Evolving User Profiles and Adoption of Cyborg Technologies: Evidence from a Repeated Cross-Sectional Study in Switzerland

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Abstract

Cyborg technologies like subcutaneous implants and brain-computer interfaces, are spreading from early-adopter communities toward the general population. Understanding this transition is timely, because further diffusion no longer hinges on early adopters' transhumanist beliefs, but on preferences of the general population. Through two cross-sectional studies in Switzerland in 2023 (n=1,000) and 2025 (n=1,078), we track the diffusion process of cyborg technologies measuring adoption, associated transhumanist beliefs, risk/benefit perceptions, and demographic characteristics. Through latent profile analysis and multinomial regression, we identify three evolving profiles: Convinced, Considering, and Skeptical individuals. Over time, the Convinced and Skeptical profiles grew. The Convinced profile shifted to more moderate risk/benefit perceptions and distanced from transhumanist beliefs, growing among young individuals and across genders. Conversely, the Skeptical profile maintained high risk perceptions that still hinder adoption. These findings capture characteristics of the increasing diffusion of cyborg technologies, and can inform both technology development and future research targeting distinct user profiles.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

Cyborg Technology, Diffusion of Innovation, Technology Adoption, Transhumanism

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1 Introduction

Once confined to science fiction, cyborg technologies such as subcutaneous implants and brain–computer interfaces (BCIs) are now increasingly visible as disruptive innovations, with the potential to transform everyday life through non-medical augmentation of human capabilities [22, 39]. While the adoption of non-medical cyborg technologies was initially limited to transhumanist and biohacker communities [34, 68], these technologies are beginning to diffuse into broader contexts. In Sweden, microchip implants for identification and payment are available to the general population [49]. In the United States, firms have experimented with employee microchipping [66]. Meanwhile, enthusiast groups continue to organize "chipping" events to promote the use of cyborg technologies [59]. Reflecting this momentum, the global market for human augmentation is projected to exceed USD 880 billion by 2032 [19].

The expansion of these technologies raises societal debates and attention from research and industry. Within pioneer communities, support for these technologies is linked to the transhumanist belief in technologically driven human evolution [7]. Potential benefits of cyborg technologies are recognized beyond these niche communities, as proponents of cyborg technologies highlight their potential to enhance productivity, efficiency, and personal capabilities [39]. On the other hand, critics and empirical research on the population point to emerging concerns about safety, privacy, and inequality [2, 12, 27]. Public figures have also weighed in, highlighting prospective opportunities and challenges. Elon Musk promotes Neuralink as a technology that, in the long term, is not limited to medical applications but can increase the bandwidth of the human brain, enabling humans to process more information [51]. On the other hand, Mark Zuckerberg speculates that individuals who will not use cyborg technologies such as AI-augmented glasses may be disadvantaged in the future [47]. Despite these high-profile discussions, however, little is known about how cyborg technologies are actually diffusing among the wider population.

To address this gap, this study presents evidence from two representative cross-sectional surveys in Switzerland (2023 and 2025), offering the first population-level view of changes in the user profiles and adoption process of cyborg technologies over time. Drawing on Rogers' theory of diffusion of innovations [54] and Moore's concept of the "chasm" between early adopters and the early majority [35], we examine how niche enthusiasm rooted in transhumanist values transitions into broader societal adoption of cyborg technologies.

To capture the value-laden nature of these adoption processes, we explore this phenomenon through a value–attitude–behavior (VAB) theoretical framework [63].

In doing so, we advance the understanding of how cyborg technologies are moving from subcultural experimentation toward mainstream adoption, highlight the evolving user profiles that emerge in the population, as well as the underlying differences in values, attitudes and demographic characteristics. Based on these aims, this study addresses the following research questions:

- RQ1: How do adoption readiness for cyborg technologies and associated levels of transhumanist value predisposition, perceived benefits and perceived risks change over time?
- RQ2: What user profiles exist in the population regarding cyborg technologies, and how did these profiles change over time?
- RQ3: How are transhumanist value predispositions, perceived benefits and perceived risks associated with user profiles, and how did these associations change over time?
- RQ4: How are demographic factors associated with different user profiles, and how did these associations change over time?

In the following sections we first introduce our theoretical framework (Section 2). Then, we present related work (Section 3), Methods (Section 4), Results (Section 5) and a Discussion of our findings (Section 6).

2 Theoretical Framework

Cyborg technologies are digital technologies that augment cognitive, physical, or sensory capacities via external devices (wearables) and internal “insideables” such as subcutaneous implants and brain–computer interfaces. The use of these technologies can restore lost functions or enhance baseline capacities, leading to a distinction between medical and non-medical augmentation [5, 50].

The integration of non-medical cyborg technologies with the body is referred to as cyborgization [23], a process that can be understood as part of the increasing digitalization of societies [29, 30]. Cyborgization depends on the widespread diffusion of non-medical cyborg technologies.

We adopt Rogers' conceptualization of Diffusion of Innovations (DoI) as the process by which an innovation spreads through a social system over time [54]. The societal-level diffusion process is associated with adoption, understood as the individual-level innovation–decision process through which people move from awareness to decision and (continued) use of technologies [54]. Diffusion proceeds through adopter categories (innovators, early adopters, early/late majority, laggards), and adoption is shaped by individual characteristics, perceived attributes of the innovation, and social context [54]. Complementing Rogers' DoI theory, Moore highlights a chasm, i.e., a discontinuity between visionary early adopters and the pragmatic early majority [35]. Moore highlights that many technologies stall at this transition unless their value proposition aligns with mainstream expectations.

For non-medical uses, early adoption is motivated by transhumanist values that endorse technologically driven enhancement of lifespan, cognition, sensorimotor function, and affect, up to superhuman capabilities [9, 28]. Accordingly, we employ a value–attitude– behavior (VAB) framework [63], including transhumanist predispositions (values) and technology-specific attitudes (perceived benefits and risks) as contributing factors to a behavioral outcome, represented by adoption readiness.

3 Related Work

We present an overview of related work to contextualize this study. In particular, we present an overview of existing research on technology acceptance models for cyborg technologies, examples of the use of value-based acceptance models in the context of innovation and emerging technologies, followed by relevant empirical findings related to cyborg technologies.

Technology Acceptance Models. Technology acceptance in HCI has long been examined through models such as TAM [14], UTAUT [64], and related frameworks emphasizing perceived usefulness, ease of use, and behavioral intention. While these models have proven robust in organizational and consumer contexts, recent work suggests limitations especially for non-medical human augmentation, where concerns extend beyond instrumentality [12, 20]. For cyborg technologies like implants, neurotechnology, and wearables, research shows that adoption decisions involve diverse factors. On the one hand, functional consideration from traditional acceptance models emerge. However, they are complemented with factors e.g. technological safety, and ethical judgment and concerns for social stigma, which traditional acceptance models do not fully capture [12, 20]. This motivates the continued and increasing research to define technology adoption frameworks that incorporate individual values and moral judgments.

Value-Based Acceptance Models. The value–attitude–behavior [63] model holds that personal values shape technology-specific attitudes, which in turn inform intentions and/or behaviors. Empirically, this pattern appears across different domains. For example, environmental values predict electric-vehicle acceptance [38]. Similarly, biospheric values (i.e. concern for nature and ecosystems) predict favorable attitudes toward renewable energy sources such as wind and solar [48]. The value-attitude-behavior model was also applied in the context of energy policies [62] and in food technology, where technophobia reduces acceptance of smart farm restaurants and 3D-printed food [26, 33]. Extending this approach to cyborg technologies, we link transhumanist predispositions (values) to perceived benefits and risks (attitudes) and to adoption readiness (intentions) at the population level.

Value Predispositions. Empirical research on non-medical cyborg technology acceptance and use reveals the importance of value predispositions. On the one hand, transhumanist motivations emerge in ethnographic and qualitative studies on biohackers pioneer communities [10, 43, 57]. In contrast, religiosity and religiously-driven moral opposition have been linked to skepticism and opposition to the adoption of cyborg technologies [55, 58, 67].

Benefit and Risk Perception. Empirical research highlighted the emergence of both functional and non-functional considerations in the acceptance of non-medical cyborg technologies, relating to both perceived benefits and risks. Beyond perceived usefulness and ease of use, empirical research highlights the emergence of ethical judgments [13, 15, 45], positive and negative emotions [3, 46, 53, 61], as well as privacy, and safety concerns related to cyborg technologies [1, 16, 18].

Demographic Differences. Existing empirical studies report evidence that the adoption process of cyborg technologies correlates with age, gender, and education/digital literacy. In particular, younger and male respondents, and those with higher literacy/education, tend to be more accepting towards non-medical cyborg technologies [21, 37, 52, 55, 67, 69].

Market Segments and User Profiles. Empirical studies reveal distinct profiles and market segments of users. Clusters emerge based on users that are ethically in favor/indifferent/against the use of non-medical cyborg technologies [4], or have apocalyptic attitudes towards non-medical cyborg technologies [40]. Recent empirical studies focusing on public opinion related to cyborg technologies identify Moderates, Tech-Ethics Advocates, and Tech-Forward Visionaries [41, 42].

4 Methods

Study Design and Participants. Data were collected in 2023 (n = 1,000) and 2025 (n = 1,078) as part of the Swiss edition of the World Internet Project, a long-term study on internet use [31, 32]. Both waves were administered online by the same professional survey company, using identical procedures.

Sampling used quota controls for age, gender, language region, household income and a three-level education variable (lower/ vocational, secondary, tertiary). These quotas were aligned with population benchmarks for Swiss internet users aged 14 and older [11]. Table 1 reports the demographic characteristics of the two samples. Because internet penetration in Switzerland exceeds 95% [60], the online population closely approximates the resident population. Survey materials were provided in German, French, and Italian, with item translations performed by native speakers. With these sample sizes, the margin of error is approximately ±2.98 percentage points at the 95% confidence level. While the two cross-sectional surveys do not refer to the same longitudinal panel, the similarity between the two waves supports meaningful cross-wave comparison. Data collection was completed online and required approximately 19 minutes on average. Only complete responses that passed quality checks (e.g., attention checks, minimum duration thresholds) were delivered to the researchers.

4.1 Measures

In this subsection, we describe all constructs used in the study and their operationalization. Full item wordings for all measures are provided in Appendix B.

Adoption Readiness. We introduce Adoption Readiness as a descriptive index of cyborg technology diffusion, capturing key stages in the adoption process: awareness, behavioral intention, and actual use. The index is not based on an existing validated scale but is grounded in Rogers' diffusion of innovations theory [54]. We operationalize these stages in a 7-point ordinal measure constructed from sequential survey items. Respondents were first asked about their awareness and current use of cyborg technologies. Aware non-users were then asked to indicate their intention to use such technologies on a 5-point Likert scale. These branching responses were integrated into a single readiness measure coded as follows: 1 = non-awareness, 2–6 = aware non-users with increasing levels of behavioral intention (from low to high), and 7 = current users. In addition, current users could additionally describe the technologies they use in an optional open-ended item. Given its construction, Adoption Readiness is a staged index in which respondents answer different items depending on their position in the adoption pathway. Its components are therefore not jointly observed for all participants and do not form a reflective psychometric construct. As such, Adoption Readiness is not suitable for factor analysis. We treat it as a descriptive ordinal indicator used for descriptive statistics and profiling, rather than as a latent factor.

Table 1: Descriptive Statistics of Study Participants by Year

Variable	2023	2025
Sample Size (n)	1000	1078
Age, Mean ± SD	47.72 ± 17.33	47.18 ± 18.2
Age Range	14-85	14-88
Gender, n (%)		
Male	501 (50.1%)	524 (48.6%)
Female	492 (49.2%)	549 (50.9%)
Other	7 (0.7%)	5 (0.5%)
Education, n (%)		
Lower	62 (6.2%)	75 (6.9%)
Professional	396 (39.6%)	484 (44.9%)
Higher	532 (53.2%)	515 (47.7%)
Other	10 (1%)	4 (0.4%)
Income (CHF/month), n (%)		
< 4000	168 (16.8%)	166 (15.4%)
4001-6000	199 (19.9%)	205 (19%)
6001-8000	199 (19.9%)	213 (19.8%)
8001-10000	180 (18%)	197 (18.3%)
10001-15000	176 (17.6%)	219 (20.3%)
> 15000	78 (7.8%)	78 (7.2%)

Transhumanist Value Predisposition. Transhumanist predisposition was measured using items derived from Bostrom's account of core transhumanist values [7]. These values emphasize the use of technology to overcome human limitations, solve major societal challenges, and shape future human evolution. Respondents rated their agreement with each statement on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Two items reflecting these themes were included in both 2023 and 2025 and form the basis for all cross-wave comparisons, ensuring measurement equivalence. Internal consistency for this two-item index was acceptable in both years ($\alpha_{2023} = .68$, $\alpha_{2025} = .65$).

In 2025, two additional items were introduced to capture further aspects of Bostrom's framework. The resulting four-item scale provides a more complete operationalization of transhumanist value orientations and shows substantially higher internal consistency ($\alpha_{2025} = .80$). Because the extended index was only fielded in 2025, we report descriptive statistics for both the 2-item and 4-item construct, but use the 2-item construct for cross-wave comparisons.

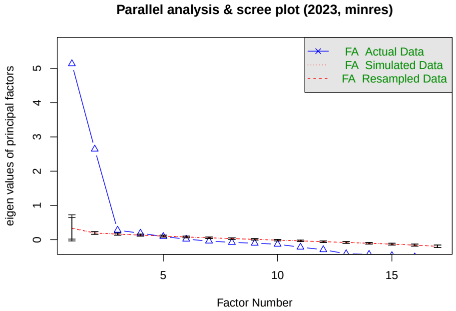

Figure 1: Scree and parallel analysis (2023)

Perceived Benefits. An eight-item scale measured participants' perceived benefits of cyborg technologies. Items were adapted from the Technology Readiness Index (which assesses people's propensity to use cutting-edge technologies [44]). Drawing on Bostrom's list of enhancement goals, we phrased items to assess the perceived potential of these technologies to improve lifespan, intellectual capabilities, bodily functions, sensory capacities, emotions, and superhuman capabilities (see Appendix B for item-level descriptions) [7]. The scale demonstrated excellent internal consistency in both waves (α_{2023} = .91, α_{2025} = .92). All items used a 5-point Likert scale (1 = very low perceived benefits, 5 = very high perceived benefits).

Perceived Risks. Participants evaluated seven risk areas associated with cyborg technologies, including privacy violation, cyber criminality, social inequalities, health hazards and technical malfunctions (see Appendix B for item-level descriptions). These categories of perceived risks recurrently emerge from empirical literature e.g. [2, 67]. The scale showed good internal consistency (α_{2023} = .85, α_{2025} = .85). All items used a 5-point Likert scale (1 = very low perceived risk, 5 = very high perceived risk).

Demographics. Demographic indicators (age, gender, education level, and monthly household income) were collected.

Open-Ended List of Devices. Current users were invited to specify which cyborg technologies they used in an optional open-ended item. This question was largely left unanswered in both survey waves, with most respondents leaving it blank. Among the few responses received, some participants listed medical devices (e.g., pacemakers, cochlear implants) despite instructions to report non-medical augmentation technologies. This confusion appeared consistently across both waves, suggesting a stable measurement error. Given the sparse responses and consistent pattern of confusion between waves, we retained all responses to maintain comparability across the two time points and avoid introducing selection bias through post-hoc exclusions.

4.2 Data Analysis

Measurement Validation. We validated our constructs in the 2023 sample and re-administered the same items in 2025 to enable temporal comparisons. We report the 2023 validation. An exploratory factor analysis using principal axis factoring with oblimin rotation on 17 items (N = 1,000) supports retaining three factors (See Figure 1) explaining 53% of total variance (KMO = .91; Bartlett's test $p < .001$). Factor 1 captured Perceived Benefits (8 items), Factor 2 reflected Perceived Risks (7 items), and Factor 3 captured Transhumanist Value Predisposition (2 items). Full 2023 factor loadings are provided in Appendix A. Appendix A also reports the factor loadings of the expanded four-item Transhumanist Predisposition scale used in 2025.

Item- and Factor-Level Comparison. We compared item-level means across waves for all constructs and reported observed mean differences at the construct level (Perceived Benefits, Perceived Risks, Transhumanist Predisposition, and Adoption Readiness). To address multiple testing, we applied a Benjamini–Hochberg False Discovery Rate (FDR) correction across the four construct-level comparisons. All p-values reported in the text and tables are FDR-adjusted, and the pattern of significance was identical when using unadjusted p-values.

Latent Profile Analysis. To identify population segments based on attitudes and adoption stage, we estimated latent profile models (LPA) using the `tidyLPA` package. LPA models class-specific means and assigns individuals to profiles probabilistically, making it suitable for mixed-scale indicators, including ordinal variables such as Adoption Readiness.

Because our research questions focus on comparing user profiles across waves, we estimated a single pooled LPA model joining responses from 2023 and 2025. This approach ensures that a consistent latent structure is applied across years, avoiding the alignment and comparability issues that arise when estimating separate models. After estimating the pooled solution, we examined how the distribution of profile membership differed across waves.

We fitted models with two, three, and four classes using the standard specification with class-specific means, equal variances, and zero covariances (Model 1 in `tidyLPA`). All models converged normally. Table 2 reports the key fit indices for these solutions. Model selection was based on multiple criteria, including AIC, BIC, SABIC, entropy, smallest class size, and interpretability. Although the four-class model achieved slightly lower information criteria and slightly higher entropy, it produced a very small class (2.6% of respondents), which may be a signal of overfitting. The three-class model provided a stronger balance of fit, class separation (entropy = .77), and interpretability, and maintained an acceptable smallest class size (12.5%). We therefore retained the three-profile solution.

The resulting profiles were well separated, theoretically coherent, and stable across waves. Based on their relative levels of Transhumanist Value Predisposition, Perceived Benefits and Risks and Adoption Readiness, we labeled the profiles *Skeptical*, *Considering*, and *Convinced*. In RQ3, we quantify how strongly each construct differentiates the profiles by calculating η^2 effect sizes from one-way ANOVAs. η^2 expresses how much variance in each construct is associated with profile membership, which we use as an indicator of how characteristic each construct is of the resulting profiles.

Multinomial Logistic Regression. To address RQ4 (how demographic factors are associated with profile membership and whether these associations changed over time) we conducted multinomial

Table 2: Model fit indices for pooled latent profile models with 2–4 classes.

Classes	LogLik	AIC	BIC	SABIC	Entropy	Smallest class (%)
2	−10,688	21,402	21,475	21,434	0.98	12.4
3	−10,388	20,812	20,914	20,857	0.77	12.5
4	−10,294	20,634	20,764	20,691	0.81	2.6

logistic regression analyses separately for the 2023 and 2025 samples. After assigning individuals to latent profiles based on the pooled LPA solution, we used `nnet::multinom` to model profile membership as a function of age, gender, education, and household income.

Software and Reproducibility. All analyses were conducted in R (version 4.4.2). Factor analysis was implemented using the `psych` package (version 2.5.6). Latent Profile Analysis was implemented using the `tidyLPA` package (version 1.1.0), multinomial regression using `nnet` (version 7.3-19), and statistical tests and effect-size computations using `rstatix` (version 0.7.2).

5 Results

The results are organized around the four research questions. We first examine temporal changes in the constructs of adoption readiness, transhumanist value predisposition, perceived benefits and risks (RQ1). Then, we identify user profiles through clustering (RQ2), and present the profiles' associations with individual value predisposition and attitudes (RQ3), as well as demographic characteristics (RQ4).

5.1 RQ1: How do adoption readiness for cyborg technologies and associated levels of transhumanist value predisposition, perceived benefits and perceived risks change over time?

Comparisons across the 2023 and 2025 survey waves, using FDR-adjusted p-values, indicate gradual but meaningful shifts in adoption readiness, transhumanist value predisposition, perceived benefits and risks toward cyborg technologies (Table 3).

Adoption readiness increased significantly between 2023 (M = 1.72, SD = 1.56) and 2025 (M = 1.96, SD = 1.81). Although average scores remain low on the seven-point adoption readiness scale, distributional changes reveal noteworthy dynamics (see Table 4). For ease of interpretation, we report results in four aggregated categories (unaware, low/medium intention, high intention, and current users) rather than all seven individual scale points. The share of respondents unaware of cyborg technologies declined from 75.3% in 2023 to 67.0% in 2025. Growth was also visible in the low/medium-intention category, which rose from 17.2% to 22.2%, while the proportion of respondents with high intention to use decreased slightly from 2.4% to 2.0%. At the same time, the proportion of current users nearly doubled, from 5.1% to 8.9%. Open-ended responses in both waves indicate some respondents conflated medical devices (e.g., pacemakers) with non-medical implants. Accordingly, the current-user figures should be interpreted as an upper bound on non-medical cyborg technology adoption.

Transhumanist value predisposition declined modestly over the two years, from M = 2.55 (SD = 0.97) to M = 2.35 (SD = 0.92). This indicates that, even as awareness and use of cyborg technologies increased, enthusiasm grounded in transhumanist ideology diminished.

The wave-level mean for perceived benefits of cyborg technologies did not show statistically significant changes (Table 3). However, the item-level patterns reveal a different dynamic (Table 5), with seven of eight benefit items declining, whereas only BENEFIT_8 increased significantly.

Perceived risks decreased significantly from 2023 to 2025. An item-level view of the responses (Table 5) shows that all areas of risk perception show a decline except for RISK_4 (pressure risk, i.e., perceived social/institutional pressure to adopt), which remained stable.

5.2 RQ2: What user profiles exist in the population regarding cyborg technologies, and how did these profiles change over time?

The pooled Latent Profile Analysis identified three distinct and interpretable population profiles: *Skeptical*, *Considering*, and *Convinced*. These profiles reflect differences in value predisposition, perceived benefits and risks, and adoption readiness. Table 6 reports their size and attitudinal characteristics for each wave.

In 2023, the *Skeptical* group comprised 40.8% of respondents, with low transhumanist predisposition and perceived benefits, high perceived risks, and minimal adoption readiness. The largest profile, *Considering* (48.1%), showed moderate transhumanist predisposition and perceived benefits, relatively high perceived risks, and low adoption readiness. The smallest profile, *Convinced* (11.1%), displayed the highest transhumanist predisposition and perceived benefits, the lowest perceived risks, and the highest readiness to adopt cyborg technologies.

The same qualitative structure reappeared in 2025 with modest shifts in prevalence. The *Skeptical* profile increased slightly to 42.6%, while the *Considering* group declined to 43.7%. The *Convinced* profile expanded to 13.7%, indicating a small increase in respondents at the most optimistic and adoption-ready end of the spectrum. A chi-square test assessing whether profile membership and survey wave were associated showed a marginal trend, $\chi^2(2, N{=}2{,}078) = 5.47$, p = .06, suggesting that overall profile distributions remained largely stable across the two years with only modest shifts.

Overall, attitudes toward cyborg technologies continue to organize into three robust and reproducible population profiles. While the underlying structure remains consistent across waves, the slight growth in the Skeptical and Convinced profiles indicates a mild

Table 3: Comparison of constructs between 2023 and 2025. AR = Adoption Readiness, TP = Transhumanist Predisposition, PB = Perceived Benefits, PR = Perceived Risks. TP, PB, PR are measured on 5-point Likert scales; AR is a 7-point staged index.

Construct	2023 M	2025 M	Diff	t-test	p-value (FDR)	Cohen's d	2023 SD	2025 SD
AR	1.72	1.96	+0.24	3.27	.001	+0.14	1.56	1.81
TP	2.55	2.35 (4-item 2.37)	-0.20	-4.84	$< .001$	-0.21	0.97	0.92 (4-item 0.87)
PB	2.40	2.41	+0.01	0.15	.885 **ns**	+0.01	0.85	0.89
PR	3.82	3.69	-0.13	-3.81	$< .001$	-0.17	0.76	0.77

Table 4: Adoption Readiness Distribution: 2023 vs 2025. Categories are aggregated from 7-point index to descriptive categories of unaware, low-intention, high intention and user.

Category	2023	2025
Unaware	753 (75.3%)	722 (67%)
Low/Medium Intention	172 (17.2%)	239 (22.2%)
High Intention	24 (2.4%)	21 (2%)
User	51 (5.1%)	96 (8.9%)

polarization trend, with the ambivalent middle shrinking but still representing the largest segment of the population.

5.3 RQ3: How are transhumanist value predisposition, perceived benefits and risks associated with user profiles, and how did these associations change over time?

To describe how strongly each attitudinal construct varies across the latent profiles, we computed eta-squared (η^2) effect sizes from one-way ANOVAs separately for 2023 and 2025. Eta-squared quantifies the proportion of variance in a construct that is attributable to differences between profiles. Importantly, this analysis is descriptive, and characterizes the distinctiveness of the profiles on each construct.

Table 7 reports the results. In both waves, Transhumanist Value Predisposition and Perceived Benefits show the largest between-profile differences. In 2023, profile membership accounted for 46% of the variance in Transhumanist Predisposition and 53% of the variance in Perceived Benefits; these values increased slightly in 2025 ($\eta^2 = .50$ and $\eta^2 = .58$, respectively).

Perceived Risks exhibited substantially smaller but still meaningful differences across profiles ($\eta^2 = .07$ in 2023; $\eta^2 = .09$ in 2025). These effects remained relatively stable across waves.

Taken together, these results indicate that the profiles differ most strongly in their levels of technological optimism (value predisposition and perceived benefits), whereas differences in perceived risks are comparatively smaller. The overall pattern is consistent across both years, with modest increases in between-profile differentiation in 2025.

5.4 RQ4: How are demographic factors associated with different user profiles, and how did these associations change over time?

To examine whether demographic factors predict membership in the Skeptical, Considering, and Convinced profiles, we estimated multinomial logistic regression models separately for the 2023 and 2025 samples. Profile membership (assigned based on the pooled LPA solution) was regressed on age, gender, education (three-level quota variable), and household income (six-level ordinal measure). Categorical predictors (gender, education, income) were dummy-coded, and age was entered as a continuous variable. The Skeptical profile served as the reference category. Odds ratios (OR) and 95% confidence intervals are reported in Table 8.

Across both years, age exhibited a small but consistent negative association with belonging to either the Considering or Convinced profiles, indicating that younger respondents were more likely to fall into the more optimistic or adoption-ready profiles. Gender effects were substantial in both years: compared to women, men had significantly higher odds of belonging to the Convinced and Considering profiles, with the effect strongest for the Convinced group. Education and income showed weaker and statistically inconsistent associations across years, with confidence intervals generally crossing 1. Model-fit indices (likelihood-ratio χ^2, McFadden R^2, AIC) are reported below the table.

Taken together, the results indicate that demographic predictors explain only a modest share of variance in profile membership. Gender shows the most consistent association, as men are more likely to belong to the Convinced and Considering profiles in both years, whereas age exhibits a smaller but stable negative effect. Socioeconomic indicators (education and income) display minimal or inconsistent associations across waves.

6 Discussion

This study provides the first population-level evidence of how cyborg technology adoption is evolving over time in Switzerland, comparing two representative cross-sectional surveys from 2023 and 2025. Results show that adoption readiness is rising alongside an increasing moderation of value predisposition and attitudes. We find three clusters of Convinced, Considering and Skeptical individuals. Over time, the Convinced and Skeptical clusters grew. Together, these dynamics suggest that cyborg technologies are moving beyond their early adopter diffusion stage, and are now on the one hand accepted by an early majority, but on the other hand are rejected by a growing skeptical portion of the population.

Table 5: Item-level mean values and changes from 2023 to 2025.

item	M 2023	M 2025	Δ M	Cohen's d	t-test	p-value
TRANSHUMAN_1	2.269	1.992	-0.277	-0.26	-5.82	0.000
TRANSHUMAN_2	2.834	2.710	-0.124	-0.11	-2.58	0.010
TRANSHUMAN_3	-	2.19	-	-	-	-
TRANSHUMAN_4	-	2.6	-	-	-	-
BENEFIT_8	1.509	2.160	0.651	0.70	16.00	0.000
BENEFIT_1	2.432	2.290	-0.142	-0.12	-2.79	0.005
BENEFIT_2	2.522	2.384	-0.138	-0.12	-2.80	0.005
BENEFIT_7	2.887	2.771	-0.116	-0.10	-2.27	0.023
BENEFIT_4	2.186	2.124	-0.062	-0.06	-1.31	0.190
BENEFIT_3	2.688	2.627	-0.061	-0.05	-1.22	0.222
BENEFIT_6	2.587	2.532	-0.055	-0.05	-1.12	0.265
BENEFIT_5	2.410	2.377	-0.033	-0.03	-0.69	0.489
RISK_7	3.496	3.239	-0.257	-0.22	-4.94	0.000
RISK_6	3.837	3.617	-0.220	-0.22	-4.96	0.000
RISK_1	4.063	3.897	-0.166	-0.17	-3.78	0.000
RISK_5	3.487	3.322	-0.165	-0.15	-3.46	0.001
RISK_2	4.208	4.125	-0.083	-0.09	-1.99	0.047
RISK_3	3.855	3.812	-0.043	-0.04	-0.90	0.367
RISK_4	3.797	3.836	0.039	0.04	0.83	0.406

Table 6: TP = Transhumanist Predisposition, PB = Perceived Benefits, PR = Perceived Risks, AR = Adoption Readiness. TP, PB, PR are measured on 5-point Likert scales; AR is a 7-point staged index.

	2023					2025				
Profile	Size (%)	**TP**	**PB**	**PR**	**AR**	Size (%)	**TP**	**PB**	**PR**	**AR**
Skeptical	408 (40.8%)	1.77	1.69	4.05	1.23	459 (42.6%)	1.66	1.62	3.95	1.30
Considering	481 (48.1%)	3.02	2.79	3.63	1.23	471 (43.7%)	2.86	2.98	3.52	1.31
Convinced	111 (11.1%)	3.39	3.36	3.77	5.64	148 (13.7%)	3.04	3.04	3.43	6.11

Table 7: Eta-squared (η^2) values indicating the proportion of variance in each construct explained by latent profile membership, separately for 2023 and 2025. Larger values indicate stronger differentiation across profiles.

Construct	**2023**	**2025**
Transhumanist Predisposition	0.46	0.50
Perceived Benefits	0.53	0.58
Perceived Risks	0.07	0.09

We acknowledge some limitations that characterize this study. First, we rely on two repeated cross-sectional surveys rather than a longitudinal panel design, which prevents tracing individual-level changes. Second, the measure of transhumanist predispositions is limited to two items in 2023, and expanded to a 4-item factor in 2025. On the one hand, the addition of two items improved psychometric realibility to .8, but on the other hand limited comparability with 2023, so we only report the results of the 4-item construct descriptively and do not use them in cross-wave comparisons. In general, the construct is exploratory and not a validated scale, so it can only provide a proxy for beliefs that characterize the transhumanist values [8]. We also acknowledge that grouping diverse technologies (BCIs, subcutaneous implants, wearables) under a single category may obscure important differences in user perception. Future work should examine these technologies separately. Furthermore, open-ended answers from users of cyborg technologies revealed that some respondents conflated medical devices (e.g. pacemakers) with non-medical cyborg technologies. As such, results related to self-reported users of cyborg technologies may be inflated. Finally, findings are limited to Switzerland. This limits the context to a developed, highly digitized [60], European country.

Notwithstanding these limitations, this study makes several contributions. First, it extends the empirical literature on the adoption of cyborg technology by providing multiyear population-level data, which contrasts with previous research that relied on single cross-sectional population samples or qualitative studies [12]. Second, it introduces transhumanist value predisposition into quantitative survey research, offering a first example of operationalization. Previously, transhumanist predispositions had prominently emerged

Table 8: Multinomial logistic regression predicting profile membership from demographics (odds ratios with 95% CI). Reference category: *Skeptical.*

	2023		2025	
Predictor	**Convinced**	**Considering**	**Convinced**	**Considering**
Age	0.97 [0.95, 0.98]	0.98 [0.97, 0.99]	0.96 [0.95, 0.98]	0.98 [0.97, 0.98]
Male (vs. Female)	3.83 [2.39, 6.16]	1.66 [1.26, 2.20]	2.19 [1.48, 3.25]	1.44 [1.10, 1.89]
Medium education	0.64 [0.26, 1.60]	0.92 [0.49, 1.72]	0.82 [0.37, 1.81]	0.69 [0.38, 1.24]
Higher education	0.87 [0.35, 2.17]	1.02 [0.54, 1.92]	0.76 [0.34, 1.72]	0.59 [0.32, 1.07]
Income (2)	1.62 [0.72, 3.66]	0.83 [0.53, 1.31]	0.63 [0.32, 1.23]	0.88 [0.56, 1.39]
Income (3)	1.08 [0.46, 2.55]	0.91 [0.58, 1.42]	0.62 [0.32, 1.21]	0.87 [0.55, 1.37]
Income (4)	1.83 [0.80, 4.21]	1.02 [0.64, 1.63]	0.85 [0.44, 1.63]	0.81 [0.50, 1.30]
Income (5)	1.94 [0.82, 4.59]	1.27 [0.78, 2.06]	0.60 [0.30, 1.17]	0.82 [0.51, 1.32]
Income (6)	2.67 [0.99, 7.23]	1.24 [0.66, 2.33]	0.65 [0.28, 1.50]	0.61 [0.32, 1.14]

Model fit:
2023: Residual deviance = 1810.0; Null deviance = 1924.0; LR $\chi^2(18)$ = 114.2, $p < .001$; McFadden R^2 = .059; AIC = 1850.
2025: Residual deviance = 2051.0; Null deviance = 2152.0; LR $\chi^2(18)$ = 100., $p < .001$; McFadden R^2 = .047; AIC = 2091.

in subcultural or ethnographic contexts related to the adoption of cyborg technologies [10, 25, 43, 57].

Our study tracks the general population over time, offering a perspective on how adoption of cyborg technologies is progressing in the Swiss population. A central finding of our study is the decline in transhumanist value predispositions, perceived benefits and risks amidst an increasing adoption of cyborg technologies. This pattern is consistent with diffusion of innovations theory and Moore's conceptualization of the chasm between early adopters and early majority [35, 54], which posits that once technologies move beyond early adopters, ideological enthusiasm gives way to more pragmatic cost–benefit assessments.

The profile analysis also revealed that polarization is intensifying. The Convinced and Skeptical clusters both grew, while the Considering group shrank, reflecting a decreasing middle ground. Importantly, adoption readiness of Convinced users increased in 2025, despite reporting lower levels of transhumanist predisposition and reduced perceptions of benefits, suggesting that practical motivations may now outweigh ideological ones. Meanwhile, the Skeptical cluster retained high risk perceptions and low adoption readiness, underscoring the persistence of barriers that remain difficult to overcome. This polarization may signal a diffusion trajectory where adoption becomes normalized for a subset of the population, while entrenched skepticism prevents broader societal consensus.

Demographic factors played a comparatively minor but reliable role in profile membership. Across both waves, younger respondents were consistently more likely to belong to the Convinced and Considering profiles, although these effects were small in magnitude. Gender differences also remained statistically significant in both years, with men showing higher odds of being in the more optimistic profiles. However, the corresponding odds ratios were smaller in 2025, indicating a modest weakening of gender-based differentiation over time. In contrast, education and income showed weak and inconsistent associations, suggesting that socioeconomic status contributes little to profile formation. These patterns partly align with prior research linking youth and male gender to greater openness toward augmentation [21, 37, 52, 55, 67, 69], yet they also challenge the assumption that cyborg technologies primarily appeal to a niche male audience, as gender differences appear to be narrowing over time.

Our findings present a nuanced picture of how the public is adopting cyborg technologies. Across both waves, risk perceptions remained moderate, stable, and widely shared, even among the most optimistic users. This indicates that openness to augmentation does not stem from disregarding risks but from weighing them against perceived personal value. In fact, perceived risks explained little variance across profiles precisely because everyone, including Convinced users, recognizes the risks associated with augmentation.

At the same time, we observe a small but notable migration out of the "Considering" profile toward both the Convinced and Skeptical groups. This shift suggests that as augmentation becomes more visible and better understood, the undecided middle begins to move towards clearer stances. Importantly, we also see continued conflation between medical and non-medical cyborg technologies, with participants often evaluating consumer enhancements through a clinical lens. This echoes prior work highlighting that users often default to medical applications when deciding on the acceptability of cyborg technologies [65].

Together, these findings carry several implications for HCI, which align with Mueller et al.'s roadmap for Human-Computer Integration [36]. First, because benefit perceptions differentiate profiles over the perception of risks, designers and communicators should prioritize clear, concrete explanations of everyday benefits, particularly for non-medical augmentations whose purpose may otherwise be unclear or ambiguous. Aligning with Villa et al. [65], unambiguous communication of function and intent can reduce speculation and uncertainty, helping users form more positive benefit perceptions, while maintaining awareness of risks. Second, our results suggest value in designing human augmentation as a continuum rather than differentiating categorically between medical and non-medical cyborg technologies. Following the "assistive augmentation" approach [24], interfaces and augmentations should allow users to choose how far they want to augment, ranging from assistive, to restorative, to optional enhancement, thereby supporting diverse motivations and reducing the perceived divide between medical and non-medical uses. Finally, because risk perceptions are moderate and stable, the design of cyborg technologies could prioritize the user's sense of control over the technology. Creating systems that make augmentation understandable, adjustable, and personally meaningful may help guide more of the population toward the positive perceptions that characterize Convinced users.

Interpreted through diffusion theory and Moore's chasm [35, 54], these findings suggest that further diffusion of cyborg technologies will hinge on catering to pragmatic preferences of the general population, rather than pioneer enthusiasm. As perceptions of risks and benefits become more moderate, priority could be given to robust, helpful applications (over disruptive prototypes) and to privacy- and security-by-design, supported by governance and regulatory efforts to respond to user concerns [1, 17, 18, 56]. The consumer trajectory of Google Glass illustrates how augmentation technologies can fail to reach a wider audience when the value proposition is ambiguous, aesthetics are stigmatized, and privacy concerns are salient in the population [6].

Taken together, these results suggest that cyborg technologies are spreading from early adopters to an early majority of the population. While adoption is expanding, ideological enthusiasm has waned and public attitudes are becoming more moderate but polarized. For developers, policymakers, and researchers, this underscores the importance of shifting focus away from visionary promises toward pragmatic value propositions that can appeal the general population.

7 Conclusion

This study offers the first population-level evidence on the evolving diffusion of cyborg technologies, based on two cross-sectional representative surveys in Switzerland. We examine changes in adoption readiness, transhumanist value predisposition, and risk/benefit perceptions between 2023 and 2025, highlighting a moderation in value predisposition and attitudes, alongside an increasing adoption readiness. We identify three distinct user profiles: Convinced, Considering, and Skeptical. Our findings show that attitudes are polarizing, with both Convinced and Skeptical groups gaining ground while the Considering profile cluster shrinks in size.

By linking diffusion of innovations theory with a value-attitude-behavior hierarchy in the adoption process, we demonstrate that the early ideological underpinnings of cyborg technology adoption lose importance in favor of pragmatic considerations. This transition reflects a movement beyond early adopter subcultures toward broader social adoption. At the same time, persistent skepticism highlights the continuing salience of perceived risks for a specific group of people.

As adoption of cyborg technologies expands, understanding these dynamics is essential for anticipating societal responses and guiding both policy and technological development in ways that are inclusive, transparent, and responsive to concerns of the population.

8 AI Disclosure Statement

ChatGPT was utilized to generate sections of R code for the analysis of data. All generated code was checked by the authors.

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A Factor Loadings

Table 9: Principal Axis Factoring Results

Variable	PA1	PA2	PA3	h^2	u^2	complexity
BENEFIT_1	0.71	-0.02	0.02	0.52	0.48	1.0
BENEFIT_2	0.79	0.02	0.01	0.63	0.36	1.0
BENEFIT_3	0.82	0.05	-0.03	0.65	0.35	1.0
BENEFIT_4	0.67	-0.05	0.09	0.53	0.46	1.0
BENEFIT_5	0.72	0.04	0.01	0.52	0.48	1.0
BENEFIT_6	0.75	-0.03	-0.01	0.57	0.43	1.0
BENEFIT_7	0.78	-0.04	-0.05	0.58	0.42	1.0
BENEFIT_8	0.66	-0.02	0.05	0.48	0.51	1.0
RISK_1	-0.02	0.73	-0.02	0.54	0.45	1.0
RISK_2	0.01	0.73	-0.04	0.55	0.45	1.0
RISK_3	0.09	0.67	-0.04	0.45	0.55	1.0
RISK_4	0.12	0.62	-0.06	0.39	0.60	1.1
RISK_5	-0.04	0.62	0.05	0.38	0.61	1.0
RISK_6	-0.09	0.72	0.03	0.53	0.46	1.0
RISK_7	-0.07	0.62	0.08	0.38	0.62	1.1
TRANSHUMAN_1	0.01	-0.01	0.99	1.00	0.01	1.0
TRANSHUMAN_2	0.30	0.06	0.36	0.32	0.68	2.0
Factor Statistics						
SS loadings	4.59	3.21	1.23			
Proportion Var	0.27	0.19	0.07			
Cumulative Var	0.27	0.46	0.53			
Proportion Explained	0.51	0.36	0.14			
Cumulative Proportion	0.51	0.86	1.00			

Table 10: Factor Correlation Matrix

Factor	PA1	PA2	PA3
PA1	1.00	-0.13	0.50
PA2	-0.13	1.00	-0.18
PA3	0.50	-0.18	1.00

Table 11: Standardized factor loadings for the 4-item Transhumanist Predisposition scale (2025).

Item	**Loading**	**h^2**
TRANSHUMAN_1	.74	.55
TRANSHUMAN_2	.69	.47
TRANSHUMAN_3	.68	.46
TRANSHUMAN_4	.74	.54
Variance explained	51%	
Cronbach's α	.80	

B Survey Item Text

Table 12: Item codes, constructs, and English translations of survey items.

Item code	Construct	Item wording (English translation)
AR_1	Awareness	Have you already heard of products of this kind (or similar ones)?
AR_2	Current use	Do you currently use products of this kind (or similar ones)?
AR_3	Device list (open)	Which non-medically necessary products do you already use? Please list all that apply.
AR_4	Intention to use	How likely are you to use wearable or implantable products once they become available and affordable?
TRANSHUMAN_1	Transhuman Predisposition	These technologies can solve almost all societal problems.
TRANSHUMAN_2	Transhuman Predisposition	These technologies can enhance human physical and mental abilities in a targeted way.
TRANSHUMAN_3 (2025+)	Transhuman Predisposition	Society and individuals have a moral obligation to use these technologies to improve themselves.
TRANSHUMAN_4 (2025+)	Transhuman Predisposition	Technological innovation can surpass what is achievable through biological evolution.
BENEFIT_1	Perceived Benefits	Significantly extend lifespan.
BENEFIT_2	Perceived Benefits	Significantly enhance thinking performance and concentration.
BENEFIT_3	Perceived Benefits	Significantly increase human productivity.
BENEFIT_4	Perceived Benefits	Better conscious control of one's feelings and emotions.
BENEFIT_5	Perceived Benefits	Significantly improve career opportunities.
BENEFIT_6	Perceived Benefits	Significantly improve well-being and quality of life.
BENEFIT_7	Perceived Benefits	Make everyday life much more comfortable.
BENEFIT_8	Perceived Benefits	Achieve a significantly higher (posthuman) form of human life.
RISK_1	Perceived Risks	Additional privacy violations may occur (e.g., health data).
RISK_2	Perceived Risks	Additional forms of cybercrime may emerge (e.g., hacking, manipulation).
RISK_3	Perceived Risks	Additional inequality may arise due to unequal access.
RISK_4	Perceived Risks	Increasing social or institutional pressure to adopt these technologies.
RISK_5	Perceived Risks	Additional health problems or physical harms may occur.
RISK_6	Perceived Risks	Malfunctions may create new problems (e.g., interference with the body).
RISK_7	Perceived Risks	Technologies may no longer be controllable by humans.