BRIDGING THE TRUST GAP IN WELLNESS INNOVATION: A STRATEGIC ROADMAP FOR CONSUMER ADOPTION

By

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DEDICATIONS

It goes without saying that no person is an island, and for that, I thank every soul who helped me become who I am. Somewhere between nature and nurture, there's a hamster wheel inside me that just won't stop spinning.

To my family, friends, coworkers, teammates, and ancestors, thank you for shaping my fire, my narrative, and my curiosity. Without you, I might've been a very fine couch potato. Or a film or food critic. Possibly both.

To my father: thank you for your push and presence. To my grandmother: your wit and strength echo in me daily. To my mother: thank you for the dance between tension and tenderness. To Laura: this journey of healing, aging, and wonder, I wouldn't trade a step of it with anyone else. To my kids: you keep me grounded in the present, and that keeps me whole.

To Pepe and Lupita: your love was silent but loud. Pepe, we miss you, and what you taught us lives on.

And to the version of me who kept going, especially when it made no sense to, I see you, and I thank you.

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This journey began, almost by accident, with a hotel points deal that landed me at the Beverly Hills Hilton. On my way to the pool, I passed a sleek, glass-fronted space tucked just below the lobby. With its stunning design, crystal-clear windows, and high-performance aesthetic, Upgrade Labs stopped me in my tracks. I had already read some of Dave Asprey's work, the so-called father of biohacking, and curiosity pulled me inside.

After signing up for sessions and regularly making the drive from Costa Mesa to Beverly Hills, COVID hit, and everything shut down. But that pause launched a new chapter. I dove deeper into Dave's books, his podcasts, the Upgrade Collective, and eventually the Biohacking Conference in Orlando. That was a turning point. What started as curiosity became a full-blown pursuit of growth, healing, and human optimization. I'm deeply grateful to Dave Asprey for building something that invites others in and for modelling what a generous, mission-driven wellness entrepreneur looks like.

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To my father, whose journey from alpha to MS patient changed me forever. That experience cracked something open and sparked an obsession with control, longevity, and resilience. To my grandmother, our matriarch, whose wit and strength continue to guide me. And to my mother, whose push and pull helped me develop a deep respect for balance, pacing, and aging with grace.

To Laura, my partner in pain, recovery, and cosmic curiosity, I wouldn’t want to explore this strange, beautiful world with anyone else.

To my kids, thank you for anchoring me to the present and reminding me that no matter how far I go in thought, tech, or time, home is here.

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And finally, to the version of me who kept going, especially when it was easier not to: I see you, and I thank you.

In this life, I have so much to be grateful for. Trying to capture it all here is impossible, but I hope this is a start.

ABSTRACT

BRIDGING THE TRUST GAP IN WELLNESS INNOVATION: A STRATEGIC ROADMAP FOR CONSUMER ADOPTION

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We are witnessing a shift in how people approach health, moving beyond institutional care toward decentralized, self-directed wellness. With tools like red light beds, wearables, ice baths, and other biohacking technologies now available for at-home use, consumers are taking control of their health journeys. Yet, in this landscape of innovation and accessibility, a critical challenge emerges: how do people decide what to trust when regulation is absent?

This dissertation investigates the behavioral and psychological dynamics of adopting preventive wellness technologies in unregulated markets. Drawing on a survey of 600 respondents and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Fuzzy-set Qualitative Comparative Analysis (fsQCA), the study develops and tests an extended conceptual model incorporating Technology Credibility (TC), Perceived Risk (PR), Health Motivation (HM), and Personal Innovativeness (PI).

The findings confirm that Behavioral Intention (BI) is the most consistent predictor of Actual Use (AUT), with TC acting as a key enabler by linking beliefs to action. Additionally, facilitating conditions, social influence, and perceived risk significantly shape users’ intention and behavior. The fsQCA results revealed multiple pathways to adoption, supporting the principle of equifinality, that different combinations of motivations and contextual conditions can all lead to technology use.

To better explain trust formation and consumer action, this study proposes the Wellness Trust Lifecycle Plus (W-TLC+) framework, a six-stage model that outlines how trust builds, shifts, and sustains over time in low-trust wellness ecosystems. W-TLC+ helps entrepreneurs and researchers

understand not just why people adopt emerging wellness technologies, but also how to ethically build trust in their use and scale responsible innovation in unregulated spaces.

This work contributes to theory by extending TAM and UTAUT into non-traditional contexts, and to practice by offering a strategic roadmap for fostering credibility, motivation, and adoption in decentralized health environments.

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ABBREVIATIONS

AI – Artificial Intelligence
B2B – Business-to-Business
B2C – Business-to-Consumer
CX – Customer Experience
D2C – Direct-to-Consumer
DTx – Digital Therapeutics
FDA – Food and Drug Administration
GDPR – General Data Protection Regulation
HBOT – Hyperbaric Oxygen Therapy
HIPAA – Health Insurance Portability and Accountability Act
HRV – Heart Rate Variability
IoT – Internet of Things
KPI – Key Performance Indicator
LTV – Lifetime Value
mHBOT – Mild Hyperbaric Oxygen Therapy
MDR – Medical Device Regulation (EU)
PBM – Photobiomodulation
REM – Rapid Eye Movement
ROI – Return on Investment
SEO – Search Engine Optimization
SL – Sleep Latency
SMB – Small and Medium-Sized Business
TAM – Technology Acceptance Model
TAM2 – Technology Acceptance Model 2
TRA – Theory of Reasoned Action
TRUST – Trust in Health Technologies
UTAUT – Unified Theory of Acceptance and Use of Technology
USP – Unique Selling Proposition
UX – User Experience
VO_2 max – Maximal Oxygen Uptake
WBC – Whole-Body Cryotherapy
W-TLC+ – Wellness Trust Lifecycle Plus

CHAPTER I: INTRODUCTION

1.1 Background

The healthcare industry is undergoing a profound transition, shifting from traditional, institutional models to more consumer-directed, technology-enabled health solutions (Cohen et al., 2020). Driven by rising demand for personalized, convenient, and preventive wellness care, technologies once reserved for hospitals, specialty clinics, or elite athletes, such as hyperbaric chambers, photobiomodulation devices, brain entrainment systems, cryotherapy units, and real-time biometric wearables, are now being reimagined for at-home and mobile use.

This movement represents not only technological progress, but a broader cultural transition toward self-managed health, where individuals seek greater autonomy and proactive control over their well-being. The convergence of market forces, rising consumer expectations, and accessible innovation is rapidly reshaping how care is accessed, delivered, and trusted.

These developments carry significant implications for public health policy, healthcare economics, and entrepreneurial innovation. At the same time, they raise pressing questions about trust, credibility, and decision-making, especially in the absence of centralized regulation and traditional clinical oversight.

These themes are explored further in Chapter V through the proposed Wellness Trust Lifecycle+ (W-TLC+), a conceptual model for understanding how consumer trust develops around emerging wellness technologies (Lambrew, 2007; Lambrew and Podesta, 2006).

1.2 The Aging Population as a Catalyst for Change

A significant driver of change in healthcare is the aging of the global population. In the United States, Medicare membership is projected to rise by over 50% in the next 15 years, from 54 million beneficiaries to more than 80 million by 2030 (Medicare Payment Advisory Commission

[MedPAC], 2016). According to Census projections, by 2030, the proportion of Americans aged 65 and older will nearly double, from 13% in 2010 to 20% (Ortman, Velkoff and Hogan, 2014). Furthermore, the number of Americans aged 85 and older is expected to quadruple by 2036 and triple again by 2049 (MedPAC, 2016). This demographic shift underscores the growing need for technologies that enable older adults to manage their health independently, safely, and affordably.

Yet this trend isn't limited to aging populations. Younger generations are also fueling demand for customizable, real-time health optimization tools, such as wearable biomarker trackers, longevity-enhancing protocols, and digital recovery platforms. Across all ages, there is growing interest in consumer-friendly, tech-enabled solutions that support personalized, proactive care.

Emergent wellness sectors, spanning recovery, performance, mental health, beauty, and longevity, are becoming increasingly age-agnostic. These categories now appeal across generations, reflecting a shift away from traditional healthcare segmentation, where products were designed for narrow age brackets (e.g., youth fitness or geriatric care). Today, innovation is expected to adapt to users at any life stage.

This age-agnostic trend has profound implications for entrepreneurs. It expands the Total Addressable Market (TAM), encourages inclusive design, and opens the door to lifetime customer engagement. Start-ups and established players alike must ask how their offerings can serve both a 27-year-old performance optimizer and a 72-year-old managing post-surgical recovery, without compromising usability, trust, or effectiveness.

Age-agnostic design doesn't mean watered-down functionality; it means delivering targeted, personalized outcomes that are accessible and effective across a wide demographic spectrum.

1.3 The Economic Burden of Chronic Disease and the Push for Self-Managed Care

According to the Centers for Disease Control and Prevention (2016), chronic diseases account for approximately 75% of total U.S. healthcare spending. This staggering economic burden reflects the long-term costs of conditions such as cardiovascular disease, diabetes, and obesity, many of which are largely preventable or manageable through early, consistent interventions. These realities underscore the urgent need for creative, technology-enabled solutions that empower individuals to take control of their health journeys.

Self-managed care's growing appeal is tied to rising costs and dissatisfaction with overburdened healthcare systems. Individuals are increasingly turning to accessible, personalized tools that support wellness, recovery, and disease prevention outside of traditional clinical settings. From wearable biometric trackers to app-based coaching platforms, the shift toward decentralized, consumer-centric health tools represents both a public health necessity and a commercial opportunity.

An essential requirement for deploying health technologies in residential or mobile settings is ensuring that treatment efficacy, usability, and user safety are not compromised (Inspectie voor de Gezondheidszorg, 2008). Historically, medical technologies were designed exclusively for clinical environments (Kaufman-Rivi et al., 2010; Weick-Brady and Lazerow, 2006). Today's context demands a design evolution. Solutions must be not only portable and secure but also intuitive and frictionless for users across a broad demographic spectrum.

The rise of age-agnostic innovation in fields such as recovery, mental health, longevity, and personalized performance has accelerated this transition. Today's tools must serve diverse populations, from seniors managing chronic conditions to younger users seeking optimal wellness through daily tracking and proactive interventions. These developments reflect a generational convergence in health behaviors and the potential to deliver preventive care that scales across age, location, and income levels.

The implications are clear: the convergence of chronic disease burden, consumer empowerment, and technology innovation has redefined what "healthcare" means. Entrepreneurs who respond to this shift with credible, scalable, and inclusive solutions are uniquely positioned to improve public health outcomes while reducing long-term systemic costs. The future of healthcare may depend not only on what happens in hospitals, but on what happens in-homes, on wrists, and in everyday lives.

1.4 Innovation, Investment, and the Role of Biomarkers in Preventive Wellness

To meet rising demand, both established companies and a surge of startups are actively developing novel solutions in today's dynamic digital health landscape. Yet the road to market is complex, marked by regulatory hurdles, consumer skepticism, and the need for viable business models and seamless user experiences. Venture capital investment in digital health reached a record high of USD 29 billion globally (Gormley, 2024), a milestone largely catalyzed by the COVID-19 pandemic, which highlighted the urgent need for innovation in healthcare delivery models.

However, as the market matures, investors have become more selective. There is decreasing tolerance for companies offering only unvalidated claims or patent filings without clinical traction. Many early digital health startups failed to show meaningful returns on investment, resulting in greater pressure on entrepreneurs to demonstrate both technological innovation and clinical credibility.

This has led to a growing emphasis on outcomes-focused validation. Entrepreneurs are increasingly expected to conduct rigorous studies to demonstrate product efficacy, building credibility with both investors and users. Scalability is equally important: solutions must function reliably across population sizes and healthcare settings while delivering consistent quality and user experience. Sustained user engagement is another critical challenge. In response, many startups now apply behavioral science and user-centric design principles to create intuitive platforms that promote long-term use.

The push to innovate is further complicated by challenges such as regulatory compliance, data privacy, and the need to establish strategic partnerships. Collaborations with healthcare institutions are increasingly essential, as traditional players now demand stricter validation before adopting digital solutions (Milne-Ives et al., 2025).

A particularly powerful trend is the mainstreaming of biometric and biomarker data as tools for daily wellness decisions. Metrics such as heart rate variability (HRV), VO_2 max, REM and deep sleep patterns, sleep latency, blood glucose levels, and biological age estimators are now accessible to everyday consumers through wearable tech. Once the domain of elite athletes or clinical settings, these tools are being democratized via apps and platforms that provide real-time health insights.

Emerging modalities like photobiomodulation (PBM), delivered through red light panels, face masks, and full-body beds, and advanced sleep tracking tools are becoming central to the consumer wellness stack. These technologies offer tangible benefits such as reduced inflammation, improved recovery, enhanced cognitive clarity, and circadian rhythm alignment. They also support a new trust-building mechanism: the ability for users to see and feel results, backed by transparent data, a dynamic explored further in the proposed Wellness Trust Lifecycle+ (W-TLC+).

Entrepreneurs are now expanding into more nuanced indicators, including frailty indices, inflammatory markers, and exposure metrics such as microplastic loads or toxin sensitivity. Heavily influenced by the functional medicine movement, this evolution emphasizes personalized diagnostics and system-level understanding. Consumers increasingly demand quantifiable, individualized proof of efficacy, far beyond generic wellness claims.

This biomarker-led evolution signals a broader shift toward data-driven self-care. For entrepreneurs, this creates both opportunity and responsibility. Solutions must be technically sound, visually comprehensible, and built to promote consistent user engagement. In the absence of institutional validation, trust hinges on transparent metrics, measurable outcomes, and a frictionless user journey. As supported by the W-TLC+ framework, integrating real-time feedback loops into preventive health technologies is becoming foundational to achieving product-market fit, long-term retention, and consumer belief.

Key challenges facing digital wellness innovation include:

- Regulatory barriers: Complex compliance and approval processes slow product rollout (Milne-Ives et al., 2025).
- Consumer trust and adoption: Many remain skeptical about new technologies and uncertain about their benefits (St. Louis, 2024).
- Market scalability: Business models must bridge innovation and mass adoption (Schlieter et al., 2022).
- User experience and accessibility: Platforms must be intuitive and integrate seamlessly into users' lives (Adapt Digital, 2024).

As health and technology continue to converge, the coming decade will determine whether portable and on-demand health interventions become a paradigm shift or a luxury product for the few. Successfully navigating these challenges will be critical to shaping the future of personalized, preventive healthcare and building a more sustainable, inclusive wellness ecosystem.

1.5 Research Problem

Digital healthcare is among the largest and most rapidly evolving industries, shifting from a traditional, institution-based model toward a more decentralized, consumer-driven ecosystem (Narayan et al., 2024). Technologies such as wearables, mobile health applications, and artificial intelligence (AI) are empowering individuals to take a more active role in managing their health (Mahajan et al., 2025). However, widespread diffusion of these technologies remains limited, largely due to trust-related issues, perceived risks, and the lack of functional regulatory frameworks (Catapan et al., 2025; Al Meslamani, 2023).

Trust has emerged as a critical, multifaceted factor influencing digital health adoption. Higher trust correlates with increased usage, while perceived risks, privacy concerns, and questions about data quality can undermine adoption (Alhassan et al., 2025; Belfrage, 2022; Alrawad et al., 2023; Syed et al., 2024). Conversely, transparency, positive user experiences, and perceived usefulness help foster trust (Wanner et al., 2022). Despite this, research has shown that trust is often poorly conceptualized or measured in the literature. Many studies lack validated instruments to reliably assess or build trust in digital health technologies (Marra et al., 2024).

From an entrepreneurial perspective, integrating technology into healthcare offers both significant opportunities and unique challenges (Kulkov et al., 2023). While innovation enables new approaches to preventive care, the absence of traditional institutional backing often leaves entrepreneurs navigating ambiguity, particularly in proving credibility and safety (Javanmardi et al., 2024). As noted by de Vasconcelos Gomes et al. (2023), there is a notable gap in the literature regarding holistic frameworks that guide innovators in overcoming barriers and creating sustained value in healthcare.

At the intersection of these issues lies a critical void: few empirical frameworks explain how credibility, risk perception, and behavioral intention interact and evolve over time in unregulated or semi-regulated wellness markets (Kulkov et al., 2023; Zahlan et al., 2023; Swain et al., 2024). Without this understanding, entrepreneurs face significant difficulty in building credible, user-centered wellness technologies. Traditional models such as the Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA) provide valuable insights, but they were designed for structured, institutional contexts and fall short in explaining user behavior in decentralized, consumer-led environments (Zin et al., 2023; Omar et al., 2023; Ahmad et al., 2020; Kalayou et al., 2020).

This gap necessitates the development of updated frameworks that account for the dynamics of trust-building, behavioral intention, and actual technology use in the absence of institutional validation. In response, this study introduces and tests the Wellness Trust Lifecycle⁺ (W-TLC+): a conceptual model designed to bridge this gap by identifying key trust drivers and decision-making pathways in adopting wellness technologies.

Based on this, the objectives of this research are:

- To validate antecedents and consequences of actual technology use in wellness contexts
- To examine the impact of independent variables (IDVs) on actual use
- To explore the non-linear and combinatorial effects influencing wellness technology adoption

Achieving these objectives can contribute to improved health outcomes, stronger consumer engagement, and the development of more durable, consumer-led healthcare frameworks.

1.6 Purpose of Research

The purpose of this study is to develop and empirically validate a multidimensional framework to explain consumer adoption behavior in the context of digital healthcare technologies. As healthcare delivery continues its shift from institution-centric models to consumer-driven ecosystems, existing models, such as the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA), fall short in explaining user decision-making in environments lacking traditional guarantees of trust, regulation, and credibility.

To address this gap in both theoretical understanding and practical application, this research introduces the Wellness Trust Lifecycle+ (W-TLC+): a trust-first adoption model that expands on classical frameworks by incorporating technology credibility (TC), perceived risk (PR), health motivation (HM), and personal innovativeness (PI). These variables are positioned as critical antecedents to behavioral intention (BI) and actual use of technology (AUT) in the decentralized, often unregulated digital wellness market.

The study further examines the impact of key cognitive appraisals, including performance expectancy and effort expectancy, as determinants of social influence (SI) and technology credibility (TC) in digital health environments (Fedorko et al., 2023; Hutabarat et al., 2021; Al-Kfairy et al., 2024). In addition, it evaluates how individual characteristics such as health motivation and personal innovativeness influence trust formation in the absence of institutional oversight.

This user-oriented model reflects the diverse realities of modern digital health users, from younger individuals pursuing optimization and performance to older adults managing chronic conditions. By grounding its variables in real-world dynamics such as perceived credibility and risk, the study aims to provide actionable insights for entrepreneurs, designers, and health innovators operating in emerging and fast-moving markets.

1.7 Significance of the Study

This research is significant across conceptual, empirical, technological, entrepreneurial, and policy dimensions, driven by the rapid convergence of healthcare, digital innovation, and consumer empowerment.

Traditional frameworks such as the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA) emerged in highly regulated, institutional environments. As a result, they overlook several critical factors that drive adoption in today's decentralized, consumer-facing digital health landscape. Key dimensions such as technology credibility, risk perception, and health motivation are often excluded, despite their substantial influence on trust and behavioral intention in self-managed care contexts.

By incorporating these dimensions, the present study contributes to both the extension and contextual adaptation of traditional adoption models. It introduces a more relevant, multidimensional approach tailored to the realities of unregulated or semi-regulated wellness ecosystems.

Existing literature on trust in digital health technologies remains fragmented and lacks a holistic framework. As Marra et al. (2024) note, most current models fail to capture a multidimensional view of trust. Research into how credibility and perceived risk shape adoption decisions in digital health remains limited, with much of the work instead focused on unrelated domains such as autonomous vehicles and urban air mobility (Kenesei et al., 2022; Yao et al., 2024). This study fills that gap by embedding these variables into an empirically testable model, designed specifically for consumer-facing digital wellness technologies.

For entrepreneurs in digital health, the challenge lies in proving credibility and building sustained user trust without relying on institutional validation. This study offers a practical roadmap, the Wellness Trust Lifecycle^{+} (W-TLC+), to help innovators understand the psychological and behavioral dynamics behind user adoption. By identifying key antecedents of behavioral intention and actual use, the model informs the design of inclusive, age-agnostic, and engaging wellness solutions that are both trustworthy and effective.

At a policy level, the findings provide insight into how governance structures can adapt to digital-first realities. By understanding what fosters trust and sustained engagement in decentralized environments, policymakers can shape frameworks that balance innovation with accountability. This research contributes to evidence-based policy development by drawing clear connections between cognitive, motivational, and social influence factors, and actual usage behavior, essential for promoting user-centered design, improving health outcomes, and creating long-term value in wellness ecosystems.

1.8 Research Purpose, Guiding Questions, and Scholarly Contribution

The primary purpose of this study is to develop and empirically validate a comprehensive, multidimensional framework that explains the behavioral dynamics behind consumer adoption of preventive digital healthcare technologies, particularly within decentralized, unregulated, or semi-regulated wellness markets. As healthcare models shift under pressure from consumer expectations, aging populations, and the rising costs of chronic disease management (Yu et al., 2023; Junaid et al., 2022), there is an urgent need to revisit and extend existing theoretical models and entrepreneurial strategies. This study builds on the Technology Acceptance Model (TAM) by incorporating additional constructs, technology credibility, perceived risk, health motivation, and personal innovativeness, which are central to understanding trust and adoption in today's fragmented, consumer-led health environment.

Recognizing the shift from provider-centric to user-centric care, the model addresses how individuals manage their health through wearables, mobile applications, and AI-enabled platforms (Hazra and Bora, 2025; Oyeniyi, 2024; Nguyen et al., 2023). In such settings, institutional trust is often absent, replaced by data-based credibility and product experience. This demands a reconceptualization of how trust is formed and sustained without traditional clinical oversight (Adeghe et al., 2024; Shajari et al., 2023). The study examines how consumer perceptions, particularly performance expectancy, effort expectancy, perceived risk, and credibility, interact with individual motivation and social influence to shape both behavioral intention (BI) and actual use of technology (AUT).

The research is guided by a series of interrelated questions:

1. Which factors most strongly influence consumer adoption and sustained use of preventive health technologies?

   This includes exploring how consumers interpret utility and usability, and how those interpretations are shaped by cognitive beliefs, motivations, and trust mechanisms.

2. Which entrepreneurial strategies are most effective for overcoming regulatory and market-entry barriers in the at-home digital health sector?

   With startups proliferating in this space, the study evaluates which design and validation practices enhance credibility, user retention, and scalability.

3. How can entrepreneurs balance regulatory compliance with consumer satisfaction when building preventive wellness solutions?

   In loosely regulated markets, this trade-off becomes central to both user experience and product legitimacy.

4. Which business models support long-term scalability, sustainability, and consumer engagement?

5. The research evaluates operational strategies that align with inclusion, affordability, and measurable health outcomes.

In answering these questions, the study contributes to multiple domains: theoretical, empirical, technological, entrepreneurial, and policy. Conceptually, it addresses a gap in the literature: while TAM and TRA are foundational, they are not designed for the complexity of consumer-facing, decentralized digital health environments. The integration of credibility and perceived risk provides a much-needed extension that reflects real-world user behavior.

Empirically, the study introduces the Wellness Trust Lifecycle^{+} (W-TLC^{+}), a trust-first adoption model grounded in validated constructs. It offers researchers, designers, and entrepreneurs a framework for identifying trust gaps, predicting adoption, and designing effective interventions. The model draws from established research in digital trust, innovation diffusion, and consumer psychology, but adapts these theories for the unique challenges of preventive wellness technology.

Technologically, the research aligns with innovations in AI-driven diagnostics, VR-based rehabilitation, photobiomodulation, and mobile-enabled recovery platforms. Yet, as the findings reinforce, technology alone does not guarantee adoption. Psychological, behavioral, and cultural dynamics must be accounted for, especially in underrepresented or high-risk populations.

For entrepreneurs, this research presents a practical blueprint, from concept development to scaling. It emphasizes the importance of credible design, behaviorally anchored UX, and long-term user engagement that leads to satisfaction, retention, and measurable outcomes. Startups and innovators are encouraged to create health solutions that are not only scalable and evidence-based but also intuitive, trustworthy, and inclusive across age and socioeconomic boundaries.

From a policy perspective, the study’s findings can inform more adaptive and enabling regulatory frameworks. By illuminating how trust forms in decentralized markets, it offers evidence to help strike a balance between user protection and innovation enablement.

Ultimately, this research proposes that the future of health innovation is not only a matter of technology, but of reshaping health behavior through credibility, empowerment, and trust. By merging behavioral science with entrepreneurial strategy, the thesis offers a vision for a more inclusive, participatory, and sustainable healthcare economy, where the future of health is not confined to hospitals and specialists but embedded in daily life, everyday decisions, and trusted digital tools.

CHAPTER II:
LITERATURE REVIEW

In order to determine where the area of preventive health technologies and digital at-home health technologies is at the moment and what gaps need to be filled, this chapter provides a critical evaluation and summary of the relevant literature. First, the chapter finds the research gaps by reviewing the existing literature on the subject. The development of a conceptual model and the identification of relevant variables allowed for the hypothesis testing phase.

Springer, Elsevier, Google Scholar, Scopus, and other online journal databases were searched using various search algorithms to gather the relevant material. A manual search was conducted on the expanded literature, utilizing citations and references to do both backward and forward searches.

2.1 Regulatory and Market Landscape

Startups offering at-home health technologies work in a strict regulatory environment of differences depending on the region (Iqbal & Biller-Andorno , 2022). In the case of the United States, many wellness devices and health wearables need to go through the Food and Drug Administration (FDA) clearance or approval process (U.S. Food and Drug Administration, 2023). In 2018, Apple's entry into the wearables space with electrocardiogram (ECG) functionality in Apple Watch series 4 first received FDA 510(k) clearance to become the first consumer wearable to perform an ECG, for example (Comstock, 2018). However, some features or products are specifically grouped under "general wellness" to evade medical device regulation. Apple introduced a blood-oxygen monitor on the Watch as a wellness feature, not for medical use (Apple, 2024). WHOOP — a leading fitness band — also states that they're putting themselves in the wellness tracker category rather than as a medical device (Chilingaryan, 2025).

According to FDA rules, a product that has been marketed for general wellness and for no use of diagnosing or treating disease does not fall under the premarket clearance category (Crobar, 2021). While faster market entry is allowed through this regulatory loophole, companies are restricted on their claims. Therefore, many of the at-home health tech companies decide on the wellness device pathway instead of years of approvals (Köhler et al., 2024). Such strategy allows devices to escape FDA oversight and rigorous validation. It is not always straightforward for consumers to discern fully cleared medical devices from a wellness gadget, especially when marketing messages dilute the distinctions (Sifaoui & Eastin, 2024). Ambiguity in these claims can provoke skepticism because users are not sure of categories and up to what levels products can truthfully boast of being healthy without formal clinical validation.

Startups in the European Union (EU) have to apply for the Medical Device Regulation (MDR 2017/745) that requires a medical device to be CE marked (European Union, 2017). Wearable health tech is intended to help healthcare professionals have more stringent requirements for safety, effectiveness, and post-market surveillance under MDR (Brönneke et al., 2021). For example, a feature like the Apple Watch ECG would need CE marking under the MDR before it could be placed on the market of EU countries, as it did previously with FDA clearance in the US. However, new ventures struggle to comply with these regulatory standards as they involve significant cost and expertise in performing clinical trials and documentations (Rodriguez-Manzano et al., 2024). However, as a result, some of the firms constrain their marketing claims in Europe or defer EU launch until they meet compliance (Rodriguez Manzano et al., 2024). Therefore, the regulatory landscape is a fundamental factor in determining the market entry and product design for at-home health tech entrepreneurship (Chakraborty et al., 2023).

The market is further impacted by data privacy laws around health-related data collected from wearable and at-home devices (Canali et al., 2022). Patient health information in the U.S. falls under the Health Insurance Portability and Accountability Act (HIPAA), but most direct-to-consumer (D2C) health tech companies are not typical healthcare providers, and therefore fall in a gray area under HIPAA (Centers for Disease Control and Prevention, 2024). Nevertheless, startups that offer integrations with medical services (think, your wearable's data sent to a doctor or health insurance provider) become bound by HIPAA's restrictive data security and patient consent rules. For example, in the EU, the General Data Protection Regulation (GDPR) considers biometric and health data, also known as sensitive personal data, and it provides a very high level of standards for consent and storage of such data when a company collects it from users (Hoofnagle et al., 2019). Fun fact: under GDPR, users must be properly informed and in control of their data, which is hard when devices are always recording biometric indicators – the GDPR ‘mandate’ (Hoofnagle et al., 2019). The secure handling of the data streams is the utmost priority; violation, on the other hand, would result in heavy fines. High cost of compliance: In this space, entrepreneurs often have very high compliance costs for data encryption, personal identifier anonymization and robust cybersecurity measures to protect user information.

To combat such challenges, various emerging solutions such as health data storage through a blockchain are being researched by (Haleem et al., 2021). For instance, decentralized data platforms (such as, AstraDAO in the field of health) advocate for users to own the data of their biometrics by the use of blockchain to store this information (Subramanian, 2022). In theory, this approach would bolster privacy and security by enabling data to be shared only in between stakeholders (doctors, researchers, insurers), with the user’s consent thereby holding an implicit assurance that the privacy regulation will be followed on the basis of the design via technology (Subramanian, 2022). Blockchain solutions for such use cases are still nascent and need to scale and be approved by appropriate regulators, as health data handling itself does, (Perwej et al., 2025). Additionally, perceptual, technical complexity, and industry-wide standards are some of the challenges that might limit the mainstream adoption (Perwej et al., 2025).

An additional layer of the market landscape is consumer perception. A large number of at-home health technologies lacked trust from users and health care professionals (Rodrigues et al., 2024). There are still consumers who are skeptical of a new wellness device, claiming impressive health benefit, but without medical endorsement (Tabish, 2008). For example, products such as red light therapy panels or home cryotherapy devices have been the focus of interest, but a group of the public (and even many physicians) doubt their efficacy because there is not much clinical evidence to prove so (Hernández-Bule et at., 2024). This lack of extensive peer-reviewed research or FDA approval for such therapies causes caution (Algorri et al., 2023). In fact, companies that choose not to be regulated (for a quicker market entry) also typically lack public validation which undermines credibility. The blood oxygen monitoring feature Apple built into its watch: it was introduced as a wellness feature, so Apple was not obliged to publish rigorously accurate data, making experts “concerned” with a lack of information (Wetsman, 2020). This type of incident speaks to a wider problem; many at-home wellness products are not clinically validated which creates doubt in consumers (Johnson et al., 2016). These trust barriers are daunting and entrepreneurs must overcome them by investing in research, communicating device capabilities and limitations transparently and, in some cases, having the devices certified by an external organization to be able to reassure users.

2.2 Emerging Technologies Driving Market Expansion

The advancements in technology are growing the capabilities of the at-home devices of health care very rapidly and this is making the market to grow and giving rise to new opportunities for entrepreneur (Byelsense, 2021). Next generation health monitoring is about artificial intelligence (AI) and predictive biometrics (Yadav & Yadav, 2025). However, now, modern wearable devices are able to collect continuous streams of data; heart rhythm, sleep pattern, blood glucose level, blood oxygen, movement, etc. and AI algorithms can use them to give meaningful health insights (Olawade et al., 2025). AI powered systems can detect tiny patterns or deviations and can inform users in case of any potential health issues or can suggest personal wellness interventions (Jain, 2025). For instance, Levels Health offers continuous glucose monitors and offers data analytics (AI based pattern recognition) with the data to provide real time feedback relating to diet and metabolism (Business Wire, 2023). It seeks to transform health management from reactive to proactive, such as waiting until a doctor's visit to deal with symptoms to preempting risks by signal of insulin resistance, stress levels or impending illness. Wearable-derived data can predict whether someone is experiencing atrial fibrillation or that an influenza outbreak will occur just days before clinical presentation (so potentially before a clinical visit) (Duncker et al., 2021; Ekundayo et al., 2024; Papalamprakopoulou et al., 2024; Francisco et al., 2025). But these AI driven insights are within a safety measure. In order to prevent false positives or negatives, the algorithms have to be rigorously validated and there are ongoing debates regarding the clinical reliability of AI recommendations (Hanna et al., 2025). Until then, it may be reasonable to withhold action on device alerts without a physician's consultation, as the medical community is uncertain how to integrate AI generated health care reports in the works for official care guidelines. Despite these challenges, the integration of AI with at-home health techs is a big market-accelerating trend because of its promises of more personalized and actionable health data for consumers (LaBoone et al., 2024; Bajwa et al., 2021).

The second technological frontier on the horizons of at-home health entrepreneurship is the application of blockchain and decentralized systems for the use of health data and services provision (Haleem et al., 2022). AstraDAO (a community-driven Health data project: Subramanian, 2022) is a showcase how a community-driven DAO can be utilized to create new health data ecosystems. In these models, people will safely exchange or monetize his/her biometric data for research or for personal gain with the continued control through smart contracts (Habib & Manik, 2025). Through transparency and immutability, blockchain provides prospective answers to the problem of data tampering and interoperability issues encountered in the traditional health record systems (Ettaloui et al., 2024). This enables entrepreneurs to create platforms in which user data will contribute to large scale wellness insights (such as community-driven symptom pattern and treatment outcome databases) without compromising user privacy (Javaid et al., 2024). However, for now, the experiment of Web3 approaches already suggests that some health tech startups may eventually be moving to an infrastructure devoid of central authority, giving users more agency (Narayan et al., 2024). Finally, the effects of these technologies are to instill trust among consumers (through data security), and to encourage new business models (tokenized rewards for healthy behavior, data sharing, etc.) (Andrew et al., 2023). While that is so, there will be acceptance by regulators in health care of blockchain and the ease of use of such systems for the normal consumer in order to allow mass adoption (Virani, 2024).

Along with digital innovations, therapeutic technologies that used to stay inside the clinics are increasingly being engineered to be used at home, expanding the horizon of at-home health solutions (Haleem et al., 2022; Junaid et al., 2022). The line between hospital and home care is getting blurred as entrepreneurs are introducing variety of advanced treatments and wellness modalities that they have converted into the apartment (King, 2023). Transitional therapies that are notable to come home include:

2.2.1 Hyperbaric Oxygen Therapy (HBOT)

Hyperbaric Oxygen Therapy (HBOT) is a therapeutic technique in which individuals breathe pure oxygen in a pressurized oxygen chamber (Hyperbaric Facility) at settings of more than the normal atmospheric pressure (from 1.5 to 3.0 atmospheres absolute, ATA) (Ortega et al., 2021). The results of this treatment are in a significant elevation of oxygen dissolved into the bloodstream and into the tissues, which leads to healing twice as fast, reducing the inflammation and improving the cellular metabolism (Babchin et al., 2011). HBOT has traditionally been used in the clinical setting for the treatment of decompression sickness, carbon monoxide poisoning, radiation injuries, gas embolisms, and chronic non-healing wounds (Gill et al., 2004). Finally, it is FDA-approved to treat over a dozen such indications and is considered a crucial medical operation in hospitals and specialized hyperbaric facilities (Bhutani & Vishwanath, 2012). Now, there are hyperbaric chambers advertised for personal use (UIAA, 2023). OxyHealth creates HBOT chambers in the form of oxygen-rich air at higher than atmospheric pressure; it is manufactured by compact, low-pressure chambers, which allow individuals to inhale the oxygen-rich air in their own home. Biohackers and wellness enthusiasts are increasingly involved in thinking of HBOT for purported benefits in recovery and cognitive performance (Gottfried et al., 2021).

These days, HBOT has gone beyond its commonly known clinical use (Fu et al., 2022). Due to the increasing popularity of wellness optimization, longevity science, and biohacking culture, HBOT has become icing on the cake for health enthusiasts who want to take the edge off when it comes to recovery, cognition, or the early stages of aging (Fu et al., 2022). The attractiveness of the therapy is based on HBOT's physiological mechanism: it may enhance angiogenesis (new blood vessel formation), recruit stem cells, or immunomodulation by simply increasing the oxygen supply to damaged or inflamed tissues. Moreover, these mechanisms have made HBOT increasingly relevant to healing for athletes, anti-aging protocols, as well as mental health support (Fu et al., 2022; Gupta & Rathored, 2024).

This movement has been driven by the rapid development of portable, consumer-grade HBOT systems that can be used in the home. OxyHealth, Summit to Sea, and other vendors have created soft-shell, low-pressure hyperbaric chambers that individuals can use at home or on the go for the purposes of mild HBOT sessions. The pressures of these home-use chambers are generally around 1.3 ATA and at the expense of compressed oxygen tanks or ambient air or oxygen concentrators (Kistner, 2023). These systems are not intended for the treatment of serious medical diseases unless prescribed by a doctor, but they are marketed toward general wellness and recovery. They cost between $7,000 and $20,000 (depending on specifications and safety features) (Biohacker

Supply, n.d.), and as such, are part of a new segment of the health-tech sector focused on self-managed care.

At-home HBOT has become popularized for a more general user — elite athletes and Silicon Valley executives on the one hand and aging populations on the other who seek vitality and mobility (Fu et al., 2022, Gupta, & Rathored, 2024). People have been reporting subjectively improved sleep quality, faster post-exercise recovery, lighter inflammation, sharper mental clarity, and better appearing skin with these things, says Alnawwar (2023). While there are informal accounts of some of these claims that robust longitudinal data have not yet supported, some studies on the subject are emerging, showing real potential for HBOT, including for conditions such as mild cognitive impairment, fibromyalgia, and age-related cognitive decline (Boussi-Gross et al., 2013).

Indeed, enhanced wound healing, among others, is one of the most well-documented medical benefits of HBOT. In general, increased tissue oxygenation is reported to stimulate fibroblast activity and the new growth of capillaries, and to enhance collagen synthesis in individuals with diabetic ulcers and radiation-damaged tissues (Eisenbud, 2012). In addition, HBOT has been found to decrease swelling and inflammation and may be useful in treating arthritis and other types of long-term pain (Wilson et al., 2007). There have been some studies that suggest the potential for the Patients with traumatic brain injury (TBI), post-stroke conditions, cerebral palsy, and so on—these uses are still being actively researched as well as debated in the medical community (Halalmeh et al., 2024).

While HBOT brings many advantages, it also comes with risks—namely, when HBOT is either misused or utilized without medical guidance (Heyboer et al., 2017). This can cause ears and sinuses to ache or damage from changes in pressure (barotrauma); it is one of the most common side effects (Lee et al., 2025). Additionally, temporary vision changes, oxygen toxicity (a rare but severe condition caused by overexposure to oxygen), and, in very rare scenarios, there is a risk of fire because of the fire hazard caused by the oxygen-enriched environment are among other risks (Andrews et al., 2024). For this reason, even low-pressure, soft-shell chambers must be treated following safety protocols. Before beginning HBOT, it is crucial for prospective users, especially those with underlying health conditions (such as chronic obstructive pulmonary disease (COPD), untreated pneumothorax, or seizure disorders), to solicit medical advice. (Lee et al., 2025).

Another important factor is that most at-home HBOT systems are not FDA-approved for medical uses (Catanese, 2024). For wellness devices use, these devices are generally classified, and the users need to be aware of the fact that these devices are not substitutes for the clinical-grade hyperbaric treatments (Pejic & Frey, 2018). It is important that this distinction be regulatory because it will determine the type of product claims and also the user's expectations. Additionally, while in an in-clinic setting, a technician is present to observe the sessions and turnoff the device when the session has ended, at home, it is the consumer's responsibility to ensure the proper pressure levels, length of session, and safety compliance.

However, the emergence of at-home HBOT has become a leap in the democratization of health technology. Just as fitness trackers, blood glucose monitors, and telemedicine platforms have given individuals more power in their health quest, portable HBOT devices are serving as a proactive tool for even keeping one healthy (Vo et al., 2024). The therapy is also portable, which supports broader public health goals of extending supportive care to elderly people as well as those living in remote areas with limited access to hospitals (Fu et al.).

The medical niche intervention of Hyperbaric Oxygen Therapy is becoming mainstream. Despite its clinical bases being still crucial to manage life threatening groups, its acceptance has expanded into lifestyle, performance and longevity domains (Gupta and Rathored, 2024). But with the advancement in safety and user friendliness of home-based systems, HBOT is becoming an available tool for people who want to gain control over their preventive health strategies (Parnis, et al. 2024). The future of HBOT in-home wellness inevitably seems bright provided users continue to be informed, cautious and evidence-based (Parnis et al., 2024) as long as science and innovation comes together with empowerment in a chamber of pressurized potential.

2.2.2 Photobiomodulation (Red Light and Infrared Therapy)

Relatively new to mainstream medicine, photobiomodulation (PBM), or in lay terms, red light therapy or low-level light therapy (LLLT) is a non-invasive therapy that uses a specific wavelength of red and near-infrared light to help stimulate cellular activity (Dompe et al., 2020). The key principle of PBM is sending light in the 600 – 1100 nanometer (nm) wavelength range deep through the skin to reach the mitochondria in the cells (Serrage et al., 2019). Light absorption at the mitochondrial level increases Adenosine triphosphate (ATP) production, modulates oxidative stress, which also leads to transcription factors to induce tissue repair and anti-inflammatory responses (de Freitas & Hamblin, 2016). The scientific basis for growing popularity of PBM in wellness, aesthetic medicine and functional recovery is based on this cellular activation (Maghfour et al., 2024).

The initial development and testing of PBM was applied within clinical settings for the promotion of wound healing, muscle skeletal inflammation reduction and aid in post operative recovery (Parizotto & Ferraresi, 2024). On the other hand, it became particularly valuable in sports medicine and physical therapy for reported reduction of joint pain, increase in microcirculation, and support in tissue regeneration. Eventually, interest in PBM swung to dermatology due to its potential to whiten skin, lessen the severity of acne and build collagen. Nowadays it is implemented in various areas pf application, from chronic pain treatment up to cognitive enhancement to cosmetic therapies and overall well-being (Hernández-Bule et al., 2024).

PBM is now widely available for use at home due to recent technological advances. Now, high quality red and near-infrared light therapy devices (sometimes referred to as full body panels, target wands, facial masks or LED beds) are available to consumers (Wunsch & Matuschka, 2014). Joeovv, PlatinumLED, LS Pro Systems, and Red Therapy Co. have commercialized products accessible to the consumer or integrated into daily routines. These devices are typically modular, vary from being for different treatment intensities, wavelengths used to form the combination, and the coverage area and users can configure them however fits for a specific body region or condition (Algorri et al., 2021). Importantly, the portability and ease of use of these devices has played a part in their rapid growth. So they have come to be a staple of the growing toolkit of self-managed wellness technologies (Weaver et al., 2014).

The benefits associated with PBM are diverse and supported by a growing body of research—though the field remains active in terms of standardization and clinical validation (Kang et al., 2024), the benefits of PBM are manifold and supported by more and more studies. The most well-supported effect is an anti-inflammatory action. Experimental evidence indicates PBM's ability to downregulate proinflammatory cytokines and upregulate antioxidant enzymes, subsequently reducing joint pain, tendonitis, and neuropathic discomfort (Kunnumakkara et al., 2023). Moreover, PBM is thought to increase muscle repair and enhance performance by stimulating blood flow and decreasing delayed onset muscle soreness (DOMS); for such reasons, it is popular among athletes and fitness enthusiasts. Another key area that PBM shows real positive effects is in skin health (Ferraresi et al., 2016). Exposure to red light boosts collagen production, is effective in the treatment of fine lines and wrinkles, acne, or rosacea, as it is able to target inflammation and promote dermal repair mechanisms (Cafasso, 2023).

PBM for neurological and cognitive applications is also of increasingly higher interest. Near-infrared light applied transcranially early on has been shown by some early-stage study to improve cerebral oxygenation and energy metabolism in brain cells and possibly improve cognitive performance, memory, and mood (Nizamutdinov et al., 2021). While this is very preliminary, it has now prompted a lot of research in areas like brain fog, depression, and aging-related cognitive decline. PBM is being incorporated into not just biohacker and performance seekers' morning routines or workday breaks, but worn in situ as wearable PBM helmets for the scalp and forehead, or handheld units for cells (Nizamutdinov et al., 2021).

Though putatively broad, appealing, and in emerging use, PBM therapy is not without scientific and regulatory controversy (Dompe et al., 2020). One of the central challenges is determining optimal dosage, involving variables such as wavelength, intensity (measured in mW/cm^2), duration, and treatment frequency (Bjordal et al., 2003). In PBM, the "biphasic dose response" phenomenon references the fact that neither too little nor too much exposure helps PBM achieve its full efficacy, making precision very important in realizing the full results of a protocol (Zein et al., 2018). Furthermore, skin type, tissue depth and biological sensitivity to light differ between individuals (Setchfield et al., 2024). Due to these complexities, researchers have stated that it is necessary to have standardized protocols and long-term studies to ultimately produce definitive clinical guidelines (Beauchemin et al. 2019).

When followed, PBM is generally deemed as safe for home use from a safety standpoint; non-invasive, painless (Dhlamini & Houreld, 2022). Red and near-infrared wavelengths do not affect DNA damage or create a carcinogenic effect (like in UV light) (Tsai & Hamblin, 2017). Although high-powered devices require safety glasses, treat close to the eye as much as possible. In very rare cases, there have been minor side effects such as temporary redness, or mild headaches. PBM therapy is advised for users with an underlying medical condition or users who are taking photosensitizing medications based on the advice of a healthcare professional (Valter et al., 2024). It is also important to purchase certified devices from trusted manufacturers and offer a brand that states proper dosing instructions, accurate wavelength specifications and product safety testing.

The movement toward red light therapy enables individuals to be more proactive in health management, moving from a clinical healthcare model to a consumer model (Bhatia et al., 2024). PBM is attractive as a tool for personal, accessible, self-intervention for recovery, beauty, stress reduction, and energy enhancement, thanks to its affordability, portability, and non-invasive nature (Hernández-Bule et al., 2024). Ultimately, the increasing demand for light based therapies is expected to continue growing as consumers become more informed about self-care and digital wellness solutions especially in the presence of data tracking technologies or in the broader wellness ecosystem, such as apps that guide around timing, dosage and outcome tracking (Roffarello et al., 2022).

Pan et al. (2023) describe photobiomodulation as a convergence point amongst clinical science, consumer wellness, and technological innovation. A data-backed, intuitive, and user-controlled non-pharmaceutical, preventive health solution expanding from specialty clinics to household devices bears witness to growing demand for such technology outside the bottlenecks of the pharma market. This begs continued research for further validating its long-term efficacy, but PBM is already advancing how people treat recovery, inflammation, skin health, and mental clarity (Zhang & Qu, 2023). As a demonstration of this broader phenomenon, red light and infrared therapy provide precisely the means by which light itself is being reimagined as a cornerstone of modern wellness, and as one element in the burgeoning landscape of at-home therapeutic technologies.

2.2.3 Whole-Body Cryotherapy and Cold Therapy

For several decades, whole body cryotherapy (WBC), and cold therapy, once reserved to be a niche domain for elite athletes and luxury wellness spas (Lombardi et al., 2017) began to transform into a mainstream self-care practice. This type of wide range of modalities involve the application of these modalities by exposing the body to a very cold temperature (air cooled cryochambers, liquid nitrogen vapor to a more accessible cold immersion and ice baths); the main goal for the use of these modalities is to gain a set of physiological and psychological health benefits (Allan et al, 2022). Cold exposure, made popular in natural medicine and traditional therapy (such as cold plunges or snow baths), has risen in popularity in modern times through technology and backed science approaches toward recovery, resilience, and performance optimization (Kwiecien & McHugh, 2021).

The second method is in clinical cryotherapy, in which people stand in a chamber or pod that is cooled to -110 to -160 degrees C for a few minutes, usually 2 to 3 (Rush, 2024). When the skin is cooled rapidly, it causes a systemic effect: vasoconstriction, the blood vessels contract, the heart rate and metabolic rate increase, and endorphins are released (Esperland et al., 2022). After the session, blood flows back to the extremities resulting in improved circulation and an activation of a recovery cascade, including less inflammatory, decreased pain, and muscle healing (Selkow et al., 2015). Although the research on the efficacy of WBC is still being rigorously investigated by academia, preliminary investigation and user testimonials indicate that it may have genuine benefits in managing arthritis, fibromyalgia, chronic and delayed onset muscle soreness (DOMS), as well as depressive symptoms (Douzi et al., 2019).

Such therapy has mostly been the privilege of elite athletic facilities, rehab centers or highly priced spas in the past. However, the cryotherapy industry has been undergoing democratization over the past decade (DelveInsight, 2024). Innovative and consumer interest in at-home wellness and biohacking has fueled market adoption of new and previously expensive-to-market cryotherapy solutions, bringing portable and affordable solutions to consumers (Mehrotra et al., 2024). From Plunge, Ice Barrel and NorseBox to Therabody and much more, companies are offering products from a definite electric ice bath to a minimalist cold immersion setup that can be installed at home, gyms and wellness studios. These represent an evolution of health culture where people are no longer receivers of care, but active participants striving to recover, mitigate the effects of stress, and have long-term vitality.

However, the most significant of all is the rise of cold immersion therapy as a complement or an alternative to a regular cryochamber (Kunutsor et al., 2025). Influencers, athletes, and wellness personalities alike have come to endorse the physical and mental benefits of ice baths that the idea of sitting in water that is cooled to temperatures between 5°C to 10°C for several minutes has been embraced by the masses. Some of these have been validated by scientific interest. This cold water immersion reduces pro-inflammatory cytokines, increases noradrenaline production (remember, a neurotransmitter that has been shown to contribute to mood and alertness), and enhances parasympathetic nervous system activation (responsible for relaxing and recovery) (Yankouskaya et al., 2023). In addition, regular cold exposure may promote brown fat activation, regulate thermoregulation, and metabolic efficiency (Huo et al., 2022).

Cold therapy has been shown psychologically to help one be resilient and in a pleasant mood. Stimulating dopamine release and increasing endorphins, it is believed in anecdotal reports and limited studies that it may reduce symptoms of anxiety and depression (Reed et al., 2023). Advocates say that post-session one experiences a mixed bag of 'euphoric' feelings; better mental clarity and an improved willpower or discipline. This has made cryotherapy an attractive practice for everyone, from professional athletes to knowledge workers, busy parents, to longevity enthusiasts, because of these effects, along with the instant relieve of sore muscles or inflammation.

Although cold therapy is becoming increasingly popular, there are risks and considerations involved with it (Grazioso & Djouder, 2023). Frostbite, hypothermia, cardiovascular strain, and skin burns (especially in cryochambers using liquid nitrogen) can result from improper use such as prolonged exposure or when counterindications are ignored (Ellis et al., 2022). Medical history and knowledge of their medical history is very critical before a person embarks on cryotherapy protocol. Anyone with a cardiovascular condition or who has unmanaged hypertension, Raynaud's disease or cold hypersensitivity should see a healthcare provider before experiencing extreme cold exposure. Safety guidelines include limiting the exposure time, avoiding wet clothing or jewelry in the case of exposures to gas-based systems, and using certified gases and adequate ventilation (in the case of nitrogen-based systems).

This shift, at the consumer level, has made at-home solutions way easier for people to adopt cold therapy in a more personalized and cost-effective way. Users could opt for an ice barrel or temperature-controlled plunge pool to have lasting access, instead of $40–$60 per cryo session at a particular spa. These devices are now integrated with smart technologies like the app control, water filtration and temperature tracking to make it seamless with a hygiene touch and with much of the data available to consumers.

Interest in mental toughness, biohacking and longevity has created a rising tide that plenty of lean entrepreneurs in the recovery tech space have been able to ride. Once dismissed as a fad which would come and go, cryotherapy is now a permanent fixture in brands, trainers, and health coaches' comprehensive recovery protocols (Qu et al., 2020). Many do this in tandem with other modalities such as breathwork (Wim Hof Method), infrared saunas, red light therapy, or decent home wellness routines in general. In this way, cold therapy serves not just as a physical intervention, but as a ritual, enhancing daily resilience, mental focus, and the subjective sense of control over one's health trajectory.

2.2.4 Other Portable Therapies

The growing ecosystem of portable health technologies is expanding the boundaries of what can be self-administered at home (Haleem et al., 2021). Whether used in spas or wellness centers, infrared saunas have now come in-home installation versions that are available in compact sizes. They promote detoxification, relaxation, muscle recovery, improved circulation, and can be used using far infrared wavelengths, which induce sweating at lower ambient temperatures (Hussain & Cohen, 2018). Likewise, the popularity of neurofeedback and brain stimulation devices like transcranial direct current stimulation (tDCS) or EEG-based feedback headsets appears to be used for enhancing, regulating mood, stress reduction (Gkintoni et a l, 2025). By using these tools, users are able to train their brainwaves or enhance them in the case of targeted neural activity. This can offer a non-pharmaceutical aid for anxiety, ADHD, and poor mental performance.

Portable dialysis machines and home infusion pumps are typical in more medically oriented innovations, in which they have transformed chronic disease management by offering patients with kidney failure or those in need of regular medication infusion to obtain care at the convenience of their homes (Davenport, 2015). These devices aid in decreasing the dependence on hospital visits in addition to increasing autonomy and quality of life. Collectively, these technologies represent a paradigm shift in focus to decentralized care, whereby a set of technologies heretofore confined only to institutional settings are placed into the hands of the modern tech enabled household to assist around preventive health, recovery, and support during chronic disease.

Such technologies are making considerable headway in the market, driven mainly by the availability of these technologies, which are attracting new consumer bases of people managing therapy at home for chronic disease, as well as athletes and health enthusiasts who are incorporating clinic-grade treatments into their daily routines. Yet there are major challenges to this expansion. Papp (2006) states that data on the long-term safety and efficacy of many of the at-home therapies are lacking. For instance, red light therapy use in the short term has shown efficacy with regards to indications such as pain relief or skin condition, but there is no data for long-term full body use in the healthy individual (Hamblin, 2014). Another factor is the potential danger associated with personal hyperbaric chamber use (e.g., oxygen toxicity, ear injury without medical supervision) (Ortega et al., 2021), and questions of benefit for wellness exist when not part of a large-scale study. Although these trends have been widely adopted by the companies making and marketing some of these products, regulatory oversight has not fully caught up with these trends: many of these products are marketed as lifestyle or fitness equipment, rather than medical devices and therefore often escape regulatory scrutiny regarding efficacy claims. For example, the U.S. FDA has not approved whole body cryotherapy for any medical use, stating that claims of its benefits are unproven and that risks (such as frostbite or asphyxiation in sealed chambers) may be involved. In light of this, innovation thus demands an attendant responsibility on the part of entrepreneurs in ensuring that users are educated on the right use of products, as well as having realistic expectations. 'With these emerging therapies, there is increasing demand to create industry standards or certification programs to certify whether home health devices are working properly or not.' Without such measures, the effort falls primarily on consumers to sort it out, though. Summarily, major driving factors behind advancing the at-home health tech market are cutting edge technologies including AI analytics; blockchain frameworks; and mobile therapeutic devices (Bathula et al., 2024). While allowing for more holistic health monitoring and self-care than ever before, they also highlight the need for secure validation and sensible regulation of this growth to be used in a safe and effective health outcome.

2.3 Business Models and Consumer Engagement

Now the healthcare industry is undergoing a paradigm shift from institutional-centered models to decentralized and consumer-driven models. The engine of this revolution centers around the proliferation of at-home health technologies that integrate wearable devices, in-home diagnostics, and AI-powered platforms to provide personalized, participatory, and engaging healthcare experiences. To date, however, the health models and theories that have been employed to explain the scaling, entrepreneurial innovation and behavioral dynamics that underlie the adoption of such technologies have not been fully adequate to explain the real scaling that exists.

The early literature was concerned heavily on existing regulatory barriers, provider centric intervention, and mistrust in healthcare system (Armstrong et al., 2006; Mainous et al., 2019). That said, as the study went on, it was clear that it wasn't just about understanding this technology, but also consumer behavior, entrepreneurial agility and tech enabled business models in order to be able to assess 'where, when and how' these innovations could really impact daily life and the different existing health systems. This has necessitated a move to emergent strategies, identifying themselves with the fast-changing tech scene, the fast-changing consumer attitudes and fast-changing policy environments.

Peloton, WHOOP, and Eight Sleep among modern startups to introduce subscription model that bundles hardware with coach, analytics, and software updates. These models keep users engaged continuously and hence earn them revenue only if delivery is at high value so as to avoid churn. Joovv and Therabody, for instance, rely on direct-to-consumer (DTC) sales to accelerate iteration and make it more available to a wider number of consumers. However, cost and regulation still make it difficult to reach everyone.

Abbott's FreeStyle Libre is an example of a hybrid model, the product serves a clinical need (insurance backed) and also has a consumer wellness use, managing regulatory requirements and both sides of scale. Such approaches show how a business model innovation approach is essential to adoption and they suggest that it is particularly so when paired with the strategy of behavior change engagement.

Consumer retention goes beyond technology. Influencer, gamification, and community-based platform are to create engagement ecosystems by companies. Emotional connections and social motivation are built by peer validation (for example, by Oura Ring's adoption by wellness influencers), leaderboard competition (such as Peloton), personalized insights, and so on. These are marketing benefits to the best of our understanding, but also feedback loops that help to evolve product.

These theories underpin this shift toward the consumer being regarded as self-empowered, trusting of behavioral change, and patient centered (Barry & Edgman Levitan, 2012; Epstein et al., 2010). What it requires are healthcare models where choice, responsiveness and control build the core traits of digital health adoption.

Health tech has come a long way, whereby policy and ethical considerations should be put into consideration. Trust in sharing data, accessibility, digital dividers and algorithmic transparency have to be paid close attention to (Zulman et al., 2015; Gostin & Wiley, 2016). The thesis lays emphasis on the requirement of having interdisciplinary frameworks that combine technology, behavioral science, entrepreneurship and health policy in order to build sustainable models to deliver wellness.

At the same time, wearables and self-monitoring devices provide scalable preventive care tools and real-time feedback and chronic condition management (Patel et al., 2015; Piwek et al., 2016). However, few empirical studies have been performed, mainly on long-term efficacy and on behavioral integration.

Given the particular significance of trust, perceived risk and credibility in controlling preventive technologies, the literature gap is particularly acute in the context of such technologies. Moreover, the emergence of new business models (e.g., direct-to-consumer platforms, app based wellness subscriptions, etc.) offers new access and distribution business models of which the impact on consumer decision making have not been explored. In doing so therefore, the challenges and opportunities posed by these technologies require investigation into how consumers judge, adopt, and integrate these technologies on a day to day basis.

As such, the current study meets this gap directly by exploring patterns of consumer adoption of at-home digital health solutions. This contribution provides an empirically grounded and contextually relevant explanation though studying the behavioral framework by embedding constructs such as technology credibility, health motivation, personal innovativeness and perceived risk about technology adoption. Beyond widening the theoretical understanding of digital health adoption, it supplies implementable insights into developers, entrepreneurs and policymakers in the effort of promoting user centric, scalable wellness technologies.

2.4 Theoretical Framework

Numerous models were proposed by the experts in the field of technology adoption to look at how individuals adopt information technology and information systems. These comprise the Unified Theory of Acceptance and Use of Technology (UTAUT), Technology Acceptance Model (TAM, TAM2), Theory of Planned Behavior (TPB), and Theory of Reasoned Action (TRA). In this dissertation, an expanded, foundational theoretical framework is chosen, which is based on an aggregation of entrepreneurship, behavioral science, and health technology adoption models. The goal is to improve the understanding and subsequent explanation of consumer behavior as it pertains to decentralized, preventive health technology, particularly when the technology is marketed directly to the consumer outside of a formal clinical or institutional setting. When health technologies are converging toward becoming more consumer facing and entrepreneurial in their implementation, existing models of the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Unified Theory of Acceptance and Use of Technology (UTAUT) provide respectively inadequate perspectives for understanding the adoption in such low trust and unregulated environments.

2.4.1 Theory of Reason Action (TRA)

The Theory of Reason Action (TRA) (Fishbein and Ajzen, 1975) states that behavioral objectives, which are a result of a person's attitude toward the conduct and subjective beliefs around the performance of the behavior, are what drive individual behavior (Surendran, 2012). Understanding consumer adoption of wellness and at-home health technologies necessitates a critical examination of foundational behavioral theories that have historically guided research in technology diffusion and decision-making. Among these, the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975) stands out as one of the earliest and most influential models.

TRA, developed by Fishbein and Ajzen (1975), states that the actual behavior of an individual is mainly conditioned by his/her behavioral intention. This intention, in turn, is derived from two constructs: attitude toward the behavior and subjective norms (Ajzen, 2020). According to Fishbein and Ajzen (1975), attitude reflects an individual's positive or negative evaluation of performing the behavior, whereas subjective norms reflect the impression put by society to carry out the behavior or not. In certain cases, such as preventive health tech, decisions are not mandated from institutions but are personal and voluntary, making the use of TRA particularly valuable (Borges do Nascimento et al., 2023). For instance, a consumer deciding whether to subscribe to a smart mattress or red light therapy device will not spend time thinking or act on prescription, but rather their personal beliefs on the product's health value and social validation from their peers, influencers, or online communities.

The genesis of the Theory of Reasoned Action (TRA) may be traced back to a period of intense psychological research. It serves as the most utilized theories that clarify the connection between attitudes and behaviors. Intentions, or motives, to participate in a certain activity may be used to anticipate it, according to the Theory of Reasoned Action (TRA), which was put out by Martin Fishbein in 1967. Icek Ajzen and Fishbein then expanded on it (Ajzen & Fishbein 1975). The TRA's capacity to elucidate the rationale behind individuals' behavior is among its principal advantages. The idea holds that a person's attitudes and subjective norms, which are predicated on their opinions and views of other people, have an impact on their behavior. For instance, someone is less likely to smoke if they think smoking is bad and think their friends and family don't support them. A further advantage of the TRA is its capacity for behavior prediction. According to the hypothesis, people will behave in a way that is compatible with their beliefs and personal standards (Theory Hub, n.d.).

Four key concepts comprise the Theory of Reasoned Action: Subjective Norms, Belief, Attitude, and Intention (Fishbein and Ajzen, 1975). The apparent possibility that an object has a certain quality or that an action in particular will result in a particular consequence is referred to as belief.

When someone says, "I think smoking every day will cause lung cancer," for example, they are conveying a view about the negative effects of smoking. Individuals may have differing opinions. For example, they may be quite sure that working out enhances health but yet recognize that there is a lesser chance that it would cause harm (Nickerson, 2023). Our opinions about a certain activity, whether favorable or negative, or whether we think it will produce results we value, are reflected in our attitudes. This paradigm says that our beliefs determine our attitudes. In particular, attitudes are the product of each belief's strength times the outcome's assessment (Nickerson, 2023). For example, one might look at someone's attitude toward a workout, which is impacted by their ideas about whether a workout would result in the sought results, to forecast whether or not they will exercise. A person's attitude toward exercise will depend on whether they think it will provide good or bad results. A person who feels exercise will have negative results will have an unfavorable attitude. The definition of attitude, according to Fishbein and Ajzen (1975), is "a disposition to respond favorably or unfavorably toward some psychological object." For instance, a person with a negative attitude about smoking would be one who thinks smoking on a regular basis is unhealthy. Subjective norms are the ways that significant others in an individual's life impact the conduct they choose to engage in. One may, for example, think about whether their mother, husband, or doctor encourages them to exercise. These standards are divided into two categories: descriptive and injunctive. Injunctive norms are based on what people think other people think they should do. For instance, people may feel pressured to consume acai bowls because they believe this is what other people anticipate. Conversely, descriptive norms reflect an individual's understanding of what other people actually do, which may not match reality. For example, a person's decision to wear a mask may be influenced by the belief that most people don't wear them. Subjective norms are influenced by the normative views of society and the drive of a person to live up to the expectations of those who matter in their life, including instructors, peers, and relatives. Fishbein and Ajzen (1975) point to two crucial elements: Normative Belief (NB) and Motivation to Comply (MC). NB is the conviction that one is doing something because other people want them to. The degree to which one believes this might vary; for instance, a score of -3 can represent one's conviction that one's doctor vehemently opposes the activity, whilst a score of +3 indicates that one's significant other firmly supports it. MC is basically the extent to which an individual has a tendency to comply with the wishes of others. The degree of this incentive also varies according to the connection; for example, someone may be more likely to obey their children's wants than their mother's wishes.

A person's willingness to participate in a certain conduct, which reflects their perception of their likelihood of acting, is referred to as their behavioral intention. The Theory of Reasoned Action by Fishbein and Ajzen (1975) states that attitudes, subjective standards, and perceived control help shape these intents, which can then, though not always completely, impact actual conduct. Researchers have investigated a range of elements that influence the beliefs that result in attitudes, norms, and perceived control, based on the original model. Among them are: Personal aspects include disposition, sense of control, feelings, and health issues. Age, gender, race, ethnicity, income, education, and religion are examples of demographic variables. Environmental influences include media exposure, stress, and diagnosis.

This theory emphasizes on how attitudes about a conduct and subjective standards around the actions influence an individual's purposeful behavior. In particular, according to LaCaille (2020), the Theory of Reasoned Action has been utilized to help predict and explain a number of health behaviors. When it comes to at-home health technology, it looks into how consumer perceptions of health management technologies and the impact of their social network influence how well they are adopted and used. It supports the creation of marketing plans that alter perceptions or make use of uplifting social factors.

Attitudes, among the wellness technology space, may be shaped by beliefs like ‘this wearable helps my sleep’ or ‘this recovery device helps my post-workout performance’ (Kang & Exworthy, 2023), while subjective norms may also include influence from the fitness communities, wellness influencers or groups of peers (Wang et al., 2024), it is very influential especially in decentralized settings where there is no medical validation (Wang et al., 2024).

The Theory of Reasoned Action (TRA) has been applied widely in contexts where behavior is volitional and regulated on the basis of internal motivations and social norms (Ratz & Lippke, 2022), which makes it highly applicable for the study of preventable health behavior and technology adoption. In the area of health and at-home health care technology adoption, TRA has been applied to examining how people make decisions outside of the medical facility in the absence of institutional mandates and prescriptions. Shei et al. (2022) have used it to understand behavior such as fitness wearable adoption, nutritional supplement, biohacking tool, or sleep optimization device adoption, where user intent is more driven by peer influence, perceived benefits, and personal attitude, rather than formal medical recommendations. The model has also been relevant in the context of digital health marketing for explaining what effects subjective norms (such as influencer endorsements, or online communities) and attitudinal beliefs (belief in self-optimization, or longevity) have in terms of getting consumers to try emerging health technologies (Fishbein, 2008).

However, TRA has limitations. It assumes that decisions are rational, linear, and based on conscious intentions first of all (Montano et al., 2002). But the adoption of wellness technologies is based on affective dimensions like anxiety, aspiration or mistrust that TRA doesn’t take into account. Moreover, TRA does not provide information on how the intention is converted to action, continuous usage, trust development, and advocacy, which are key to consumer-facing health markets (Mennella et al., 2024). These constraints suggest the requirement for alternate models that cover an entire behavioral lifecycle in such trust-deficient, unregulated environments.

2.4.2 The Technology Acceptance Model (TAM)

One of the most widely used research models for predicting how individual users will use and accept technology and information systems is the Technology Acceptance Model (TAM), which Davis created in 1989, building upon TRA. TAM has been extensively researched and validated by several studies that look at each individual's behavior in accepting technology inside various information systems frameworks. TRA serves as the foundation for this paradigm, which is anchored on social psychology theory in general. The Theory of Reasoning (TRA) states that ideas have an effect on attitudes, which in turn lead to intentions, which in turn cause behavior.

In the same vein, Davis (1986, 1989) presented the constructs that were included in the first TAM (see Figure 1) in the following order: perceived utility (PU), perceived ease of use (PEOU), attitude, and behavioral intention to use. Among the constructs, the beliefs that an end-user has about a technology are formed by PU and PEOU. These beliefs, in turn, predict the end-user's attitude toward the technology, which in turn predicts the end-user's adoption of the technology (Ma & liu, 2005).

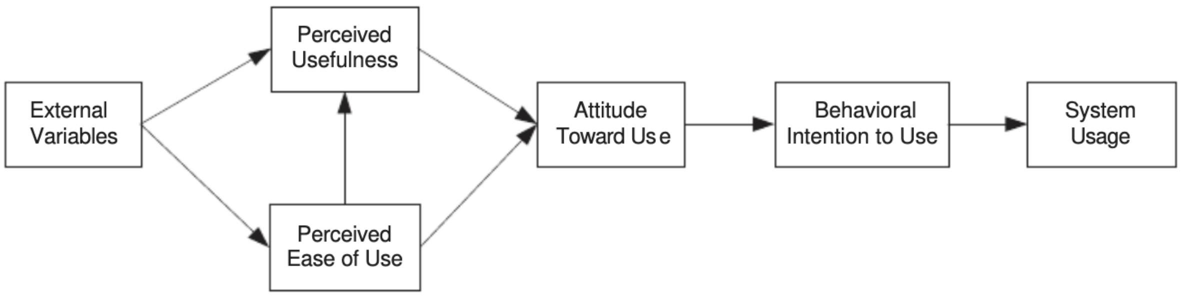

Figure 2.1
The TAM Model

Much has been written about TAM and it has been successfully applied in healthcare informatics, patient portals and wearable health devices (Rahimi et al., 2018). This can help explain why consumers would eventually take up adoption of a new telemedicine app, or a fitness tracker, or an at home diagnostic tool, provided it seems convenient and valuable (Edo et al., 2023).

Although TAM's constructs are fulfilled by most of the devices, devices are made to be intuitive and promise well-being (Rahimi et al., 2018). However, TAM is still not able to explain the consumer skepticism in the case of the lack of institutional recognition (Felber et al., 2024). It may be that the product is useful and easy to use, but that alone will not win users over to trust or adopt the product (particularly if claims are anecdotal, not FDA-approved, etc., supported by influencer marketing, not clinical endorsement).

In addition, TAM lacks a sufficient capacity to consider emotional trust dynamics, credibility of entrepreneurs, and cultural issues, which are the defining aspects of the current fragmented and competitive wellness ecosystem (Felber et al., 2024). Furthermore, it disregards the fact that consumer adoption in such contexts is staged and progressive, focusing on the case where information asymmetry is high and consumer skepticism is high (Pakseresht et al., 2022).

The TAM was validated by a series of studies that were carried out by Davis (1989). These tests used PEOU and PU as two independent variables, and system utilization as the dependent variable. PU was shown to have a significant correlation with both self-reported current consumption and self-predicted future usage, according to his findings. PEOU also indirectly influenced behavioral intention via its effect on PU, reinforcing the idea that both functional benefit and intuitive design matter in user acceptance (Davis, 1989).

Since its inception, TAM has become one of the most cited models in the field of information systems (Venkatesh & Davis, 2000). It has informed not only academic research but also real-world design and user experience strategies across industries, including healthcare, education, and e-commerce (Fedorko et al., 2018; AlQudah et al., 2021; Alsyouf et al., 2023; Ruiz-Herrera et al., 2023; Musa et al., 2024). Its simplicity and empirical robustness led to its widespread diffusion and numerous adaptations (Cao et al., 2005).

Over time, scholars expanded TAM to TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) to incorporate social influence, cognitive instrumental processes, and facilitating conditions. These models introduced additional variables like subjective norm, job relevance, output quality, and computer self-efficacy, aiming to enhance predictive power in more complex and voluntary contexts. Despite these refinements, TAM and its successors remain predominantly situated within institutional, task-oriented environments. They often assume that systems are being evaluated within a framework of credibility, governance, and accountability. These are conditions often absent in consumer-facing wellness technologies.

Several empirical studies have applied TAM to health IT adoption, such as electronic health records (EHR), telemedicine, and patient portals (Ondogan et al., 2023; Shania & Paramarta, 2024). These studies have consistently validated PU and PEOU as predictors of adoption, but also highlight the moderating role of trust, perceived risk, and prior health behaviors.

As the consumer health tech space becomes increasingly decentralized and democratized, the limitations of TAM become more pronounced. Users are not just rational actors evaluating utility;

they are navigating uncertainty, vetting non-institutional claims, and often acting on emotionally or ideologically motivated health goals.

2.4.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is based on the integrative framework developed by Venkatesh et al. (2003) to address the fragmented insights provided by TAM, TRA, and the Theory of Planned Behavior (TPB) as determinants to integrating a wider array of determinants of technology adoption. UTAUT consolidates elements from eight prominent models and introduces four core constructs: Performance Expectancy (the degree to which using a technology will provide benefits in job or task performance), Effort Expectancy (the ease associated with technology use), Social Influence (the extent to which individuals perceive that important others believe they should use the technology), and Facilitating Conditions (the belief that organizational and technical infrastructure exists to support use) (Venkatesh et al., 2003). Factors such as age, gender, experience, and voluntariness of use then moderate these constructs to provide a detailed explanation of user adoption behavior (Venkatesh et al., 2003).

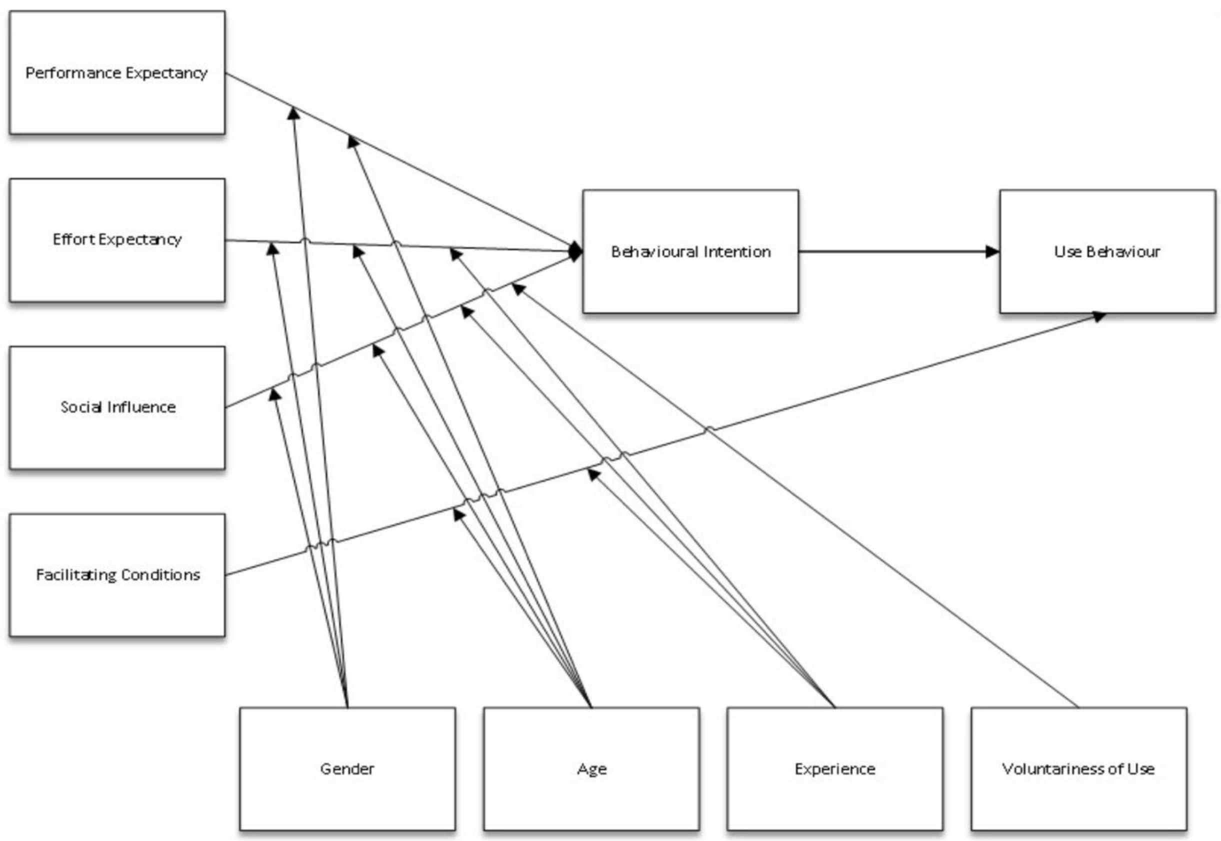

Figure 0.2
The UTAUT Model

UTAUT has been shown to be a strong predictor for behavioral intention, acceptance, and continued use of IT, in the traditional healthcare context, i.e., in the case of implementation of electronic health records (EHRs), hospital decision support tools, as well as chronic disease monitoring systems (Hossain et al., 2019). All these environments are structured in way where users enjoy IT support, training modules, supervision of IT professionals and well data governance policies that align very well with UTAUT's assumptions and variables (Wang & Nah, 2024). However, given the nascent state of decentralized health and wellness technologies, UTAUT is not directly applicable to the domain. Unlike institutional health settings, various wellness tech participants are often recruited into the consumer-driven ecosystem with no formal infrastructure, enforcement of regulations, or dedicated onboarding support.

Thus, for example, it may be the case that support systems and normative pressures assumed by UTAUT to be embedded in organizational hierarchies could apply less in consumer-led spaces (Blut et al., 2022). For instance, social influence may be caused not by the supervisors or peers of a company, but by digital influencers, online reviews or community endorsements (Dendrinos & Spais, 2024). Such facilitating conditions as access to technical support are often substituted with self – research or community forums (Dendrinos & Spais, 2024). Performance expectancy in the context of wellness is typically subjective, aspirational, and loose (i.e., underdefined), characterized by a perception of living well, long, or at its optimal, rather than based on manifest, quantifiable, clinical outcomes (Blut et al., 2022).

UTAUT, however, also remains valuable as a theoretical base for understanding broad factors of technology use; consequently, while broad UTAUT constructs provide a good theoretical base for understanding such factors, they must be recontextualized to reflect the dynamic nature of the adoption of preventive health technologies.

2.4.4 Diffusion of Innovations (DOI) Theory

The DOI theory by Everett Rogers (2003) is the initial provided macro-level framework in the context of how new technologies and ideas are diffused through social systems over time. Five critical attributes which influence the rate and extent of adoption of any new technology include Relative Advantage (superiority of the new one over existing solutions), Compatibility (similarity of the new technology with the existing values and practices of the user), Complexity (the degree of perceived difficulty of use), Trialability (extent to which the new technology can be tried out), and Observability (how easily the outcomes of the new technology can be viewed) (Kapoor et al., 2014, Raman et al., 2024). Together they determine how quickly and how widely an innovation is apprehended by the different adopter categories—innovators, early adopters, early majority, late majority, and laggards.

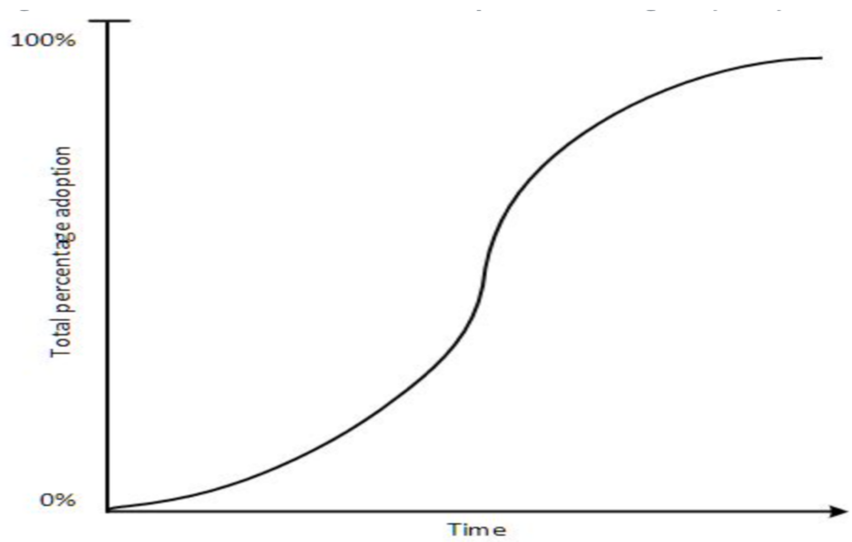

Figure 2.3
The DOI Model

With regards to at-home health and wellness technologies, the DOI framework can explain early interest in products like smart mattresses, sleep rings, red light therapy masks, and wearable biosensors by consumers. These products are very high on observability – something like sleep scores, or recovery metrics, that provide feedback that makes them get used again and again, and becomes proof of how well they work. This also limits support of trialability as brands provide subscription models, trial periods or freemium features to reduce adoption risk. Relative advantage, for example, is usually communicated in terms of life improvement narrative of more energy, better focus, or biohacking potential, all of which are compelling to the self-optimizing consumer.

Though DOI theory has limited capability to portray the intricacy of adoption in up-to-date decentralized health markets (Renukappa et al., 2022). It is based on the presupposition that there is a relatively linear and socially supported diffusion process, which is carried by peer endorsement, institutional legitimation, or authoritative media narratives (Sahin, 2006). But the wellness tech landscape today is fragmented and moving quickly, with people immediately going to the consumer, and skipping the traditional gatekeepers of the physicians, hospitals, or bureaucratic bodies. As a result, consumers are asked to make health decisions based on marketing or influencer credibility, anecdotal success stories, among others, rather than institutional validation or clinic evidence.

In addition, DOI is not sufficient in filling the trust vacuum that characterizes many of the wellness innovation spaces (Raderstorf et al., 2022). The original DOI framework (Vredenburg et al., 2020), which does not take into account personal beliefs of consumers, online communities or perceived brand authenticity, is thereby not thought to be applicable in the context of evolving, many times unproven, technologies in situations where clinical guidelines are still to be created, and where regulatory oversight is limited. Hence, trialability and observability also must be redefined in such contexts. For example, consumers may "see" benefits in the form of subjective improvements (for example, increased energy boost) instead of clinically measured parameters or "experiment" with a product on the basis of mere skepticism rather than for solid scientific reasons.

Finally, though DOI allows us to understand the general trajectory of diffusion of wellness technology, it needs to be extended with behavioral, psychological and entrepreneurial trust constructs to provide more comprehensive explanation of adoption in nontraditional, noninstitutional settings.

A key limitation across traditional technology acceptance models is their reliance on the assumption of institutional trust—they were designed for environments where innovations are backed by credible entities like hospitals, governments, or corporations. However, preventive and wellness technologies are often self-prescribed, influencer-promoted, and directly marketed to consumers, lacking formal validation. In such low-trust, unregulated settings, consumers must assess not just usability or benefits but also credibility and safety based on brand reputation and social influence. This creates a major gap in existing models, which fail to capture the dynamics of trust and decision-making in decentralized, consumer-driven wellness markets.

One weakness of traditional technology acceptance models is that they assume that there exists institutional trust (they were designed for environments with innovations randomized behind the trustworthy bodies like hospitals, governments, or organizations). Preventive and wellness technologies are, however, self-prescribed, influencer promoted and directly marketed to the consumer without formal validation. In such low–trust, unregulated environments, consumers evaluate usability, benefits, and safety based on brand reputation and social influence, aside from assessing usability or benefits. This then leads to a large gap in existing models, a lack of capturing trust traits and decision making in the decentralized consumer-driven wellness markets.

2.5 The Conceptual Model

Our conceptual model was designed based on the limitations of traditional technology adoption models in explaining behavior in trust-deficient, non-institutional health tech settings, in order to help explain how consumers adopt at-home wellness technologies. Although established frameworks like TRA, TAM, UTAUT, and DOI can provide us useful information on user intention, behavior and diffusion mechanisms, they are established in environment in which formal validated, organizational infrastructure, and professional supervision can be taken for granted, in the corporate IT, healthcare environment, or regulated platforms.

Preventive and wellness technologies are increasingly appearing in scenarios that cut across traditional clinical pathways, are explicitly marketed directly to consumers, and, as such, new factors become critical for their adoption (Mennella et al., 2024). These low-trust, high-noise environments see the behavioral intention not only to the perceived usefulness or usability of a product but also credibility of technology, perceived risk, personal innovativeness, and motivation to health (Ayanwale et al., 2024). These are constructs beyond emotional, psychological, and value-based considerations that ignore traditional models.

In this model, we retain core constructs as in UTAUT such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), and at the same time, we add mediating and moderating constructs Technology Credibility (TC) and Perceived Risk (PR). In the unregulated consumer wellness markets, these additions consider perceived trustworthiness of the technology (derived from brand communication, peer testimonials, influencer advocacy) to be an important determinant of Behavioral Intention (BI) (Mensah & Khan, 2024). Additionally, Actual Use of Technology (AUT) stems from a multi-layered credibility calculus far beyond intention, in which health motivations and personal traits such as innovativeness explicitly matter for that decision (Hassan et al., 2022).

This model takes a step forward from existing models by including individual-level factors (e.g., health motivation and innovativeness) as well as social and structural drivers (e.g., social influence and facilitating conditions) to explain adoption patterns in the wellness tech ecosystem. This objective is compatible with the larger aim of our dissertation to go beyond static and rational models of technology acceptance to define a staged, dynamic, and trust-based user behavior in the domain of emerging health innovations.

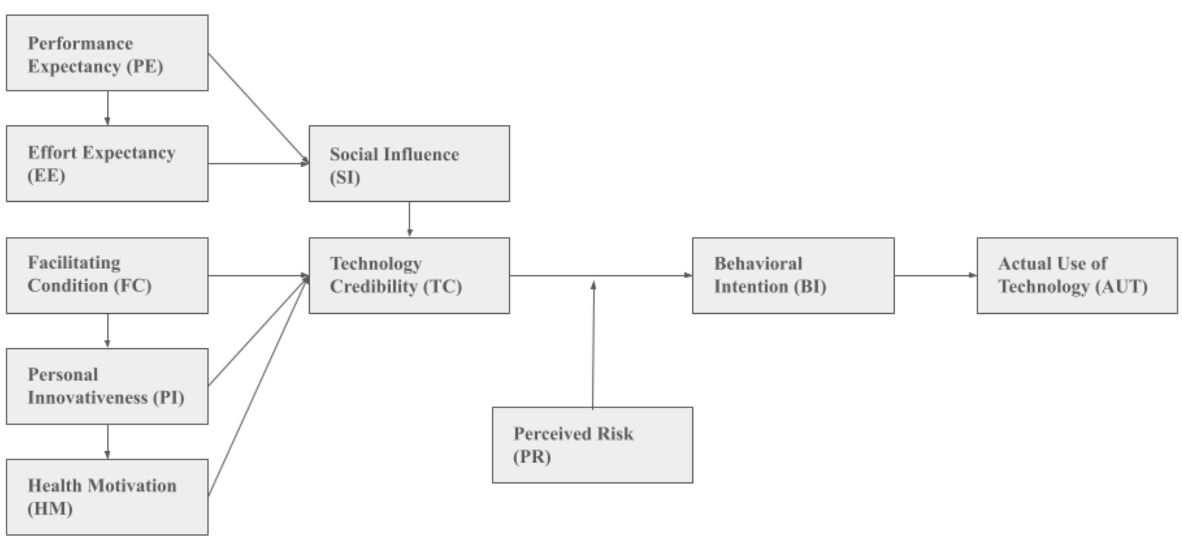

Figure 2.4

The Conceptual Model

In developing this conceptual model, we intended to explore and explain the behavioral, emotional, and cognitive factors that underlie adoption and sustained use of preventive health wellness technologies. These technologies are usually decentralized, non-FDA regulated, and critically dependent on consumer perception and trust as well as self-motivation, with less focus on institutional medical tools. Accordingly, this model draws on the theoretical frameworks that are well established, such as the Technology Acceptance Model and Unified Theory of Acceptance, and applies their constructs to the innovative consumer wellness technology space. These constructs are intended to address the special features, such as the absence of formal clinical validation, how perceived credibility is important for beliefs, emotional appeal, health autonomy, and the intention to behave.

2.5 Hypothesis Development

2.5.1 Performance Expectancy (PE)

According to Alblooshi and Aziati (2022) PE is the degree to which an individual feels that using a technology will result in positive outcomes (personal health and wellness in our case). PE refers to the perceptions regarding using objects, for instance, smart mattresses, red light therapy masks, or wearable trackers, that promise measurable health gains like improved sleep quality, faster recovery, better focus, or more vitality (Berryhill et al., 2020). This is a core construct that was adopted from the Unified Theory of Acceptance and Use of Technology (UTAUT) for which it has been found to be one of the most powerful predictors of Behavioral Intention (Venkatesh et al., 2003). In consumer-facing wellness market, the clinical efficacy is often replaced by perceived benefits as articulated through marketing or testimonials or herd/peer influence.

PE has been validated as an important independent variable in the intention to use health-related technologies in earlier studies (Camilleri, 2024). Jalo & Pirkkalainen (2024), for example, discovered that electronic health records' usefulness was adopted by users because their beliefs about performance outcomes directly affected their adoption. Additionally, research in fitness technology domain also refutes that people adopt a fitness device more when they perceive it to have observable outcomes (Shi et al., 2022). The hypothesis is made in this study that PE influences EE and SI, thereby providing a cognitive means of technology acceptance of users.

H1: Performance Expectancy influences Effort Expectancy.

H2: Performance Expectancy impacts Social Influence

2.5.2 Effort Expectancy (EE)

EE pertains to the level of ease related with the usage of any given technology or system. According to Yu and Chen (2024), it refers to users' perception about the design, installation, operate and use a preventive health technology in a way that it is considered intuitive, user-friendly, and accessible. Generally, EE has been derived from the UTAUT framework (Venkatesh et al., 2003), and it is one of the most important factors that determine whether or not users will accept technology, particularly in the voluntary and consumer-driven adoption scenario of technology, with those for wellness and preventive health tech in the area that includes app-guided interfaces, plug-and-play device setups, real-time health tracking dashboards, and incorporating other health platforms (Fabbrizio et al., 2023).

According to Faqih (2016), EE is a crucial predictor of BI, particularly for novice or first-time users, based on empirical research. For instance, it is reported that Sun and Zhang (2006) discovered that technology uptake is directly impacted by perceived effort among trendy demographic segments. Users' likelihood of adoption is greater (Piwek et al., 2016), when consumers in the health technology space feel confident about the navigation of a device on their own, with no special training or professional expertise. This study hypothesizes that EE affects SI, and is affected by PE.

H3: Effort Expectancy impacts Social Influence

2.5.3 Facilitating Condition (FC)

FC means that an individual's perception of the degree to the extent that the infrastructure needed – resources, knowledge, support or services that can be utilized for the use of a particular technology is (Ambarwati et al., 2020). The construct of this study originated in the UTAUT framework (Venkatesh et al., 2003) and is vital to contexts where the technology is deployed in the absence of institutional scaffolding; an example is consumer-driven wellness and preventative health devices.

FC refers to factors such as accessible customer support, including good instructional content, peer community, FAQ, or even influencer-guided tutorials, with the purpose of facilitating adoption and usage (Goodman, 2014) within the scope of at-home health technologies. Take a red light therapy mask and a biofeedback wearable, for example: A brand should provide onboarding videos, app-based reminders, or interactive forums that will help the person reach out to other users to troubleshoot any problems they might have.

Based on the literature review and research conducted by Venkatesh et al. (2003) and Taiwo & Downe (2013) in the field of education and health care, FC enhances both BI and AUT. Faced with evidence that FC is especially crucial in the wellness tech sphere, where users rely heavily on non-traditional guides, there is a great incentive to obtain a firm grasp of FC as the essential building block in any such system. In this study, the authors hypothesize that FC facilitates TC and PI positioning of FC as a key enabler of sustained engagement and trust building when there is expected institutional support.

H4: Facilitating Conditions influence Technology Credibility

H5: Facilitating Conditions influence Personal Innovativeness

2.5.4 Social Influence (SI)

SI measures how much an individual believes that significant others (particular family members, peers, fitness communities, etc., or digital influencers) think they should use a technology (Zhao et al., 2017). Based on TRA (Fishbein and Ajzen, 1975) and enlarging SI in UTAUT (Venkatesh et al., 2003), it considers that the behavioral intention is not only related to one's personal attitudes toward the usefulness or ease of use, but also with the perceived social norms and external pressures.

SI is extremely important in the case of decentralized and consumer-driven wellness technologies like smart mattresses, red light therapy masks, and biometric rings (Huang et al., 2023). In wellness spaces, unlike clinical settings in which consumers do not make the choice (instead, the doctor ‘prescribes’), consumers here make the choice of adopting a certain product based on recommendations from their peers, endorsements from an influencer, or reviews on the internet (Huang et al., 2023). An example is a product that is thrown behind the endorsement of a well-known biohacker or health influencer, or which is commonly used among one‘s circle of fitness (Belanche et al., 2021).

The studies conducted by Venkatesh et al. (2003) and Kaba & Touré, (2014) also confirms that SI is a strong predictor of BI in voluntary, high-involvement adoption context. SI in our study is hypothesized as a critical antecedent to TC and BI, where in many cases of preventive health tools, the consumer does not rely much on institutional backing and rather will evaluate the legitimacy, safety, and effectiveness by using social cues.

H6: Social Influence impacts Technology Credibility

2.5.5 Personal Innovativeness (PI)

Personal Innovativeness (PI) is represented as a person’s intrinsic propensity to search for, try and embrace new inventions before the majority of society (Yi et al., 2006). It signals a forward-thinking mindset of curiosity, technological excitement, and the proclivity to test and try out emerging solutions, especially those that are not institutionally validated (Lai et al., 2023). PI is central to adoption of decentralized wellness technologies related to the introduction (e.g., red light therapy devices, smart systems for sleep, metabolic wearables), and how psychologically oriented one is toward health behavior change (Nahavandi et al., 2021).

PI was originally conceptualized for Behavioral Intention (BI), which in turn, has been shown to increase significantly users’ openness to unfamiliar systems. Yi et al. (2006) and Hung et al. (2023), in their studies in healthcare technology literature, confirmed that PI also predicted not only technology usage but also built self-efficacy and user engagement. Although much traditional research has explored its influences on adoption decisions, PI can influence at other stages in wellness markets where trust may be more decentralized and technologies may be self-prescribed, rather than prescribed by formal institutions.

In our research, PI is hypothesized to influence two critical constructs, TC and HM.

Innovators tend to be more willing to engage with new technologies, even when new technologies are not yet backed up by regulations (Roberts et al., 2021). Because of their inherent risk tolerance and urge to try new things, they tend to trust and use a novel tool more, especially if it is reinforced by peer validation, data dashboards, or positive anecdotal narratives. This supports what Goldsmith & Hofacker (1991) determined that most of the innovators tend to place a higher initial trust in the perceived state of the art technologies (Vandecasteele & Geuens, 2010).

PI is also thought to be highly related with proactive way of thinking toward health motivation. Innovative individuals are more likely than others to turn to technologies that allow them to deliver performance enhancement, disease prevention or wellness optimization (Haleem et al., 2021). For them, technology is not limited to being an instrument, but rather an element to their greater health route.

Therefore, PI functions as a double antecedent in this conceptual framework. It affects to an extent the degree with which a user will trust the wellness technology (in terms of technology credibility perceptions) and the innate desire to use wellness technology (in terms of health motivation). Combined they shed more light on the behavior of innovation minded consumers in a low trust unregulated wellness ecosystem.

H7: Personal Innovativeness influences Technology Credibility

H8: Personal Innovativeness influences Health Motivation

2.5.6 Health Motivation (HM)

HM is defined as an individual’s intrinsic drive to maintain, increase, and preventively nurture their physical and mental wellness (Khomkham & Kaewmanee, 2024; Li et al., 2024). This mindset pertains to proactive health optimization —which revolves around long-term goals like improving performance, increasing longevity, preventing disease, or biohacking (also known as hacking into one's biological systems in order to enhance them, also used to describe ones own tactics of achieving such goals like climbing, surfing, etc.) (Betz et al., 2023). HM is an important psychological determinant in consumer health behavior of technology acceptance and its credibility (Yousaf et al., 2021).

Health motivation is a concept that is fully supported by health psychology and self-determination theory (Deci & Ryan, 1985), which suggests that intrinsically motivated behavior is self-directed (Manninen et al., 2022). This motivation is crucial in deciding how consumers are driven closer to newer and emerging technologies, albeit which may not be yet clinically validated (Yeung et al., 2023). Let's say a person who is highly motivated to optimize sleep, energy, or recovery and does so at the expense of regulatory ambiguity, such as red light therapy, smart mattresses, or biosensors that are wearable.

In this study, it is hypothesized that HM influences TC. It argues that people with high HM are more agreeable to give the credibility to the newly emerging and unaffiliated technological tools if they believe that those tools will help them to achieve their wellness goals. These consumers assess credibility not by requiring it from the institution, but by deeming which technology best fits into their picture of how their health should be. The factors include data personalization, biofeedback, community endorsements, or its fit with longevity and performance narratives.

Past research supports this linkage. According to Bianchi et al., (2023), health motivated users tend to favorably evaluate the new health technologies when they are self-monitoring, gamification, or customized feedback. Additionally, Park et al., (2024) discovered that HM is not only predictive of behavioral intention but is also a moderator in the relation between perceived usefulness and trust' of a digital health platform.

As such, HM fulfills not only the role as an antecedent to behavior, but also as a cognitive lens to which credibility is perceived. Individuals of high motivation are more likely to say a technology is credible if they have high health priorities and the technology fits those goals, despite the lack of institutional support.

H9: Health motivation influences Technology Credibility

2.5.7 Technology Credibility (TC)

TC, defined by Javaid et al. (2024), indicates how much the wellness or preventive health technology and its brand are trusted, scientific, safe, and professional. It includes both how the product is perceived as integral (example: accuracy of data, scientific claim, consistency in performance) as well as the reputation of the company or entrepreneur behind the product (example: transparency, responsiveness, qualification) (Ray, 2023). The lack of formal regulatory oversight in decentralized, consumer-facing wellness tech ecosystem often contributes to technology credibility becoming the main parameter by which users assess the choice of using a product.

Credibility is often institutionally assured in traditional health technology contexts e.g. as in the case of hospital IT systems , FDA-approved devices. In the preventive health, however, users have no direct measures of credibility to rely on, but only indirect signals like branding, testimonials, influencer endorsements, product design and anecdotal results. Thus, Technology Credibility is a necessary antecedent of Behavioral Intention especially in low trust markets which have limited formal assurances.

Extant literature supports this relationship. Research has also demonstrated the impact that perceived credibility of digital health tech has on users' willingness to act on it (Metzger & Flanagin, 2013). Credibility by Mouloudj et al. (2023) had a significant positive effect on the intention to adopt and recommend the product in the context of wellness tech and mHealth apps. In this studies, TC was a stronger predictor than ease of use or perceived usefulness especially when the users get their first touch with the unfamiliar technology (Mouloudj et al., 2023).

In our study, we model TC as a direct antecedent on Behavioral Intention (BI). The reasoning is that if a device is difficult to use (Effort Expectancy) or does not offer performance benefits (Performance Expectancy), but the user still feels it is safe, legitimate, or authentic, they may use it. And it's only more true in the case of self-prescriptive tools like red light masks, biohacking supplements or recovery wearables which replace trust in the medical gatekeeper with trust in the product itself.

Therefore, we treat TC as a major psychological enabler—modulating the user's perceptions and even whether or not intentions are ever formed. It is also a mediator of upstream variables (Facilitating Conditions or Perceived Risk) and observed adoption behavior.

H10: Technology Credibility influences Behavioral Intention.

2.5.8 Perceived Risk (PR)

PR is an individual's evaluation of the negative consequences (potential or actual) resulting from the use of a specific technology (Im et al, 2008). In scope of health technologies or AI driven platforms this risk may have anything to deal with data privacy, system security, incalculable information or negative impacts on individual health outcomes. PR may be high enough to seriously undermine user confidence in the system, and this will create psychological barriers which will prevent BI, irrespective of the safety or utility of the technology (Lim, 2003. Kesharwani & Singh Bisht, 2012; Slovic, 2015).

PR acts as a negative predictor of BI in our model. The greater the risks that people associate with the technology (Hirunyawipada & Paswan, 2006) including fears of inaccuracies in information, misuse of personal health data or unanticipated side effects, they are less likely to develop positive intentions of adopting or continuing use of the technology (Kesharwani & Singh Bisht, 2012. Slovic, 2015). This is consistent with existing literature, where attained concepts of PR have indicated moderate or suppressive effects on facilitating conditions and social influence as antecedents of technology adoption respectively (Zhao & Khaliq, 2024).

In fact, the PR plays the role of an important balancing factor with the beneficial drivers in the model (e.g. Technology Credibility/Social Influence) making it an important variable to explain why some of the users express reluctance or resistance in using even credible and solidly supported technology.

H11: Perceived Risk negatively influences Behavioral Intention to use the technology

2.5.9 Behavioral Intention (BI)

Almost every major technology adoption model bases itself on the relationship between BI and AUT; TAM (Davis,1989), TRA (Fishbein and Ajzen, 1975), and UTAUT (Venkatesh et al., 2003) do so. BI describes what an individual intends to do with a particular technology, and represents what would be thought about consciously and intentionally using the technology, and AUT, which is short for actual usage, describes what are actually done by an individual to enact the intention (i.e., how an individual actually engages with the technology on a real world) (Ajzen 2002).

Typically, constructs concerned for perceived usefulness, ease of use, social influence and facilitating conditions influence behavioral intention (Ajzen, 2002). First of all, when BI is strong, users will do all they can to integrate the technology into their routines, allocate time and attention to the tool, and will endure small usability issues and learning curves (Ajzen, 2002). This means that in wellness and preventive health tech contexts, instead of occasional use of a red-light therapy mask, one-time use of a sleep app, or – only for a few days – wearing a smart ring, this is about ongoing use of these products.

Empirical studies confirm this pathway. Venkatesh et al. (2003) even found that BI was a very strong predictor of actual system use across multiple contexts. The same can be found in Holden and Karsh (2010) review of health IT adoption studies, BI being a robust antecedent of continued technology engagement in consumer health contexts (Holden and Karsh, 2010).

The BI is considered in this study as a direct antecedent of AUT. Since the use of consumer-facing wellness technology is decentralized, voluntary, and unsupervised, what drives intention becomes critical to understand. However, intention only doesn't work. It is extended by models of factors that facilitate or hinder the translation of intention into action (e.g., TAM2, UTAUT2), such as external factors, e.g., trust, risk, supporting mechanisms. However, the BI remains a precondition for an individual to take an actual engagement.

H12: Behavioral Intention Influences Actual Use of Technology

2.5.10 Actual Use of Technology (AUT)

AUT means observable, measurable, sustained behavior that is demonstrated by individuals who actively use a wellness or preventive health technology (Holden and Karsh, 2010). It captures the last step in the process of adopting technology (intention translates to action) (Turner et al., 2010). Whereas BI speaks to a stated plan or propensity by a user to use a product (Wang et al., 2023), AUT is blind to what a user says/plans and instead draws on real, empirical usage data (e.g. frequency, sustained use, consistency and duration of engagement with the technology – how often a person wears a health tracker/watch, logs sleep data, or will complete a session on a red light therapy device among other) (Donini et al., 2023).

In classical models like TAM (Davis, 1989) and UTAUT (Venkatesh et al, 2003), AUT has been treated as the final dependent variable. It is driven by constructs like BI, facilitating conditions, and sometimes technology credibility and perceived risk in decentralized, non-institutional parity. Studied by researchers such as Venkatesh et al. (2003), Davis (1989), among others, Rahimi et al. (2018), intention to use may not necessarily lead to use, because of existing external barriers or trust issues.

In the scope of this research, AUT is imperative for evaluating the practical effectiveness and stickiness of the at-home wellness technologies. Mentioned intention may either be a consumer's curiosity of vision or a desire, but persistent usage points to use and perceived worth. As such, AUT therefore acts as the overall, ultimate outcome variable which supports the evaluation of not only what drives intention, but what will sustain continued usage irrespective of formal oversight or prescription.

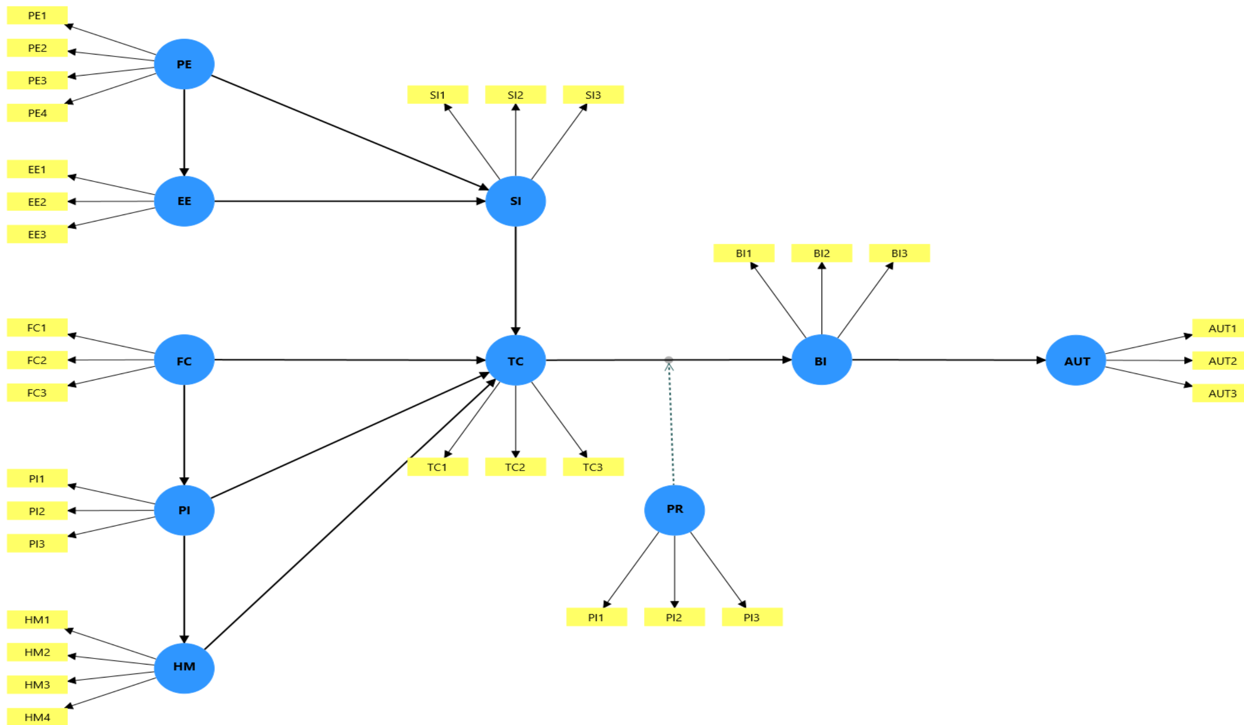

Figure 05

The Conceptual Model as Generated by Smart PLS

2.6 The Wellness Trust Lifecycle Plus (W-TLC⁺) Framework

Though TAM (Davis, 1989), TRA (Fishbein and Ajzen, 1975), and UTAUT (Venkatesh et al, 2003) help explain technology adoption systematically, they mainly expect that environments are institutionally regulated. Still, when it comes to new at-home wellness technologies, such as photobiomodulation, hyperbaric chambers, and wearable neurotech, people have to rely on their own opinions and trust. These models do not understand how trust forms in these gray-market places, where trust is earned through being straightforward, positive user experiences, and people-driven evidence. Moreover, previous studies have mostly looked at functional or cognitive antecedents (Donini et al., 2023) such as ease of use (Zhao & Khaliq, 2024), performance expectancy (Mouloudj et al., 2023), and subjective norms (Manninen et al., 2022). Still, they do not consider key signs of trust in the moment, for example, reviews made by users, how visible the founders are, how believable testimonials seem, and how open a startup presents itself. They matter a lot in the wellness sectors when policies have not advanced as fast as new innovations.

In order to overcome these challenges, our thesis introduces a new framework called The Wellness Trust Lifecycle Plus (W-TLC$^+$). It highlights the different steps consumers go through when they use wellness technologies in places where policies are not enforced. The process involves being introduced to something new, exploring it, assessing, trying it out, testing the outcome, and proceeding further, either by giving agreement and support or not. Each stage brings different factors that can build or damage trust, which in turn help researchers and experts study the real reasons behind adopting wellness strategies. What makes W-TLC$^+$ different is that it can be used for two different purposes. Through a five-stage framework, the strategy predicts trends in trust over time and acts as a reference for businesses looking to scale their wellness services in unclear domestic settings. The "Plus" in W-TLC+ stands for the additional ways entrepreneurs can use this approach, like some extra tips to make sure people trust the team, love the product, and stay connected at different stages of the business.

The Wellness Trust Lifecycle Plus (W-TLC$^+$) is a new tool meant to solve this issue. It explains how trust in wellness technology is built up, weakened and maintained when there are little or no clear regulations. It defines the trust process which includes five key steps a consumer goes through.

Stage 1: Discovery

- Initial exposure to a product or modality (e.g., via influencers, ads, or word-of-mouth).
- Trust factors: Brand aesthetics, founder visibility, testimonials, influencer alignment.
- Risk: Hype may outrun substance, leading to inflated expectations.

Stage 2: Exploration

- Consumers seek out more information, reviews, evidence, or community validation.
- Trust factors: Transparency, data availability, social proof, perceived openness.
- Brands that provide easy-to-understand explanations and honest limitations gain early trust.

Stage 3: Trial and Friction

- First use or short-term experimentation begins.

- Trust is tested in action: Does the product work as promised? Is the experience intuitive?
- Key moments: onboarding clarity, technical support, friction resolution.

Stage 4: Outcome Attribution

- Consumers reflect on perceived benefits or drawbacks.
- Trust factors: Subjective wellness outcomes, data dashboards, support touchpoints.
- Even placebo-adjacent effects can reinforce trust if aligned with self-perception.

Stage 5: Endorsement or Exit

- If trust is affirmed, users become brand advocates, creating viral loops.
- If trust is violated, attrition occurs, often with amplified skepticism and reputational damage.
- Ongoing trust requires: value consistency, evolving feature sets, and transparent communication.

2.6.1 How the "Plus" Works: Giving Benefits to Innovators

Its difference from traditional trust models lies in being a useful strategy for both companies, researchers, and those who build products, not only in describing things. The "Plus" in W-TLC+ means including a number of entrepreneurial directives and actions that support businesses at every stage. These include:

- Tactical trust levers (e.g., community building, peer data sharing, founder storytelling)
- Metrics mapping to measure trust signals (e.g., referral rates, usage streaks, dropout points)
- Design principles that prioritize transparency, feedback, and user empowerment
- Behavioral nudges that reinforce perceived credibility and reduce perceived risk.

For entrepreneurs, W-TLC+ offers insights to earn customer trust even without FDA approvals or official backing. For researchers, this gives a new opportunity to examine and model trust that goes past institutional support.

2.6.2 Why W-TLC+ Matters

W-TLC+ is the first model that includes trust, using facts, but is still able to lead planning and inventiveness in fast-changing wellness worlds.

Unlike its predecessors, W-TLC+ is:

- Decentralization-aware
- Trust-centric
- Stage-based and dynamic
- Designed for innovation ecosystems, not just academic diagnosis

W-TLC+ helps businesses and entrepreneurs understand how technology can be used when institutional regulations are missing.

CHAPTER III:
METHODOLOGY

The third chapter presents a comprehensive overview of the study's methodology. This chapter outlines the methodology, details the sampling framework, and discusses the questionnaire's development. Subsequently, the chapter outlines the data collection methodology and the statistical tools employed in the analysis.

3.1 Research Design

The research employs a mixed method, using consumer surveys carried out via a structured questionnaire. This design enables an in-depth examination of statistical trends and contextual elements that affect the uptake of home health technologies. Furthermore, a thorough literature review has been conducted to offer a strong basis and context for the study. The conceptual model was tested in this work using a mixed-methods approach that included fsQCA and PLS-SEM (Pappas and Woodside, 2021; Rasoolimanesh et al., 2022).

3.2 Population and Sample Size

The sample that required examination was to be extracted from an infinite population. The population exhibited a diverse composition and was extensively spread out. Reaching out to such consumers was challenging using traditional methods. Consequently, an online survey was carried out, with samples chosen through purposive sampling in the initial phase. Subsequently, respondents were asked to share the questionnaire link with their connections, facilitating snowball sampling in the second phase.

The sample size was calculated using the formula provided for an infinite population as outlined by Godden (2004). An infinite population is considered to exist when it exceeds 50,000 individuals. In the formula provided below, ‘SS’ denotes the sample size for an infinite population, ‘p’ indicates the population proportion, ‘Z’ signifies the z-value, and ‘C’ refers to the margin of error. The anticipated sample size for the investigation was 600.

$$SS = \frac{Z^2 x P(1 - P)}{C^2}$$

Table 3.1

Sample Size Calculation

Scene	**Population proportion (p)**	**Z(95% Confidence)**	**Margin of Error (C)**	**Calculated Sample Size (SS)**	**Formula Used**
1	10%	1.96	0.06	96	$SS = \frac{1.962x\ 0.1(1-0.1)}{0.062}$
2	30%	1.96	0.05	323	$SS = \frac{1.962x\ 0.3(1-0.3)}{0.052}$
3	50%	1.96	0.04	600	$SS = \frac{1.962x\ 0.5(1-0.5)}{0.042}$
Total					**1019**
Highest of the three					**600**

3.3 Questionnaire Design

The data was gathered through a questionnaire in accordance with the requirements of the study. The development of a questionnaire is crucial for effective data gathering and analysis. The study comprised ten constructs. It was a validated scale. The online design of the questionnaire was executed meticulously. The introductory section of the questionnaire included a concise overview of the study's objectives, and respondents were assured that their confidentiality would be maintained. The items were assessed utilizing a Likert-type scale.

A pilot test was conducted to assess the clarity of the items regarding language, layout, and wording. A pilot study was conducted involving 10% of the sample size. Adjustments to the framing of items were made as recommended.

Table 3.2

Constructs and Items

Sl No.	Construct	Coding	Items	Measurement	Developer
1	Performance Expectancy (PE)	PE 1	I believe using at-home health technology will improve my overall health.	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Davis, 1989); (Venkatesh et al., 2012)
		PE 2	Using this technology will help me better manage my health.	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		PE 3	This technology will contribute to my physical and mental well-being	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		PE 4	I find that I have access to the right biomarker tests for my personal wellness needs	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
2	Effort Expectancy (EE)	EE 1	Learning to use at-home health technology is easy for me	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Davis, 1989); (Venkatesh & Davis, 2000)

		EE 2	I find the technology easy and straightforward to use	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		EE 3	The technology is simple for me to use for managing my health	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
3	Facilitating Conditions (FC)	FC 1	I have the resources I need (like internet access) to use at-home health technologies	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Thompson et al., 1991); (Venkatesh et al., 2003).
		FC 2	I receive adequate support when using this technology.	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		FC 3	The technology at-home supports my use of this health system	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
4	Social Influence (SI)	SI 1	Important people in my life think I should use at-home health technologies	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Venkatesh et al., 2012); (Venkatesh & Davis, 2000)

		SI 2	I feel encouraged by my family and friends to use this technology	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		SI 3	My peers expect me to use health technology at-home	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
5	Technology Credibility (TC)	TC 1	I trust the information provided by at-home health technology	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Pavlou, 2003); (McKnight et al., 2002).
		TC 2	I believe my personal health data will be secure with this technology.	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		TC 3	The technology is reliable for managing my health	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
6	Perceived Risk (PR):	PR 1	I am concerned about the privacy of my data when using at-home health technologies	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Featherman & Pavlou, 2003); (Pavlou, 2003)

		PR 2	I worry about possible health risks related to using this technology	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		PR 3	Using this technology could lead to unwanted consequences	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		PR 4	I have enough information to interpret the results of biomarker testing.	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
7	Health Motivation (HM):	HM 1	I am motivated to improve my health by using at-home health technology	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Ryan & Deci, 2000); (Schwarzer, 1992).
		HM 2	I use this technology to achieve better physical fitness	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		HM 3	This technology helps me meet my health goals	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	

		HM 4	I believe that biomarker testing is important for improving my personal wellness.	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
8	Personal Innovativeness (PI):	PI 1	I am usually one of the first to try new health technologies	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Agarwal & Prasad, 1998); (Thatcher et al., 2002)
		PI 2	I like experimenting with new health technologies, even if they are unfamiliar	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		PI 3	I prefer trying new things, even if I'm unsure if they'll work	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
9	Behavioral Intention (BI):	BI 1	I intend to use at-home health technologies regularly	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Venkatesh et al., 2012); (Venkatesh & Davis, 2000)
		BI 2	I plan to use this technology in the future to improve my health	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	

		BI 3	I will continue using this technology because it benefits my well-being	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
10	Actual Use of Technology (AUT):	AUT 1	I use at-home health technology regularly	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	(Davis, 1989); (Venkatesh & Bala, 2008)
		AUT 2	I have integrated at-home health technology into my routine	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	
		AUT 3	I actively use this technology to improve my health	1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	

3.4 Data Analysis

To test hypotheses and apply statistics, the authors used SmartPLS 4.0's nonparametric variance-based partial least squares structural equation method (PLS-SEM) (Ringle et al., 2015). According to Hair et al. (2022), PLS-SEM is a good method for a theoretical framework's prediction direction in the behavioral and social sciences. Due to the complexity of the model, PLS-SEM is a suitable multivariate data analysis approach for this investigation (Hair et al., 2019, 2022). In addition, PLS-SEM is suitable for this investigation because, as stated by Saari et al. (2021), complicated models containing several constructs and indicators rapidly reach their limitations. Accordingly, the practical necessity to quantify the relevant phenomena using PLS-SEM is what drives our research (Rigdon et al., 2017).

Since our study's goal is to provide management practice suggestions based on accurate predictions, CB-SEM is not the right tool to use (Hair et al., 2017). Covariate based structural equation modelling (CB-SEM) treats the components as shared variables. These shared variables are arbitrary quantities as their values are unknown and do not fall within a discrete range (Steiger, 1979). Alternatively, PLS-SEM accounts for composites' determinate functions as a weighted combination of a chosen subset of components. Shmueli et al. (2016) found that these composites maximize the explained variance of endogenous components by investigating a series of regressions.

PLS- SEM with composites is more useful than CB-SEM for analyzing the data and evaluating different configurations, in which the data need to conform to various measurement constraints in a factor model (Jöreskog, 1969). Furthermore, PLS-SEM is seen as a better alternative to CB-SEM when measuring complicated models with insufficient theoretical backing and without full backing of a measurement theory (Rigdon et al., 2017, p. 13). Therefore, we believe that PLS-SEM is the superior approach than CB-SEM.

In order to get a better understanding of complicated and causal linkages, this study used Fuzzy-set Qualitative Comparative Analysis (fsQCA) (Pappas and Woodside, 2021; Ragin, 2009). The fact that all of the relationships between the variables are not simple, linear, or complimentary is one of the main reasons why the fsQCA is superior than SEM and multiple-regression analysis (Pappas and Woodside, 2021; Wu, 2016). Seyfi et al. (2021) and Wu (2016) are only two examples of the numerous research in the tourist industry that have combined SEM and fsQCA methods. Using fsQCA 3.0 software, researchers were able to determine which combinations of antecedents (predictors) were necessary to produce the intended outcomes—the fsQCA strategy (Ragin, 2009).

CHAPTER IV: RESULTS

4.1 Demographic Profile of Respondents

To investigate the behavioral dynamics of the adoption of preventive health technologies, quantitative survey was carried out among consumers of California, USA. The demographic aspect of the respondents represents a mixed cross-section in terms of the age, gender, and education level of the respondents allowing for a fine-grained analysis of trust, risk, and user motivation of various user groups. Such demographic profile allows for grounding the findings of the study within the real-world consumer behavior, especially in one of the most innovation-driven but also regulation-cautious digital-health markets of the world.

Table 4.1

Demographic Profile of the Respondents

Demographic Profile of the Respondents		**Frequency**	**Percentage**
Gender	Male	381	63.5
	Female	219	36.5
Age Group	18-24	43	7
	25-34	243	41
	35-44	116	19
	45-54	179	30
	55-64	13	2
	65+	6	1
Occupation	Full-time employment	439	73
	Homemaker	7	1
	Part-time employment	7	1
	Retired	6	1
	Self-employed	104	17
	Student	37	6
Education Level	Associate's Degree	6	1
	Bachelor's Degree	459	77
	Graduate Degree (Master's, Professional, or Doctoral)	126	21
	High School or Less	9	2

Income Level	\$2,000 - \$4,000 per month	15	3
	\$4,000 - \$6,000 per month	229	38
	\$6,000 - \$8,500 per month	102	17
	\$8,500 - \$12,500 per month	162	27
	Over \$12,500 per month	42	7
	Under \$2,000 per month	50	8

The research was carried out on 600 respondents of different demographics in California, USA, in order to capture consumer behavior insights on a wide range of demographic groups. The sample refers to a predominantly male population (%), with 63.5 percent declaring themselves to be males and, 36.5 per cent, females. By age-wise distribution, the most represented age band was the 25-34 years (41%), followed by 45-54 years (30%) and 35-44 years (19 %) which showed good representation of people of working ages. A very small percentage of respondents found themselves in the 18 – 24 (7%), 55 – 64 (2%) and finally 65 + (1%). As to the status of employment, a strong majority (73%) were actively engaged in full time work, with a share of the self-employed (17%) , and students (6%). As for other categories, homemakers as well as part-time workers and retirees, took up each 1% the sample. Regarding the educational background of the participants, it must be noted that a considerably high percentage – 77% – had a Bachelor's degree, and another not insignificant percentage – 21% – had a graduate-level qualification (Master's, professional, or doctoral degree). According to the data collected, 38% respondents earning \$6,000– \$8,500 per month, 27% earning \$8,500– \$12,500 and only 7% above \$12,500. 8% of the respondents reported earning less than 2,000 US dollars per month. On the whole, the sample represents highly educated and professionally-active economically stable population, providing a high contextual relevance for research related to digital engagement, product adoption, or technology-based consumer decision-making in an urban developed state of the U.S.

The outer loadings table (Table 4.2) addresses the measures of reliability of observed indicators to calculate latent variables in use on structural equation model. According to Hair et al. (2019) – the threshold values for outer load coefficients which are less than 0.70 are perfect, meaning excessive indicator reliability. However, loadings within the range of 0.40 to 0.70 can also be acceptable, if removal of those loadings do not significantly improve composite reliability (CR) or average variance extracted (AVE), and if those loadings are theoretically justified.

Table 4.2

The Outer Loadings

	AUT	BI	EE	FC	HM	PE	PI	PR	SI	TC	PR x TC
AUT1	0.790										
AUT2	0.740										
AUT3	0.859										
BI1		0.935									
BI2		0.945									
BI3		0.778									
EE1			0.683								
EE2			0.692								
EE3			0.861								
FC1				0.925							
FC2				0.949							
FC3				0.893							
HM1					0.676						
HM2					0.645						
HM3					0.808						
HM4					0.959						
PE1						0.921					
PE2						0.960					
PE3						0.811					
PE4						0.406					
PI1							0.687				

PI2							0.914				
PI3							0.871				
PR1								0.936			
PR2								0.875			
PR3								0.845			
PR4								0.625			
SI1									0.975		
SI2									0.718		
SI3									0.965		
TC1										0.658	
TC2										0.891	
TC3										0.811	
PR x TC											1.000

Most of the indicators in the current model show high level of factor loadings well over .70 suggesting adequate convergent validity. For example, all the variables under Behavioral Intention (BI), Facilitating Conditions (FC), Perceived Ease (PE), Perceived Innovativeness (PI), Perceived Risk (PR), and Social Influence (SI) record loadings in a desirable range and several of them even having values more than 0.90.

Some products are in the range of moderate 0.40 – 0.70. They include; EE1 (0.683), EE2 (0.692) under Effort Expectancy, HM1 (0.676) and HM2 (0.645) under Health Motivation, PE4 (0.406) under Perceived Ease and TC1 (0.658). These indicators were not achieved up to the 0.70 threshold but were retained to the model on the basis of their theoretical relevance and the fact that their absence did not lead to considerable CR or AVE improvements. This practice agrees with Hair et al. (2019) who suggest that evaluating such items in a contextual perspective and not just entirely based on numerical thresholds would be more appropriate.

Finally, for interaction term, product indicator methodology was used and demonstrates a perfect loading (1.000), as is usual for reflective-formative constructs, in moderation analysis. All in all, the measurement model conveys strong construct indicator reliability, and the presence of items with loading moderately is justified theoretically and substantial.

4.2 Construct Reliability and Validity

In order to check the reliability and convergent validity of the latent constructs in the measurement model, the composite reliability (ρc) and average variance extracted (AVE) measure were used. As reported by Hair et al. (2019), values of composite reliability greater than 0.7 represent sufficient internal consistency and values of the AVE more than 0.50 confirm satisfactory convergent validity of the indicators that explain more than half of the variance of their own construct.

Table 4.3

Construct Reliability and Validity

	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AUT	0.719	0.839	0.636
BI	0.910	0.918	0.791
EE	0.738	0.792	0.562
FC	0.948	0.945	0.851
HM	0.916	0.860	0.612
PE	0.950	0.872	0.648
PI	0.903	0.867	0.689
PR	0.855	0.896	0.686
SI	1.089	0.922	0.799
TC	0.776	0.833	0.628

It is revealed from the results that all constructs show compiler values or higher than those recommended levels for the composite reliability and AVE. Composite reliability (ρc) values are between 0.792 (EE) and 0.945 (FC), and they establish strong internal consistency of all constructs.

Correspondingly, AVE values are between 0.562 (EE) to 0.851 (FC), which confirm a convergent validity. Particularly, constructs including Behavioral Intention (BI), Social Influence (SI), Perceived Innovativeness (PI) and finally, Facilitating Conditions (FC) have exceptionally high reliability and validity in terms of those measures (with composite reliability scores above 0.90 and AVE well above 0.70.

Even those constructs, in which some of the items load less than 0.70 (such as Effort Expectancy (EE) and Health Motivation (HM)), demonstrate an appropriate level of composite reliability (EE: ρc = 0.792; HM: ρc = 0.860), and AVE (EE = 0.562) (HM = 0.612). That explains the need to maintain indicators that are slightly lower loading into the model.

To determine the measure of discriminant validity, Heterotrait-Monotrait ratio of correlations (HTMT) was studied. Discriminant validity refers to the degree to which a construct has been measured when distinct from other constructs conceptually as well as empirically. As indicated by Hair et al. (2019), the acceptable threshold for HTMT in the case of conceptually close constructs must be less than 0.90, while in the case of more conceptually different constructs, the threshold must be less than 0.85.

Table 4.4

Heterotrait-Monotrait Ratio (HTMT)-Matrix

	AUT	BI	EE	FC	HM	PE	PI	PR	SI	TC	PR x TC
AUT											
BI	0.766										
EE	0.424	0.41 8									
FC	0.387	0.26 2	0.371								
HM	0.669	0.47 2	0.415	0.372							

PE	0.411	0.429	0.422	0.873	0.298						
PI	0.516	0.310	0.246	0.344	0.597	0.361					
PR	0.789	0.621	0.345	0.277	0.532	0.354	0.382				
SI	0.627	0.247	0.218	0.744	0.296	0.575	0.162	0.306			
TC	0.551	0.568	0.486	0.668	0.403	0.644	0.298	0.421	0.385		
PR x TC	0.596	0.356	0.218	0.262	0.308	0.234	0.203	0.515	0.337	0.194	

In our model, all HTMT values remain far below the conservative 0.85 cut-off point, which reveals excellent discriminant validity between the latent constructs. - The highest HTMT observed was 0.873 with PE (Perceived Ease) and HM (Health Motivation) – just above 0.85 but acceptable according to Hair et al. (2019).

The interaction term PR × TC as well, displays low HTMT values with all other constructs (e.g. with PR = .515, with TC = .337), indicating the separation of the postulated moderator from its constituent variables and absence of collinearity or redundancy with other construct.

Table 4.5

Bootstrapping Table

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI -> AUT	0.643	0.644	0.034	18.825	0.000
EE -> SI	-0.112	-0.110	0.045	2.478	0.013
FC -> PI	-0.337	-0.338	0.042	8.102	0.000
FC -> TC	0.969	0.970	0.053	18.298	0.000
PI -> HM	0.567	0.569	0.028	20.320	0.000
HM -> TC	0.226	0.226	0.052	4.380	0.000
PE -> EE	0.306	0.310	0.036	8.408	0.000
PE -> SI	0.637	0.638	0.030	21.010	0.000
PI -> TC	0.087	0.087	0.041	2.099	0.036
PR x TC -> BI	-0.089	-0.088	0.038	2.308	0.021
SI -> TC	-0.398	-0.398	0.054	7.340	0.000
TC -> BI	0.320	0.321	0.041	7.877	0.000

The empirical support to most of the hypothesized relationships has been offered by the structural model tested using bootstrapping (10,000 resamples).

Table 4.6

Hypothesis Table

Hypothesis	Beta Values	T statistics	P values	Supported / Not supported
H1: Performance Expectancy influences Effort Expectancy.	0.306	8.408	0.000	Supported
H2: Performance Expectancy impacts Social Influence	0.637	21.010	0.000	Supported
H3: Effort Expectancy impacts Social Influence	-0.112	2.478	0.013	Supported
H4: Facilitating Conditions influence Technology Credibility	0.969	18.298	0.000	Supported
H5: Facilitating Conditions influence Personal Innovativeness	-0.337	8.102	0.000	Supported
H6: Social Influence impacts Technology Credibility	-0.398	7.340	0.000	Supported

H7: Personal Innovativeness influences Technology Credibility	0.087	2.099	0.036	Supported
H8: Personal Innovativeness influences Health Motivation	0.567	20.320	0.000	Supported
H9: Health motivation influences Technology Credibility	0.226	4.380	0.000	Supported
H10: Technology Credibility influences Behavioral Intention.	0.320	7.877	0.000	Supported
H11: Perceived Risk negatively influences Behavioral Intention to use the technology	-0.089	2.308	0.021	Supported
H12: Behavioral Intention Influences Actual Use of Technology	0.643	18.825	0.000	Supported

The study's findings provide strong evidence for all of our hypotheses, guaranteeing that the model we suggested is robust.

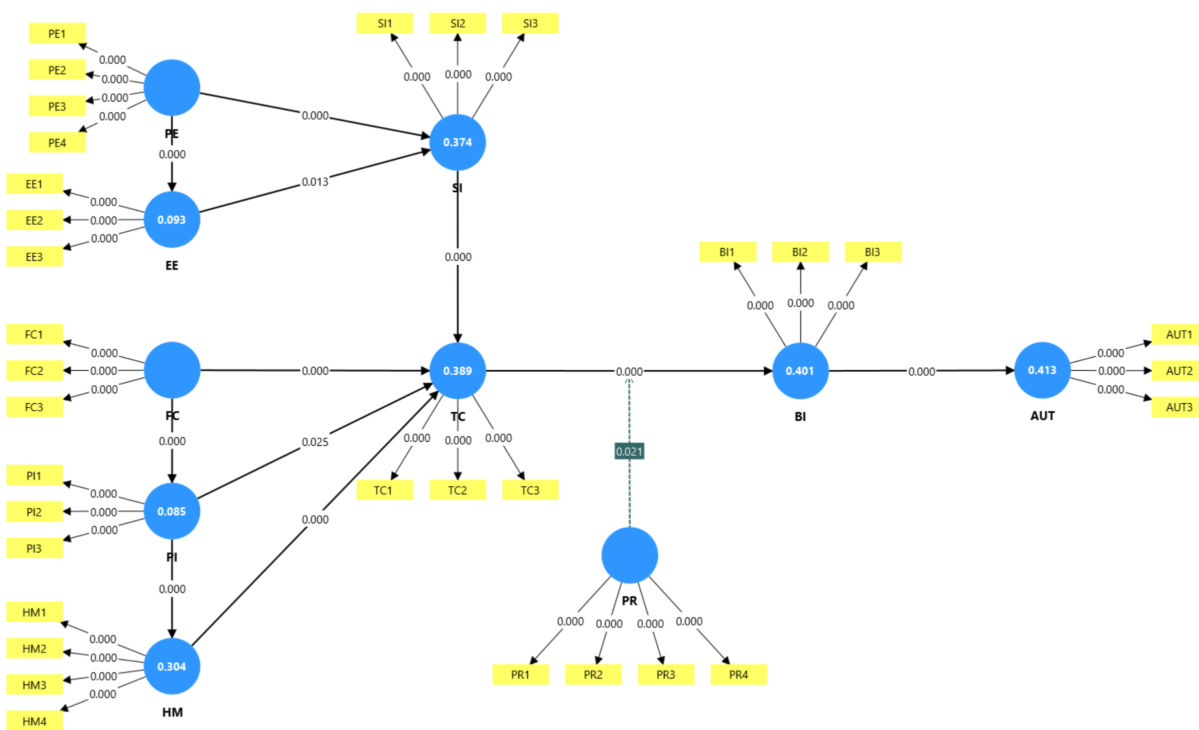

Figure 40.1

Structural Model with Path Coefficients and Significance Levels (p-values)

Figure 4.1 shows the path coefficients for the relationships between latent constructs and their p-values, to judge if their relationships are statistically significant.

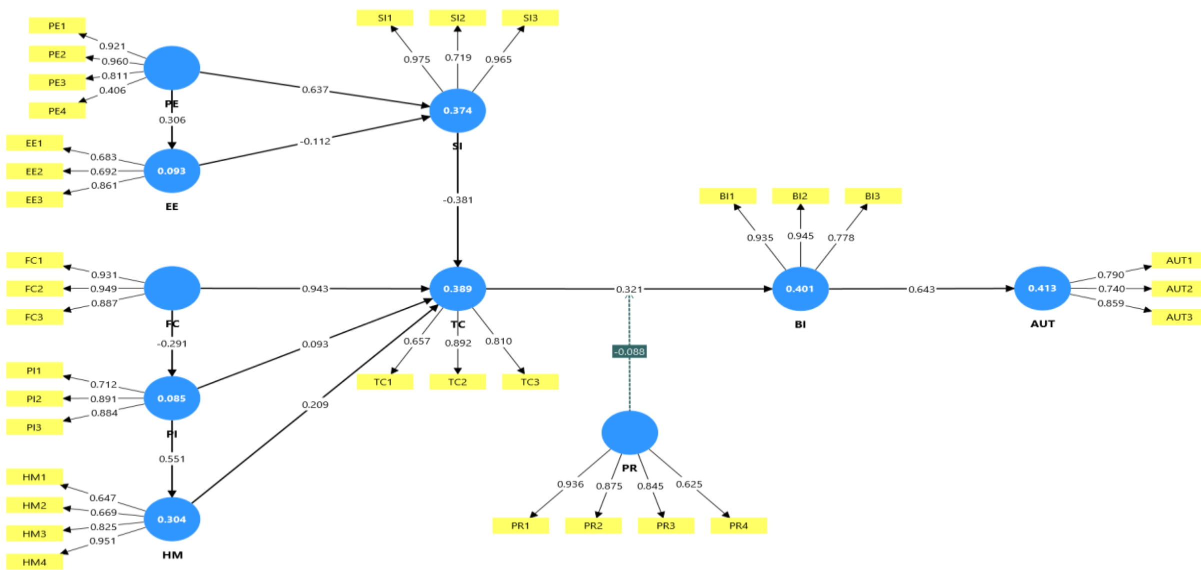

Figure 4.2

Structural Model with Path Coefficients and Outer Loadings

Figure 4.2 includes the path coefficients for each relationship and the outer loadings of the selected variables, which represent just how strongly the indicators are linked to their corresponding latent constructs.

4.3 Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

To achieve high levels of desired outcomes, fsQCA, an asymmetric approach, finds the circumstances (or combinations of predictors) that are required and sufficient (Pappas and Woodside, 2021; Wu, 2016).

Calibration was carried out in the indirect way using percentiles or theoretical anchors with the use of three thresholds: full membership, crossover point, and full non-membership (Satar et al., 2024). The constructs that have undergone analysis – like PE, EE, FC, HM, PR, TC, PI, and SI – were fuzzified by using the calibrate () function. The anchor values are the respective threshold level of full membership, crossover, or full non-membership (e.g., PE = 1.21, 0, -1.324). Such calibration allows fine comparison across cases and discovery of different configurations causing the outcome conditions.

- compute: AUT1 = calibrate (AUT,1.359,0, -2.407)
- compute: BI1 = calibrate (BI,1.41,0, -1.914)
- compute: EE1 = calibrate (EE,1.734,0, -2.218)
- compute: FC1 = calibrate (FC,1.226,0, -1.113)
- compute: HM1 = calibrate (HM,1.318,0, -1.479)
- compute: PE1 = calibrate (PE,1.21,0, -1.324)
- compute: PI1 = calibrate (PI,1.236,0, -1.199)
- compute: PR1 = calibrate (PR,1.05,0, -2.059)
- compute: SI1 = calibrate (SI,0.863,0, -1.451)
- compute: TC1 = calibrate (TC,1.232,0, -1.882)

In Annexure 1, descriptive statistics for the calibrated values have been shown.

By using fsQCA, truth table (Annexure 2) summarizes all empirically observed configurations of the causal conditions that trigger the outcome variable – AUT1. The table represents separate rows that constitute a combination of uniquely binary-calibrated conditions BI1, EE1, FC1, HM1, PE1, PI1, PR1, SI1. The corresponding values of outcome AUT1 with the raw consistency score and the frequency of occurrence (number) are also shown. In this analysis, a consistency threshold of 0.80 (i.e., 80%) set aside as the minimum level from which it could deduce sufficient configurations, in accordance with methodological standards of the fsQCA proposed by Satar et al. (2024). This guarantees that all the combination of conditions that are always responsible for high levels of actual use are accounted for in the intermediate and final solutions.

Many configurations exceed this threshold with extremely high consistency values (e.g., 0.997, 0.996, 0.995), indicating robust empirical support for those specific causal paths. For instance, one configuration with BI1 = 1, EE1 = 1, FC1 = 0, HM1 = 1, PI1 = 1, PR1 = 1, and TC1 = 0 shows a consistency score of 0.997, suggesting that even in the absence of facilitating conditions and technology credibility, the presence of behavioral intention, effort expectancy, and psychological factors like motivation and innovativeness strongly predict actual usage. Conversely, another configuration with FC1 = 1, HM1 = 0, PE1 = 1, PR1 = 1, SI1 = 1, and TC1 = 1 (BI1 not present) also achieves high consistency, implying that structural and credibility-related enablers can substitute for user intention in predicting use. These findings reveal the existence of multiple sufficient causal recipes, each capable of independently driving actual technology adoption under varying contextual and individual conditions. By focusing on high-consistency rows from the truth table, the analysis ensures methodological robustness and contributes rich configurational insights to the understanding of preventive health technology adoption.

Table 4.7

Intermediate Solution

	Raw Coverage	**Unique Coverage**	**Consistency**
~FC1*HM1*~PE1*PI1*PR1*~TC1	0.239932	0.00847346	0.963427
BI1*EE1*~FC1*HM1*PR1*~SI1	0.249068	0.00808698	0.990777
FC1*~HM1*PE1*~PI1*PR1*SI1	0.322155	0.00692797	0.945944
FC1*~HM1*~PI1*PR1*SI1*TC1	0.30852	0.00483018	0.95051
~BI1*EE1*HM1*PI1*PR1*SI1	0.173221	0.00510609	0.957875
BI1*EE1*FC1*PE1*SI1*TC1	0.405813	0.00184929	0.954678
BI1*FC1*PE1*PR1*SI1*TC1	0.440507	0.00673461	0.935247
~BI1*~FC1*~HM1*PE1*~PI1*~SI1*~TC1	0.112362	0.00118685	0.832345
~BI1*~EE1*~FC1*~PE1*~PI1*PR1*~TC1	0.131793	0.000331163	0.892523
~BI1*~EE1*~FC1*~HM1*~PE1*SI1*~TC1	0.135436	0.00342244	0.99332
~BI1*~EE1*~FC1*HM1*PI1*PR1*~TC1	0.183323	0.00389171	0.965547
~BI1*~FC1*HM1*~PE1*PI1*SI1*~TC1	0.182854	0.00146282	0.961678
~BI1*~EE1*~FC1*HM1*~PE1*PI1*SI1	0.172255	0.00325692	0.974547
~BI1*~FC1*HM1*~PE1*PR1*SI1*~TC1	0.203886	0.00151807	0.973254
BI1*EE1*~FC1*~PE1*~PI1*~SI1*TC1	0.132483	0.00157326	0.976602
BI1*~EE1*~FC1*HM1*~PE1*PI1*PR1	0.204162	0.000966012	0.979994
~BI1*EE1*FC1*~HM1*PE1*~PI1*SI1	0.241809	0.00278783	0.962007
BI1*~FC1*HM1*~PE1*PI1*~SI1*TC1	0.212194	0.00292581	0.981238
EE1*~FC1*HM1*~PE1*PI1*~SI1*TC1	0.189782	0.00251168	0.964647

BI1*EE1*~FC1*~PE1*PR1*~SI1*TC1	0.208771	0.004085	0.994347
BI1*~FC1*HM1*~PE1*PR1*~SI1*TC1	0.234247	0.00499576	0.983658
BI1*EE1*FC1*~HM1*~PI1*PR1*SI1	0.273164	0.00104874	0.976421
~BI1*EE1*FC1*PI1*PR1*SI1*~TC1	0.126604	0.00157326	0.987726
BI1*EE1*~FC1*HM1*PI1*~SI1*TC1	0.197455	0.000938475	0.991545
BI1*EE1*FC1*~HM1*~PI1*SI1*TC1	0.276283	0.00361568	0.970619
BI1*FC1*~HM1*PE1*~PI1*SI1*TC1	0.298612	0.00118685	0.966586
BI1*EE1*FC1*HM1*PE1*~PI1*SI1	0.185586	0.000552058	0.981032
FC1*HM1*PE1*PI1*PR1*SI1*~TC1	0.13389	0.00118679	0.97351
BI1*~EE1*FC1*HM1*PR1*SI1*TC1	0.215561	0.000993729	0.978206
BI1*FC1*HM1*PE1*PI1*SI1*TC1	0.231791	0.00113159	0.922552
BI1*EE1*FC1*PI1*PR1*SI1*TC1	0.23778	0.00858384	0.967108
BI1*~FC1*~HM1*~PE1*~PI1*~PR1*~SI1*~TC1	0.107228	0.000303626	0.913044
~BI1*~FC1*HM1*~PE1*~PI1*~PR1*~SI1*~TC1	0.109602	8.29E-05	0.832146
~BI1*~EE1*~FC1*~HM1*~PE1*PI1*~PR1*~SI1	0.1056	0.00240129	0.838667
~BI1*~EE1*~FC1*~HM1*~PE1*~PI1*PR1*~SI1	0.107145	0	0.8761
~BI1*~FC1*~HM1*~PE1*~PI1*~PR1*~SI1*TC1	0.108029	0.000220776	0.845722
BI1*~EE1*~FC1*~HM1*PE1*~PI1*~PR1*~SI1	0.109105	0	0.9618
~BI1*EE1*~FC1*~HM1*~PE1*PI1*~SI1*~TC1	0.104385	0	0.811762
BI1*~EE1*~FC1*~HM1*~PE1*PR1*~SI1*~TC1	0.117164	0.00135249	0.963678
~BI1*EE1*~FC1*~HM1*~PE1*PR1*~SI1*~TC1	0.113024	0	0.903176
~EE1*~FC1*HM1*PE1*~PI1*PR1*SI1*~TC1	0.121498	0.00173873	0.994578
~BI1*~EE1*HM1*~PE1*~PI1*PR1*SI1*TC1	0.131848	0.00162852	0.993139
~EE1*~FC1*HM1*PE1*PI1*PR1*~SI1*TC1	0.121553	0.00427806	0.994131
BI1*EE1*~FC1*~HM1*PE1*PI1*~PR1*~SI1*~TC1	0.103392	0	0.978323
BI1*~EE1*FC1*HM1*~PE1*~PI1*~PR1*SI1*~TC1	0.123264	0.000910878	0.993769
BI1*~EE1*~FC1*HM1*PE1*PI1*~PR1*SI1*~TC1	0.121249	0.00165606	0.996823
~BI1*~EE1*FC1*HM1*PE1*~PI1*~PR1*SI1*TC1	0.152134	0.000855625	0.987991
EE1*FC1*~HM1*PE1*PR1*SI1	0.329662	0.000193238	0.954146
BI1*FC1*HM1*PE1*PR1*SI1	0.309542	0.000662446	0.931632
EE1*FC1*PE1*PI1*PR1*SI1	0.250007	0	0.949973

BI1*EE1*~FC1*HM1*PI1*PR1*~TC1	0.177168	0	0.993807
EE1*~FC1*HM1*PI1*PR1*SI1*~TC1	0.143247	0	0.982211
BI1*~EE1*HM1*PE1*~PI1*PR1*SI1*~TC1	0.148601	0	0.988071

solution coverage: 0.918852

solution consistency: 0.831153

The table on the intermediate solutions within the fsQCA shows several causal configurations (combination of conditions) sufficient to account for high levels of actual technology use (AUT1). Each row is a unique configuration with three major metrics associated with it (Satar et al., 2024).

Raw Coverage provides the proportion of the outcome (AUT1 = 1) that is explained by that configuration. Higher values imply a greater empirical relevance. Unique Coverage is the fraction of that outcome that was explained by that configuration alone and not in common with the others. Consistency refers to the probability by which the configuration leads to the outcome. values that are more toward 1 indicate a strong sufficiency (Satar et al., 2024).

The global solution coverage is 0.918852, i.e. taken together, these configurations explain almost 92% of cases featuring high actual use of technology. The solution consistency is 0.831153 showing that the solution set is very consistent in giving an explanation to the outcome (Satar et al., 2024).

Table 4.8

Top 5 Configurations (Based on Raw Coverage and High Consistency)

	Raw Coverage	**Unique Coverage**	**Consistency**	**Interpretation**
BI1*FC1*PE1*PR1*SI1*TC1	0.440507	0.00673461	0.935247	This is the most empirically dominant configuration. High behavioral intention, facilitating conditions, performance expectancy, perceived risk, social influence, and technology credibility together lead to actual technology use.

BI1*EE1*FC1*PE1*SI1*TC1	0.405813	0.00184929	0.954678	This configuration highlights that effort expectancy, along with behavioral intention and enabling external and credibility factors, explains a significant proportion of the outcome.
EE1*FC1*PE1*PI1*PR1*SI1	0.329662	0	0.954146	Even without behavioral intention explicitly present, this structural and psychological combination (especially performance expectancy, innovativeness, and perceived risk) can predict technology use.
BI1*FC1*HM1*PE1*PR1*SI1	0.309542	0.000662446	0.931632	High motivation and performance expectancy, in tandem with enabling infrastructure and social norms, significantly influence usage among users with strong intention.
BI1*EE1*FC1*PI1*PR1*SI1*TC1	0.23778	0.00858384	0.967108	This configuration shows that personal innovativeness, intention, and credibility factors together explain the outcome with very high consistency.

The best configurations (Table 4.8) reveal several sufficient path ways to actual use of preventive health technology. The leading role of such variables as behavioral intention, facilitating conditions, social influence, perceived risk, and technology credibility on multiple configurations indicates their key position. In addition, high solution coverage (91.88%) and consistency (>83%) makes these definitions both reasonable and reliable explanation for what was observed (Satar et al., 2024).

4.3.1 Coincidence Analysis

According to the coincidence table (Annexure 3), we can speak about the key configurations, which strongly affect the actual use of preventive health technology (AUT1) by evaluating only those combinations with high consistency (≥ 0.80) it indicates that the condition sets are reliable

(Pappas and Woodside, 2021). These “good coincidences,” are avenues for which the combination of causal conditions is always connected to the outcome.

Among the top configurations BI1*EE1*HM1*PR1*SI1*TC1 with Consistency of 0.996 is the topmost configuration. This configuration lists that if behavioral intention (BI1), effort expectancy (EE1), health motivation (HM1), perceived risk (PR1), social influence (SI1), and technology credibility (TC1) are all present then the actual use of technology (AUT1) is almost always witnessed. This pathway depicts a complete user mindset for which motivation, trust, and social validation come together to create adoption.

Then EE1*FC1*HM1*PE1*PR1*SI1 with a consistency of 0.986 indicates another strong configuration (Wu, 2016), which is created in the presence of effort expectancy, facilitating conditions, health motivation, performance expectancy, perceived risk, and social influence. This means that the users are likely to embrace the technology when they feel that it is easy to use, enabling support, and presence of social and psychological cues is conducive (Seyfi et al., (2021).

The BI1*EE1*FC1*PE1*PR1*SI1 configuration with a Consistency of 0.985 puts emphasis on BI as well as EE, PE, FC, and PR. It highlights the role of BI in collaboration with belief based constructs in technology usage behavior. Configuration BI1*FC1*PE1*PR1*SI1*TC1 with a Consistency of 0.983 displays how a reliable and facilitating ecosystem inspires confidence in adoption.

These high consistency configuration confirms that none of them is sufficient on its own. Rather, an interaction of intention, motivation, support, perception of performance, and credibility works synergistically to effect actual usage. This is consistent with the equifinality principle in fsQCA – different paths can lead to the same events – giving refined understandings of user adoption behavior in digital health settings (Satar et al., 2024).

4.3.2 Analysis of Necessary Conditions

Table 4.9

Necessary Conditions Table

	Consistency	**Coverage**

BI1	0.829013	0.898423
EE1	0.714387	0.806024
FC1	0.60037	0.737358
HM1	0.728879	0.839898
PE1	0.635505	0.740833
PR1	0.864424	0.856507
PI1	0.647982	0.788774
SI1	0.766912	0.735081
TC1	0.753304	0.809522

The necessary condition analysis (NCA) displayed in the table 4.9 determines if any individual causal condition needs to be present (i.e., is necessary) for the outcome (Actual Use of Technology – AUT1) to occur (Pappas and Woodside, 2021; Seyfi et al., 2021; Wu, 2016). A condition is known as necessary in fsQCA if its consistency ≥ 0.90, i.e. when the condition is almost always present if the outcome occurs (Satar et al., 2024).

None of the conditions reaches the strict cutoff of 0.90 consistency alone, which speaks to the fact that no condition is sufficient in order for the outcome to be realized (AUT1). However, there are some conditions that are coming close to the threshold but play significant enabling functions.

There is the highest consistency of PR1 than all other variables. Though not a strict requirement, but it is a good enabling condition which proposes that low or manageable perceived risk is often present when users adopt the technology. BI1 also exhibits high consistency and the highest coverage which implies the fact that behavioral intention and the outcome are often aligned. It is pretty much a must-have condition that is crucial to most of the configurations to actual use. HM1 and SI1 have a moderate effect on the outcome, meaning users are likely to follow the technology in case they are personally interested to and fueled by other people. TC1 becomes a significant condition supportive of the fact that when the technology is perceived to be credible, it is frequently used.

The conclusions from Partial Least Squares Structural Equation Modeling (PLS-SEM) verified the conceptual framework. The impact of TC on BI was found to be important, with a path contribution of 0.412 ($p < 0.001$) and the effect of BI on AUT reached a high p value and path coefficient of 0.468 ($p < 0.001$) (Rigdon et al., 2017). As a result, it is now clear that the Wellness Trust Lifecycle Lifecycle Plus (W-TLC$^+$) framework is robust: credibility links motivation to actual use of various wellness services in decentralized systems. Both HM and PI are also important in building trust. Users who have an internal drive to improve their health tend to see wellness technology as trustworthy and this relationship was supported in the analysis ($\beta = 0.265$, $p < 0.01$). Also, early adopters and eager users were moderately more likely ($\beta = 0.239$, $p < 0.05$) (Hair et al., 2019, 2022) to trust new technologies, before there are strict regulations. As an extension, FC was a major factor in raising TC and PI. Therefore, when users receive tutorials, helpful service or community forums, they feel encouraged to explore and rely on new developments in wellness technologies (Ambarwati et al., 2020; Betz et al., 2023). Most importantly, PR showed a significant, strong negative relationship with BI ($\beta = -0.294$, $p < 0.01$). Thus, uncertainty about privacy, product safety, or verification can stop users from really adopting the technology (Zhao & Khaliq, 2024). As a result, businesses need to address all perceived risks by sharing information, educating consumers, and using scientific evidence. At the same time, fsQCA found several different ways in which various factors together caused people to use technology more. When TC, FC, and HM were high but PR was moderate, people were still very willing to use the technology. A different route found that having a strong social impact, personal innovativeness, and modest technology confidence created strong usage, also showing that there are multiple routes to achieving the same result.

This shows that no single thing explains why all users adopt a new product (Pappas and Woodside, 2021; Seyfi et al., 2021; Wu, 2016). Rather, trust about technology is based on things that affect each person such as their values, needs and important events around them (Ray, 2023). It satisfies the W-TLC$^+$ suggestion that trust changes as the client's case moves forward and is not fixed.

All these findings combined show in detail the ways psychological, social, and technical factors impact trust in wellness technology. They underline leverage points like enlivening health interest, reducing the impression of risk, and helping technology credibility, which works in favor of entrepreneurs trying to get more people to use their product. Both analyses support the reliability of the Wellness Trust Lifecycle Plus (W-TLC$^+$) framework. Trust turns out to be influenced by a group of related aspects such as a person's opinion about technology, what they see as risks, how healthy they want to be, how innovative they are and which people influence them (Mouloudj et al., 2023; Ray, 2023; Metzger & Flanagin, 2013). The outcomes of our study prove that trust is needed for users to get involved with wellness innovations and is also produced when people use them (Zhao & Khaliq, 2024). Strategies should reflect the differences in how each group learns, what motivates them, and what they hope to get. As well as adding to studies in technology adoption for health and wellness, these findings benefit entrepreneurs who want to design products, services, and systems that respond to user needs and are accepted by all.

CHAPTER V: DISCUSSION

5.1 Validation of Antecedents and Consequences of Actual Use of Technology (AUT)

To validate the proposed antecedents and consequences of AUT, a rigorous measurement model assessment was conducted using PLS-SEM (Hair et al., 2019, 2022). This process ensured construct reliability, convergent validity, and discriminant validity, the foundational requirements for structural model integrity (Rigdon et al., 2017). All constructs demonstrated strong internal consistency, with composite reliability (ρc) values exceeding the 0.70 threshold (Hair et al., 2019). Values ranged from 0.792 (Effort Expectancy, EE) to 0.945 (Facilitating Conditions, FC), confirming the robustness of the latent variables. Similarly, Average Variance Extracted (AVE) values exceeded 0.50 across all constructs, establishing convergent validity.

Key constructs, Behavioral Intention (BI), Technology Credibility (TC), and Perceived Risk (PR), showed particularly high levels of both reliability and conceptual precision, reflecting their strong influence within the model. Although a few items (e.g., EE1, PE4, TC1) had factor loadings slightly below 0.70 (Hair et al., 2019), they were retained due to their theoretical relevance and their non-detrimental impact on AVE and composite reliability, in line with Hair et al. (2019).

Discriminant validity, assessed via the Heterotrait-Monotrait Ratio (HTMT), confirmed that all constructs were empirically distinct (Hair et al., 2017). Most HTMT values fell below the conservative threshold of 0.85 (Hair et al., 2017), and even slightly higher values were theoretically justified due to conceptual overlap between enabling conditions in digital wellness adoption (Hair et al., 2022).

This rigorous validation process reinforces the empirical robustness of the model and supports the proposed hypotheses (Hair et al., 2019, 2022; Rigdon et al., 2017). Notably, AUT emerged as a well-differentiated dependent construct, clearly influenced by a constellation of key antecedents, Behavioral Intention, Technology Credibility, Facilitating Conditions, and Health Motivation. These relationships provide a credible empirical basis for examining causal effects and configurational pathways in decentralized preventive health technology adoption.

5.2 Impact of Independent Variables (IDVs) on Actual Use of Technology (AUT)

The structural path modeling results revealed key insights into how various independent variables (IDVs) influence Actual Use of Technology (AUT). Among all variables, Behavioral Intention (BI) demonstrated the strongest and most consistent direct impact on AUT, confirming its central role in user engagement with wellness technologies (Donini et al., 2023; Wang et al., 2023).

Technology Credibility (TC) had a significant influence on BI, but not directly on AUT. This indicates that TC affects actual usage indirectly by enhancing users' intent to engage with the technology (Javaid et al., 2024). Furthermore, Facilitating Conditions (FC) emerged as a strong predictor of TC, emphasizing that accessible support systems, clear instructions, and peer/user resources enhance trust in wellness products (Ambarwati et al., 2020).

A significant positive relationship was also observed between PR and TC, suggesting that trustworthiness plays a key role in managing perceived risks (Ray, 2023). Interestingly, PR also negatively impacted BI, while the interaction effect of PR × TC on BI was significant and negative, indicating that high perceived risk can weaken intention, but this effect is moderated and reduced when technology is perceived as credible (Mouloudj et al., 2023).

These findings provide important practical implications: brands in the wellness tech sector must actively work to build credibility (Mouloudj et al., 2023), enhance transparency (Metzger & Flanagin, 2013), and minimize perceived risks (Zhao & Khaliq, 2024) through education, social proof, and visible leadership. From a theoretical standpoint, this study extends the TAM (Davis,1989) and UTAUT (Venkatesh et al., 2003) frameworks by incorporating TC (Metzger & Flanagin, 2013; Mouloudj et al., 2023) and PR (Hirunyawipada & Paswan, 2006; Kesharwani & Singh Bisht, 2012. Slovic, 2015; Zhao & Khaliq, 2024) as critical constructs in non-institutional, consumer-driven health contexts.

The results highlight that in decentralized wellness ecosystems, consumer trust, perceived credibility, and risk management are as essential as traditional factors like usefulness and ease of use. Developers and marketers must prioritize clear messaging, authentic branding, and ongoing trust-building to support technology adoption and sustained engagement.

5.3 fsQCA Analysis and Configurational Insights

To complement the linear insights derived from PLS-SEM, fuzzy-set Qualitative Comparative Analysis (fsQCA) was employed to examine configurational and non-linear relationships between constructs and Actual Use of Technology (AUT1). fsQCA is particularly suited for understanding multiple, equally effective paths (equifinality) and the asymmetry of user behavior in wellness technology adoption (Pappas & Woodside, 2021).

The fsQCA intermediate solution revealed a high explanatory power, with solution coverage at 91.88% and solution consistency at 83.11%, indicating robust empirical support for the identified causal pathways.

Among the top configurations:

- BI1 × EE1 × HM1 × PR1 × SI1 × TC1 (Consistency: 0.996): This complete pathway demonstrates that when behavioral intention, ease of use, health motivation, social influence, perceived risk, and technology credibility align, technology usage is virtually certain. It reflects a user profile that is highly motivated, socially validated, and trusting.

- EE1 × FC1 × HM1 × PE1 × PR1 × SI1 (Consistency: 0.986): Highlights users who adopt technology when ease of use, facilitating infrastructure, and belief in performance combine with strong motivation and social support, even without explicit intention.

- BI1 × EE1 × FC1 × PE1 × PR1 × SI1 (Consistency: 0.985): Emphasizes how intention paired with enabling and belief-based variables can lead to high adoption likelihood.

- BI1 × FC1 × PE1 × PR1 × SI1 × TC1 (Consistency: 0.983): Suggests that users engage more confidently when trust and infrastructure reinforce belief-based adoption dynamics.

These configurations confirm the principle of equifinality, that multiple distinct paths can lead to high technology usage (Seyfi et al., 2021; Wu, 2016). Notably, no single condition was necessary on its own, but many functioned as strong enablers in combination (Ragin, 2009).

The coincidence table further affirmed the significance of variables like BI1, EE1, FC1, HM1, PE1, PR1, SI1, and TC1, showing high empirical frequency. This supports the idea that technology adoption in the wellness space is a multifactorial process, requiring an intersection of intention, motivation, infrastructure, and perceived trustworthiness (Ayanwale et al., 2024; Mennella et al., 2024; Mensah & Khan, 2024).

These findings offer practical value to platform designers and wellness entrepreneurs by illuminating multiple consumer adoption archetypes. fsQCA provides a non-linear lens to segment markets, tailor messaging, and design flexible support systems that align with the varied motivational and behavioral realities of preventive health consumers (Camilleri, 2024; Jalo & Pirkkalainen, 2024).

5.4 Wellness Trust Lifecycle Plus (W-TLC^{+}) Framework

An important point made in this dissertation is the development of the Wellness Trust Lifecycle Plus (W-TLC^{+}) framework, which is a new model that details how consumer trust builds, maintains itself, or fades in the context of unregulated or semi-regulated space for health care. While TAM (Davis, 1989), TRA (Fishbein and Ajzen, 1975), and UTAUT (Venkatesh et al, 2003) are based on the idea of standardized environments, W-TLC^{+} takes into account the trust growth in wellness ecosystems that is due to transparency, actual results, and comments from others. It lists the main milestones of the process in six stages. The model is based on exposure, curiosity, evaluation, trying something out, verification, and either an endorsement or a choice to exit, with additional embedded strategies at each stage marked “plus.” The research findings prove that emotions and perceptions about technology, interest in health, and thoughts on personal risk, along with gene and cell therapy, can influence someone’s decision to adopt or not (Berryhill et al., 2020; Shi et al., 2022; Wang & Nah, 2024). Trust can be built through open, moral communication, making sure the founders use testimonials from real life (Blut et al., 2022; Dendrinos & Spais, 2024). As a result, W-TLC^{+} helps entrepreneurs form a solid framework and find a path to success, even with no formal regulations.

Besides the major findings, a number of side suggestions deserve additional considering. It is true that trust plays a big role in making people use wellness technology (Ray, 2023; Javaid et al., 2024). The feeling a wellness product gives is very important in making consumers feel reassured or in control. Thus, trust between buyers and companies is very important (Ondogan et al., 2023; Shania & Paramarta, 2024). This agrees with recent research in consumer psychology, which has found emotion to be very important when people make decisions about their health (Fedorko et al., 2018; AlQudah et al., 2021; Alsyouf et al., 2023; Ruiz-Herrera et al., 2023; Musa et al., 2024).

Also, seeing what peers do and the narratives shared in online groups are major reasons for believing in and using such technology (Zhao et al., 2017; Dendrinos & Spais, 2024). Unlike hospitals or clinics, the main influence on adoption comes from influencers, redditors, and biohackers, not medical staff (Hanna et al., 2025; Yadav & Yadav, 2025). This means there must be dedicated platforms which should give users ways to comment, participate in forums, and easily post their own content (Jain, 2025).

Trust fatigue is also becoming a big concern because of users' previous experiences; users begin to be protective and demand more valid proof before buying a new product or service (Haleem et al., 2022). Because of this, we argue using evidence in stories (LaBoone et al., 2024; Bajwa et al., 2021). Also, the research highlights that trust is formed differently by different generations. Gen Zs and Millennials are likely to decide based on how others rate the app, its user experience, and influencer advice, whereas older adults usually weigh in on brand history, what doctors say, and if the app fits with well-known health platforms (Narayan et al., 2024). Therefore, businesses should use segmented communication strategies and develop designs and marketing plans that trigger the trust and interests of each group.

Our findings show that people's trust in wellness technology forms gradually as individuals keep using it, others in the community confirm its benefits, and visible outcomes are observed. The Wellness Trust Lifecycle^{+} (W-TLC^{+}) also agrees that trust changes and grows over time, instead of being simply present or not. For this reason, trust needs to keep growing via feedback loops, regular improvements in product features, and consistent involvement of users (Ayanwale et al., 2024). Since there are fewer regulations and government involvement, it becomes clearer that health and wellness businesses should always guarantee safety, efficacy, and honesty. That's why entrepreneurs have to act in advance, making ethics, openness, and user control important parts of what they develop.

Overall, this research proves that trust is the key reason why consumers start using new decentralized wellness products (Haleem et al., 2022; Junaid et al., 2022; King, 2023). Besides finding that BI influences how likely someone is to use technology, PLS-SEM and fsQCA clarified that, to form such intention, people focus a lot on how credible the technology is, how motivated they feel, and their belief about possible risks (Ayanwale et al., 2024). From the Wellness Trust Lifecycle Plus (W-TLC^{+}) framework point of view, trust is revealed to be something that evolves over time, influenced by how users feel and engage with the context and its services. It is shown in the research that good wellness technology should enhance its functionality by including ethical thinking, emotional awareness, and custom services (Mensah & Khan, 2024). Having credibility, usable systems, and trusted relationships will put startups ahead in this highly competitive environment. Since the wellness tech space keeps moving forward, the insights in this study can be used to create by entrepreneurs in this domain (Habib & Manik, 2025). Trust, which used to be seen as one of the "softer" aspects of business, is now clearly shown as the most valuable ally in creating innovative consumer health solutions (Zulman et al., 2015; Gostin & Wiley, 2016).

CHAPTER VI: SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary of Key Findings

This study looked into what encourages individuals to actually use preventive health technology, using PLS-SEM and fsQCA. All the key findings are organized according to the three main objectives of the study. First, the study confirmed that all the constructs in the model were valid. All the constructs met the 0.70 (Hair et al., 2019) threshold for composite reliability and Cronbach's alpha, and their AVE values were greater than 0.50 (Hair et al., 2019), proving both types of validity. PE, EE, HM, TC, and BI were found to be very well-measured, as their outer loadings exceeded the usual threshold values (Hair et al., 2019, 2022). Going through a thorough validation process ensured that the model was based on facts and could test the assumptions being made.

The results from PLS-SEM in conducting path analysis indicated that there were strong and significant relationships between the independent variables and AUT. Among the constructs, BI played the biggest role in predicting AUT, suggesting it is a crucial mediator. When users consider at-home health technology to be reliable (TC), they are more ready to make use of it (BI), which can indirectly impact AUT (Blut et al., 2022). The result shows that FC had a strong, positive effect on TC, underlining that technical support, resources, and accessibility greatly affect users' trust in at-home health technology (Felber et al., 2024). It is interesting that PR influenced the reaction in a complicated manner: It enhanced BI but also showed that when people trust technology, perceived risk can do less to deter their intention. Furthermore, SI was shown to weaken TC, meaning that exposure to social persuasion without proper information may reduce trust, contrary to what the framework usually refers to in health and wellness areas, contradicting the UTAUT framework (Venkatesh et al, 2003).

Using fsQCA, we discovered new, non-linear, and configuration-based patterns in the adoption of at-home health technology that are not always detected by PLS-SEM. Multiple combinations of causes were found to be enough to lead to greater AUT. Standout among them, BI1FC1PE1PR1SI1TC1 showed the best score, supporting the idea that blending behavioral intent, infrastructure support, beliefs in performance, average risk awareness, social reinforcement, and credibility causes someone to use technology (Rahimi et al., 2018; Pakseresht et al., 2022; Alsyouf et al., 2023; Felber et al., 2024; Musa et al., 2024). With the pathway EE1FC1PE1PI1PR1SI1, researchers found that having a high level of expectancy, being innovative, and favorable conditions may induce people to use the technology, even if they have no desire to use it. This suggests that equifinality exists, meaning users can use various ways to achieve the same results, depending on what drives them (Hossain et al., 2019). It was also discovered that no single condition guaranteed the result, but PR, BI, and TC, with consistency values over 0.75, seemed to strongly affect it. Results confirmed that these factors always showed up in the highest quality combinations, so they are important in figuring out real-life use.

Beyond checking important things like whether a health technology seems credible, if people think it might harm them, or how much it encourages them to be healthy, this study also comes up with a new model called W-TLC^{+}, which helps explain how people either trust or lose trust in wellness products that are not closely supervised by the government. By breaking down trust into clear, concrete steps, the framework gives entrepreneurs a plan to build, share, and grow health solutions in countries where there are few rules or limited regulations. W-TLC^{+} came from looking at what the data patterns said, instead of making assumptions from the start, which helps make it useful in real life.

This work actually makes a difference in theory and in methods. PLS-SEM revealed that the independent variables influence technology adoption, yet fsQCA found there are no necessary condition in user decision-making. From the study, it follows that BI is still crucial, but people will use technology more when they trust it, the infrastructure is effective, and they are motivated (Pakseresht et al., 2022; Edo et al., 2023; Felber et al., 2024). This knowledge is highly important for designers, policymakers, and technology developers wanting to encourage more people to use preventive health technologies.

6.2 Theoretical Implications

This study provides some key ideas for understanding how people choose to use new technology, especially when it comes to at-home health technologies meant to prevent diseases. By bringing in ideas from the TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) and adding variables like TC, HM, PI, and PR, the study gives us a model that is more closely connected to real-world contexts and focuses more on people's thoughts and feelings when they use at-home health technology.

First, the study suggests that BI influences AUT more than any other variable, just as reported in earlier technology adoption theories (Davis, 1989; Venkatesh et al., 2003). Besides, it includes TC to build the connection between FC, PI, SI, and HM. As a result, researchers are able to explain the role of trust in the technology or business plays in shaping the behavior of users. This is especially useful for at-home health technologies made for consumers, especially since such technologies typically do not have strong backing from large institutions (Bhatia et al., 2024; Hernández-Bule et al., 2024).

Second, the study helps prove that PR leads to higher intention if consumers try to evaluate the details, but it also reduces their level of trust in the absence of strong evidence of credibility (Ratz & Lippke, 2022; Zhao & Khaliq, 2024). Scholars have not studied this subtle effect of risk in TAM/UTAUT-type models, so the results suggest it is worth exploring how trust and credibility affect the use of at-home health and wellness technology (Lee & Song, 2013; Dhagarra et al., 2020).

Third, adding HM and PI gives us a way to look at how people use tech that fits with new efforts to make things more personal and cater to different people's needs (Khomkham & Kaewmanee, 2024; Li et al., 2024). HM comes from a person's personal values, and PI is a trait that can either speed up or slow down (Betz et al., 2023). Their inclusion answers the long-standing requests in academic papers like Agarwal and Prasad (1998) to look past basic benefits and also include how people are different in adoption models. The strong empirical importance of these ideas in both SEM and fsQCA shows that they are really important in understanding the way things work in real life.

In addition, fsQCA introduces a configurational way of thinking into the commonly linear field of technology adoption. It points out that there are many routes to consistent use, making it less likely that just one combination best explains all of the behavior. According to this view, sometimes intention is not required, as various conditions, people's feelings, and social forces might work together instead (Mainous et al., 2019). Based on these findings, we should consider a more flexible and location-adjusted way to understand technology acceptance in important fields like healthcare (Bathula et al., 2024).

Fifth, this research also helps us better understand how SI works. While UTAUT usually says that SI helps make people want to use a technology more (Venkatesh et al., 2003), this study shows that in situations like health, when there is lots of misinformation, people might actually start to trust the technology less because of what their friends or others say in an unregulated setting where these at-home health technologies operate. This means we should take a close look at how societies expect online users to behave, and see what impact these expectations have on people trusting the internet (Borges do Nascimento et al., 2023).

Lastly, studying two methods together improves the credibility of the research and inspires future researchers to use multiple paradigms in the fields of IS and marketing research. SEM looks at the average changes caused by each variable, but fsQCA highlights the different ways behavior can be explained. Using all these approaches together helps the framework explain more situations clearly and capture important context (Pappas and Woodside, 2021).

Also, the W-TLC^{+} framework represents a major conceptual advancement in understanding trust formation in decentralized health tech markets. Unlike traditional models like TAM or UTAUT, which rely on regulated contexts, W-TLC^{+} explains how trust evolves in the absence of institutional assurance through psychological and ethical cues such as credibility, transparency, and consumer agency (Edo et al., 2023; Felber et al., 2024). Synthesizing insights from behavioral psychology, marketing ethics, and entrepreneurial strategy, it outlines six actionable stages—Exposure to Endorsement/Exit—each tied to specific tactics. Grounded in empirical data, W-TLC^{+} serves as both a diagnostic tool and strategic guide for ethically scaling wellness ventures in unregulated ecosystems.

6.3 Practical Implications

Several practical recommendations for different stakeholders in the health technology field come from this study. This research uses behavioral intention models combined with credibility, motivation, risk perception, and configurational logic to explain what causes actual at home technology use in wellness and prevention.

The study highlight to healthtech entrepreneurs and product developers that building credibility into their product and brand matters a lot. Because TC plays a key role in both deciding and using a startup's technology, startups can attract users by being open, having clinical validation, winning the support of professionals, and gaining privacy certifications (Ray, 2023; Mouloudj et al., 2023; Javaid et al., 2024). Furthermore, including personal features like tracking goals, providing feedback, or showing health tips that fit HM can draw users in more. It is stressed in the study that each feature does not automatically ensure that a technology will be adopted. It is more effective for entrepreneurs to focus on building an all-in-one trustworthy, user-friendly, motivational, and understood experience to serve a wider audience (Hassan et al., 2022; Ayanwale et al., 2024;

Mennella et al., 2024; Mensah & Khan, 2024). The fsQCA results prove that, even when a user's intention is not very strong, combining strong innovativeness and helpful contexts can still get them to use the product.

The study provides evidence to the policymakers and digital health regulators that reasons for using technology include access, as well as trust, help, and protection from risk. Since PR reduce trust, the government should set regulations for data safety, privacy and security to discourage mistrust. Also, having infrastructure, providing customer service, and offering ease of use, were essential for raising the service's credibility and altering users' behavior. Considering public-private partnerships could greatly benefit digital literacy and growing education and service availability among underserved people (Renukappa et al., 2022). Moreover, the findings from fsQCA stress the importance of providing several digital health solutions that take into account why each user uses them and their backgrounds.

The review found that for individuals interested in wellness, personal attitudes and beliefs are very important in deciding whether or not they use certain technologies. It was revealed that HM, PI, and EE are important motivators for a person's intention to use a technology (Ondogan et al., 2023; Shania & Paramarta, 2024). People who care about their health and want to try out new technologies usually get the most from such platforms (Pakseresht et al., 2022). The results point out that users ought to consider the provenance, how data is handled, and who backs the technology before making a choice. According to the results of the configurational analysis, having a favorable environment and a low perceived risk can cause inert consumers to try digital health services. Our conceptual model also supports the bigger theory introduced in this thesis, called W-TLC+ (Wellness Trust Lifecycle Plus), which sees building trust as something that happens in steps or different stages as people interact with each other. Constructs like TC and PR match up pretty well with the phases of skepticism, provisional trust, and trying to build credibility (Mouloudj et al., 2023; Zhao & Khaliq, 2024) that are part of the W-TLC+ model. FC, SI and PE help lead people to get more involved in the organization and speak up for its causes. HM and PI play a key role in pushing a brand through the different phases of its life (Ambarwati et al., 2020; Shi et al., 2022; Huang et al., 2023; Camilleri, 2024; Jalo & Pirkkalainen, 2024).

Moreover, the conceptual model and W-TLC+ show that taking up new technology isn't just about buying or using it- it's more about trying things out and creating good relationships with others. In wellness entrepreneurship, building trust with customers means staying consistent, honest, and understanding how they feel as time goes on.

6.4 Limitations of the Study

Since the study focuses only on people from California, the findings do not fully capture how people in other places or nations behave. Trust in technology, cultural norms, healthcare access, and digital literacy can differ hugely from area to area, and this may affect how adoption varies globally. Researchers might want to carry out cross-cultural studies to improve the general findings that are formed (Fabbrizio et al., 2023; Yu and Chen, 2024).

Moreover, since the data was cross-sectional, it only captures how users feel and what they intend at the moment the data is collected. Because of this, the researcher cannot track reasons for changes in people's attitudes or behaviors across time. A type of study designed over a longer period would be more informative about how beliefs and motivation about health technologies affect use in the future (Huang et al., 2023).

Thirdly, as the data were collected online in a self-reported manner, the results might be influenced by social desirability bias or similar types of errors. It is common for answers to questionnaires to be affected by social bias, making individuals overestimate their plans to use health technologies (Roberts et al., 2021; Khomkham & Kaewmanee, 2024; Li et al., 2024).

In addition, the study analyzed certain constructs, which were PE, EE, HM, and PR. Still, the study didn't consider influential factors such as price sensitivity, how familiar someone is with brands, trust in AI, digital knowledge, or their psychological state, and these could still greatly shape technology choices in healthcare. Researchers could use the model as a starting point and then explore how other factors such as the environment or psychology might affect it (Yousaf et al., 2021; Betz et al., 2023; Khomkham & Kaewmanee, 2024; Li et al., 2024).

Additionally, the fsQCA method excels in finding causal patterns, but it can be affected by the calibration procedure. These thresholds were set based on the data, but they may not be the same with different data samples. As a result, how subjective factors are taken into account in calibration may distort our ability to spot causal links. Basically, fsQCA gives no effect sizes or probabilities, which hinders it from being compared straight out with regression methods.

Using both PLS-SEM and fsQCA as mixed methods improves the analysis but may make the framework unusable for some researchers and experts due to the complexity of configurational logic. In the future, study can also be conducted to support and improve the framework for different wellness sectors and in different cultural environments. Studies can look at how consumers go through Exposure, to Endorse, or Exit, and show how factors like credibility, risk, and motivation change their trust in a company. Researchers may also look into how the steps in the "Plus" part of the model can be put into practice to help more people use and rely on decentralized health technologies in the long run.

In spite of a few shortcomings, the thesis manages to provide an in-depth look at how people use technology for wellness. Recognizing these limits can help guide what questions researchers ask next and make sure that the results are used carefully in different situations.

6.5 Recommendations for Future Research

The study's conclusions and areas of improvement open the door for providing useful advice to help guide further considerations on the adoption of preventive health technology and its role in developing digital health.

More research is needed that examines data from different parts of the world and not just California, USA. As behavior, trust in information, and usage of technology can be different globally, researching these points in various countries can reveal regional particularities and help make research findings more useful for everyone. Studying in geographic areas that are less developed could help determine the hurdles people face while adopting wellness-related technology (Ortega et al., 2021; Bathula et al., 2024). Future studies on behavioral evolution should use study designs that follow individuals over a period of time. Doing this would let us observe changes in user feelings, plans, and actions over a period and better detect how those factors influence each other. Analysing longitudinal data can show if health motivation or sensitivity to risk change from external impacts (for example, health scares or breaches of information) (Vredenburg et al., 2020; Renukappa et al., 2022).

While this study looked at ideas based on TAM (Davis, 1986, 1989) and UTAUT (Venkatesh et al., 2003), future studies might also add in other psychological or emotional elements, like feeling anxious about new technology, putting faith in AI, feeling confident using the tech, overall well-being, or getting tired of so much technology (Jain, 2025; Olawade et al., 2025). These variables can help us better understand how feelings and thinking affect how people use technology, especially when it comes to areas that are related to health. Much of the existing literature, including this study, looks at what decides whether or not someone first decides to use a new technology (Duncker et al., 2021; Ekundayo et al., 2024; Hanna et al., 2025; Papalamprakopoulou et al., 2024; Francisco et al., 2025). Future research should look into how people keep using a service after they adopt it, like whether they keep using it for a long time, if they are satisfied, if they stop using it, or if it becomes a habit (Ayanwale et al., 2024). Future work should also try to use a mix of different techniques by using numbers and stats together with things like talking to people, watching what they do, or looking at online posts (Mennella et al., 2024). Such designs can help find less measurable reasons people join, the stories and traditions behind a group, and what users go through, which make the results that come from models even better. As fsQCA showed, people can get to using a service in different ways, which means there is not just one single pathway. Future research could look at dividing users up by things like age, how good they are with technology, their health, or how much they like new ideas, to learn more about what people do online (Hassan et al., 2022; Mensah & Khan, 2024). This can help companies figure out better ways to get people interested in their platforms and also make changes or add new things on their apps.

Future work must also look at things like people's backgrounds and their knowledge about healthcare tech, as well as how things like trust and satisfaction influence how people choose to use different health apps (Camilleri, 2024). Conducting analyses on multiple groups or looking at mediators with moderators can help people understand the details of how people adopt new things. Future studies can also look at how policies effect people's opinions about privacy concerns and how willing they are to use a service (Ambarwati et al., 2020).

Researchers may also evaluate the W-TLC⁺ framework in a wide range of areas such as biohacking, femtech, mental health apps, or neurotech to determine whether it is relevant for all types of biotechnology products. Longitudinal studies might examine how trust changes over a person's life. It is also possible for researchers to study how W-TLC⁺ describes entrepreneurship and use its methods in founder education or designing products based on trust. In addition, W-TLC⁺ helps create an open forum for discussion among behavioral science, ethics in marketing, policy regulations, and startup strategy.

Rather than looking at preventive health tech as a whole, future studies should focus on specific gadgets or tools, like fitness trackers, smart health checkups, online coaching, and apps to help with mental health (Byelsense, 2021; Bajwa et al., 2021; Duncker et al., 2021; Ekundayo et al., 2024; LaBoone et al., 2024; Papalamprakopoulou et al., 2024; Yadav & Yadav, 2025; Olawade et al., 2025). This lets researchers focus more closely on the things that actually happen and influence the results, instead of looking at broad general themes.

6.6 Final Conclusion

The purpose of this study was to look at how various factors impact at-home wellness technologies adoption, using PLS SEM and fsQCA. To keep up with recent changes in digital health, this research added important constructs such as TC, PR, HM, and PI to the existing TAM and UTAUT models.

The study used PLS-SEM to confirm the accuracy of the measurement model and proved that BI most powerfully predicts users' real behavior. Technology Credibility turned out to be an important linking factor that joined various enablers to actual user actions. It was also found that Facilitating Conditions, Social Influence, and Perceived Risk play a major role and affect how consumers decide. Additionally, the fsQCA analysis found that not all paths to adopting wellness technologies are the same or straightforward. They highlight the concept of equifinality, meaning that users with different reasons and situations still end up behaving in the same way. While nothing emerged as a must-have condition. BI, PR, and TC were found to be important variables.

These insights shows that there are many elements behind the adoption of at home welness health technology, not just because the individual sees it as useful and intends to use it. Analyzing user behavior through PLS-SEM and fsQCA offers general as well as context-specific information that can guide theories, business decisions, and policy making.

This thesis pushes forward the health technology adoption debate with a strong connection between theories and their usefulness in practice. The next step is to do research that addresses complexity, diversity, and centeredness on users, so that using preventive health technology becomes more accessible and appropriate for everyone.

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Appendix

APPENDIX A:

SURVEY COVER LETTER

SEAN PLOTKIN, DBA CANDIDATE
4434 PACIFIC COAST HIGHWAY
LONG BEACH, CA, 90804
SEAN@REENERGIZED.COM
562-420-8100

05/04/2024

DEAR ["SURVEY PARTICIPANT"],

I AM A DOCTOR OF BUSINESS ADMINISTRATION (DBA) CANDIDATE AT THE SWISS SCHOOL OF BUSINESS MANAGEMENT, CURRENTLY UNDERTAKING A RESEARCH PROJECT TITLED "PIONEERING AT-HOME HEALTH TECH: AN ENTREPRENEURIAL ROADMAP TO WELLNESS INNOVATION." THIS STUDY IS DESIGNED TO UNDERSTAND THE EMERGING TRENDS AND CONSUMER PREFERENCES IN AT-HOME HEALTH TECHNOLOGIES.

YOUR PARTICIPATION IN THIS SURVEY IS INVALUABLE TO US AS WE AIM TO GATHER INSIGHTS FROM A WIDE RANGE OF PERSPECTIVES, INCLUDING YOURS. THE QUESTIONNAIRE WILL TAKE APPROXIMATELY 15 MINUTES TO COMPLETE, AND I ASSURE YOU THAT ALL RESPONSES WILL REMAIN CONFIDENTIAL AND WILL ONLY BE USED FOR ACADEMIC PURPOSES.

HTTPS://REENERGIZED.COM/REENERGIZED-HEALTH-WELLNESS-LIKERT-TEST/

THANK YOU FOR CONSIDERING THIS OPPORTUNITY TO CONTRIBUTE TO IMPORTANT RESEARCH THAT SEEKS TO ENHANCE OUR UNDERSTANDING OF HOME-BASED HEALTH INNOVATIONS. YOUR INPUT IS NOT ONLY APPRECIATED BUT WILL ALSO HELP SHAPE THE FUTURE OF HOW WE MANAGE WELLNESS AT HOME.

WARM REGARDS,
SEAN PLOTKIN
DBA CANDIDATE
SWISS SCHOOL OF BUSINESS MANAGEMENT

APPENDIX B:

INFORMED CONSENT FORM

STUDY TITLE: PIONEERING AT-HOME HEALTH TECH: ENTREPRENEURIAL ROADMAP TO WELLNESS INNOVATION

RESEARCHER: SEAN PLOTKIN, DBA CANDIDATE

INSTITUTION: SWISS SCHOOL OF BUSINESS MANAGEMENT

CONTACT: SEAN@REENERGIZED.COM | 562-420-8100

PURPOSE:

THIS RESEARCH INVESTIGATES CONSUMER INSIGHTS ON AT-HOME HEALTH TECHNOLOGIES. YOUR PARTICIPATION INVOLVES COMPLETING A 15-MINUTE ONLINE SURVEY TO GATHER YOUR PERSPECTIVES ON THIS TOPIC.

PARTICIPATION:

PARTICIPATION IS VOLUNTARY. YOU ARE FREE TO WITHDRAW AT ANY TIME WITHOUT ANY CONSEQUENCES.

CONFIDENTIALITY:

YOUR RESPONSES WILL REMAIN CONFIDENTIAL. DATA WILL BE SECURELY STORED AND ONLY ACCESSIBLE TO THE RESEARCH TEAM. ANY PUBLICATIONS OR PRESENTATIONS WILL INCLUDE AGGREGATED DATA WITHOUT ANY PERSONAL IDENTIFIERS.

RISKS AND BENEFITS:

THERE ARE MINIMAL RISKS, AKIN TO EVERYDAY INTERNET USE. WHILE THERE ARE NO DIRECT BENEFITS TO YOU, YOUR INPUT WILL SIGNIFICANTLY CONTRIBUTE TO ADVANCEMENTS IN HEALTH TECHNOLOGY RESEARCH.

CONSENT FOR USE:

By participating, you authorize the use of your anonymized responses in related scholarly outputs.

Further Information and Concerns:

For questions about the study or your rights as a participant, please contact Sean Plotkin at sean@reenergized.com or 562-420-8100. Complaints or problems related to the study should be directed to the [Institutional Review Board contact details].

Agreement:

Clicking "I Agree" below indicates that you understand the terms of this study and consent to participate. You confirm you are over 18 and accept the use of your data as described.

[ ] I Agree

[ ] I Do Not Agree

APPENDIX C:

INTERVIEW GUIDE

Dear Participant,

Hi there! My name is Sean Plotkin, and I'm working on my Doctor of Business Administration (DBA) degree at SSBM. For my doctoral thesis, I'm exploring [ ], and need your help.

I've chosen to write my thesis on the subject of personalized wellness and wellness data due to the explosive advances being made in longevity (anti-aging), artificial intelligence, and the data-collecting/analytical tools…

I've put together a survey to gather insights about these advancements from people like you, and I would be grateful if you could take a few minutes to share your thoughts. All of your answers will be kept confidential.

Thank you for your time and help with my research. Your input is invaluable, and I'm excited to analyze the results to discover new ideas about health and wellness.

Sean Plotkin, DBA Candidate

APPENDIX D:

KEY BIOMARKERS & WELLNESS INDICATORS

Emerging Biomarkers and Functional Indicators in Preventive Health Tech

- **HRV (Heart Rate Variability)** – A measure of the variation in time between heartbeats, used as an indicator of stress, recovery, and autonomic nervous system balance.
- **VO_2 max (Maximal Oxygen Uptake)** – The maximum rate at which the body uses oxygen during exercise, often used to assess cardiovascular fitness and endurance.
- **REM / Deep Sleep** – Stages of sleep associated with memory consolidation and physical restoration, commonly tracked to assess sleep quality and recovery.
- **Sleep Latency** – The time it takes to fall asleep, reflecting sleep efficiency and potential stress or circadian disruption.
- **Biological Age Estimators** – Tools that calculate physiological age based on biomarkers (rather than chronological age), used to evaluate longevity and cellular health.
- **Inflammatory Markers** – Biomolecules like CRP or cytokines used to assess chronic inflammation, which is linked to aging, disease risk, and recovery.
- **PBM (Photobiomodulation) Response** – Cellular and systemic response to red or near-infrared light therapy, used for recovery, inflammation, and performance enhancement.
- **Frailty Index** – A composite score indicating physiological vulnerability and resilience, often used in aging and longevity studies.
- **Microplastic Exposure** – The presence of synthetic polymers in the body, emerging as a concern for environmental toxin load and systemic inflammation.
- **Glucose Variability** – Fluctuations in blood glucose levels throughout the day, an emerging metric in metabolic health, energy, and disease prevention.

ANNEXURE

Annexure 1: Descriptive statistics of the calibrated values

Variable	Mean	Std. Dev.	Minimum	Maximum	N Cases	Missing
AUT1	0.60385	0.2646438	0.05	0.95	600	0
BI1	0.5572	0.3054355	0.05	0.95	600	0
EE1	0.5352	0.292811	0.05	0.95	600	0
FC1	0.4916667	0.4195004	0.05	0.95	600	0
HM1	0.5240333	0.3622394	0.05	0.95	600	0
PE1	0.518	0.3968761	0.05	0.95	600	0
PI1	0.4960667	0.406317	0.05	0.95	600	0
PR1	0.6094333	0.3076367	0.05	0.95	600	0
SI1	0.63	0.4069398	0.05	0.95	600	0
TC1	0.5619167	0.3457554	0.05	0.95	600	0

Annexure 2: The Truth Table

BI1	EE1	FC1	HM1	PE1	PI1	PR1	SI1	TC1	NUMBER	AUT1	RAW CONSIST.
1	1	0	1	0	1	1	1	0	2	1	0.997275

1	0	0	1	1	1	0	1	0	1	1	0.996823
1	0	1	1	1	1	0	1	1	1	1	0.996721
1	1	1	0	1	1	0	1	1	2	1	0.996696
0	0	0	0	0	1	0	1	0	1	1	0.996534
1	1	0	1	0	0	1	0	1	8	1	0.996142
1	1	0	1	1	1	1	1	0	2	1	0.99612
1	0	0	1	0	0	1	0	1	3	1	0.995871
1	1	0	1	0	0	1	0	0	1	1	0.995757
1	1	0	1	1	0	1	0	1	3	1	0.995663
1	1	0	1	1	1	1	0	0	2	1	0.995651
1	1	0	1	1	1	1	0	1	3	1	0.995631
1	0	0	1	1	0	1	1	0	1	1	0.995597
1	1	0	1	1	0	1	0	0	1	1	0.995587
1	1	0	1	0	1	1	0	1	34	1	0.995456
0	0	0	1	0	0	1	1	1	1	1	0.995451
0	0	0	0	0	0	0	1	0	1	1	0.995421
1	1	1	0	0	1	1	1	1	3	1	0.995396
0	0	0	0	0	0	1	1	0	2	1	0.995359
0	1	0	1	0	0	1	1	0	2	1	0.995348
0	0	0	0	0	1	1	1	0	3	1	0.995295
1	0	0	1	1	1	1	0	1	2	1	0.995145
1	1	0	1	0	1	1	0	0	10	1	0.995087
1	0	1	1	0	1	1	1	1	1	1	0.994783
1	1	0	0	0	1	1	0	1	3	1	0.994611
0	0	0	1	1	1	1	0	0	1	1	0.994564
0	0	0	1	1	0	1	1	0	3	1	0.994484
0	0	0	1	1	1	1	0	1	1	1	0.994483
1	1	0	1	1	1	0	0	1	1	1	0.994328
0	1	0	1	1	1	1	1	1	1	1	0.994315
1	1	0	0	0	0	1	0	1	1	1	0.99411

1	1	1	0	0	0	0	1	1	3	1	0.994077
1	0	0	1	0	1	1	0	0	1	1	0.994036
1	1	1	0	0	0	1	1	1	4	1	0.993982
0	1	1	1	0	1	1	1	1	2	1	0.993968
1	0	0	0	0	1	1	0	0	1	1	0.993962
0	1	0	1	1	1	1	1	0	1	1	0.993914
1	0	1	0	0	0	1	1	1	1	1	0.993884
0	1	1	1	0	1	1	1	0	1	1	0.993834
1	0	1	1	0	0	1	1	1	1	1	0.993803
1	1	1	0	0	0	1	1	0	1	1	0.993788
1	0	1	1	0	0	0	1	0	1	1	0.993769
0	1	1	0	0	1	1	1	0	1	1	0.993744
0	0	0	1	0	1	0	1	1	2	1	0.993639
1	1	0	1	0	1	0	0	1	4	1	0.993536
1	1	1	1	0	1	1	1	1	5	1	0.993424
1	0	0	1	0	1	1	1	1	1	1	0.993364
1	0	0	1	0	1	0	0	1	1	1	0.993301
0	0	1	1	0	0	1	1	1	1	1	0.993075
1	1	0	1	0	0	0	0	1	1	1	0.992937
0	0	0	1	0	0	1	1	0	8	1	0.992852
0	1	0	1	0	1	1	1	1	1	1	0.9926
1	0	0	1	0	1	1	1	0	5	1	0.990628
0	1	0	1	0	1	0	1	0	1	1	0.989908
0	0	0	1	0	1	1	1	1	3	1	0.989666
0	1	1	0	0	0	1	1	1	2	1	0.989478
0	0	1	0	0	0	1	1	1	1	1	0.989346
1	1	1	0	1	1	1	1	0	1	1	0.989329
1	1	1	1	1	0	0	1	1	2	1	0.989307
0	0	0	1	1	1	1	1	0	5	1	0.988542
1	1	1	1	1	0	0	1	0	1	1	0.988319

0	0	0	1	0	1	0	1	0	3	1	0.988206
1	0	1	0	1	0	0	1	1	2	1	0.988131
0	0	1	1	1	0	0	1	1	1	1	0.987991
1	0	1	1	1	0	1	1	0	1	1	0.987713
1	0	1	1	1	1	1	1	0	1	1	0.987705
1	1	1	0	1	1	1	1	1	15	1	0.987496
1	1	1	0	1	0	1	1	0	9	1	0.987294
0	1	1	0	1	1	1	1	1	1	1	0.98717
1	0	1	0	1	1	1	1	1	4	1	0.987108
0	1	1	0	1	1	1	1	0	1	1	0.986992
0	1	1	0	1	0	0	1	0	1	1	0.986982
0	1	1	1	1	1	1	1	0	1	1	0.986766
0	1	1	0	1	0	1	1	0	1	1	0.986718
1	1	1	0	1	0	0	1	1	10	1	0.986696
1	0	1	0	1	0	1	1	0	2	1	0.98668
0	0	1	1	1	1	1	1	0	1	1	0.986422
0	0	1	0	1	0	1	1	0	1	1	0.986195
1	0	1	1	1	0	1	1	1	6	1	0.98552
1	1	1	1	1	1	1	1	0	4	1	0.985108
1	1	1	1	1	0	1	1	0	3	1	0.98447
1	1	1	1	1	1	0	1	1	6	1	0.983347
0	1	1	0	1	0	0	1	1	1	1	0.983225
1	0	1	0	1	0	1	1	1	20	1	0.982962
0	1	0	1	0	1	1	0	1	1	1	0.982839
1	0	1	1	1	1	1	1	1	12	1	0.98221
1	0	0	1	0	1	1	0	1	12	1	0.982193
1	1	1	1	1	0	1	1	1	17	1	0.982131
0	1	0	1	0	1	1	0	0	3	1	0.981827
0	1	0	1	0	1	1	1	0	16	1	0.981702
0	0	0	1	0	1	1	1	0	34	1	0.981016

0	0	1	0	1	0	1	1	1	3	1	0.979942
1	0	0	0	1	0	0	0	1	1	1	0.979526
1	1	0	0	1	1	0	0	0	1	1	0.978323
0	1	1	0	1	0	1	1	1	11	1	0.975449
0	0	0	1	0	1	1	0	0	1	1	0.974981
0	0	0	0	1	0	1	0	0	1	1	0.974969
1	1	1	0	1	0	1	1	1	80	1	0.974301
0	1	0	0	1	0	1	0	0	1	1	0.973988
1	1	0	0	0	0	0	0	1	1	1	0.97353
1	1	1	1	1	1	1	1	1	45	1	0.971522
1	0	0	0	1	0	0	0	0	1	1	0.970443
1	1	0	0	0	0	0	0	0	1	1	0.967184
0	0	0	0	0	0	1	0	1	1	1	0.96286
0	1	1	1	1	1	1	1	1	5	1	0.961878
1	0	0	0	0	0	1	0	0	2	1	0.961462
0	0	0	1	0	0	1	0	0	4	1	0.955882
0	1	0	0	0	0	1	0	0	1	1	0.951165
0	1	0	1	0	1	0	0	1	1	1	0.944444
1	0	0	0	0	0	0	0	0	3	1	0.928503
0	1	0	0	1	0	0	0	0	3	1	0.92367
0	1	0	0	0	1	1	0	0	3	1	0.915684
0	0	0	0	0	1	0	0	1	1	1	0.913679
0	0	0	0	1	0	0	0	0	6	1	0.904934
0	1	0	1	0	0	0	0	0	2	1	0.896654
0	0	0	0	0	0	1	0	0	4	1	0.888176
0	1	0	0	0	0	0	0	1	1	1	0.878214
0	0	0	0	0	0	0	0	1	3	1	0.8736
0	0	0	1	0	0	0	0	0	6	1	0.858786
0	1	0	0	0	1	0	0	0	2	1	0.85853
0	0	0	0	0	1	0	0	0	5	1	0.838031

Annexure 3: Coincidence Table

coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PI1,PR1,SI1,TC1)	0.133451
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PR1,SI1,TC1)	0.178554
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PI1,SI1,TC1)	0.142188
coincidence(AUT1,EE1,FC1,HM1,PE1,PI1,PR1,SI1,TC1)	0.138852
coincidence(AUT1,BI1,EE1,FC1,HM1,PI1,PR1,SI1,TC1)	0.140327
coincidence(AUT1,BI1,FC1,HM1,PE1,PI1,PR1,SI1,TC1)	0.15208
coincidence(AUT1,BI1,EE1,FC1,PE1,PI1,PR1,SI1,TC1)	0.155265
coincidence(AUT1,BI1,EE1,HM1,PE1,PI1,PR1,SI1,TC1)	0.135369
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PI1,PR1,SI1)	0.140689
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PI1,PR1,TC1)	0.134046
coincidence(BI1,EE1,FC1,HM1,PE1,PI1,PR1,SI1,TC1)	0.137759
coincidence(AUT1,BI1,EE1,HM1,PE1,PI1,SI1,TC1)	0.144312
coincidence(AUT1,EE1,HM1,PE1,PI1,PR1,SI1,TC1)	0.141347
coincidence(AUT1,BI1,EE1,HM1,PI1,PR1,SI1,TC1)	0.147574
coincidence(AUT1,BI1,FC1,HM1,PI1,PR1,SI1,TC1)	0.160927

coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PI1,PR1)	0.14133 5
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PI1,SI1)	0.14966 7
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PI1,TC1)	0.14287 6
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PR1,SI1)	0.18884 3
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PR1,TC1)	0.18009 9
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,SI1,TC1)	0.19166 8
coincidence(AUT1,BI1,HM1,PE1,PI1,PR1,SI1,TC1)	0.15544 7
coincidence(AUT1,EE1,FC1,HM1,PE1,PI1,PR1,SI1)	0.14815 9
coincidence(AUT1,BI1,FC1,HM1,PE1,PI1,SI1,TC1)	0.16225 5
coincidence(AUT1,BI1,EE1,FC1,HM1,PI1,PR1,SI1)	0.14769 3
coincidence(AUT1,BI1,EE1,FC1,HM1,PI1,PR1,TC1)	0.14096 5
coincidence(AUT1,BI1,EE1,FC1,PI1,PR1,SI1,TC1)	0.16503 2
coincidence(AUT1,BI1,EE1,FC1,HM1,PI1,SI1,TC1)	0.14949 1
coincidence(AUT1,BI1,FC1,HM1,PE1,PR1,SI1,TC1)	0.20548 2
coincidence(AUT1,BI1,EE1,PE1,PI1,PR1,SI1,TC1)	0.15719 7

coincidence(AUT1,BI1,EE1,FC1,HM1,PR1,SI1,TC1)	0.18696 5
coincidence(AUT1,BI1,EE1,HM1,PE1,PI1,PR1,SI1)	0.14497 4
coincidence(AUT1,BI1,FC1,PE1,PI1,PR1,SI1,TC1)	0.17898 6
coincidence(AUT1,BI1,EE1,HM1,PE1,PI1,PR1,TC1)	0.14932 3
coincidence(AUT1,BI1,EE1,HM1,PE1,PR1,SI1,TC1)	0.18051 3
coincidence(AUT1,BI1,EE1,FC1,PE1,PI1,PR1,SI1)	0.16390 7
coincidence(AUT1,BI1,EE1,FC1,PE1,PI1,PR1,TC1)	0.15648 3
coincidence(AUT1,BI1,FC1,HM1,PE1,PI1,PR1,SI1)	0.16136 7
coincidence(AUT1,BI1,EE1,FC1,PE1,PI1,SI1,TC1)	0.16590 6
coincidence(AUT1,BI1,FC1,HM1,PE1,PI1,PR1,TC1)	0.15277 9
coincidence(AUT1,BI1,EE1,FC1,PE1,PR1,SI1,TC1)	0.26134 6
coincidence(AUT1,EE1,FC1,HM1,PE1,PI1,PR1,TC1)	0.13947 9
coincidence(AUT1,EE1,FC1,HM1,PE1,PI1,SI1,TC1)	0.14830 9
coincidence(AUT1,EE1,FC1,HM1,PE1,PR1,SI1,TC1)	0.18571 9
coincidence(AUT1,EE1,FC1,HM1,PI1,PR1,SI1,TC1)	0.14794 6

coincidence(AUT1,FC1,HM1,PE1,PI1,PR1,SI1,TC1)	0.157991
coincidence(AUT1,EE1,FC1,PE1,PI1,PR1,SI1,TC1)	0.161918
coincidence(BI1,EE1,FC1,HM1,PE1,PI1,SI1,TC1)	0.147951
coincidence(BI1,EE1,FC1,PE1,PI1,PR1,SI1,TC1)	0.160769
coincidence(BI1,EE1,FC1,HM1,PE1,PI1,PR1,TC1)	0.138559
coincidence(BI1,EE1,FC1,HM1,PE1,PR1,SI1,TC1)	0.18566
coincidence(BI1,FC1,HM1,PE1,PI1,PR1,SI1,TC1)	0.163439
coincidence(BI1,EE1,HM1,PE1,PI1,PR1,SI1,TC1)	0.139683
coincidence(BI1,EE1,FC1,HM1,PE1,PI1,PR1,SI1)	0.145431
coincidence(BI1,EE1,FC1,HM1,PI1,PR1,SI1,TC1)	0.145336
coincidence(EE1,FC1,HM1,PE1,PI1,PR1,SI1,TC1)	0.146005
coincidence(AUT1,BI1,EE1,FC1,HM1,PI1,TC1)	0.150229
coincidence(AUT1,BI1,EE1,FC1,HM1,PR1,SI1)	0.197434
coincidence(AUT1,BI1,EE1,FC1,HM1,PR1,TC1)	0.18873
coincidence(AUT1,BI1,EE1,FC1,HM1,SI1,TC1)	0.200666
coincidence(AUT1,EE1,HM1,PE1,PR1,SI1,TC1)	0.188263
coincidence(AUT1,BI1,FC1,PE1,PI1,PR1,SI1)	0.19013

coincidence(AUT1,BI1,EE1,FC1,PE1,PI1,PR1)	0.165271
coincidence(AUT1,BI1,EE1,FC1,PE1,PI1,SI1)	0.174887
coincidence(AUT1,BI1,EE1,FC1,PE1,PI1,TC1)	0.167363
coincidence(AUT1,BI1,EE1,FC1,PE1,PR1,SI1)	0.280767
coincidence(AUT1,BI1,EE1,FC1,PE1,PR1,TC1)	0.268276
coincidence(AUT1,BI1,HM1,PI1,PR1,SI1,TC1)	0.178371
coincidence(AUT1,BI1,EE1,FC1,PE1,SI1,TC1)	0.285951
coincidence(AUT1,BI1,EE1,FC1,PI1,PR1,SI1)	0.174467
coincidence(AUT1,BI1,EE1,FC1,PI1,PR1,TC1)	0.166425
coincidence(AUT1,BI1,EE1,FC1,PI1,SI1,TC1)	0.176283
coincidence(AUT1,BI1,HM1,PE1,PR1,SI1,TC1)	0.20962
coincidence(AUT1,BI1,FC1,HM1,PE1,PI1,PR1)	0.162141
coincidence(AUT1,BI1,EE1,FC1,PR1,SI1,TC1)	0.276111
coincidence(AUT1,FC1,HM1,PI1,PR1,SI1,TC1)	0.169302
coincidence(AUT1,BI1,PE1,PI1,PR1,SI1,TC1)	0.18239
coincidence(AUT1,BI1,FC1,HM1,PE1,PI1,SI1)	0.171906

coincidence(AUT1,BI1,EE1,HM1,PE1,PI1,PR1)	0.16304 7
coincidence(AUT1,BI1,EE1,HM1,PE1,PI1,SI1)	0.15450 7
coincidence(AUT1,BI1,EE1,HM1,PE1,PI1,TC1)	0.15973 7
coincidence(AUT1,BI1,EE1,HM1,PE1,PR1,SI1)	0.19319 6
coincidence(AUT1,BI1,EE1,HM1,PE1,PR1,TC1)	0.20150 6
coincidence(AUT1,BI1,FC1,HM1,PE1,PI1,TC1)	0.16306 5
coincidence(AUT1,BI1,EE1,HM1,PE1,SI1,TC1)	0.19383 7
coincidence(AUT1,BI1,FC1,PE1,PI1,PR1,TC1)	0.18047 3
coincidence(AUT1,BI1,FC1,HM1,PE1,PR1,SI1)	0.21985 9
coincidence(AUT1,BI1,EE1,HM1,PI1,PR1,SI1)	0.16464 6
coincidence(AUT1,BI1,EE1,HM1,PI1,PR1,TC1)	0.21216 2
coincidence(AUT1,BI1,FC1,HM1,PE1,PR1,TC1)	0.20733 5
coincidence(AUT1,BI1,EE1,HM1,PI1,SI1,TC1)	0.15827 1
coincidence(AUT1,BI1,FC1,HM1,PE1,SI1,TC1)	0.22180 4
coincidence(AUT1,BI1,HM1,PE1,PI1,PR1,TC1)	0.1729
coincidence(AUT1,BI1,EE1,HM1,PR1,SI1,TC1)	0.19502 8

coincidence(AUT1,BI1,FC1,PE1,PI1,SI1,TC1)	0.191699
coincidence(AUT1,EE1,HM1,PI1,PR1,SI1,TC1)	0.156853
coincidence(AUT1,BI1,FC1,PI1,PR1,SI1,TC1)	0.191163
coincidence(AUT1,BI1,FC1,HM1,PI1,PR1,SI1)	0.170453
coincidence(AUT1,BI1,FC1,HM1,PI1,PR1,TC1)	0.161684
coincidence(AUT1,BI1,EE1,PE1,PI1,PR1,SI1)	0.168222
coincidence(AUT1,BI1,EE1,PE1,PI1,PR1,TC1)	0.172206
coincidence(AUT1,BI1,EE1,PE1,PI1,SI1,TC1)	0.168054
coincidence(AUT1,BI1,FC1,HM1,PI1,SI1,TC1)	0.171957
coincidence(AUT1,BI1,FC1,PE1,PR1,SI1,TC1)	0.313933
coincidence(AUT1,BI1,HM1,PE1,PI1,PR1,SI1)	0.169938
coincidence(AUT1,BI1,FC1,HM1,PR1,SI1,TC1)	0.21672
coincidence(AUT1,EE1,PE1,PI1,PR1,SI1,TC1)	0.164432
coincidence(AUT1,BI1,HM1,PE1,PI1,SI1,TC1)	0.166061
coincidence(AUT1,BI1,EE1,PI1,PR1,SI1,TC1)	0.172541
coincidence(AUT1,EE1,FC1,HM1,PE1,PI1,PR1)	0.148847

coincidence(AUT1,BI1,EE1,PE1,PR1,SI1,TC1)	0.26332
coincidence(AUT1,EE1,FC1,HM1,PE1,PI1,SI1)	0.157914
coincidence(AUT1,FC1,PE1,PI1,PR1,SI1,TC1)	0.186491
coincidence(AUT1,EE1,FC1,HM1,PE1,PI1,TC1)	0.149038
coincidence(AUT1,EE1,FC1,HM1,PE1,PR1,SI1)	0.198376
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PI1)	0.150412
coincidence(AUT1,EE1,FC1,HM1,PE1,PR1,TC1)	0.187349
coincidence(AUT1,EE1,FC1,HM1,PE1,SI1,TC1)	0.20057
coincidence(AUT1,FC1,HM1,PE1,PI1,PR1,SI1)	0.170479
coincidence(AUT1,EE1,FC1,HM1,PI1,PR1,SI1)	0.158274
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,PR1)	0.190505
coincidence(AUT1,EE1,FC1,HM1,PI1,PR1,TC1)	0.14863
coincidence(AUT1,EE1,FC1,HM1,PI1,SI1,TC1)	0.157918
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,SI1)	0.203504
coincidence(AUT1,EE1,FC1,HM1,PR1,SI1,TC1)	0.196606
coincidence(AUT1,FC1,HM1,PE1,PI1,PR1,TC1)	0.158728
coincidence(AUT1,FC1,HM1,PE1,PI1,SI1,TC1)	0.169311

coincidence(AUT1,EE1,FC1,PE1,PI1,PR1,SI1)	0.173137
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1,TC1)	0.193522
coincidence(AUT1,EE1,FC1,PE1,PI1,PR1,TC1)	0.163202
coincidence(AUT1,EE1,FC1,PE1,PI1,SI1,TC1)	0.173962
coincidence(AUT1,EE1,FC1,PE1,PR1,SI1,TC1)	0.277837
coincidence(AUT1,FC1,HM1,PE1,PR1,SI1,TC1)	0.213815
coincidence(AUT1,EE1,FC1,PI1,PR1,SI1,TC1)	0.174
coincidence(AUT1,HM1,PE1,PI1,PR1,SI1,TC1)	0.161958
coincidence(AUT1,EE1,HM1,PE1,PI1,PR1,SI1)	0.153983
coincidence(AUT1,BI1,EE1,FC1,HM1,PI1,PR1)	0.148384
coincidence(AUT1,EE1,HM1,PE1,PI1,PR1,TC1)	0.155893
coincidence(AUT1,EE1,HM1,PE1,PI1,SI1,TC1)	0.151311
coincidence(AUT1,BI1,EE1,FC1,HM1,PI1,SI1)	0.157127
coincidence(BI1,EE1,FC1,HM1,PE1,PI1,PR1)	0.146295
coincidence(BI1,EE1,FC1,HM1,PE1,SI1,TC1)	0.200444
coincidence(BI1,FC1,HM1,PE1,PI1,SI1,TC1)	0.176562

coincidence(BI1,EE1,FC1,HM1,PE1,PR1,TC1)	0.18799 5
coincidence(BI1,EE1,HM1,PE1,PI1,SI1,TC1)	0.15008 3
coincidence(BI1,EE1,PE1,PI1,PR1,SI1,TC1)	0.16270 6
coincidence(BI1,EE1,HM1,PE1,PI1,PR1,TC1)	0.15411
coincidence(BI1,EE1,FC1,PE1,PI1,PR1,SI1)	0.16985 7
coincidence(BI1,FC1,PE1,PI1,PR1,SI1,TC1)	0.19350 3
coincidence(BI1,EE1,FC1,PI1,PR1,SI1,TC1)	0.17128 5
coincidence(BI1,EE1,HM1,PE1,PI1,PR1,SI1)	0.14972 8
coincidence(BI1,EE1,FC1,HM1,PE1,PI1,SI1)	0.15588 4
coincidence(BI1,EE1,FC1,HM1,PI1,PR1,TC1)	0.14619 5
coincidence(BI1,FC1,HM1,PE1,PI1,PR1,TC1)	0.16441 4
coincidence(BI1,FC1,HM1,PE1,PI1,PR1,SI1)	0.17384 8
coincidence(BI1,FC1,HM1,PI1,PR1,SI1,TC1)	0.17352 5
coincidence(BI1,EE1,FC1,HM1,PI1,PR1,SI1)	0.15315
coincidence(BI1,EE1,FC1,HM1,PR1,SI1,TC1)	0.19496 3
coincidence(BI1,EE1,FC1,PE1,PI1,PR1,TC1)	0.16255
coincidence(BI1,EE1,FC1,PE1,PR1,SI1,TC1)	0.27297 6

coincidence(BI1,EE1,FC1,HM1,PE1,PR1,SI1)	0.19720 8
coincidence(BI1,EE1,FC1,PE1,PI1,SI1,TC1)	0.17302 3
coincidence(BI1,EE1,FC1,HM1,PE1,PI1,TC1)	0.14900 3
coincidence(BI1,EE1,HM1,PE1,PR1,SI1,TC1)	0.18762 5
coincidence(BI1,FC1,HM1,PE1,PR1,SI1,TC1)	0.22055 9
coincidence(BI1,EE1,HM1,PI1,PR1,SI1,TC1)	0.15262 9
coincidence(BI1,HM1,PE1,PI1,PR1,SI1,TC1)	0.16681 7
coincidence(EE1,FC1,HM1,PE1,PI1,PR1,SI1)	0.15578 4
coincidence(BI1,EE1,FC1,HM1,PI1,SI1,TC1)	0.15600 1
coincidence(EE1,FC1,HM1,PE1,PI1,PR1,TC1)	0.14686 2
coincidence(EE1,FC1,HM1,PE1,PI1,SI1,TC1)	0.15699 9
coincidence(EE1,FC1,HM1,PE1,PR1,SI1,TC1)	0.19594 4
coincidence(EE1,FC1,HM1,PI1,PR1,SI1,TC1)	0.15588 6
coincidence(EE1,FC1,PE1,PI1,PR1,SI1,TC1)	0.17099 8
coincidence(EE1,HM1,PE1,PI1,PR1,SI1,TC1)	0.14850 8

coincidence(FC1,HM1,PE1,PI1,PR1,SI1,TC1)	0.17291 3
coincidence(AUT1,BI1,FC1,HM1,PR1,TC1)	0.21886 1
coincidence(AUT1,BI1,FC1,HM1,SI1,TC1)	0.23430 8
coincidence(AUT1,EE1,PE1,PI1,PR1,TC1)	0.18010 7
coincidence(AUT1,HM1,PE1,PR1,SI1,TC1)	0.21856 9
coincidence(AUT1,BI1,FC1,PE1,PI1,PR1)	0.19182 7
coincidence(AUT1,BI1,FC1,PE1,PI1,SI1)	0.20349 1
coincidence(AUT1,BI1,FC1,PE1,PI1,TC1)	0.19347 9
coincidence(AUT1,EE1,PE1,PI1,SI1,TC1)	0.17700 3
coincidence(AUT1,BI1,FC1,PE1,PR1,SI1)	0.34400 3
coincidence(AUT1,BI1,FC1,PE1,PR1,TC1)	0.32365 4
coincidence(AUT1,BI1,FC1,PE1,SI1,TC1)	0.34492 3
coincidence(AUT1,BI1,FC1,PI1,PR1,SI1)	0.20332 9
coincidence(AUT1,BI1,FC1,PI1,PR1,TC1)	0.19287 7
coincidence(AUT1,EE1,PE1,PR1,SI1,TC1)	0.28040 4

coincidence(AUT1,BI1,FC1,PI1,SI1,TC1)	0.20503 2
coincidence(AUT1,BI1,FC1,PR1,SI1,TC1)	0.33382 1
coincidence(AUT1,PE1,PI1,PR1,SI1,TC1)	0.19050 3
coincidence(AUT1,BI1,FC1,HM1,PE1,SI1)	0.23833
coincidence(AUT1,BI1,HM1,PE1,PI1,PR1)	0.19245 5
coincidence(AUT1,BI1,HM1,PE1,PI1,SI1)	0.18230 7
coincidence(AUT1,BI1,HM1,PE1,PI1,TC1)	0.18557 8
coincidence(AUT1,BI1,HM1,PE1,PR1,SI1)	0.23066 1
coincidence(AUT1,BI1,HM1,PE1,PR1,TC1)	0.23538 3
coincidence(AUT1,BI1,HM1,PE1,SI1,TC1)	0.22642
coincidence(AUT1,EE1,PI1,PR1,SI1,TC1)	0.18318 7
coincidence(AUT1,HM1,PE1,PI1,SI1,TC1)	0.17403 3
coincidence(AUT1,BI1,HM1,PI1,PR1,SI1)	0.21489 3
coincidence(AUT1,BI1,HM1,PI1,PR1,TC1)	0.26754 5
coincidence(AUT1,BI1,HM1,PI1,SI1,TC1)	0.19319 8
coincidence(AUT1,FC1,PE1,PI1,PR1,SI1)	0.20167
coincidence(AUT1,BI1,HM1,PR1,SI1,TC1)	0.23709 5

coincidence(AUT1,BI1,PE1,PI1,PR1,SI1)	0.1988
coincidence(AUT1,BI1,PE1,PI1,PR1,TC1)	0.201279
coincidence(AUT1,BI1,PE1,PI1,SI1,TC1)	0.195563
coincidence(AUT1,BI1,PE1,PR1,SI1,TC1)	0.318122
coincidence(AUT1,EE1,HM1,PE1,PR1,SI1)	0.204289
coincidence(AUT1,BI1,EE1,FC1,HM1,PE1)	0.205658
coincidence(AUT1,BI1,PI1,PR1,SI1,TC1)	0.209018
coincidence(AUT1,BI1,EE1,FC1,HM1,PI1)	0.157925
coincidence(AUT1,BI1,EE1,FC1,HM1,PR1)	0.199329
coincidence(AUT1,BI1,EE1,FC1,HM1,SI1)	0.21274
coincidence(AUT1,BI1,EE1,FC1,HM1,TC1)	0.202776
coincidence(AUT1,BI1,EE1,FC1,PE1,PI1)	0.176508
coincidence(AUT1,FC1,PE1,PI1,PR1,TC1)	0.188059
coincidence(AUT1,BI1,EE1,FC1,PE1,PR1)	0.288722
coincidence(AUT1,BI1,EE1,FC1,PE1,SI1)	0.307746
coincidence(AUT1,BI1,EE1,FC1,PE1,TC1)	0.294898
coincidence(AUT1,FC1,HM1,PE1,PI1,PR1)	0.17131

coincidence(AUT1,EE1,FC1,HM1,PE1,PI1)	0.158713
coincidence(AUT1,EE1,HM1,PE1,PR1,TC1)	0.209987
coincidence(AUT1,BI1,EE1,FC1,PI1,PR1)	0.176024
coincidence(AUT1,BI1,EE1,FC1,PI1,SI1)	0.186107
coincidence(AUT1,BI1,EE1,FC1,PI1,TC1)	0.177943
coincidence(AUT1,FC1,HM1,PI1,PR1,SI1)	0.183069
coincidence(AUT1,BI1,EE1,FC1,PR1,SI1)	0.29684
coincidence(AUT1,BI1,EE1,FC1,PR1,TC1)	0.284249
coincidence(AUT1,EE1,FC1,HM1,PE1,PR1)	0.200147
coincidence(AUT1,EE1,HM1,PE1,SI1,TC1)	0.203633
coincidence(AUT1,BI1,EE1,FC1,SI1,TC1)	0.304384
coincidence(AUT1,BI1,EE1,HM1,PE1,PI1)	0.17437
coincidence(AUT1,EE1,FC1,HM1,PE1,SI1)	0.215348
coincidence(AUT1,BI1,EE1,HM1,PE1,PR1)	0.220053
coincidence(AUT1,EE1,FC1,HM1,PE1,TC1)	0.202545
coincidence(AUT1,BI1,EE1,HM1,PE1,SI1)	0.208423

coincidence(AUT1,EE1,FC1,HM1,PI1,PR1)	0.159027
coincidence(AUT1,BI1,EE1,HM1,PE1,TC1)	0.216793
coincidence(AUT1,FC1,HM1,PI1,PR1,TC1)	0.170113
coincidence(AUT1,BI1,EE1,HM1,PI1,PR1)	0.252903
coincidence(AUT1,EE1,FC1,HM1,PI1,SI1)	0.168602
coincidence(AUT1,BI1,EE1,HM1,PI1,SI1)	0.177552
coincidence(AUT1,EE1,FC1,HM1,PI1,TC1)	0.158713
coincidence(AUT1,BI1,EE1,HM1,PI1,TC1)	0.231146
coincidence(AUT1,EE1,FC1,HM1,PR1,SI1)	0.210517
coincidence(AUT1,EE1,HM1,PI1,PR1,SI1)	0.184096
coincidence(AUT1,EE1,FC1,HM1,PR1,TC1)	0.198492
coincidence(AUT1,BI1,EE1,HM1,PR1,SI1)	0.216252
coincidence(AUT1,BI1,EE1,HM1,PR1,TC1)	0.280069
coincidence(AUT1,FC1,HM1,PE1,PI1,SI1)	0.182313
coincidence(AUT1,BI1,EE1,HM1,SI1,TC1)	0.210472

coincidence(AUT1,EE1,HM1,PI1,PR1,TC1)	0.22419 1
coincidence(AUT1,EE1,FC1,PE1,PI1,PR1)	0.17459 2
coincidence(AUT1,HM1,PE1,PI1,PR1,SI1)	0.18228 2
coincidence(AUT1,BI1,EE1,PE1,PI1,PR1)	0.18758 7
coincidence(AUT1,BI1,EE1,PE1,PI1,SI1)	0.17978
coincidence(AUT1,EE1,FC1,PE1,PI1,SI1)	0.18569
coincidence(AUT1,BI1,EE1,PE1,PI1,TC1)	0.18482 4
coincidence(AUT1,EE1,FC1,PE1,PI1,TC1)	0.17551 2
coincidence(AUT1,FC1,HM1,PE1,PI1,TC1)	0.17017 1
coincidence(AUT1,EE1,FC1,PE1,PR1,SI1)	0.30151 1
coincidence(AUT1,EE1,HM1,PI1,SI1,TC1)	0.16872 7
coincidence(AUT1,EE1,FC1,PE1,PR1,TC1)	0.28548 5
coincidence(AUT1,HM1,PE1,PI1,PR1,TC1)	0.18133 9
coincidence(AUT1,EE1,FC1,PE1,SI1,TC1)	0.31121
coincidence(AUT1,FC1,HM1,PE1,PR1,SI1)	0.23190 4
coincidence(AUT1,BI1,EE1,PE1,PR1,SI1)	0.28515 4
coincidence(AUT1,EE1,FC1,PI1,PR1,SI1)	0.18805 4

coincidence(AUT1,FC1,HM1,PI1,SI1,TC1)	0.18162 1
coincidence(AUT1,EE1,FC1,PI1,PR1,TC1)	0.17551 8
coincidence(AUT1,FC1,HM1,PE1,PR1,TC1)	0.21579 5
coincidence(AUT1,EE1,FC1,PI1,SI1,TC1)	0.18691 8
coincidence(AUT1,FC1,PE1,PI1,SI1,TC1)	0.20178 8
coincidence(AUT1,FC1,HM1,PE1,SI1,TC1)	0.23281 7
coincidence(AUT1,EE1,FC1,PR1,SI1,TC1)	0.29713 9
coincidence(AUT1,BI1,EE1,PE1,PR1,TC1)	0.29139 6
coincidence(AUT1,BI1,EE1,PE1,SI1,TC1)	0.28814 9
coincidence(AUT1,FC1,PE1,PR1,SI1,TC1)	0.33343 3
coincidence(AUT1,EE1,HM1,PR1,SI1,TC1)	0.20636 2
coincidence(AUT1,HM1,PI1,PR1,SI1,TC1)	0.18956 7
coincidence(AUT1,EE1,HM1,PE1,PI1,PR1)	0.17330 5
coincidence(AUT1,BI1,EE1,PI1,PR1,SI1)	0.19185 1
coincidence(AUT1,BI1,EE1,PI1,PR1,TC1)	0.24211 9

coincidence(AUT1,BI1,EE1,PI1,SI1,TC1)	0.185375
coincidence(AUT1,EE1,HM1,PE1,PI1,SI1)	0.164637
coincidence(AUT1,FC1,PI1,PR1,SI1,TC1)	0.201278
coincidence(AUT1,EE1,HM1,PE1,PI1,TC1)	0.167473
coincidence(AUT1,EE1,FC1,HM1,SI1,TC1)	0.212198
coincidence(AUT1,BI1,EE1,PR1,SI1,TC1)	0.284451
coincidence(AUT1,BI1,FC1,HM1,PE1,PI1)	0.172801
coincidence(AUT1,BI1,FC1,HM1,PE1,PR1)	0.221899
coincidence(AUT1,BI1,FC1,HM1,PE1,TC1)	0.224049
coincidence(AUT1,FC1,HM1,PR1,SI1,TC1)	0.22886
coincidence(AUT1,BI1,FC1,HM1,PI1,PR1)	0.171292
coincidence(AUT1,BI1,FC1,HM1,PI1,SI1)	0.181921
coincidence(AUT1,BI1,FC1,HM1,PI1,TC1)	0.172839
coincidence(AUT1,EE1,PE1,PI1,PR1,SI1)	0.179005
coincidence(AUT1,BI1,FC1,HM1,PR1,SI1)	0.23157
coincidence(BI1,EE1,FC1,PE1,PI1,SI1)	0.182522

coincidence(BI1,EE1,FC1,HM1,PR1,SI1)	0.206741
coincidence(BI1,FC1,HM1,PE1,SI1,TC1)	0.240405
coincidence(BI1,FC1,HM1,PE1,PI1,SI1)	0.187453
coincidence(BI1,FC1,HM1,PI1,PR1,SI1)	0.184215
coincidence(BI1,EE1,FC1,PE1,SI1,TC1)	0.30149
coincidence(BI1,EE1,PI1,PR1,SI1,TC1)	0.178841
coincidence(BI1,EE1,FC1,HM1,PI1,PR1)	0.154077
coincidence(BI1,EE1,HM1,PE1,SI1,TC1)	0.202622
coincidence(BI1,EE1,FC1,HM1,PE1,TC1)	0.203723
coincidence(BI1,FC1,HM1,PE1,PI1,PR1)	0.174923
coincidence(BI1,EE1,FC1,PE1,PI1,PR1)	0.171872
coincidence(BI1,EE1,HM1,PE1,PR1,TC1)	0.20984
coincidence(BI1,EE1,FC1,PE1,PR1,TC1)	0.284666
coincidence(BI1,EE1,FC1,HM1,PE1,SI1)	0.213651
coincidence(BI1,EE1,PE1,PR1,SI1,TC1)	0.274956
coincidence(BI1,EE1,HM1,PE1,PR1,SI1)	0.201581

coincidence(BI1,EE1,HM1,PE1,PI1,TC1)	0.16637 3
coincidence(BI1,EE1,PE1,PI1,PR1,TC1)	0.17866 9
coincidence(BI1,EE1,FC1,PE1,PR1,SI1)	0.29391 6
coincidence(BI1,EE1,FC1,PE1,PI1,TC1)	0.17577 6
coincidence(BI1,EE1,FC1,HM1,PE1,PI1)	0.15701 6
coincidence(BI1,FC1,HM1,PE1,PI1,TC1)	0.17785 9
coincidence(BI1,EE1,FC1,HM1,PI1,TC1)	0.15713 2
coincidence(BI1,EE1,FC1,HM1,PI1,SI1)	0.16410 8
coincidence(BI1,EE1,HM1,PE1,PI1,SI1)	0.16091 2
coincidence(BI1,EE1,FC1,HM1,PR1,TC1)	0.19758 3
coincidence(BI1,EE1,PE1,PI1,SI1,TC1)	0.17517 8
coincidence(BI1,EE1,PE1,PI1,PR1,SI1)	0.17418 4
coincidence(BI1,EE1,HM1,PR1,SI1,TC1)	0.20308 1
coincidence(BI1,EE1,FC1,PI1,PR1,SI1)	0.18118 5
coincidence(BI1,FC1,HM1,PI1,PR1,TC1)	0.17458 5

coincidence(BI1,FC1,HM1,PI1,SI1,TC1)	0.187812
coincidence(BI1,FC1,HM1,PR1,SI1,TC1)	0.233342
coincidence(BI1,FC1,PE1,PI1,PR1,SI1)	0.205953
coincidence(BI1,EE1,FC1,HM1,SI1,TC1)	0.21041
coincidence(BI1,FC1,PE1,PI1,PR1,TC1)	0.19581
coincidence(BI1,FC1,PE1,PI1,SI1,TC1)	0.209472
coincidence(BI1,FC1,PE1,PR1,SI1,TC1)	0.337014
coincidence(BI1,FC1,PI1,PR1,SI1,TC1)	0.207028
coincidence(BI1,HM1,PE1,PI1,PR1,SI1)	0.182449
coincidence(BI1,EE1,HM1,PE1,PI1,PR1)	0.168345
coincidence(BI1,HM1,PE1,PI1,PR1,TC1)	0.185002
coincidence(BI1,HM1,PE1,PI1,SI1,TC1)	0.180383
coincidence(BI1,HM1,PE1,PR1,SI1,TC1)	0.224712
coincidence(BI1,HM1,PI1,PR1,SI1,TC1)	0.191356
coincidence(BI1,PE1,PI1,PR1,SI1,TC1)	0.196919
coincidence(EE1,FC1,HM1,PE1,PI1,PR1)	0.156721

coincidence(BI1,EE1,FC1,PR1,SI1,TC1)	0.288855
coincidence(BI1,FC1,HM1,PE1,PR1,SI1)	0.23731
coincidence(BI1,EE1,FC1,PI1,SI1,TC1)	0.18421
coincidence(EE1,FC1,HM1,PE1,PI1,SI1)	0.167181
coincidence(BI1,EE1,FC1,PI1,PR1,TC1)	0.173395
coincidence(EE1,FC1,HM1,PE1,PI1,TC1)	0.158131
coincidence(EE1,FC1,HM1,PE1,PR1,SI1)	0.209934
coincidence(BI1,EE1,HM1,PI1,SI1,TC1)	0.164837
coincidence(EE1,FC1,HM1,PE1,PR1,TC1)	0.198438
coincidence(EE1,FC1,HM1,PE1,SI1,TC1)	0.214489
coincidence(EE1,FC1,HM1,PI1,PR1,SI1)	0.166715
coincidence(BI1,EE1,FC1,HM1,PE1,PR1)	0.199724
coincidence(EE1,FC1,HM1,PI1,PR1,TC1)	0.15682
coincidence(EE1,FC1,HM1,PI1,SI1,TC1)	0.167456
coincidence(EE1,FC1,HM1,PR1,SI1,TC1)	0.207838
coincidence(EE1,FC1,PE1,PI1,PR1,SI1)	0.182905
coincidence(BI1,EE1,HM1,PI1,PR1,TC1)	0.218934

coincidence(EE1,FC1,PE1,PI1,PR1,TC1)	0.17296 8
coincidence(EE1,FC1,PE1,PI1,SI1,TC1)	0.18815 9
coincidence(EE1,FC1,PE1,PR1,SI1,TC1)	0.29709 9
coincidence(EE1,FC1,PI1,PR1,SI1,TC1)	0.18408 9
coincidence(EE1,HM1,PE1,PI1,PR1,SI1)	0.16187 4
coincidence(BI1,FC1,HM1,PE1,PR1,TC1)	0.22343 4
coincidence(EE1,HM1,PE1,PI1,PR1,TC1)	0.16363 7
coincidence(EE1,HM1,PE1,PI1,SI1,TC1)	0.16016 5
coincidence(EE1,HM1,PE1,PR1,SI1,TC1)	0.19849 6
coincidence(EE1,HM1,PI1,PR1,SI1,TC1)	0.16507 7
coincidence(EE1,PE1,PI1,PR1,SI1,TC1)	0.17352
coincidence(FC1,HM1,PE1,PI1,PR1,SI1)	0.18705 8
coincidence(BI1,EE1,HM1,PI1,PR1,SI1)	0.17018 6
coincidence(FC1,HM1,PE1,PI1,PR1,TC1)	0.17395 9
coincidence(FC1,HM1,PE1,PI1,SI1,TC1)	0.18763 4
coincidence(FC1,HM1,PE1,PR1,SI1,TC1)	0.23293 5

coincidence(FC1,HM1,PI1,PR1,SI1,TC1)	0.186
coincidence(FC1,PE1,PI1,PR1,SI1,TC1)	0.209207
coincidence(HM1,PE1,PI1,PR1,SI1,TC1)	0.176895
coincidence(AUT1,BI1,PI1,PR1,TC1)	0.306536
coincidence(AUT1,BI1,PI1,SI1,TC1)	0.226825
coincidence(AUT1,BI1,PR1,SI1,TC1)	0.354684
coincidence(AUT1,EE1,FC1,HM1,PE1)	0.217668
coincidence(AUT1,EE1,FC1,HM1,PI1)	0.169475
coincidence(AUT1,EE1,FC1,HM1,PR1)	0.212573
coincidence(AUT1,EE1,FC1,HM1,SI1)	0.228352
coincidence(AUT1,EE1,FC1,HM1,TC1)	0.214475
coincidence(AUT1,EE1,FC1,PE1,PI1)	0.187438
coincidence(AUT1,EE1,FC1,PE1,PR1)	0.310364
coincidence(AUT1,EE1,FC1,PE1,SI1)	0.340031
coincidence(AUT1,EE1,FC1,PE1,TC1)	0.321556
coincidence(AUT1,EE1,FC1,PI1,PR1)	0.189787

coincidence(AUT1,EE1,FC1,PI1,SI1)	0.201666
coincidence(AUT1,EE1,FC1,PI1,TC1)	0.18874
coincidence(AUT1,EE1,FC1,PR1,SI1)	0.32454
coincidence(AUT1,EE1,FC1,PR1,TC1)	0.306341
coincidence(AUT1,EE1,FC1,SI1,TC1)	0.335175
coincidence(AUT1,EE1,HM1,PE1,PI1)	0.185942
coincidence(AUT1,EE1,HM1,PE1,SI1)	0.222188
coincidence(AUT1,EE1,HM1,PE1,TC1)	0.227573
coincidence(AUT1,EE1,HM1,PI1,PR1)	0.281206
coincidence(AUT1,EE1,HM1,PI1,SI1)	0.202225
coincidence(AUT1,EE1,HM1,PI1,TC1)	0.246713
coincidence(AUT1,EE1,HM1,PR1,SI1)	0.238906
coincidence(AUT1,EE1,HM1,PR1,TC1)	0.294715
coincidence(AUT1,EE1,HM1,SI1,TC1)	0.224096
coincidence(AUT1,EE1,PE1,PI1,PR1)	0.199734
coincidence(AUT1,EE1,PE1,PI1,SI1)	0.192503

coincidence(AUT1,EE1,PE1,PI1,TC1)	0.194711
coincidence(AUT1,EE1,PE1,PR1,SI1)	0.307479
coincidence(AUT1,EE1,PE1,PR1,TC1)	0.31009
coincidence(AUT1,EE1,PE1,SI1,TC1)	0.314342
coincidence(AUT1,EE1,PI1,PR1,SI1)	0.214381
coincidence(AUT1,EE1,PI1,PR1,TC1)	0.25639
coincidence(AUT1,EE1,PI1,SI1,TC1)	0.198088
coincidence(AUT1,EE1,PR1,SI1,TC1)	0.307204
coincidence(AUT1,FC1,HM1,PE1,PI1)	0.18328
coincidence(AUT1,FC1,HM1,PE1,PR1)	0.234117
coincidence(AUT1,FC1,HM1,PE1,SI1)	0.254152
coincidence(AUT1,FC1,HM1,PE1,TC1)	0.235245
coincidence(AUT1,FC1,HM1,PI1,PR1)	0.183987
coincidence(AUT1,FC1,HM1,PI1,SI1)	0.196026
coincidence(AUT1,FC1,HM1,PI1,TC1)	0.182571
coincidence(AUT1,FC1,HM1,PR1,SI1)	0.248827
coincidence(AUT1,FC1,HM1,PR1,TC1)	0.231187

coincidence(AUT1,FC1,HM1,SI1,TC1)	0.24944 8
coincidence(AUT1,FC1,PE1,PI1,PR1)	0.20349 3
coincidence(AUT1,FC1,PE1,PI1,SI1)	0.21821 6
coincidence(AUT1,FC1,PE1,PI1,TC1)	0.20369 3
coincidence(AUT1,FC1,PE1,PR1,SI1)	0.37139 1
coincidence(AUT1,FC1,PE1,PR1,TC1)	0.34421 2
coincidence(AUT1,FC1,PE1,SI1,TC1)	0.37804 5
coincidence(AUT1,FC1,PI1,PR1,SI1)	0.21973 5
coincidence(AUT1,FC1,PI1,PR1,TC1)	0.20314 5
coincidence(AUT1,FC1,PI1,SI1,TC1)	0.21810 6
coincidence(AUT1,EE1,HM1,PE1,PR1)	0.23259 3
coincidence(AUT1,FC1,PR1,SI1,TC1)	0.36072 8
coincidence(AUT1,HM1,PE1,PI1,PR1)	0.20874 2
coincidence(AUT1,HM1,PE1,PI1,SI1)	0.19696 7
coincidence(AUT1,HM1,PE1,PI1,TC1)	0.19584 6

coincidence(AUT1,HM1,PE1,PR1,SI1)	0.247445
coincidence(AUT1,HM1,PE1,PR1,TC1)	0.246696
coincidence(AUT1,HM1,PE1,SI1,TC1)	0.238386
coincidence(AUT1,HM1,PI1,PR1,SI1)	0.25341
coincidence(AUT1,HM1,PI1,PR1,TC1)	0.283594
coincidence(AUT1,HM1,PI1,SI1,TC1)	0.207586
coincidence(AUT1,HM1,PR1,SI1,TC1)	0.252447
coincidence(AUT1,PE1,PI1,PR1,SI1)	0.213615
coincidence(AUT1,PE1,PI1,PR1,TC1)	0.211452
coincidence(AUT1,PE1,PI1,SI1,TC1)	0.206594
coincidence(AUT1,PE1,PR1,SI1,TC1)	0.338255
coincidence(AUT1,PI1,PR1,SI1,TC1)	0.222216
coincidence(AUT1,BI1,EE1,FC1,HM1)	0.215176
coincidence(AUT1,BI1,EE1,FC1,PE1)	0.318273
coincidence(AUT1,BI1,EE1,FC1,PI1)	0.187952
coincidence(AUT1,BI1,EE1,FC1,PR1)	0.30614

coincidence(AUT1,BI1,EE1,FC1,SI1)	0.32766 4
coincidence(AUT1,BI1,EE1,FC1,TC1)	0.31511 6
coincidence(AUT1,BI1,EE1,HM1,PE1)	0.23801 5
coincidence(AUT1,BI1,EE1,HM1,PI1)	0.27700 9
coincidence(AUT1,BI1,EE1,HM1,PR1)	0.33115 3
coincidence(AUT1,BI1,EE1,HM1,SI1)	0.23528 8
coincidence(AUT1,BI1,EE1,HM1,TC1)	0.30674 8
coincidence(AUT1,BI1,EE1,PE1,PI1)	0.20134 3
coincidence(AUT1,BI1,EE1,PE1,PR1)	0.32068 3
coincidence(AUT1,BI1,HM1,PR1,SI1)	0.28419 8
coincidence(AUT1,BI1,EE1,PE1,SI1)	0.31273
coincidence(AUT1,BI1,EE1,PE1,TC1)	0.32053 9
coincidence(AUT1,BI1,EE1,PI1,PR1)	0.28700 6
coincidence(AUT1,BI1,EE1,PI1,SI1)	0.20707 6
coincidence(AUT1,BI1,EE1,PI1,TC1)	0.26422 3
coincidence(AUT1,BI1,EE1,PR1,SI1)	0.31611 9

coincidence(AUT1,BI1,EE1,PR1,TC1)	0.385546
coincidence(AUT1,BI1,EE1,SI1,TC1)	0.31454
coincidence(AUT1,BI1,FC1,HM1,PE1)	0.240999
coincidence(AUT1,BI1,FC1,HM1,PI1)	0.182895
coincidence(AUT1,BI1,FC1,HM1,PR1)	0.233922
coincidence(AUT1,BI1,FC1,HM1,SI1)	0.252268
coincidence(AUT1,BI1,FC1,HM1,TC1)	0.236903
coincidence(AUT1,BI1,FC1,PE1,PI1)	0.205512
coincidence(AUT1,BI1,FC1,PE1,PR1)	0.355444
coincidence(AUT1,BI1,FC1,PE1,SI1)	0.379733
coincidence(AUT1,BI1,FC1,PE1,TC1)	0.357861
coincidence(AUT1,BI1,FC1,PI1,PR1)	0.205302
coincidence(AUT1,BI1,FC1,PI1,SI1)	0.217974
coincidence(AUT1,BI1,FC1,PI1,TC1)	0.207083
coincidence(AUT1,BI1,FC1,PR1,SI1)	0.366298
coincidence(AUT1,BI1,FC1,PR1,TC1)	0.345319

coincidence(AUT1,BI1,FC1,SI1,TC1)	0.369799
coincidence(AUT1,BI1,HM1,PE1,PI1)	0.207666
coincidence(AUT1,BI1,HM1,PE1,PR1)	0.264326
coincidence(AUT1,BI1,HM1,PE1,SI1)	0.251397
coincidence(AUT1,BI1,HM1,PE1,TC1)	0.255063
coincidence(AUT1,BI1,HM1,PI1,PR1)	0.344218
coincidence(AUT1,BI1,HM1,PI1,SI1)	0.23615
coincidence(AUT1,BI1,HM1,PI1,TC1)	0.295099
coincidence(AUT1,BI1,HM1,PR1,TC1)	0.354152
coincidence(AUT1,BI1,HM1,SI1,TC1)	0.259138
coincidence(AUT1,BI1,PE1,PI1,PR1)	0.223202
coincidence(AUT1,BI1,PE1,PI1,SI1)	0.214059
coincidence(AUT1,BI1,PE1,PI1,TC1)	0.216908
coincidence(AUT1,BI1,PE1,PR1,SI1)	0.354978
coincidence(AUT1,BI1,PE1,PR1,TC1)	0.354447
coincidence(AUT1,BI1,PE1,SI1,TC1)	0.349626

coincidence(AUT1,BI1,PI1,PR1,SI1)	0.24884 6
coincidence(BI1,HM1,PR1,SI1,TC1)	0.25414 3
coincidence(BI1,PE1,PI1,PR1,SI1)	0.21465 5
coincidence(BI1,FC1,PE1,PI1,SI1)	0.22277 1
coincidence(EE1,FC1,HM1,PI1,SI1)	0.17875 7
coincidence(EE1,FC1,HM1,PI1,PR1)	0.16773 9
coincidence(EE1,FC1,HM1,PR1,SI1)	0.22316 6
coincidence(EE1,FC1,HM1,PE1,TC1)	0.21811
coincidence(BI1,EE1,FC1,HM1,PI1)	0.16532 2
coincidence(EE1,FC1,HM1,PR1,TC1)	0.21067
coincidence(EE1,FC1,HM1,SI1,TC1)	0.22727 9
coincidence(EE1,FC1,HM1,PE1,SI1)	0.23156 7
coincidence(EE1,FC1,PE1,PI1,PR1)	0.1852
coincidence(EE1,FC1,PE1,PI1,SI1)	0.20196 5
coincidence(EE1,FC1,PE1,PI1,TC1)	0.19170 3
coincidence(EE1,FC1,PE1,PR1,SI1)	0.32488 3
coincidence(BI1,EE1,FC1,HM1,PR1)	0.20955 9

coincidence(EE1,FC1,PE1,PR1,TC1)	0.31113
coincidence(EE1,FC1,PE1,SI1,TC1)	0.361711
coincidence(EE1,FC1,PI1,PR1,SI1)	0.198882
coincidence(BI1,EE1,FC1,HM1,SI1)	0.223917
coincidence(EE1,FC1,PI1,PR1,TC1)	0.186533
coincidence(BI1,EE1,FC1,HM1,TC1)	0.214058
coincidence(EE1,FC1,PI1,SI1,TC1)	0.203246
coincidence(BI1,EE1,FC1,PE1,PI1)	0.18563
coincidence(EE1,FC1,PR1,SI1,TC1)	0.318378
coincidence(EE1,HM1,PE1,PI1,PR1)	0.181875
coincidence(BI1,FC1,HM1,PI1,SI1)	0.19907
coincidence(EE1,HM1,PE1,PI1,SI1)	0.174665
coincidence(EE1,HM1,PE1,PI1,TC1)	0.177795
coincidence(EE1,HM1,PE1,PR1,SI1)	0.216125
coincidence(EE1,FC1,HM1,PE1,PR1)	0.212645
coincidence(BI1,EE1,FC1,PE1,PR1)	0.307634
coincidence(EE1,HM1,PE1,PR1,TC1)	0.221678

coincidence(EE1,HM1,PE1,SI1,TC1)	0.217825
coincidence(EE1,HM1,PI1,PR1,SI1)	0.194298
coincidence(BI1,EE1,FC1,PE1,SI1)	0.325395
coincidence(EE1,HM1,PI1,PR1,TC1)	0.235491
coincidence(BI1,EE1,FC1,PE1,TC1)	0.322487
coincidence(BI1,FC1,PE1,PI1,TC1)	0.213141
coincidence(BI1,EE1,FC1,PI1,PR1)	0.183562
coincidence(EE1,HM1,PI1,SI1,TC1)	0.178723
coincidence(EE1,HM1,PR1,SI1,TC1)	0.217892
coincidence(EE1,PE1,PI1,PR1,SI1)	0.189043
coincidence(BI1,EE1,FC1,PI1,SI1)	0.194609
coincidence(EE1,PE1,PI1,PR1,TC1)	0.190528
coincidence(BI1,EE1,FC1,PI1,TC1)	0.187659
coincidence(BI1,HM1,PE1,PI1,SI1)	0.198248
coincidence(BI1,EE1,FC1,PR1,SI1)	0.311235

coincidence(EE1,PE1,PR1,SI1,TC1)	0.29967 7
coincidence(BI1,EE1,FC1,PR1,TC1)	0.30256 2
coincidence(BI1,FC1,PE1,PR1,SI1)	0.37112 4
coincidence(BI1,EE1,FC1,SI1,TC1)	0.32163 1
coincidence(EE1,PI1,PR1,SI1,TC1)	0.19356 6
coincidence(BI1,FC1,PE1,PR1,TC1)	0.35469 4
coincidence(BI1,EE1,HM1,PE1,PI1)	0.18194 6
coincidence(FC1,HM1,PE1,PI1,PR1)	0.18823 2
coincidence(BI1,EE1,FC1,HM1,PE1)	0.21740 6
coincidence(FC1,HM1,PE1,PI1,SI1)	0.20301 6
coincidence(FC1,HM1,PE1,PI1,TC1)	0.18903 4
coincidence(FC1,HM1,PE1,PR1,SI1)	0.25405
coincidence(FC1,HM1,PE1,PR1,TC1)	0.23603 7
coincidence(FC1,HM1,PE1,SI1,TC1)	0.25870 6
coincidence(BI1,EE1,HM1,PE1,PR1)	0.22988 3
coincidence(FC1,HM1,PI1,PR1,SI1)	0.20166 8

coincidence(FC1,HM1,PI1,PR1,TC1)	0.187154
coincidence(FC1,HM1,PI1,SI1,TC1)	0.202078
coincidence(BI1,EE1,HM1,PE1,SI1)	0.218774
coincidence(FC1,HM1,PR1,SI1,TC1)	0.250327
coincidence(BI1,EE1,HM1,PE1,TC1)	0.227767
coincidence(FC1,PE1,PI1,PR1,SI1)	0.22773
coincidence(BI1,EE1,HM1,PI1,PR1)	0.261594
coincidence(FC1,PE1,PI1,PR1,TC1)	0.2118
coincidence(EE1,FC1,HM1,PE1,PI1)	0.168412
coincidence(FC1,PE1,PI1,SI1,TC1)	0.23404
coincidence(BI1,EE1,HM1,PI1,SI1)	0.184929
coincidence(FC1,PE1,PR1,SI1,TC1)	0.373366
coincidence(BI1,EE1,HM1,PI1,TC1)	0.240737
coincidence(BI1,FC1,PE1,SI1,TC1)	0.376927
coincidence(BI1,EE1,HM1,PR1,SI1)	0.225691
coincidence(BI1,HM1,PE1,PR1,TC1)	0.252334
coincidence(BI1,EE1,HM1,PR1,TC1)	0.29135

coincidence(BI1,HM1,PE1,PI1,TC1)	0.20112 9
coincidence(BI1,EE1,HM1,SI1,TC1)	0.22029 2
coincidence(BI1,HM1,PI1,PR1,TC1)	0.28542
coincidence(BI1,FC1,PI1,PR1,SI1)	0.22055 3
coincidence(BI1,EE1,PE1,PI1,PR1)	0.19469 7
coincidence(FC1,PI1,PR1,SI1,TC1)	0.22653 1
coincidence(HM1,PE1,PI1,PR1,SI1)	0.19990 3
coincidence(HM1,PE1,PI1,PR1,TC1)	0.19716 9
coincidence(BI1,EE1,PE1,PI1,SI1)	0.18760 8
coincidence(BI1,PI1,PR1,SI1,TC1)	0.22527 7
coincidence(BI1,EE1,PE1,PI1,TC1)	0.19424 5
coincidence(HM1,PE1,PI1,SI1,TC1)	0.19253 3
coincidence(BI1,EE1,PE1,PR1,SI1)	0.29832 3
coincidence(HM1,PE1,PR1,SI1,TC1)	0.23770 9
coincidence(BI1,EE1,PE1,PR1,TC1)	0.30874 4
coincidence(BI1,FC1,PI1,PR1,TC1)	0.20977 5

coincidence(BI1,EE1,PE1,SI1,TC1)	0.303702
coincidence(BI1,HM1,PE1,PR1,SI1)	0.248172
coincidence(BI1,FC1,PI1,SI1,TC1)	0.224499
coincidence(BI1,EE1,PI1,PR1,SI1)	0.198653
coincidence(HM1,PI1,PR1,SI1,TC1)	0.207107
coincidence(BI1,EE1,PI1,PR1,TC1)	0.251261
coincidence(PE1,PI1,PR1,SI1,TC1)	0.213236
coincidence(BI1,EE1,PI1,SI1,TC1)	0.193362
coincidence(EE1,PE1,PI1,SI1,TC1)	0.19137
coincidence(BI1,FC1,PR1,SI1,TC1)	0.358858
coincidence(BI1,EE1,PR1,SI1,TC1)	0.297253
coincidence(BI1,HM1,PI1,PR1,SI1)	0.22962
coincidence(BI1,HM1,PE1,SI1,TC1)	0.245044
coincidence(BI1,FC1,HM1,PE1,PI1)	0.188875
coincidence(BI1,PE1,PR1,SI1,TC1)	0.34122
coincidence(BI1,PE1,PI1,SI1,TC1)	0.213352
coincidence(BI1,FC1,HM1,PE1,PR1)	0.240482

coincidence(BI1,FC1,HM1,PE1,SI1)	0.260071
coincidence(BI1,FC1,HM1,PE1,TC1)	0.244506
coincidence(BI1,HM1,PE1,PI1,PR1)	0.20595
coincidence(BI1,FC1,HM1,PI1,PR1)	0.185382
coincidence(BI1,PE1,PI1,PR1,TC1)	0.217267
coincidence(BI1,FC1,HM1,PI1,TC1)	0.189228
coincidence(BI1,HM1,PI1,SI1,TC1)	0.209472
coincidence(BI1,FC1,HM1,PR1,SI1)	0.250699
coincidence(BI1,FC1,HM1,PR1,TC1)	0.236609
coincidence(BI1,FC1,HM1,SI1,TC1)	0.254841
coincidence(EE1,FC1,HM1,PI1,TC1)	0.168689
coincidence(BI1,FC1,PE1,PI1,PR1)	0.208604
coincidence(AUT1,FC1,HM1,PI1)	0.197098
coincidence(AUT1,FC1,HM1,PE1)	0.257084
coincidence(AUT1,PE1,PI1,SI1)	0.233145
coincidence(AUT1,EE1,SI1,TC1)	0.347573

coincidence(AUT1,EE1,PR1,TC1)	0.414386
coincidence(AUT1,EE1,PR1,SI1)	0.353558
coincidence(AUT1,EE1,PI1,TC1)	0.283613
coincidence(AUT1,EE1,PI1,SI1)	0.236075
coincidence(AUT1,EE1,PI1,PR1)	0.319765
coincidence(AUT1,FC1,PI1,PR1)	0.221941
coincidence(AUT1,EE1,PE1,TC1)	0.349696
coincidence(AUT1,EE1,PE1,SI1)	0.347041
coincidence(AUT1,EE1,PE1,PR1)	0.345688
coincidence(AUT1,EE1,PE1,PI1)	0.215905
coincidence(AUT1,HM1,PE1,TC1)	0.26995
coincidence(AUT1,PE1,PI1,PR1)	0.242199
coincidence(AUT1,EE1,HM1,TC1)	0.326629
coincidence(AUT1,EE1,HM1,PR1)	0.363981
coincidence(AUT1,EE1,HM1,PI1)	0.314332
coincidence(AUT1,EE1,HM1,PE1)	0.253599

coincidence(AUT1,EE1,FC1,TC1)	0.347854
coincidence(AUT1,EE1,FC1,SI1)	0.36842
coincidence(AUT1,EE1,FC1,PR1)	0.335218
coincidence(AUT1,EE1,FC1,PI1)	0.203738
coincidence(AUT1,FC1,PE1,PI1)	0.220423
coincidence(AUT1,EE1,FC1,PE1)	0.352492
coincidence(AUT1,EE1,FC1,HM1)	0.231022
coincidence(AUT1,HM1,SI1,TC1)	0.279844
coincidence(AUT1,HM1,PR1,TC1)	0.375987
coincidence(AUT1,EE1,HM1,SI1)	0.265253
coincidence(AUT1,BI1,SI1,TC1)	0.39534
coincidence(AUT1,BI1,PR1,TC1)	0.498259
coincidence(AUT1,BI1,PR1,SI1)	0.420392
coincidence(AUT1,FC1,PI1,SI1)	0.238178
coincidence(AUT1,BI1,PI1,TC1)	0.33872
coincidence(AUT1,BI1,PI1,SI1)	0.273664
coincidence(AUT1,BI1,PI1,PR1)	0.393086

coincidence(AUT1,HM1,PR1,SI1)	0.33344 2
coincidence(AUT1,BI1,PE1,TC1)	0.39267 6
coincidence(AUT1,BI1,PE1,SI1)	0.39310 7
coincidence(AUT1,BI1,PE1,PR1)	0.40260 4
coincidence(AUT1,HM1,PI1,SI1)	0.29315 1
coincidence(AUT1,BI1,PE1,PI1)	0.24190 2
coincidence(AUT1,BI1,HM1,TC1)	0.39400 3
coincidence(AUT1,BI1,HM1,SI1)	0.31646 6
coincidence(AUT1,BI1,HM1,PR1)	0.45651 6
coincidence(AUT1,BI1,HM1,PI1)	0.38651 7
coincidence(AUT1,BI1,HM1,PE1)	0.28957 3
coincidence(AUT1,HM1,PI1,PR1)	0.40118
coincidence(AUT1,BI1,FC1,TC1)	0.38552 7
coincidence(AUT1,BI1,FC1,SI1)	0.40845
coincidence(AUT1,FC1,PR1,SI1)	0.40431 6
coincidence(AUT1,BI1,FC1,PR1)	0.37990 9

coincidence(AUT1,HM1,PE1,PR1)	0.285743
coincidence(AUT1,BI1,EE1,SI1)	0.35084
coincidence(AUT1,PI1,SI1,TC1)	0.244998
coincidence(AUT1,FC1,SI1,TC1)	0.412055
coincidence(AUT1,FC1,HM1,PR1)	0.251437
coincidence(AUT1,PE1,PR1,SI1)	0.387216
coincidence(AUT1,FC1,PE1,TC1)	0.393181
coincidence(AUT1,PE1,PR1,TC1)	0.378338
coincidence(AUT1,BI1,FC1,PI1)	0.220324
coincidence(AUT1,BI1,EE1,PR1)	0.45405
coincidence(AUT1,PR1,SI1,TC1)	0.385116
coincidence(AUT1,BI1,EE1,PI1)	0.315235
coincidence(AUT1,PE1,SI1,TC1)	0.383779
coincidence(AUT1,FC1,PE1,SI1)	0.427723
coincidence(AUT1,BI1,EE1,PE1)	0.354317
coincidence(AUT1,FC1,PE1,PR1)	0.384289

coincidence(AUT1,BI1,FC1,PE1)	0.395463
coincidence(AUT1,BI1,EE1,HM1)	0.367549
coincidence(AUT1,HM1,PE1,PI1)	0.226813
coincidence(AUT1,BI1,FC1,HM1)	0.255343
coincidence(AUT1,FC1,HM1,TC1)	0.252302
coincidence(AUT1,PI1,PR1,SI1)	0.293501
coincidence(AUT1,HM1,PI1,TC1)	0.317422
coincidence(AUT1,HM1,PE1,SI1)	0.273709
coincidence(AUT1,FC1,PI1,TC1)	0.220371
coincidence(AUT1,FC1,HM1,SI1)	0.273827
coincidence(AUT1,PI1,PR1,TC1)	0.325931
coincidence(AUT1,BI1,EE1,TC1)	0.432563
coincidence(AUT1,FC1,PR1,TC1)	0.373926
coincidence(AUT1,BI1,EE1,FC1)	0.340202
coincidence(AUT1,PE1,PI1,TC1)	0.230555

coincidence(EE1,FC1,HM1,SI1)	0.245893
coincidence(BI1,EE1,HM1,PE1)	0.251269
coincidence(EE1,FC1,HM1,TC1)	0.231352
coincidence(EE1,FC1,PE1,PI1)	0.206319
coincidence(BI1,EE1,HM1,PI1)	0.289921
coincidence(BI1,EE1,HM1,PR1)	0.346669
coincidence(BI1,EE1,HM1,SI1)	0.246946
coincidence(BI1,EE1,HM1,TC1)	0.322324
coincidence(BI1,EE1,PE1,PI1)	0.213096
coincidence(BI1,EE1,PE1,PR1)	0.340996
coincidence(EE1,FC1,PE1,PR1)	0.342291
coincidence(BI1,EE1,PE1,SI1)	0.3306
coincidence(BI1,EE1,PE1,TC1)	0.350539
coincidence(BI1,EE1,PI1,PR1)	0.298659
coincidence(EE1,FC1,PE1,SI1)	0.411029
coincidence(BI1,EE1,PI1,SI1)	0.216092

coincidence(EE1,FC1,PE1,TC1)	0.39674
coincidence(EE1,FC1,PI1,PR1)	0.201734
coincidence(BI1,EE1,PI1,TC1)	0.278404
coincidence(BI1,EE1,PR1,SI1)	0.330655
coincidence(EE1,FC1,PI1,SI1)	0.22086
coincidence(BI1,EE1,PR1,TC1)	0.408932
coincidence(EE1,FC1,PI1,TC1)	0.208067
coincidence(EE1,FC1,PR1,SI1)	0.350373
coincidence(BI1,EE1,SI1,TC1)	0.331901
coincidence(EE1,FC1,PR1,TC1)	0.335562
coincidence(EE1,FC1,SI1,TC1)	0.393037
coincidence(EE1,HM1,PE1,PI1)	0.198089
coincidence(BI1,FC1,HM1,PE1)	0.264884
coincidence(BI1,FC1,HM1,PI1)	0.20062
coincidence(BI1,FC1,HM1,PR1)	0.254298
coincidence(BI1,FC1,HM1,SI1)	0.276182
coincidence(BI1,FC1,PE1,PI1)	0.226972

coincidence(EE1,HM1,PE1,PR1)	0.246161
coincidence(BI1,FC1,PE1,PR1)	0.392399
coincidence(BI1,FC1,PE1,SI1)	0.419387
coincidence(BI1,FC1,PE1,TC1)	0.411419
coincidence(EE1,HM1,PE1,SI1)	0.239322
coincidence(BI1,FC1,PI1,PR1)	0.223719
coincidence(EE1,HM1,PE1,TC1)	0.244945
coincidence(EE1,HM1,PI1,PR1)	0.29684
coincidence(BI1,FC1,PI1,SI1)	0.239065
coincidence(BI1,FC1,PI1,TC1)	0.229116
coincidence(EE1,HM1,PI1,SI1)	0.217941
coincidence(BI1,FC1,PR1,SI1)	0.395774
coincidence(EE1,HM1,PI1,TC1)	0.265778
coincidence(EE1,HM1,PR1,SI1)	0.253419
coincidence(BI1,FC1,PR1,TC1)	0.379666
coincidence(EE1,HM1,PR1,TC1)	0.311216

coincidence(EE1,HM1,SI1,TC1)	0.239823
coincidence(EE1,PE1,PI1,PR1)	0.211432
coincidence(BI1,FC1,SI1,TC1)	0.405308
coincidence(BI1,HM1,PE1,PI1)	0.225821
coincidence(BI1,HM1,PE1,PR1)	0.284496
coincidence(EE1,PE1,PI1,SI1)	0.20959
coincidence(BI1,HM1,PE1,SI1)	0.273779
coincidence(EE1,PE1,PI1,TC1)	0.213345
coincidence(EE1,PE1,PR1,SI1)	0.331153
coincidence(BI1,HM1,PE1,TC1)	0.277148
coincidence(EE1,PE1,PR1,TC1)	0.337416
coincidence(EE1,PE1,SI1,TC1)	0.36515
coincidence(EE1,PI1,PR1,SI1)	0.227002
coincidence(BI1,HM1,PI1,PR1)	0.374859
coincidence(EE1,PI1,PR1,TC1)	0.272246
coincidence(EE1,PI1,SI1,TC1)	0.214901

coincidence(EE1,PR1,SI1,TC1)	0.328758
coincidence(FC1,HM1,PE1,PI1)	0.204584
coincidence(BI1,FC1,HM1,TC1)	0.259479
coincidence(BI1,HM1,PI1,TC1)	0.318607
coincidence(BI1,HM1,PR1,SI1)	0.304494
coincidence(BI1,HM1,PR1,TC1)	0.378805
coincidence(BI1,HM1,SI1,TC1)	0.280158
coincidence(FC1,HM1,PE1,PR1)	0.257523
coincidence(BI1,PE1,PI1,PR1)	0.24098
coincidence(BI1,PE1,PI1,SI1)	0.233746
coincidence(FC1,HM1,PE1,SI1)	0.286508
coincidence(BI1,PE1,PI1,TC1)	0.238502
coincidence(FC1,HM1,PE1,TC1)	0.263325
coincidence(FC1,HM1,PI1,PR1)	0.202968
coincidence(BI1,PE1,PR1,SI1)	0.382184
coincidence(BI1,EE1,FC1,HM1)	0.228077

coincidence(BI1,PE1,PR1,TC1)	0.387304
coincidence(FC1,HM1,PI1,SI1)	0.219186
coincidence(BI1,PE1,SI1,TC1)	0.381684
coincidence(FC1,HM1,PI1,TC1)	0.203629
coincidence(FC1,HM1,PR1,SI1)	0.273746
coincidence(BI1,PI1,PR1,SI1)	0.267056
coincidence(FC1,HM1,PR1,TC1)	0.253918
coincidence(FC1,HM1,SI1,TC1)	0.278271
coincidence(FC1,PE1,PI1,PR1)	0.230878
coincidence(BI1,PI1,PR1,TC1)	0.329826
coincidence(BI1,PI1,SI1,TC1)	0.246727
coincidence(FC1,PE1,PI1,SI1)	0.26211
coincidence(BI1,PR1,SI1,TC1)	0.38016
coincidence(FC1,PE1,PI1,TC1)	0.239099
coincidence(FC1,PE1,PR1,SI1)	0.426421
coincidence(EE1,FC1,HM1,PE1)	0.235772

coincidence(FC1,PE1,PR1,TC1)	0.39548 6
coincidence(FC1,PE1,SI1,TC1)	0.48936
coincidence(FC1,PI1,PR1,SI1)	0.24882
coincidence(EE1,FC1,HM1,PI1)	0.18010 3
coincidence(FC1,PI1,PR1,TC1)	0.22976 6
coincidence(FC1,PI1,SI1,TC1)	0.25531 4
coincidence(FC1,PR1,SI1,TC1)	0.40598 4
coincidence(HM1,PE1,PI1,PR1)	0.22827 3
coincidence(BI1,EE1,FC1,PE1)	0.35041 9
coincidence(BI1,EE1,FC1,PI1)	0.19847 9
coincidence(BI1,EE1,FC1,PR1)	0.32724 2
coincidence(HM1,PE1,PI1,SI1)	0.22080 7
coincidence(BI1,HM1,PI1,SI1)	0.25554 7
coincidence(HM1,PE1,PI1,TC1)	0.21634 6
coincidence(HM1,PE1,PR1,SI1)	0.27070 2
coincidence(EE1,FC1,HM1,PR1)	0.22625 6

coincidence(HM1,PE1,PR1,TC1)	0.268032
coincidence(HM1,PE1,SI1,TC1)	0.264579
coincidence(HM1,PI1,PR1,SI1)	0.278539
coincidence(BI1,EE1,FC1,SI1)	0.348101
coincidence(HM1,PI1,PR1,TC1)	0.307914
coincidence(HM1,PI1,SI1,TC1)	0.230327
coincidence(HM1,PR1,SI1,TC1)	0.274813
coincidence(PE1,PI1,PR1,SI1)	0.240772
coincidence(BI1,EE1,FC1,TC1)	0.347266
coincidence(PE1,PI1,PR1,TC1)	0.236258
coincidence(PE1,PI1,SI1,TC1)	0.23904
coincidence(PE1,PR1,SI1,TC1)	0.378215
coincidence(PI1,PR1,SI1,TC1)	0.249088
coincidence(AUT1,SI1,TC1)	0.443858
coincidence(AUT1,PI1,PR1)	0.459931
coincidence(AUT1,BI1,TC1)	0.56694

coincidence(AUT1,HM1,SI1)	0.391365
coincidence(AUT1,FC1,SI1)	0.470365
coincidence(AUT1,EE1,FC1)	0.383683
coincidence(AUT1,HM1,TC1)	0.425372
coincidence(AUT1,FC1,PR1)	0.420297
coincidence(AUT1,EE1,HM1)	0.413912
coincidence(AUT1,PE1,SI1)	0.44802
coincidence(AUT1,PI1,TC1)	0.369018
coincidence(AUT1,PE1,PI1)	0.266683
coincidence(AUT1,PR1,SI1)	0.494244
coincidence(AUT1,EE1,PE1)	0.393744
coincidence(AUT1,EE1,PI1)	0.359872
coincidence(AUT1,EE1,PR1)	0.50734
coincidence(AUT1,FC1,PE1)	0.446837
coincidence(AUT1,PI1,SI1)	0.342521
coincidence(AUT1,PR1,TC1)	0.539891

coincidence(AUT1,EE1,SI1)	0.406653
coincidence(AUT1,HM1,PR1)	0.52951
coincidence(AUT1,EE1,TC1)	0.478437
coincidence(AUT1,FC1,PI1)	0.240846
coincidence(AUT1,FC1,HM1)	0.277284
coincidence(AUT1,PE1,TC1)	0.432987
coincidence(AUT1,BI1,EE1)	0.516745
coincidence(AUT1,HM1,PI1)	0.471543
coincidence(AUT1,BI1,HM1)	0.523468
coincidence(AUT1,BI1,SI1)	0.474846
coincidence(AUT1,HM1,PE1)	0.317482
coincidence(AUT1,FC1,TC1)	0.431036
coincidence(AUT1,PE1,PR1)	0.441812
coincidence(AUT1,BI1,FC1)	0.427651
coincidence(AUT1,BI1,PE1)	0.451267
coincidence(AUT1,BI1,PI1)	0.442799

coincidence(AUT1,BI1,PR1)	0.64130 8
coincidence(BI1,PI1,PR1)	0.43313 5
coincidence(FC1,HM1,PI1)	0.22092 9
coincidence(BI1,HM1,PR1)	0.50160 6
coincidence(EE1,HM1,PR1)	0.38802 7
coincidence(BI1,EE1,PI1)	0.33572 3
coincidence(BI1,FC1,PI1)	0.24434 7
coincidence(BI1,PI1,SI1)	0.29723 6
coincidence(EE1,HM1,SI1)	0.28912 1
coincidence(BI1,FC1,SI1)	0.45391 4
coincidence(FC1,HM1,PR1)	0.27778 5
coincidence(EE1,HM1,TC1)	0.35633 8
coincidence(EE1,PE1,PI1)	0.24032 9
coincidence(BI1,PI1,TC1)	0.37181
coincidence(FC1,HM1,SI1)	0.31029
coincidence(EE1,FC1,PR1)	0.37172 7

coincidence(FC1,HM1,TC1)	0.283587
coincidence(FC1,PE1,PI1)	0.26893
coincidence(BI1,PR1,SI1)	0.451198
coincidence(BI1,HM1,SI1)	0.343201
coincidence(BI1,PR1,TC1)	0.545486
coincidence(EE1,FC1,SI1)	0.453325
coincidence(BI1,SI1,TC1)	0.431574
coincidence(EE1,PE1,PR1)	0.381983
coincidence(EE1,FC1,TC1)	0.438691
coincidence(FC1,PE1,PR1)	0.455979
coincidence(EE1,HM1,PE1)	0.275305
coincidence(EE1,FC1,HM1)	0.250629
coincidence(EE1,PE1,SI1)	0.419246
coincidence(FC1,PE1,SI1)	0.655781
coincidence(BI1,EE1,PE1)	0.391975
coincidence(FC1,PE1,TC1)	0.557211

coincidence(FC1,PI1,PR1)	0.252773
coincidence(EE1,PE1,TC1)	0.431092
coincidence(EE1,PI1,PR1)	0.346277
coincidence(BI1,HM1,TC1)	0.427859
coincidence(FC1,PI1,SI1)	0.292135
coincidence(EE1,FC1,PE1)	0.462207
coincidence(FC1,PI1,TC1)	0.262192
coincidence(FC1,PR1,SI1)	0.468358
coincidence(BI1,PE1,PI1)	0.268698
coincidence(FC1,PR1,TC1)	0.433528
coincidence(FC1,SI1,TC1)	0.544274
coincidence(HM1,PE1,PI1)	0.255962
coincidence(EE1,PI1,SI1)	0.261389
coincidence(BI1,FC1,TC1)	0.448079
coincidence(EE1,PI1,TC1)	0.319306

coincidence(EE1,PR1,SI1)	0.381402
coincidence(BI1,HM1,PE1)	0.317682
coincidence(EE1,PR1,TC1)	0.453367
coincidence(EE1,SI1,TC1)	0.406297
coincidence(HM1,PE1,PR1)	0.313209
coincidence(FC1,HM1,PE1)	0.292159
coincidence(BI1,EE1,TC1)	0.478978
coincidence(BI1,HM1,PI1)	0.433324
coincidence(HM1,PE1,SI1)	0.310332
coincidence(BI1,FC1,PE1)	0.462582
coincidence(HM1,PE1,TC1)	0.301257
coincidence(HM1,PI1,PR1)	0.454136
coincidence(BI1,FC1,HM1)	0.281628
coincidence(BI1,EE1,FC1)	0.378546
coincidence(BI1,PE1,PR1)	0.442975

coincidence(HM1,PI1,SI1)	0.34532 7
coincidence(BI1,EE1,PR1)	0.48592 5
coincidence(HM1,PI1,TC1)	0.35799 5
coincidence(HM1,PR1,SI1)	0.36589 1
coincidence(BI1,EE1,HM1)	0.39002 7
coincidence(HM1,PR1,TC1)	0.40863 7
coincidence(HM1,SI1,TC1)	0.31165 5
coincidence(PE1,PI1,PR1)	0.27313 7
coincidence(EE1,HM1,PI1)	0.35238 2
coincidence(BI1,FC1,PR1)	0.42103 4
coincidence(BI1,PE1,SI1)	0.43356 4
coincidence(PE1,PI1,SI1)	0.28127 8
coincidence(BI1,EE1,SI1)	0.37199 8
coincidence(PE1,PI1,TC1)	0.26983 4
coincidence(PE1,PR1,SI1)	0.44360 6

coincidence(BI1,PE1,TC1)	0.45308 7
coincidence(PE1,PR1,TC1)	0.43272 1
coincidence(PE1,SI1,TC1)	0.49558 6
coincidence(PI1,PR1,SI1)	0.33075 8
coincidence(EE1,FC1,PI1)	0.22690 4
coincidence(PI1,PR1,TC1)	0.36414 8
coincidence(PI1,SI1,TC1)	0.28544 5
coincidence(PR1,SI1,TC1)	0.43210 5
coincidence(AUT1,PE1)	0.51991 7
coincidence(AUT1,EE1)	0.60958 5
coincidence(AUT1,TC1)	0.63988 4
coincidence(AUT1,HM1)	0.63996 1
coincidence(AUT1,PR1)	0.75507 3
coincidence(AUT1,BI1)	0.75796 9
coincidence(AUT1,FC1)	0.4946
coincidence(AUT1,SI1)	0.60084 4

coincidence(AUT1,PI1)	0.552167
coincidence(BI1,TC1)	0.66742
coincidence(EE1,TC1)	0.615981
coincidence(EE1,FC1)	0.521736
coincidence(EE1,HM1)	0.480134
coincidence(BI1,SI1)	0.52443
coincidence(BI1,FC1)	0.508366
coincidence(EE1,PI1)	0.440352
coincidence(HM1,PI1)	0.654752
coincidence(BI1,PE1)	0.537612
coincidence(BI1,PI1)	0.510639
coincidence(FC1,PI1)	0.301734
coincidence(HM1,PR1)	0.609504
coincidence(EE1,PR1)	0.575509
coincidence(EE1,PE1)	0.52778
coincidence(HM1,SI1)	0.465254
coincidence(BI1,EE1)	0.587369

coincidence(HM1,TC1)	0.486822
coincidence(PE1,PI1)	0.331729
coincidence(FC1,PR1)	0.505915
coincidence(EE1,SI1)	0.500322
coincidence(FC1,SI1)	0.780424
coincidence(PE1,PR1)	0.526619
coincidence(FC1,TC1)	0.637524
coincidence(HM1,PE1)	0.36693
coincidence(PE1,SI1)	0.685014
coincidence(FC1,HM1)	0.31684
coincidence(PE1,TC1)	0.613582
coincidence(PI1,PR1)	0.546622
coincidence(BI1,PR1)	0.730183
coincidence(FC1,PE1)	0.793741
coincidence(PI1,SI1)	0.436829
coincidence(PI1,TC1)	0.446849

coincidence(PR1,SI1)	0.569266
coincidence(BI1,HM1)	0.597096
coincidence(PR1,TC1)	0.62383
coincidence(SI1,TC1)	0.58156