially during illness, work stress, or fatigue.

Commercialization & Strategic Partnerships in Triathlon

Expert P2 was highly selective about brand influence. He evaluated technology based on performance value, not sponsorship, and was not influenced by promotional partnerships (e.g., IRONMAN –Zwift). His subscription model included Strava Premium, Rouvy, and Whoop, which he accepted despite cumulative cost due to training benefit and integration. He used the free version of TrainingPeaks and noted that Rouvy's IRONMAN partnership initially attracted him but did not determine retention. He avoided products without proven functionality, even if highly visible in elite racing contexts.

Future of Digital Triathlon

Expert P2 viewed triathlon as innovation-forward and referenced national teams (e.g., Norway) as catalysts for emerging tech adoption. He was enthusiastic about real-time metabolic sensors, particularly non-invasive lactate and VO_2 monitors, which he saw as the next major leap. He also envisioned shoe-based sensors for running economy. He dismissed virtual racing as illegitimate due to calibration disparities and platform inconsistencies. He felt that digital competition lacked fairness, motivation, and realism, though it remained useful for structured intervals.

Important Quotes

"With lactate and VO_2 testing, I've finally trained correctly as before, I was guessing my threshold zones."
"With AI, you miss that trust and human adjustment."
"If I forget my chest strap, I panic since wrist-based heart rate isn't accurate."
"Triathlon is definitely one of the most innovative sports… Brands constantly test new things."
"Virtual racing is complete nonsense… Drafting and power adjustments don't seem fair."
"Real-time lactate tracking would be awesome. Even better live VO_2 monitoring."

.8 Summary of Interview Expert C1

Technology Usage & Performance Tracking

Expert C1 integrated a wide array of digital tools into his coaching methodology. He used Garmin and Wahoo devices, chest straps, power meters, and cadence sensors for athlete monitoring, as well as core temperature and HRV tracking. For swimming, he applied the Sonr real-time coaching system, allowing voice feedback mid-session. Across disciplines, he focused on discipline-specific metrics, such as power-to-heart-rate ratios, cadence, pace, and stroke count. His primary platforms included TrainingPeaks and WKO for planning and post-session analytics, supplemented by Garmin Connect and AeroTune. He also used Zwift and Rouvy selectively, depending on the athlete's context, especially in winter.

Athlete Technology Adoption

He rated the perceived usefulness of digital technologies at 7/7, emphasizing their role in individualizing training and adjusting plans in real-time. Ease of use was rated at 6/7, though he acknowledged that data complexity overwhelmed some athletes, especially in TrainingPeaks Premium. He reported technostress among athletes who obsess over metrics, highlighting his role as a data filter to protect athlete focus. He did not use AI-generated training plans but adopted AI-driven tools for diagnostics and thresholds (e.g., via WKO). He viewed AI as a complementary assistant, not a replacement, coaching required empathy, intuition, and situational adaptation.

Commercialization & Strategic Partnerships in Triathlon

Expert C1 emphasized performance value over commercial visibility in tech adoption. He praised partnerships like Rouvy– IRONMAN for their utility, citing race course simulations as valuable. He recommended such platforms when they aligned with athlete goals but rejected tools that lacked measurable benefit, regardless of brand affiliation. He supported subscription models when coupled with product development and appreciated flexible models like Zwift's summer pause option. He saw a growing price-performance disparity in high-end wearables, but noted that value could still be found in budget-conscious options. TrainingPeaks Premium, for example, justified its cost through functionality and federation adoption.

Future of Digital Triathlon

Expert C1 remained skeptical about virtual racing as a future format, particularly outside of regulated settings like Arena Games. He cited fairness and verification issues, especially with treadmill and trainer calibration. He emphasized that in-person racing remains the core of the sport. Regarding innovation, he highlighted the sport's rapid commercialization of elite technologies, such as aerodynamic sensors, which were once banned in cycling but are now mainstream in triathlon. He supported hybrid AI-human coaching models, but stressed that data abundance created cognitive overload, making data literacy and filtering essential in the future.

Important Quotes

"AI can assist coaches, but it can't replace them since it lacks experience, intuition, and psychological insights."

"TrainingPeaks Premium overwhelms many athletes as they start overanalyzing everything."

"Triathlon is no longer just borrowing tech from cycling and running as it has become its own industry."

"Rouvy is one of the best tech-triathlon partnerships as the value is obvious for athletes preparing for races."
"With TrainingPeaks Premium, athletes suddenly see so many data points they start obsessing."
"Some innovations get banned in cycling but are adopted in triathlon as brands are quick to bring high-end tech to everyday athletes."
"Virtual racing will stay niche as remote races are impossible to verify."

.9 Summary of Interview Expert R3

Technology Usage & Performance Tracking

Expert R3 used a multisport watch, chest strap, and headset for guided workouts, occasionally considering a Stryd foot pod. His running metrics focused on heart rate, pace, and cadence, while cycling was tracked by speed, despite his coach prescribing training based on power. He previously used the Whoop band but stopped due to psychological strain from recovery metrics. Platforms included TrainingPeaks for structured planning, Zwift for indoor cycling, and Strava for social engagement. Platform integration was crucial (rated 7/7), and although he appreciated current syncing across Zwift, Garmin, and TrainingPeaks, occasional issues disrupted continuity.

Athlete Technology Adoption

He rated technology's contribution to performance at 5–6/7, while ease of use was rated only 2/7, reflecting challenges navigating data and interpreting metrics independently. Initially, he experienced technostress from overanalyzing data, particularly Whoop's psychological impact on recovery and pre-race metrics, but this reduced after delegating data interpretation to his coach. He adopted technologies largely through Social Influence (rated 7/7), such as peer recommendations and training group standards. He found gamification on Zwift motivating, particularly for achieving in-platform badges, which positively reinforced training consistency.

Commercialization & Strategic Partnerships in Triathlon

Expert R3's platform and device choices were not shaped by sponsorships, unless accompanied by clear personal benefit. For example, although aware of Rouvy's IRONMAN affiliation, he preferred Zwift for usability and interface. He cancelled Strava Premium due to limited added value and now uses Komoot for route planning. His loyalty to TrainingPeaks stemmed from its ability to track chronic training load (CTL) and adjust sessions to align with work stress. He emphasized the need for cost–value justification, accepting subscriptions only when the features clearly enhanced training outcomes.

Future of Digital Triathlon

Expert R3 considered virtual racing useful for training engagement but not a viable format for formal competition, citing calibration issues and fairness concerns. He expressed moderate interest in innovations such as real-time wind resistance tracking or heat adaptation sensors, but found them non-essential at his performance level. Regarding AI, he remained skeptical of fully automated coaching. He stated that tools like Garmin's "unproductive" score failed to account for real-life recovery, demonstrating the limits of AI-driven diagnostics in capturing athlete context. He favored human guidance with AI support only if contextual data were integrated.

Important Quotes

"At some point, I noticed that my mood depended too much on the Whoop data, and that's when I stopped using it."
"I just follow the plan since I have a coach, I don't overanalyze my data anymore."
"I love collecting achievements on Zwift."
"Only if it gave me a financial benefit, otherwise I prefer Zwift."
"I'd rate ease of use at 2, not easy at all. You have to know what you're doing."
"Virtual racing fills a gap, but it won't be bigger than real triathlon."

.10 Summary of Interview Expert C2

Technology Usage & Performance Tracking

Expert C2, coaching at national federation level, implemented a highly instrumented approach to athlete monitoring. His teams used heart rate straps, power meters, GPS sensors for open-water swimming, and core temperature sensors in partnership with Core. Athletes also used Whoop bands or Oura rings independently. He monitored metrics such as heart rate, HRV, resting heart rate, and core temperature, especially critical during altitude training camps. For data management and training prescription, he used TrainingPeaks, with seamless integration rated at 7/7, while praising Garmin Connect for additional tracking continuity.

Athlete Technology Adoption

He rated trust in performance data such as power and heart rate at 7/7, but noted that ease of use was only 4/7 due to the volume of data streams across athletes. He perceived technostress among elite athletes, especially from Whoop's negative recovery feedback, which occasionally undermined race-day confidence. He viewed AI coaching tools as acceptable for parameter suggestions but rejected full replacement of human coaches, citing the necessity of tactical adjustment, psychological nuance, and intuition. Coaching at the elite level required interpretation beyond algorithmic pattern recognition.

Commercialization & Strategic Partnerships in Triathlon

Expert C2 confirmed that the federation partnered with TrainingPeaks to provide athletes with free access and had begun piloting Core sensors. However, he emphasized that performance utility, not financial incentive, was the primary criterion for adoption. He categorized Whoop as overpriced and opaque, critiquing its algorithmic logic and monthly fee structure. He strongly differentiated between price-justified tools like power meters (which had become more affordable) and products offering limited incremental value. Integration with the training system was key, standalone or fragmented tools were not adopted.

Future of Digital Triathlon

He saw triathlon's innovation as industry-driven, comparing it to Apple's strategy of creating needs through perceived value. While optimistic about technology's role, he cautioned against overcommercialization and highlighted the psychological burden of cognitive overload, both among athletes and coaches. He was highly skeptical of virtual racing, noting treadmill calibration issues and the lack of standardization, which compromised fairness. He did not view formats like Arena Games as sustainable in elite racing. His most desired future innovation was a real-time, implantable lactate monitor, which would eliminate the outdated process of blood sampling.

Important Quotes

"At the highest level, coaching is about dialogue, and AI cannot replace that."

"Athletes psych themselves out if their Whoop says they're not ready, so these tools impact mindset."

"Triathletes adopt tech quickly, but it's the industry that creates demand, just like Apple."

"If a product doesn't help our athletes, we don't take the deal, even if there's money involved."

"We'd love a real-time lactate sensor, still having to prick ears feels outdated."

"Virtual racing isn't a serious format, not until treadmill accuracy improves."

.11 Summary of Interview Expert C3

Technology Usage & Performance Tracking

Expert C3 applied a hybrid device setup in her training, combining Garmin devices for multi-sport tracking and Apple Watch for more accurate sleep monitoring. Her main metrics included heart rate, pace, cadence, and power for cycling. She adjusted heart rate zones based on her current training block and used step frequency in running. She wore her Apple Watch overnight, believing it provided more reliable sleep data than Garmin. For data reflection, she used Garmin Connect and Strava, with occasional use of MyFitnessPal. In racing, she minimized wearables to reduce distraction and focused on internal pacing.

Athlete Technology Adoption

She rated the impact of technology on her performance as 5–6/7, and ease of use as 6/7 after an initial learning curve. She typically served as a technology adopter within her peer group, exploring tools independently before recommending them. While she saw value in structured data, she balanced it with subjective perception, hiding pace fields during recovery runs and choosing not to sync all sleep or stress data when it added psychological load. She remained skeptical of AI coaching due to its lack of emotional context, stating that a coach's ability to adapt plans during illness or fatigue was irreplaceable.

Commercialization & Strategic Partnerships in Triathlon

Expert C3 evaluated tools through a pragmatic lens, avoiding products adopted purely due to brand sponsorship. She previously paid for Zwift but discontinued it due to pricing and switched to MyWhoosh as a freemium alternative. She frequently trialed free versions of apps and only committed to paid models when benefits were tangible. She used a human coach rather than subscribing to digital coaching platforms. She was not influenced by event sponsorships, preferring recommendations from professionals and her own product tests.

Future of Digital Triathlon

She anticipated the increased use of AI in data interpretation, especially for making feedback more actionable. She suggested platforms should offer user-friendly guidance, translating HRV or recovery scores into specific, tailored suggestions (e.g., "this means reduce intensity today"). She did not believe more metrics were needed, rather she advocated for smarter data integration. Regarding virtual racing, she had not yet participated but considered it an interesting option for age-groupers, provided it remained accessible and well-regulated. Her current focus remained on improving training quality, not expanding digital racing formats.

Important Quotes

"I use MyWhoosh because it’s free, I just want to ride, and I don’t care if fewer people are on the platform."
"AI coaching is improving, but a human coach can adapt to real-life factors like fatigue or illness in a way AI can’t."
"I don’t need a virtual reward to stay motivated, gamification doesn’t matter to me."
"If I worried about data privacy, I’d have to stop using GPS entirely."
"Virtual racing will grow, but right now, it’s mainly for elites, I’d consider it if it became more mainstream for amateurs."
"We don’t need more metrics as we need better data connections that factor in real-world conditions like wind and elevation."
"It would be great if AI could explain training data better, like ‘This number means X, and you should adjust Y to improve it.’"

.12 Summary of Interview Expert R4

Technology Usage & Performance Tracking

Expert R4 used a Garmin watch, Garmin bike computer, chest strap, and crank-based power meter for indoor and outdoor training. He tracked heart rate, power, pace, and HRV, with a strong focus on analyzing interval performance and long-term progression. He emphasized the interaction between power and heart rate, using this to assess training effectiveness. He previously used the Whoop band but discontinued it after noticing a negative psychological impact from its recovery scores. He relied on Garmin Connect for long-term data storage, used Strava mainly for social sharing, and performed indoor intervals on Zwift. He also tested a long-distance training plan from Pushing Limits that synchronized automatically with Garmin.

Athlete Technology Adoption

He rated both ease of use and impact on performance highly. While confident in using technology, he noted that interpreting certain metrics could be challenging without coaching input. He described himself as self-reliant in adoption decisions and rarely influenced by peers. He trusted metrics like power and heart rate but was critical of subjective recovery scores and found sleep tracking inconsistently helpful. While open to AI-supported feedback tools, he rejected AI-only coaching, arguing that human oversight was essential for adapting to individual circumstances such as fatigue, illness, or stress. Although not driven by platform rewards, he acknowledged that Zwift’s visual and interactive design helped him stay engaged during indoor training.

Commercialization & Strategic Partnerships in Triathlon

Expert R4 viewed most brand sponsorships with skepticism and emphasized performance and usability over marketing. He believed that race environments like Challenge Roth had become overly commercial. While he paid for subscriptions to Zwift and TrainingPeaks, he canceled Strava Premium due to limited value and used Komoot for route planning. He said he was willing to switch platforms only if a new solution clearly outperformed his current setup and offered better data continuity or training benefit. He considered Garmin's integration and durability to be a fair long-term investment, despite the high upfront cost.

Future of Digital Triathlon

He expected triathlon to continue integrating advanced diagnostics and envisioned tools capable of synthesizing data from multiple sources, such as sleep, training load, and nutrition. He was particularly interested in the potential of wearable or implantable devices for continuous tracking of lactate, glucose, and oxygen consumption. At the same time, he warned against information overload and emphasized the need for smart feedback systems that translate complex metrics into actionable insights. He viewed virtual racing as a helpful training format but not a legitimate form of competition due to equipment inconsistencies and fairness concerns.

Important Quotes

"I compare my current power output with past intervals as tracking progress over months or years is more important than a single workout."

"AI could improve training by integrating all data sources, but human oversight is still necessary."

"I considered canceling Zwift because of the price increase, but I'd miss the visuals and movement as it adds something to training."

"Garmin devices are expensive, but they last for years, and Garmin Connect is free, so overall it's worth it."

"Missing a sleep score streak by one point actually annoyed me for a second, but then I thought, why does this even matter?"

"A real-time glucose and lactate sensor, an implantable chip that tracks blood sugar and mineral levels could revolutionize endurance sports, would be a game-changer."

.13 Summary of Interview Expert P3

Technology Usage & Performance Tracking

Expert P3 structured his training primarily around heart rate and power metrics. His core devices included a chest strap, multisport watch, and Wahoo bike computer. While running was guided by heart rate, he did not use power data for that discipline. Swimming was performed by feel without data reliance. In earlier training phases, he worked with a regional training center where daily data, zones, resting heart rate, sleep, weight, and wellness, were logged in Excel and shared with coaches via OneDrive. Today, he relied less on structured tracking due to academic demands but continued to log essential values using the Wahoo app.

Athlete Technology Adoption

He rated technology's performance value as high but had grown increasingly selective in how he used metrics. In the past, he experienced psychological stress from elevated pre-race heart rate readings, which led him to skip chest straps before warm-ups. This adjustment helped reduce overreliance on data. He considered AI-based coaching potentially helpful for affordability and beginner support but maintained that human coaches were essential for adapting to personal life circumstances. He currently self-coached and designed his training based on years of experience, supplementing his sessions with qualitative feedback from his body and external cues.

Commercialization & Strategic Partnerships in Triathlon

Expert P3 evaluated technology purchases based on price-performance value. He praised his Wahoo bike computer for its reliability and cost-effectiveness and used Komoot for route planning. In contrast, he found Zwift's subscription price high and looked for ways to reduce costs, such as using free trials. Nonetheless, he continued using it during the winter for structured sessions. He acknowledged that he had been influenced by elite-level sponsorships, for example, switching from Garmin to Wahoo after seeing it adopted by a pro cycling team, but emphasized that final decisions were always function-based.

Future of Digital Triathlon

He viewed AI as a supportive analytical tool but not a replacement for coaching judgment. He expressed concern about the growing ability of wearable platforms to predict illness or performance readiness with high accuracy, noting the ethical implications of such developments. He also questioned the value of virtual racing as a spectator or athlete format, citing a lack of excitement compared to real-world events. For him, the visual features of platforms like Rouvy enhanced training engagement, but he preferred real-world races and training for their authenticity and motivation.

Important Quotes

"I track my resting heart rate closely, but sometimes I worry too much, looking back the stress itself might have made me feel worse."

"I used to be a Garmin user, but when I saw UAE Team switch to Wahoo, I became curious and bought a Wahoo instead."

"Gamification makes a huge difference since if I see someone ahead of me in a Rouvy race, I push myself to catch them."

"Komoot's integration with my bike computer is seamless as every route syncs automatically, and that's really convenient."

"I hope my training data is secure since companies are already using fitness data to adjust insurance plans, and that's unsettling."

"Arena Games didn't impress me as it's just not as exciting as real Super League Triathlon."

"AI coaching is definitely the future, especially since it's cheaper than a human coach."

"If I could improve one thing, it would be wrist-based heart rate tracking as it's still not accurate enough."

.14 Summary of Interview Expert P4

Technology Usage & Performance Tracking

Expert P4 used discipline-specific tools in training, including Polar swim sensors for heart rate, stroke count, and turn analysis, a bike computer with power measurement, and a GPS-enabled watch for running. He regularly tracked pace, cadence, heart rate, and lactate values, supported by frequent lactate testing via ear-prick samples. Although he had access to sleep and HRV tracking tools like Whoop and Oura, he preferred assessing recovery subjectively each morning, adjusting session timing accordingly. He used TrainingPeaks at his coach's request and uploaded sessions through Garmin Connect. Zwift and Rouvy were used seasonally for indoor sessions.

Athlete Technology Adoption

He rated ease of use at 7/7 and described his platform setup as straightforward. He considered performance data useful but not essential to every session, rating perceived impact at 4/7. He valued objective measures like lactate and power but emphasized enjoyment and mental freshness. For example, he hid pace displays during recovery runs and prioritized feel over numbers when appropriate. His training plans were shaped primarily by his coach, though he retained freedom in choosing brands. He expressed openness to AI-supported suggestions but viewed full AI coaching as inadequate for interpreting fatigue, emotions, or competition context.

Commercialization & Strategic Partnerships in Triathlon

Expert P4 remained cautious about pricing structures and often avoided premium services. He discontinued Zwift due to cost and accessed it through rotating free trials. He preferred MyWhoosh as a free alternative. He found some tools, such as chest straps, overpriced relative to functionality, while praising others like bike computers for their value and durability. He saw integration across platforms as increasingly important, citing frustration when device updates broke syncing capabilities. He viewed professional endorsements more as functional references than as persuasive marketing, stating he was more influenced by what professional cyclists used than by event sponsors.

Future of Digital Triathlon

He believed virtual cycling had a future as a training aid but viewed virtual triathlon racing as fundamentally limited, particularly due to unequal treadmill calibration and the impracticality of virtual swimming. He described a past virtual triathlon experience as unfair due to equipment discrepancies. His interest in innovation focused on practical enhancements, such as waterproof headphones for swimming, rather than speculative features. He welcomed AI for data interpretation but stressed that final decisions should remain with the coach or athlete. He expected future improvements in feedback clarity and cross-device data synthesis, rather than new metrics.

Important Quotes

"Indoor cycling is efficient, but four-hour sessions on the trainer are awful."
"I don’t always follow the data strictly, as sometimes you just need to train for fun."
"I refuse to pay for Zwift, therefore I just keep creating new email addresses for the free trial."
"I don’t need premium TrainingPeaks since I just check my heart rate, session time, and watts. That’s enough."
"Pro teams requested a bell function for electronic shifting, and it was implemented within a year, so some innovations happen fast, but most take time."
"Virtual cycling will continue to grow, but virtual triathlon won’t since it’s just too inconsistent."
"AI can be useful, but it won’t replace human coaches as every athlete responds differently to training, and AI can’t account for that."

"I have no concerns about data privacy as race results are public anyway, so why hide training data?"

.15 Summary of Interview Expert P5

Technology Usage & Performance Tracking

Expert P5 used a Garmin bike computer, chest strap, power meter, and a core temperature sensor in daily training. She also employed lactate measurement tools in selected blocks to support performance diagnostics. Her core tracked metrics included heart rate, power, pace, sleep, and resting heart rate. She wore her watch overnight to monitor recovery but interpreted sleep and resting heart rate trends with caution, using them as complementary signals rather than decision drivers. She consistently used TrainingPeaks and Garmin Connect to manage training loads and communicate with coaches.

Athlete Technology Adoption

She rated technology's performance contribution at 6–7/7 and ease of use at 5/7, noting that while devices were intuitive, interpreting advanced data could be overwhelming, particularly for younger athletes or those unfamiliar with physiological metrics. She trusted objective metrics like power and heart rate, but considered tools like sleep tracking less reliable. She observed technostress in some athletes, especially when recovery scores contradicted their subjective state. For her own training, she balanced data with intuition and used digital feedback as a supplement. She expressed skepticism toward AI coaching, stating it lacked the relational and situational awareness required at high performance levels.

Commercialization & Strategic Partnerships in Triathlon

Expert P5 described brand partnerships as helpful when they improved platform or device integration. She found Garmin's ecosystem particularly functional due to its consistent syncing and broad adoption. While open to using new tools, she evaluated them strictly by value and performance, not marketing. She used premium features only when necessary and otherwise preferred free versions of platforms. She had discontinued Zwift in favor of outdoor winter riding and saw limited justification for ongoing subscriptions unless aligned with personal training objectives.

Future of Digital Triathlon

She remained critical of virtual racing, especially in light of her experience attending Arena Games in London, where inaccurate treadmill calibration affected competitive fairness. She considered such formats more suited to entertainment than legitimate racing. She supported innovations that brought practical value, such as non-invasive, real-time lactate monitoring, but did not seek additional metrics. Instead, she hoped for better interpretation tools that reduced decision complexity for athletes. She saw promise in AI-supported tools for diagnostics, but not as coaching replacements.

Important Quotes

"Even in winter, I prefer training outside if needed, I use a gravel bike or just bundle up."
"I stopped using Zwift because it didn't appeal to me enough to justify it."
"If a platform doesn't integrate well, using it isn't fun."
"Subscription-based models aren't for me as I only pay for TrainingPeaks."
"I don't let training data dictate everything, since body awareness is still my priority."
"Arena Games showed how virtual racing is developing, but treadmill accuracy made results unfair."
"AI coaching can analyze data, but it can't replace the human ability to understand an athlete's psychology and needs."
"Real-time lactate measurement, like glucose sensors, would change endurance sports completely."

.16 Summary of Interview Expert C4

Technology Usage & Performance Tracking

Expert C4 applied a broad set of digital tools in both his coaching and personal training practice. He used a Garmin watch with chest strap, power meter, and bike computer, while relying on TrainingPeaks and Garmin Connect for planning and data analysis. In coaching, he emphasized the interaction between heart rate and power, using longitudinal patterns to assess athlete development. He also recommended Zwift and Rouvy for interval training, especially for time-constrained athletes. Virtual sessions were used for precision, but he stressed the importance of maintaining real-world training to develop pacing intuition.

Athlete Technology Adoption

He rated digital technologies as highly effective (5–6/7) and very user-friendly (7/7), though he acknowledged that athletes often experienced cognitive overload. He assumed the role of a data filter, helping athletes interpret the most relevant metrics and avoid over-focusing on less meaningful data points. He observed technostress particularly in younger athletes who became anxious when faced with recovery scores that conflicted with how they felt. He saw value in AI tools for diagnostics but considered AI coaching insufficient for nuanced athlete development. He maintained that intuition, coaching experience, and personal relationships remained central.

Commercialization & Strategic Partnerships in Triathlon

Expert C4 viewed commercial partnerships as beneficial when they led to product improvement and user integration. He praised collaborations like Zwift–Wahoo for their practical enhancements and training realism. However, he was critical of overhyped or overpriced tools, especially high-end watches that offered marginal benefits over lower-tier models. While subscriptions such as Zwift and TrainingPeaks were justified for their functionality, he cautioned that rising costs could become exclusionary for some athletes. His product choices were based on utility, not sponsorship exposure, and he did not adopt platforms solely based on brand visibility.

Future of Digital Triathlon

He expressed skepticism about the long-term legitimacy of virtual triathlon formats, citing the absence of fair standardization and the impracticality of virtual swimming. While acknowledging the temporary value of Arena Games during the pandemic, he believed real-world racing would remain central. He strongly advocated for future innovations such as implantable lactate sensors, calling the current process of manual sampling outdated. He emphasized the need for better filtering and simplification of data presentation, warning that athletes were already becoming overwhelmed by the sheer volume of information.

Important Quotes

"Virtual training is a huge improvement over the past, but it should complement, not replace, outdoor experience."

"With Zwift, you can ride at night or follow structured intervals without any traffic, so it's a game changer for busy athletes."

"Technology is powerful, but it doesn’t replace experience and intuition, as you still have to feel your body."

"The market is evolving faster than ever since ten years ago, no one believed home setups could mimic lab diagnostics."

"AI will never replace the human element, as it can support, but not substitute, coaching."

"Some watches now cost as much as a smartphone, but that kind of price jump isn't always justified."

"TrainingPeaks should become more intuitive, especially for athletes who feel lost in too much data."

Appendix C: Survey

.1 Outline of survey questions

Q No.	Question	Question Type	Answer Options
Qualifying Question			
1	Do you have experience in triathlon?	Multiple choice	Yes; No
Athletic Background			
2	What is your primary role in triathlon?	Multiple choice	Professional athlete; Recreational triathlete; Coach
3	How many years have you been involved in triathlon?	Multiple choice	Less than 1 year; 1-3 years; 4-6 years; 7-10 years; More than 10 years
4	Do you train with a coach?	Multiple choice	Yes, with a professional coach; Yes, with an experienced triathlete; No, I train independently
Use of Digital Training Tools & Virtual Platforms			
5	Which training tools do you currently use?	Multiple choice (multiple selections possible)	GPS watch (Garmin, Polar, Suunto, etc.); Power meter (cycling or running); Heart rate monitor (chest strap, wrist-based); Smart trainer (Wahoo, Tacx, etc.); Digital training apps (e.g., TrainingPeaks); Virtual training platforms (Zwift, Rouvy, MyWhoosh); Bike computer; Cadence sensor; Core body temperature sensor; Lactate meter; Whoop Band; None of the above; Other:
6	Which performance metrics do you track most frequently?	Multiple choice (multiple selections possible)	Heart rate; Heart rate variability (HRV); Pace; Power output (watts); Cadence; VO2 max; Body temperature; Recovery status (e.g., Garmin Body Battery); Sleep metrics; Training Stress Score (TSS); Predicted race times (e.g., Garmin 5K, 10K, marathon); Lactate threshold; None
Consumer Adoption of Digital Sports Technologies			
7	How do you usually adopt new sports technologies (e.g., power meters, AI coaching, virtual training)?	Multiple choice	I actively seek out and test new innovations before most athletes.; I adopt new technologies early, but only after some proof of effectiveness.; I adopt technology when it becomes common among other triathletes.; I wait until it is widely accepted and becomes a standard.; I avoid new technologies unless I am forced to adopt them.
8	Do you believe digital sports technologies enhance your training quality and performance?	5-point Likert scale	Not at all (1) - Absolutely (5)
9	How easy is it for you to set up and use digital training technologies (e.g., Zwift, power meters, heart rate monitors)?	5-point Likert scale	Extremely difficult (1) - Extremely easy (5)
10	How much does seeing professional athletes, coaches, or training partners use a technology influence your decision to adopt it?	5-point Likert scale	None at all (1) - A great deal (5)

11	How important is seamless integration between your wearable technology and training platforms (e.g., Garmin, TrainingPeaks, Zwift)?	5-point Likert scale	Not at all important (1) - Extremely important (5)
12	To what extent do you find gamified training elements (e.g., leaderboards, virtual races, achievements on Strava, Zwift) engaging in your training?	5-point Likert scale	Not at all engaging (1) - Extremely engaging (5)
13	Do you feel digital sports technologies provide a good return on investment for your training?	5-point Likert scale	Very poor ROI (1) - Excellent ROI (5)
14	How often do you track your training metrics (e.g., power, heart rate, HRV, cadence)?	5-point Likert scale	Every session (1) - Never (5)
15	What are the biggest barriers preventing you from adopting new digital training tools? (Select all that apply)	Multiple choice (multiple selections possible)	High costs; Complexity of setup and use; Lack of compatibility with existing devices; Privacy concerns (data security); Preference for traditional training methods; None of the above
16	To what extent do you prefer intuition-based performance assessment (e.g., listening to your body, perceived effort) over digital metrics and data analysis?	Multiple choice	Fully rely on digital metrics and technology; Somewhat rely on digital metrics; A balanced mix of intuition and digital data; Somewhat rely on intuition; Fully rely on intuition and subjective feeling
17	Have you ever avoided or discontinued using a digital training tool because you felt it interfered with your natural training intuition or decision-making?	Multiple choice	Yes, I prefer making training decisions without digital feedback; Yes, but only for certain aspects of training; No, digital tools complement my intuition; No, I fully trust digital insights
18	How often do you feel overwhelmed or stressed by analyzing training data?	5-point Likert scale	Always (1) - Never (5)
Quality Control Question			
19	To ensure high-quality responses, please select Strongly Agree for this question.	5-point Likert scale	Strongly disagree (1) - Strongly agree (5)
Strategic Partnerships & Commercialization of Digital Triathlon			
20	To what extent do partnerships between triathlon brands and technology companies contribute to the development of digital training tools? (e.g., new virtual training options or improved data analytics)	5-point Likert scale	None at all (1) - A great deal (5)
21	Do triathlon brands and technology companies anticipate athlete needs, or do they respond too slowly to emerging trends? (e.g., in AI-based training, virtual racing, or new wearables)	Multiple choice	They are proactive and anticipate needs.; They respond but often too slowly.; They mostly focus on commercial interests.
22	Would you be more likely to adopt a new digital training platform if it was officially partnered with a well-known triathlon organization (e.g., IRONMAN, PTO, Challenge Family)?	5-point Likert scale	Extremely unlikely (1) - Extremely likely (5)

23	How important is a free trial period in determining whether you commit to a paid subscription for a digital training platform?	5-point Likert scale	Not at all important (1) - Extremely important (5)
24	If you subscribe to a training platform, what is the primary reason for staying?	Multiple choice (multiple selections possible)	My historical data is stored there; The regular use improves my training; The social and interactive features keep me engaged; Other (please specify)
Strategic Partnerships & Commercialization of Digital Triathlon			
25	Do you believe virtual racing should be officially recognized in competitive triathlon rankings?	Multiple choice	Yes, it is a legitimate race format ; No, it should remain a training tool; Not sure
26	What do you see as the biggest future challenge in digital triathlon?	Multiple choice	High costs of digital training tools and platforms; Technology reliability and accuracy; Privacy and data security; Overcommercialization of training tools; Skepticism from traditional athletes and coaches towards digital training methods; Limited access to high-speed internet and smart training setups in certain regions; Overload of training data leading to cognitive fatigue and mental stress; Balancing digital technologies with human expertise and intuition; Ensuring continued athlete engagement through gamification and personalization; Market saturation and platform fatigue (e.g., too many digital training options, leading to declining long-term user engagement); I don't expect any future challenges.
27	Do you think AI-based coaching (e.g., adaptive training algorithms) can fully replace human coaches in triathlon training?	Multiple choice (multiple selections possible)	Yes, AI will eventually be as effective or better than human coaches; AI can be useful, but human coaches are still necessary for mental and strategic aspects; No, AI lacks the human intuition and experience required for high-level coaching; I do not know
28	What improvements or new products would you like to see in digital triathlon technologies?	Open-ended question	
Demographic Questions			
29	How old are you?	Multiple choice	Less than 18; 18-24; 25-34; 35-44; 45-54; 55-64; 65+; Prefer not to say
30	What gender do you identify with?	Multiple choice	Male; Female; Non-binary/Third gender; Prefer not to say
31	In which country do you currently reside?	Multiple choice	Portugal; France; Spain; Italy; Germany; Switzer- land; Belgium; the Nether- lands; Denmark; Norway; Sweden; United Kingdom; United States; Other (can be specified)
32	What is your highest level of education?	Multiple choice	Less than high school degree; High school graduate; Vocational training; Bachelor’s degree (or equivalent); Master’s degree (or equivalent); Doctoral degree; Prefer not to say
33	What was your total household income (in EUR) before taxes in the past year?	Multiple choice	Less than €25,000; Between €25,000 and €49,999; Between €50,000 and €99,999; Between €100,000 and €199,999; More than €200,000; Prefer not to say

.2 Descriptive Overview of the Sample

The final dataset included 257 valid responses, with recreational athletes comprising the majority (67.3%, n = 173), and professional athletes and coaches each representing 16.3% (n = 42).

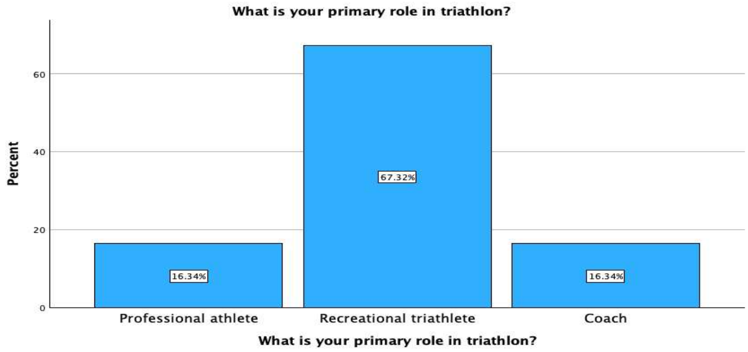

Figure 24: Distribution of Athlete Roles

There were mostly male respondents (68.09%) versus 31.13% female. Most participants were between 25 and 54 years old, with the 25–34 (29.18%) and 35–44 (24.90%) groups forming the largest age cohorts. The sample was predominantly German (89.9%), with a small share from other European countries and the U.S. (*Figures 25-27*).

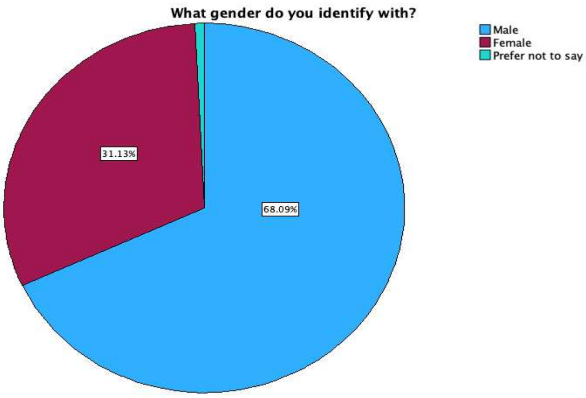

Figure 25: Gender Distribution of Participants

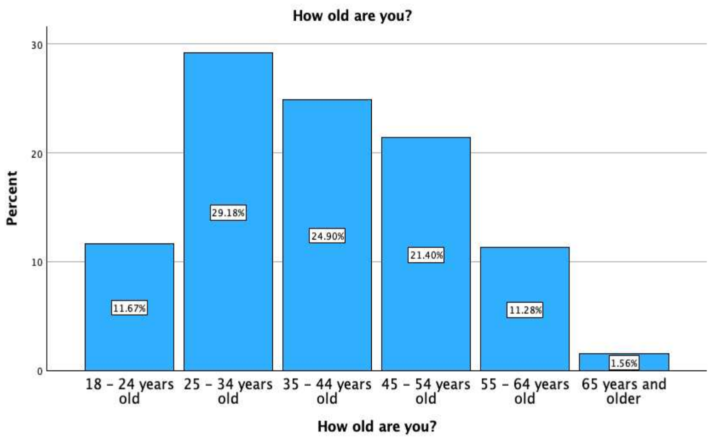

Figure 26: Age Distribution of Participants

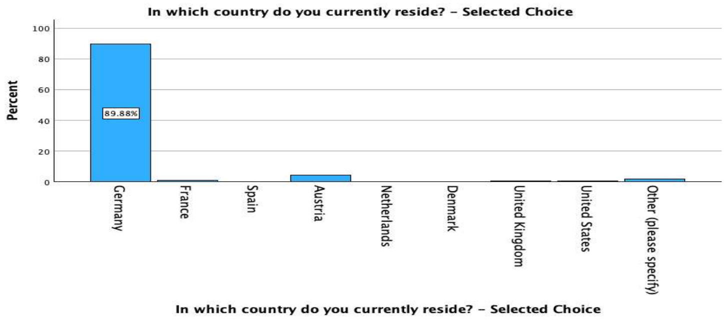

Figure 27: Geographic Distribution of Participants

Educational levels were high: 63.4% held a university degree (25.7% bachelor's, 37.7% master's). Household income varied, though ~60% reported earning €50,000–199,999 annually; 11.3% chose not to disclose their income (*Figure 28 - 29*).

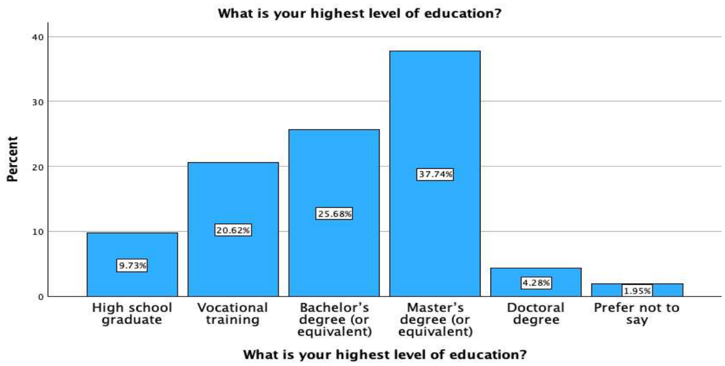

Figure 28: Educational Attainment of Patricipants

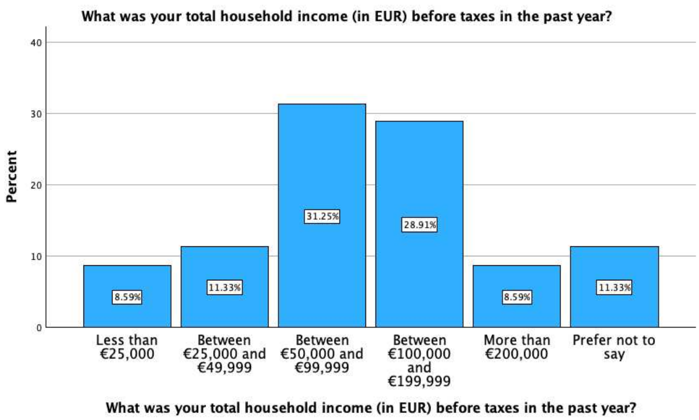

Figure 29: Income Levels of Participants

Coaching arrangements differed by role. Nearly all professionals (95.2%) trained with a certified coach. In contrast, 50.3% of recreational athletes trained independently, while 17.9% relied on experienced peers. Among coaches, 83.3% trained alone, reflecting their dual role (*Figure 30*).

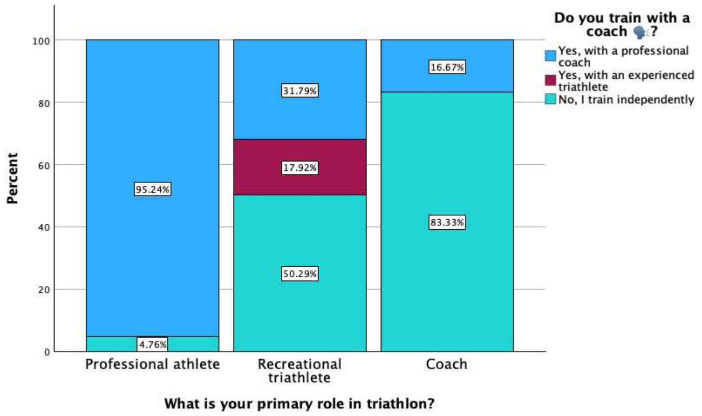

Figure 30: Coach Usage by Athlete Role

Triathlon experience was higher among elite users: over 90% of professionals and coaches had been active for seven or more years, while recreational athletes displayed more variation (*Figure 31*).

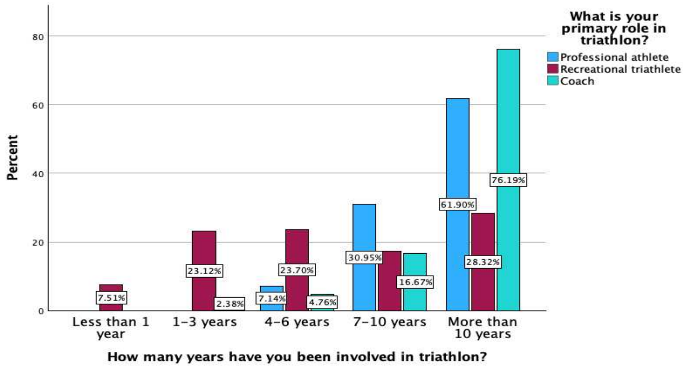

Figure 31: Triathlon Experience by Athlete Role

Education and income also varied by role. Among coaches, 33.3% held a master's degree, and 35.7% a bachelor's. Recreational athletes followed with 46.2% and 23.1%, respectively. In contrast, one-third of professionals had vocational training, and another third held only a high school diploma. Regarding income, 88.1% of coaches and 54.7% of recreational athletes earned €50,000–199,999 annually, while professionals showed wider dispersion, with 11.9% earning below €25,000 and 16.7% above €200,000 (*Figure 32-33*).

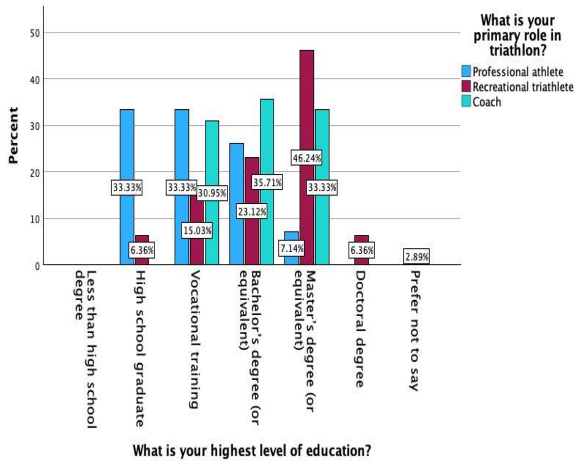

Figure 32: Education Level by Athlete Role

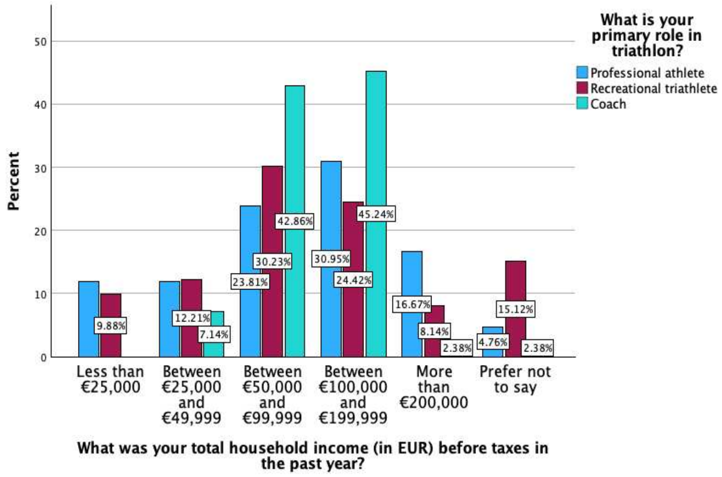

Figure 33: Income Level by Athlete Role