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Opting out of generative AI: a behavioral experiment examining the role of education in Perplexity AI avoidance

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ABSTRACT

The rise of conversational AI (CAI), powered by large language models, is transforming how individuals access and interact with digital information. However, these tools may inadvertently amplify existing digital inequalities. This study investigates whether differences in formal education are associated with CAI avoidance, i.e., the deliberate refusal or discontinuation of engaging with a CAI when the opportunity and demand arises. We leverage behavioral data from an online experiment (N = 1636) where participants were randomly assigned to one of three groups: a control group, a traditional online search task, or a CAI task (Perplexity AI). Task avoidance (operationalized as survey abandonment or providing unrelated responses during task assignment) was significantly higher in the CAI group (51 %) compared to the search (30.9 %) and control (16.8 %) groups, with the highest CAI avoidance among participants with lower education levels (~74.4 %). Structural equation modeling based on the theoretical framework UTAUT2 and LASSO regressions reveal that education is strongly associated with CAI avoidance, even after accounting for various cognitive and affective predictors of technology adoption. These findings underscore education's central role in shaping AI adoption and the role of self-selection biases in AI-related research, stressing the need for inclusive design to ensure equitable access to emerging technologies.

1. Introduction

The rapid advancement of generative artificial intelligence (genAI) has transformed the way individuals interact with digital information (Stokel-Walker and Van Noorden, 2023). Some of these tools are designed to provide users with natural and dynamic means of searching for and retrieving information in a natural language dialogue (Radlinski and Craswell, 2017). Unlike traditional search engines, which return information on specific keywords in "single shot" interfaces, *conversational search AIs* such as Perplexity AI or Bing Copilot[1] and more recently ChatGPT, Gemini and Claude, ask follow-up questions, clarify intent, and personalize responses based on previous prompts and answers. Similarly to traditional search engines, they can provide sources for their information. Since large language models (LLMs) captured the public interest with the advent of ChatGPT, conversational AI (CAI) has been integrated into

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[1] The best known conversational Gen-AIs only introduced search capabilities much later, e.g., ChatGPT in October 2024 and Gemini in March 2025.

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applications for, among others, customer service, e-commerce, and education, enhancing user experience by delivering more tailored and dynamic responses to our information needs (Casheekar et al., 2024). Studies have found that users often prefer conversational search systems, possibly due to improved speed of task completion, efficiency, and user-friendliness (Dubiel et al., 2018; Kaushik and Jones, 2023).

Despite this apparent preference for more dynamic information-seeking tools, questions about their accessibility and equitable use have recently emerged (Kacperski et al., 2025; Khowaja et al., 2024). The digital divide concept is central to understanding the challenges faced by users of emerging technologies like CAI; specifically, the concept refers to the disparities in access to, use of, and benefit from digital technologies among different social groups (Lythreatis et al., 2022; Nguyen et al., 2021). Research consistently shows that older adults and women, as well as individuals with lower socio-economic backgrounds and education, tend to report and display lower levels of technology acceptance (Cruz-Jesus et al., 2016; Elena-Bucea et al., 2021; Kacperski et al., 2025). Differences in the willingness to use CAI could exacerbate existing skill gaps and lead to disadvantaged individuals missing out on opportunities for productivity improvement and personalized learning (Capraro et al., 2024).

The literature highlights that technology adoption is shaped not only by drivers (e.g., motivation, self-efficacy) but also barriers such as perceived risks, lack of opportunity, or limited ability (Ram and Sheth, 1989; Michie et al., 2011). In this context, we define CAI avoidance as the deliberate refusal or discontinuation of engaging with a CAI system when the opportunity and requirement to do so arises. This construct is conceptually distinct from non-use due to external factors (e.g., lack of access or need); avoidance occurs despite availability and external demands, reflecting internal barriers or concerns. Empirical evidence on AI adoption suggests that both types of factors play an important role; for example, Nakagomi et al. (2025) reported that the most commonly cited reasons for AI non-use were a lack of perceived need (i.e., an external demand), and lack of knowledge on how to use it (i.e., an internal (perceived) barrier). In a recent study with faculty members who reported avoiding AI, Shata (2025) identified five primary barriers: lack of readiness, low perceived value, identity tensions, threats to human creativity, and ethical risks. Therefore, CAI avoidance is a theoretically meaningful outcome that captures active user resistance and disengagement.

Our study focuses on how individuals' educational attainment influences the behavior of engaging with or avoiding a task to use a fully fledged CAI, compared to two other tasks: searching online in the traditional way and a control condition. We focus our analysis on education primarily due to its policy relevance and malleability. Unlike age or gender, which are immutable characteristics, educational disparities can be meaningfully addressed through interventions, such as targeted digital literacy programs, simplified user interface design, or tailored onboarding experiences. Moreover, the role of education in technology adoption remains underexplored within the Unified Theory of Acceptance and Use of Technology (UTAUT2) framework (for a review, see Alsharhan et al., 2024). While age and gender are routinely included as moderators, educational attainment is often omitted, partly due to cross-cultural variation and the difficulty of accounting for informal or lifelong learning.

Finally, recognizing that participation in surveys about emerging technologies typically skews toward individuals with higher educational attainment, who see themselves as beneficiaries of digitalization (Grewenig et al., 2023) and that intrinsic motivation is a major driver to participation in research studies (Silber et al., 2023), it is essential to examine how self-selection biases might influence the research trajectory of CAI development. If research predominantly represents the perspectives of digitally empowered citizens, CAI could evolve in a way that further excludes lower-educated individuals by prioritizing the needs and experiences of those already at an advantage, underscoring the urgent need for inclusive research designs and targeted interventions to ensure equitable CAI adoption and use.

1.1. The role of education in AI and CAI adoption

In recent years, there has been a rapid increase in research examining individuals' willingness to adopt artificial intelligence (AI) across diverse fields, including health care, computational tasks, and scientific research (for reviews, see Kabalisa and Altmann, 2021; Kelly et al., 2023; Radhakrishnan and Chattopadhyay, 2020). More recently, attention has turned to understanding the adoption of conversational AI tools powered by newer-generation genAI models (see, e.g., a review on privacy, security, and trust in CAI; Leschanowsky et al., 2024). In general, there appears to be a consensus that the adoption of AI is, among other things, dependent on a variety of demographic and socio-economic factors: age, gender, income, education, and political stance (e.g., Bentley et al., 2024; Eder and Sjøvaag, 2024; Kacperski et al., 2025; C. Wang et al., 2024). Still, a review of studies on chatbot adoption reported that moderators, especially demographics, were not considered in 63 % of reviewed studies, with age, gender, and technology experience being the most employed (Alsharhan et al., 2024).

Studies do indicate that advanced educational degrees have been associated with higher AI knowledge and skills (Eder and Sjøvaag, 2024; C. Wang et al., 2024), reliance on AI recommendations (Biswas and Murray, 2024), enthusiasm towards and support for developing AI (Zhang and Dafoe, 2019), intention to adopt due to higher AI self-efficacy (Hong, 2022), trust and expectations about usefulness (Araujo et al., 2020), and adoption of transcription and translation tools (Goldenthal et al., 2021), while those with lower education are more negative, or, at best, more indifferent or ambiguous (Bao et al., 2022). Specifically with regards to CAI, the Pew Recent Center reported that US adults with higher educational degrees are more likely to report having used ChatGPT (McClain, 2024). In a purely academic context, more years of education positively affected reported usage and attitudes towards CAI (Stöhr et al., 2024). In the tourism sector, individuals with bachelor's and above degrees reported higher acceptance of hotel-assistant CAIs, possibly due to a better understanding of their capabilities (Tavitiyaman et al., 2022).

However, the above adoption studies draw conclusions from self-reported survey data. Actual behavioral measures are so far lacking: to the best of our knowledge, only two studies have previously explored the association of socio-demographic factors and CAI adoption with behavioral data, both finding education to be associated with initial adoption: one study tracked German users'

ChatGPT usage behavior with digital traces (Kacperski et al., 2025); another study used Bing search queries related to ChatGPT as a proxy for its access and usage across the US (Daepp and Counts, 2024).

1.2. UTAUT2 and CAI adoption

To better understand the interplay of various acceptance determinants and education, we draw on the Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh et al., 2003, updated in 2012 to the UTAUT2), a widely used framework for studying technology adoption. The UTAUT2 posits that constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit play key roles in shaping behavioral intention and that behavioral intention (BI) predicts actual behavior, a premise central to many technology adoption studies. The underlying rationale is that individuals' intentions, which encompass their motivation and readiness to engage with a particular technology, are the most direct and observable precursors to action. Recently, a research agenda employing the UTAUT2 to study AI adoption has been proposed (Venkatesh, 2022), and the UTAUT2 model has started to be well-employed for this purpose (e.g., see reviews of Kelly et al., 2023; Leschanowsky et al., 2024; Radhakrishnan and Chattopadhyay, 2020). For example, Leschanowsky et al. (2024) found that six studies used the framework in a review related to CAIs' privacy, security, and trust. Additionally, studies have found evidence of the relationship of UTAUT2 variables such as performance and effort expectancy with CAI adoption specifically (Budhathoki et al., 2024; Ma and Huo, 2023; Vimalkumar et al., 2021).

The UTAUT2 considers moderators in line with literature on the digital divide: it posits that specific subgroups are less likely to engage with novel technologies, particularly those who are already at a disadvantage, such as older adults, women, or individuals with lower education (Venkatesh et al., 2016). Evidence in the UTAUT2 literature supports this position, demonstrating that education shapes how participants perceive the usefulness and ease of use of technologies like internet use (Niehaves and Plattfaut, 2010). Education has been shown to be a significant moderator in the adoption-perception-use relationship towards Facebook when Facebook first emerged, even as all other UTAUT2 factors were significant (Liew et al., 2014). The adoption of internet banking and mobile internet banking app usage, for example, has also been found to be more commonly undertaken by users with higher education due to higher performance expectancy, trust, and locus of control (Abu-Shanab, 2011). At the same time, some partial or null effects are also reported in the literature for the moderating effect of education on UTAUT2 variables, for example, for mobile app adoption and mobile phone data usage, where at most, it moderated social influence (Hew et al., 2015; Li et al., 2014). In a study of the use of government internet services, education had a significant main effect, but when UTAUT2 factors, especially performance expectancy, and experience, were included, the relationship disappeared (van Dijk et al., 2008). It suggests that education's moderating role in technology adoption is context-dependent and not as applicable to certain specific technological innovations.

1.3. Technology avoidance in the CAI context

While most research emphasizes technology adoption, avoidance captures a complementary facet of user behavior that can directly inform policy efforts to reduce digital inequality by identifying and addressing underlying barriers. Technology avoidance aligns with the Capability, Opportunity, Motivation–Behavior (COM-B) framework, which posits that non-engagement arises not only from a lack of opportunity or ability but also from low motivation, self-efficacy, or perceived risk (Michie et al., 2011). Likewise, the Innovation Resistance Theory (IRT) suggests that emotional, functional, and psychological barriers, such as habit persistence, perceived risks, and conflicts with prior beliefs, can lead to consumers' deliberate rejection of innovations (Ram and Sheth, 1989).

In the context of AI, avoidance is increasingly salient. Recent studies have begun to examine reasons for non-use, including concerns about privacy, security, and trust in CAI (Leschanowsky et al., 2024; Perrig et al., 2023), AI-related anxiety (Wang and Wang, 2022), and low perceived competence or digital skills (Said et al., 2023). Perrig et al. (2023) assessed the psychometric properties of trust scales in AI contexts and found that trust and distrust function as distinct constructs, supporting the view that avoidance and adoption are not merely opposites but involve separate underlying processes. Wang and Wang (2022) developed and validated a multi-item scale for AI anxiety, showing that it captures a general unease about AI's societal implications that can lead to avoidance. Said et al. (2023) demonstrated that individuals' knowledge and confidence in their understanding of AI shape perceived risks and benefits, with greater knowledge linked to risk blindness and greater confidence associated with emphasizing benefits.

More broadly, Nakagomi et al. (2025), using a large population-based dataset from Japan, reported that the most commonly cited reasons for AI non-use were a lack of perceived need (i.e., "not necessary", 39.5 %) and knowledge (i.e., "don't know how to use", 18.5 %), underscoring both motivational and perceived capability-based constraints (i.e. self-efficacy; Bandura, 1997). Focusing on AI avoidance among highly educated individuals (i.e., faculty members), Shata (2025) found five key primary barriers (lack of readiness, low perceived value, identity tensions, threats to human creativity, and ethical risks) mirroring barriers to adoption as outlined in IRT.

1.4. Research agenda

We conducted an online experimental study in which participants were randomized into a control group, a group tasked with performing a traditional online search, and a group instructed to use a CAI (Perplexity AI) to inform themselves about a policy. A disproportionately high attrition rate occurred in the CAI group − 377 out of 736 (∼51 %) of the assigned participants: and the abandonment of the survey at the moment of the task assignment is an indicator of avoidance of the task. We thus formulated a first explorative hypothesis to support our observation statistically:

H1: Participants are significantly more likely to disengage at the moment of task assignment if assigned to use a CAI compared to control and traditional online search tasks.

To better understand this behavior, we turned to prior research, which has found in behavioral data that usage of CAI is significantly associated with user socio-demographics (Kacperski et al., 2025) and might be fueling an AI digital divide concerning educational levels (Daepp and Counts, 2024). We thus tested differences in education on CAI avoidance:

H2: Participants with lower education levels are significantly more likely to disengage at the moment of task assignment if allocated to the CAI group.

To explore the mechanisms driving the avoidance in the CAI group, we leveraged data collected in the same sample before group assignment: we asked UTAUT2 variables (Venkatesh et al., 2012) and variables related to CAI affect such as anxiety, optimism, and pessimism. We focus on associations with educational levels.

H3: Higher education levels are positively associated with UTAUT2 constructs and positive affective variables but negatively associated with negative affective variables (i.e., anxiety, pessimism, disadvantage).

H4: UTAUT2 constructs and positive affective variables are negatively associated with avoidance, and negative affective variables will be positively associated with CAI avoidance.

We then conducted an exploratory analysis using structural equation modeling to fit the UTAUT2 (Unified Theory of Acceptance and Use of Technology) framework. Our goal was to examine if education remains relevant as a predictor of CAI avoidance after introducing it into the framework or whether factors included in the UTAUT2 will explain away all avoidance effects.

H5: Participants with lower educational levels show higher CAI avoidance even after controlling for all other variables included in the UTAUT2 framework.

We further assessed the robustness of education as a predictor of CAI avoidance by conducting a LASSO regression (using 10-fold cross-validation) to select relevant variables among demographics and affective scales (Perrig et al., 2023; Said et al., 2023; Y.-Y. Wang and Wang, 2022).

H6: The LASSO procedure will consistently select educational attainment as a key predictor of CAI avoidance. Affective and demographic variables are included in the model.

We contribute to the literature in two ways: firstly, we focus on the under-researched variable of educational level and its effect on the avoidance of a specific AI technology, CAI; this gives insights into the existence of a digital divide (Alsharhan et al., 2024). Secondly, unlike most studies that rely on self-reports of adoption or report behavioral intention only (for a review, see Kelly et al., 2023), we report a behavioral metric of CAI engagement when faced with the task of using Perplexity AI to search for information, reducing errors stemming from social desirability and false recall, and improving predictive validity.

2. Methodology

2.1. Experimental design

We used data collected in the Seek2Judge project, which was reviewed by the institutional ethics board of the University of Konstanz. Participants were part of a larger study on online search and political attitude change and were sampled from an online market research panel by European panel provider Bilendi GmbH. They received a letter of information, gave explicit consent, and then completed an initial survey in August 2023. The initial survey collected data on socio-demographics and items related to political interests. Individuals who completed the initial survey were invited and consented to participate in the experiment conducted over one week, from September 5th to September 13th, 2023.

Before answering the items, participants were introduced to the topic: “*Artificial intelligence (AI) is increasingly used in conversational systems like ChatGPT, BingChat, Bard to enable human-like conversations, often in online chats. The following questions will focus on this application of AI, which we will always call “Chatbot” in the questions.*” An image of the ChatGPT interface was provided to illustrate a CAI. Later questions also included another reminder, “*In the following questions the term ”Chatbot“ refers to AI-supported conversational systems such as ChatGPT, BingChat or Bard*.”.

Participants then completed the baseline survey, which included adapted UTAUT2 items (Venkatesh et al., 2012) and a set of affective CAI-related items introduced in recent literature (Perrig et al., 2023; Said et al., 2023; Y.-Y. Wang and Wang, 2022); see Appendix G.

They were then randomly assigned to one of three groups, namely (1) control (n = 458), (2) search (n = 444), and (3) CAI (n = 734); the unequal realized sample sizes reflect the oversampling following differential task abandonment at assignment (highest in the CAI group) rather than planned unequal allocation. The control group was asked to think about a German renewable energy transition policy, the *Erneuerbare Energien Gesetz* (EEG), consider its pros and cons and then write their opinion. They were asked to spend 5 minutes to complete this task, during which they could not progress in the survey. The search group was instructed to search online to inform themselves about the EEG and the pros and cons of its introduction and to provide resources and links they found online; they could not proceed until 5 minutes had elapsed. The CAI group was directed to interact with a CAI (Perplexity AI) about the EEG and the pros and cons of its introduction through a provided link that opened a new tab with the Perplexity interface. Here, while the 5-minute wait was initially mandatory, the timer and the restriction were removed as attrition was disproportionately high in this group.[2] We find no evidence that the removal of the mandatory dwell time had an effect; indeed, CAI avoidance increased after the timer was

[2] We monitored the functioning of perplexity.ai and did not observe any changes in their operation.

removed across the tested models, likely due to motivational effects (e.g., initial participants tend to be more motivated to complete surveys and therefore are less likely to abandon it). No interactions with the groups were found (Appendix C1). In all models, we add a control variable for the presence of the mandatory dwell time (binary). The CAI group had to provide the URL of the conversation log. After completing the task, participants filled out further survey items about the EEG.

The chosen CAI, Perplexity AI, is powered by a large language model (OpenAI's GPT-3.5 by the time of data collection; the same underlying model used for ChatGPT at the time) and generates responses based on search results. It was also launched around the same time as ChatGPT, in December 2022. It was chosen because, at the time of data collection, it had a few advantages over more well-known models: (1) it did not require a log-in account to initiate a conversation, (2) it was one of the few publicly available CAIs with incorporated backend web-search to provide current sources, which we deemed important for trust and (3) it generated a shareable link to the conversation log, facilitating data collection.

2.2. Participants

Our final sample consisted of N = 1636 German-speaking residents of Germany between 25 and 64 years old: 458 in the control group, 444 in the search, and 734 in the CAI. Of the final sample, 780 (47.7 %) identified as women and 856 (52.3 %) as men (the German population skews 50.3 % female), so our sample includes more men than the general population. The participants' median age was 48 (mean = 46.8, SD = 11.95); 20.1 % between 25 and 34, 24 % between 35 and 44, 21.8 % between 45 and 54, and 34.1 % between 55 and 64. The figures for the German population for the same age cohorts are 24.7 %, 25.1 %, 23 %, and 27.2 % – suggesting that our sample might be somewhat older than the general population. Educational attainment was measured using the education scale from the European Social Survey and then summarized into four categories: low (elementary school or equivalent, n = 192, 11.7 %), medium (low secondary education, n = 509, 31.1 %), high (high school/vocational certificate or equivalent, n = 427, 26.1 %), and very high (university degree, n = 508, 31.1 %). The German population has more individuals in the low (18.9 %) and high (35.1 %) groups and fewer in the middle (25.7 %) and very high (20.3 %) groups. For distribution across intervention groups, see Appendix A. The results presented in this study are robust across both weighted and unweighted analyses (see below). German population statistics are sourced from the Federal Statistical Office (Statistisches Bundesamt, 2024).

Following Austin (2009), an absolute standardized mean difference (SMD) under 0.1 typically suggests adequate covariate balance across treatment groups. Although all absolute SMDs in our study are below this benchmark, values for women (0.094) and those with high education (0.094) are close to it (Appendix B). To address these discrepancies and deviations from the German population distribution, we conducted analyses using two separate weighting strategies, applied independently to each intervention group: poststratification weights (based on age, gender, and education) and raked (and trimmed) weights (derived from the marginal means of the same variables). The poststratification weighting produced three extreme weights (over 5 times the median) and a coefficient of variation (CV) of 0.59. Raked-trimmed weighting yielded no extreme weights, a CV of 0.50, and trimmed only 1.04 % of weights; for the CAI group, the CV is 0.43. High CVs (such as those above > 0.5) are associated with loss of efficiency (reduced effective sample size) inducing larger standard errors and variance, i.e., tests are more conservative and more care should be exerted when interpreting non-significant results. Further details concerning weight calculation (and diagnostics) can be found in Appendix B. We report the raked and trimmed weighted results in the main text; unweighted and poststratification weighted analyses, showing negligible differences, are included in Appendix C, D and F.

2.3. Measurements

Our dependent variable, task avoidance, is a binary behavioral measure (1 = avoidance; 0 = engagement). Specifically, task avoidance was coded as 1 if participants met any of the following conditions: (a) in the control task, they submitted unrelated text rather than providing an opinion about EEG (or abandoned the survey during the task interval, n = 8); (b) in the search task, they either failed to provide any links or submitted unrelated content as a resource (or abandoned the survey during the task interval, n = 60); and (c) in the CAI task, they did not submit a valid link to Perplexity AI; effectively, they had to abandon the survey because the provision of the link was a compulsory field. Conversely, participants who fulfilled the task requirements were coded as 0 (i.e., engaged).

Participants responded to UTAUT2 items assessing behavioral intention (BI), performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit using a 7-point Likert scale ranging from "strongly disagree" to "strongly agree." They also reported the different CAI they had used in the past (referred to as CAI diversity; only 37 participants reported having used Perplexity AI previously) and the types of usage (referred to as applications, e.g., writing or programming). For the UTAUT2 framework, we derived a binary experience variable from the reported applications, indicating whether participants had any prior CAI usage. Finally, we included scales related to CAI trust (n = 2. α = 0.91; Perrig et al., 2023) and anxiety (n = 3, α = 0.71; Wang and and Wang, 2022), which we averaged to have a single indicator, as well as single items on negativity, optimism, fear, perceived advantages, and perceived disadvantages (Said et al., 2023). A complete list of items is available in Appendix G.

2.4. Statistical models

To examine the treatment effects on avoidance, we conducted a logistic regression with task avoidance as the dependent variable. The analysis compared group assignments (control, search, CAI) moderated by education while controlling for age and gender, attentiveness (measured via three attention checks distributed across the survey, before the task assignment, in the form of "This is an attention test. Please check 'strongly agree/disagree' here."), and the timing condition (whether the survey was completed with the mandatory dwell time in place or after its removal). Age and attentiveness were scaled and centered.

We used the R lavaan package (Rosseel, 2012) to fit structural equation models (SEMs) to examine CAI avoidance (DV) using the UTAUT2 framework. We modeled behavioral intention (BI) influenced by UTAUT2 variables (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonistic motivation, and habit), demographics (gender, age, and education), and experience. Following Venkatesh et al. (2012), moderation analysis included simple interaction between demographics and experience with UTAUT2 constructs: facilitating conditions, hedonistic motivation, and habit. In turn, BI, demographics, experience and facilitating conditions, hedonistic motivation, and habit served as predictors of CAI avoidance. Attentiveness was included as a control variable in the BI and avoidance modeling, while the timing condition was only included in the avoidance modeling. All predictors are scaled and centered for easy comparison. Fig. 3 illustrates our model.

We use the WLSMV (Weighted Least Squares Mean and Variance adjusted) estimator, as recommended by Beauducel and Herzberg (2006), for models with categorical or ordinal outcomes to fit the SEMs. Binary outcomes can be interpreted as ordinal (engagement < avoidance), and WLSMV handles it accordingly. Compared to logistic regression (not supported in lavaan), WLSMV estimates tend to be more conservative, as the method penalizes extreme values and adjusts for distributional assumptions. However, the WLSMV estimates are not directly comparable to those from logistic regression (which are in log-odds), as they represent changes in the latent thresholds that separate the binary categories (avoidance vs. engagement), generally resulting in smaller coefficient values.

Social influence, habit, and behavioral intention were each measured using the single survey item with the highest factor loading, as reported in the UTAUT2 framework (Venkatesh et al., 2012). In our main structural equation modeling (SEM) analyses, we treat the reported score on the single item (manifest indicator) as the observed measure of the construct. We also conducted analyses using fixed factor loadings from the original UTAUT2 as a robustness check, which yielded highly consistent results (Appendix D4).

In all SEM models, we standardize all latent variables to unit variance and ensure that the factor loadings for latent variables are constrained to be equal across groups, i.e., the relationship between observed UTAUT2 indicators (survey items) and their respective latent constructs remains consistent across all experimental groups (control, search, CAI). Although we only report on the CAI group, this approach helps improve the precision and reliability of the latent constructs by leveraging data from all groups during the model estimation.

3. Results

Avoidance rates for the control, search, and CAI are 16.8 % (N = 77), 30.9 % (N = 137), and 51 % (N = 374), respectively; statistically, we find support for **H1**: CAI avoidance was higher than search avoidance, OR = 2.29, 95 % CI [1.75, 2.99], $p < .001$, and search avoidance was higher than avoidance in the control group, OR = 2.25, 95 % CI [1.59, 3.19], $p < .001$ (Appendix C1).

We find support for the hypothesis that participants with lower education levels are more likely to avoid the CAI task (**H2**), as indicated by a significant interaction between linearized education and CAI group assignment; OR = 0.34, 95 % CI [0.17, 0.68], $p =$ .002 (Appendix C2). Additionally, we find a significant interaction between linearized education and search group assignment; OR = 0.36, 95 % CI [0.16, 0.80], p = .012. Fig. 1 illustrates these interactions; the observed interaction between the quadratic education term and search group assignment is statistically significant (p = .009; Appendix C3). Exploratively, we included age and gender as moderators (Appendix C4), finding significant interactions between age and the CAI group ($p =$ .001), age and the search group ($p <$ .001), gender and the CAI group ($p =$ .019), but not gender and the search group. In this model, the interaction between education and

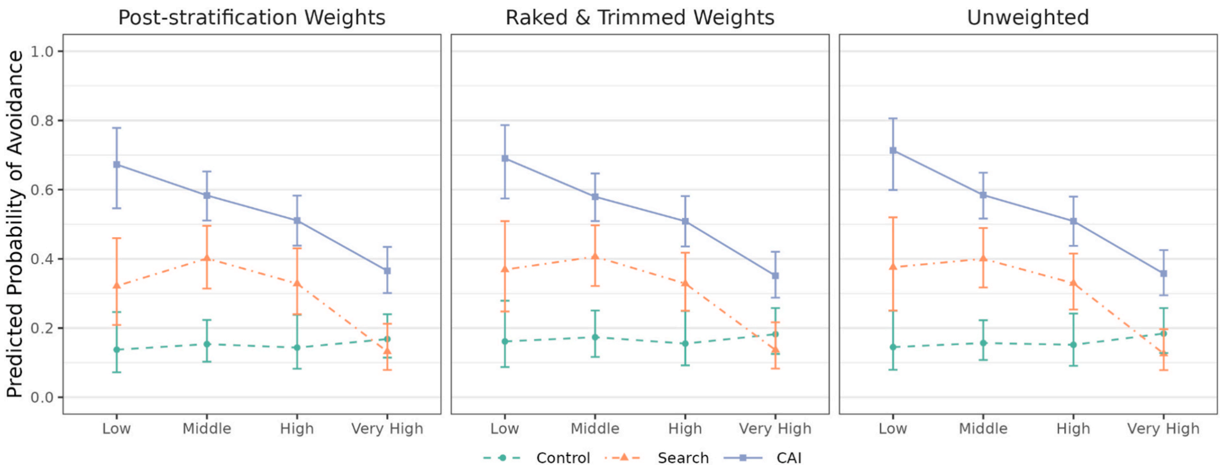

Fig. 1. Predicted avoidance probability by education level and experimental group under different weighting schemes. The left panel shows unweighted estimates, the middle panel applies raking with trimming, and the right panel uses post-stratification weights. The estimates are calculated using marginal means via the emmeans R package (Lenth, 2024). Error bars represent 95 % confidence intervals.

Table 1
Variable distribution across education. Each of the three sections in the table corresponds to variables associated with experience, UTAUT2, affective, and text metrics. p_{adj} (X^2) denotes the Bonferroni-adjusted p-value from a chi-square test across educational levels, and p_{adj} (trend) the BH-adjusted p-value from a linear regression. [(i)]Applications and diversity ignore participants who have not used CAIs before to avoid zero-inflation issues (the experience variable captures the relationship).

	Overall(N = 1636)	Low(n = 192)	Middle(n = 509)	High(n = 427)	Very High(n = 508)	p_{adj} (X^2)	p_{adj} (trend)
Experience: Yes	707 (43.2 %)	54 (28.1 %)	156 (30.6 %)	188 (44.0 %)	309 (60.8 %)	< .001	.000
Applications (n > 0)	2.2 (1.4)	1.8 (1.2)	1.9 (1.4)	2.0 (1.1)	2.7 (1.5)	**< .001**	**< .001**
CAI diversity (n > 0)	1.4 (0.7)	1.2 (0.5)	1.2 (0.4)	1.3 (0.6)	1.5 (0.9)	**< .001**	**< .001**
Behavioural Intention (BI)	3.7 (2.0)	3.0 (1.8)	3.2 (1.8)	3.8 (1.9)	4.4 (2.0)	**< .001**	**< .001**
Performance Expectancy	4.2 (1.7)	3.6 (1.7)	3.8 (1.7)	4.2 (1.6)	4.7 (1.7)	**< .001**	**< .001**
Effort Expectancy	4.3 (1.7)	3.5 (1.8)	3.9 (1.7)	4.5 (1.6)	4.9 (1.6)	**< .001**	**< .001**
Social Influence	2.9 (1.9)	2.5 (1.8)	2.5 (1.7)	2.9 (1.9)	3.6 (2.0)	**< .001**	**< .001**
Facilitation Conditions	4.3 (1.9)	3.3 (1.9)	3.8 (1.9)	4.5 (1.8)	5.0 (1.6)	**< .001**	**< .001**
Hedonistic Motivation	3.8 (1.9)	3.2 (1.8)	3.4 (1.8)	3.9 (1.8)	4.4 (1.8)	**< .001**	**< .001**
Habit	2.6 (1.9)	2.1 (1.6)	2.2 (1.6)	2.5 (1.8)	3.2 (2.1)	**< .001**	**< .001**
Trust	3.4 (1.8)	3.1 (1.7)	3.1 (1.7)	3.5 (1.7)	3.7 (1.8)	**< .001**	**< .001**
Anxiety	3.7 (1.5)	3.8 (1.6)	3.7 (1.4)	3.6 (1.5)	3.6 (1.5)	1.000	1.000
Negativity	2.9 (1.1)	3.0 (1.2)	3.0 (1.1)	2.9 (1.1)	2.8 (1.1)	0.842	0.123
Optimism	2.7 (1.1)	2.5 (1.2)	2.6 (1.1)	2.7 (1.1)	3.1 (1.1)	**< .001**	**< .001**
Pessimism	3.0 (1.2)	3.1 (1.2)	3.1 (1.2)	2.9 (1.1)	2.8 (1.2)	**.008**	**.001**
Perceived advantages	2.5 (1.1)	2.2 (1.1)	2.4 (1.1)	2.6 (1.1)	2.8 (1.1)	**< .001**	**< .001**
Perceived disadvantages	2.4 (1.1)	2.4 (1.1)	2.4 (1.1)	2.3 (1.1)	2.4 (1.1)	1.000	1.000

the search group remain significant ($p = .025$), while the interaction between education and the CAI group is significant for the unweighted model ($p = .006$) and the poststratification model ($p = .024$) but not for the trimmed and raked model ($p = .056$).

Table 1 presents the distributions of study variables across educational groups. We find support for **H3**: Higher education is positively associated with higher scores on all UTAUT2 variables (all $p_{adj} < .001$)—including all metrics for experience—and with more positive affective responses toward CAIs (trust, optimism, and expectations of profiting from AI), (all $p_{adj} < .001$), while it is negatively associated with lower scores on only one negative affective scales (i.e., pessimism, p_{adj} $(X^2) = .008$)—other negative scales (anxiety, negativity and perceived disadvantages from AI) were not significant (i.e., neither support nor contradict **H3**).

All variables that were associated with education are also associated with CAI avoidance (Table 2), i.e., **H4** is supported for all variables (all p's $< .020$) except for anxiety and disadvantage. Additionally, experience, behavioral intention, performance expectancy, social influence, facilitating conditions, and habit are associated with online search avoidance (all p's $< .023$).

Fig. 2 illustrates how the variables positively associated with education are also negatively associated with CAI avoidance and vice versa. For example, the higher educational attainments, the more experience with CAIs, and the more experience with CAIs, the less likely participants were to avoid the task. It also illustrates a similar phenomenon for age and, to a much lesser degree, gender. This

Table 2
Variable distribution and intervention groups and avoidance behavior. Each of the three sections in the table corresponds to variables associated with experience, UTAUT2, and affective items. p_{adj} (X^2) denotes the Bonferroni-adjusted p-value from a chi-square test comparing avoidance (Yes vs. No). [(i)]Applications for CAI and CAI diversity ignore participants who have not used CAIs before to avoid zero-inflation issues (the experience variable captures the relationship).

	CAI avoidance			Search avoidance			Control task avoidance		
	No (n = 374)	Yes (n = 360)	p_{adj} (X^2)	No (n = 307)	Yes (n = 137)	p_{adj} (X^2)	No (n = 381)	Yes (n = 77)	p_{adj} (X^2)
Experience: Yes	207 (57.5 %)	113 (30.2 %)	<.001	157 (51.1 %)	38 (27.7 %)	<.001	159 (41.7 %)	33 (42.9 %)	1.000
Applications (n > 0)	2.6 (1.6)	1.9 (1.2)	**<.001**	2.1 (1.3)	1.9 (1.1)	1.000	2.2 (1.3)	2.4 (1.8)	1.000
CAI diversity (n > 0)	1.5 (0.9)	1.2 (0.5)	**.001**	1.3 (0.6)	1.5 (0.8)	1.000	1.3 (0.5)	1.6 (1.1)	1.000
Behavioural Intention (BI)	4.3 (1.9)	3.2 (1.9)	**<.001**	4.0 (2.0)	3.2 (2.0)	**.002**	3.7 (2.0)	3.4 (2.1)	1.000
Performance Expectancy	4.6 (1.6)	3.8 (1.7)	**<.001**	4.4 (1.6)	3.7 (1.8)	**.001**	4.2 (1.7)	3.9 (1.8)	1.000
Effort Expectancy	4.8 (1.5)	3.8 (1.7)	**<.001**	4.7 (1.6)	3.7 (1.8)	**<.001**	4.4 (1.8)	4.0 (1.9)	1.000
Social Influence	3.2 (2.0)	2.6 (1.8)	**<.001**	3.3 (1.9)	2.6 (1.9)	**.023**	2.8 (1.9)	3.0 (1.9)	1.000
Facilitation Conditions	4.9 (1.6)	3.7 (1.9)	**<.001**	4.8 (1.7)	3.5 (2.0)	**<.001**	4.3 (1.9)	3.8 (1.9)	.569
Hedonistic Motivation	4.3 (1.8)	3.4 (1.8)	**<.001**	4.1 (1.9)	3.4 (1.9)	**.013**	3.8 (1.9)	3.6 (1.9)	1.000
Habit	3.0 (2.0)	2.1 (1.6)	**<.001**	2.7 (1.9)	2.3 (1.9)	.790	2.5 (1.8)	2.8 (2.1)	1.000
Trust	3.8 (1.8)	3.1 (1.7)	**<.001**	3.5 (1.7)	3.1 (1.8)	.349	3.4 (1.7)	3.2 (1.9)	1.000
Anxiety	3.6 (1.5)	3.7 (1.4)	1.000	3.5 (1.5)	3.7 (1.6)	1.000	3.7 (1.5)	3.8 (1.7)	1.000
Negativity	2.8 (1.1)	3.0 (1.1)	**.020**	2.8 (1.1)	3.0 (1.2)	.768	2.9 (1.1)	2.8 (1.2)	1.000
Optimism	3.0 (1.1)	2.5 (1.1)	**<.001**	2.9 (1.1)	2.7 (1.2)	1.000	2.7 (1.1)	2.8 (1.3)	1.000
Pessimism	2.8 (1.2)	3.2 (1.1)	**.003**	2.8 (1.1)	3.0 (1.3)	1.000	2.9 (1.2)	2.9 (1.2)	1.000
Perceived advantages	2.7 (1.1)	2.3 (1.0)	**<.001**	2.6 (1.1)	2.6 (1.1)	1.000	2.4 (1.1)	2.7 (1.3)	1.000
Perceived disadvantages	2.4 (1.1)	2.4 (1.1)	1.000	2.3 (1.1)	2.6 (1.2)	.247	2.3 (1.1)	2.4 (1.2)	1.000

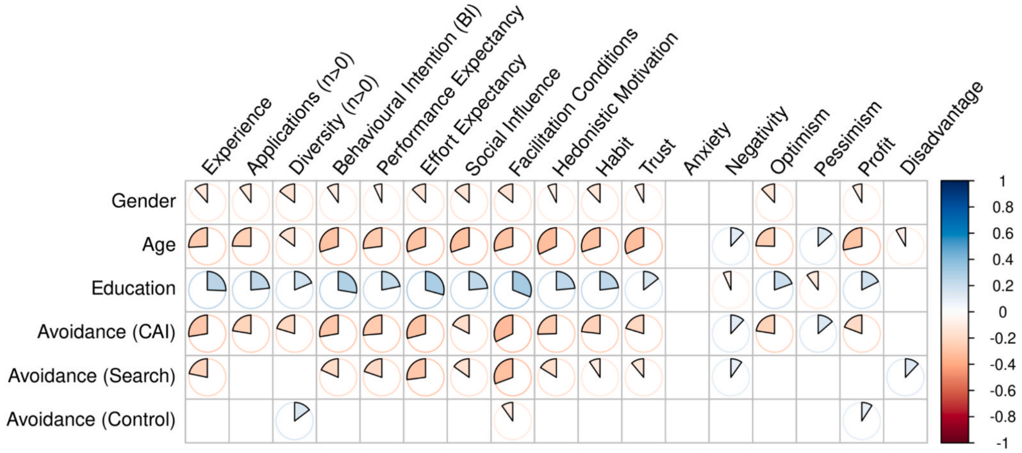

Fig. 2. Pearson correlation between variables and socio-demographics. Education is linearized (low < middle < high < very high). Avoidance correlations (last three rows) are calculated within each treatment group. Only statistically significant correlations are shown ($p < 0.05$).

pattern is also evident in online search avoidance behavior, although the associations are weaker than the ones for CAI avoidance.

To understand the role of education in the presence of the UTAUT2 variables, we employ a structural equation model approach (Fig. 3) where we show that education is significantly associated with avoidance in the CAI group (**H5**). The magnitude of the education point estimate (0.23) is comparable to established moderators of the UTAUT: age (0.32), gender (0.22), and experience (0.20). All diagnostic metrics indicated an acceptable fit according to cut-off values (Kline, 2016): CFI > 0.9, TLI > 0.9, RMSEA < 0.08, SRMR < 0.08, and Rel. X2 < 3. The variance explained (R2) for the behavioral intention and avoidance are 0.79 and 0.35, respectively. Cronbach's alphas are > 0.9 for multi-item UTAUT2 constructs (Appendix E).

As an additional robustness check, we report that the education point estimate is consistent across variations of UTAUT2 models, regardless of weights (Appendix D1), absence or presence of interaction effects (Appendix D1 and D2), absence or presence of the experience variable (as, per H2, more educated individuals might also have more likely previous experience with CAIs) (Appendix D2), absence or presence of facilitating conditions and habit (Appendix D2 and D3), removing the behavioral intention (BI) path (Appendix D4) and including factor loadings for single-item variables (Appendix D4). Focusing only on the BI path (Appendix D5), i.e.,

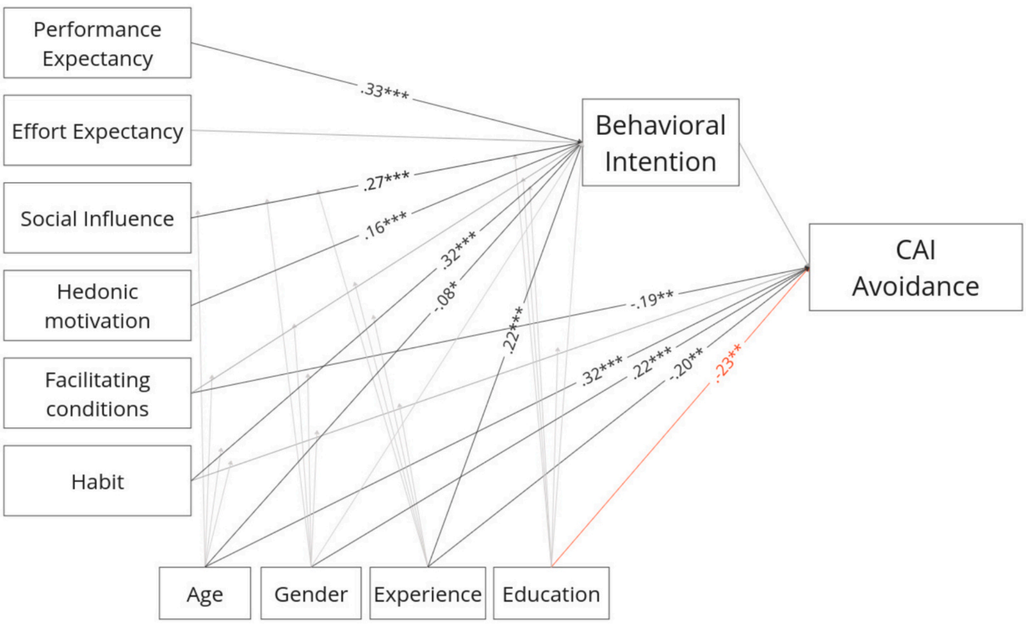

Fig. 3. Structural equation model estimates for a UTAUT2 model and Education on CAI avoidance. We incorporated educational levels as a predictor of behavioral intention and CAI avoidance in the original UTAUT2 model. We also included interaction terms (with education) following existent interactions with demographics in the original model. Darker lines represent statistically significant relationships.

Table 3
LASSO and logistic regression on CAI avoidance. Results from LASSO regression with 10-fold cross-validation and corresponding logistic regression models. LASSO was used to select variables, while logistic regression provided more interpretable coefficient estimates to assess robustness. The table includes variable selection using the optimal regularization parameter that minimizes the mean squared error (λ_{min}) and the more parsimonious model corresponding to the largest lambda value within one standard error of the minimum error (λ_{1se}). See Appendix F for other weights.

	Raked and Trimmed			
	λ_{min}		λ_{1se}	
	LASSO	GLM	LASSO	GLM
Gender	0.06	0.173**	0.03	0.190**
Age	0.09	0.241***	0.07	0.240***
Education	−0.07	−0.181**	−0.05	−0.182**
Experience	−0.07	−0.226**	−0.06	−0.223**
Trust				
Anxiety				
Negativity	0.01	0.034	0.00	0.030
Optimism	−0.02	−0.042	−0.01	−0.060
Pessimism	0.02	0.054	0.01	0.036
Perceived advantages				
Perceived disadvantages	0.01	−0.033		
Attentiveness	−0.04	−0.061	−0.00	−0.069
Mandatory dwell time (timer)	−0.02	−0.163*		

BI as a dependent variable (without CAI avoidance), we find statistically significant effects consistent with Fig. 3 (but with different magnitudes for the estimates), except for education, which is now significant predictor of BI (0.05, $p < .001$) and age, which is not a significant predictor of BI. In line with Venkatesh et al. (2012), BI is only a significant predictor of avoidance itself if we remove UTAUT2 latent variables as predictors of avoidance (Appendix D3).

LASSO regression with 10-fold cross-validation was applied to identify associations between demographic variables, affective CAI variables, and experience, controlling for attentiveness and the timer. Our results support **H6**: education was consistently selected by the LASSO regression and maintained statistical significance in subsequent logistic regression models (Table 3). Other demographic variables, namely gender, age, and experience, also emerged as robust predictors of CAI avoidance. Although the LASSO procedure also identified several affective variables, these did not achieve statistical significance in the logistic regression analyses.

4. Discussion

Results across multiple analytical approaches consistently support hypotheses regarding task avoidance in response to different intervention types and education. Avoidance rates differed markedly across groups, with CAI eliciting significantly higher avoidance than the search and control conditions (H1). We found significant interactions between demographic variables and CAI avoidance, with lower education associated with higher avoidance (H2). In line with H3 and H4, we observed that higher education was positively associated with UTAUT2 constructs, CAI experience, and favorable affective scores and that these variables were, in turn, associated with lower avoidance. Structural equation modeling further confirmed the central role of education in shaping behavioral intentions and avoidance within the CAI context (H5), with education explaining variance comparable to established UTAUT2 socio-demographic predictors. Similarly, LASSO regression consistently identified education as a predictor of CAI avoidance (H6), reinforcing its role in shaping engagement with AI, even when avoidance entailed forfeiting a monetary reward. Our study focused on individuals aged 25 to 64, a cohort with largely completed formal education and generally active in the labor market, often participating in online studies to supplement their income (Keusch, 2015).

While task avoidance was present in both the CAI and search groups, it was notably higher in the CAI group despite that task being simpler: the search task involved more procedural demands, as participants had to navigate to a search engine, manage browser tabs, choose relevant links, and copy a resource, requiring more effort and self-direction. Given that our sample consisted of online panelists likely familiar with similar tasks, we interpret the higher avoidance in the CAI condition not as a reflection of task difficulty but as an expression of their reluctance to use CAI specifically. This is particularly striking given that the CAI task required minimal action (clicking a link, entering a prompt, and copying a link) and was accompanied by visually-aided instructions. The mechanisms behind this reluctance to engage with the task could be explained by the UTAUT2 latent and affective variables as suggested by generally strong correlations. For example, perceived task difficulty is captured by effort expectancy, which, as per the original UTAUT2 specification and our modeling, is not theorized to influence task avoidance directly but behavioral intention (Venkatesh et al., 2012) and, empirically, self-perceived lack of knowledge (i.e., low self-efficacy) emerged as the second most important reason to not use CAIs (Nakagomi et al., 2025). Alternatively, in a recent systematic review, Leschanowsky et al. (2024) suggested that reluctance around CAI may also stem from entangled perceptions of privacy, security, and trust, conceptually overlapping constructs yet rarely studied together in the CAI context. Avoidance may reflect a resistance rooted in broader trust-related dynamics, extending beyond the technology itself to include concerns about the companies and politics behind it; however, such concerns are more likely to be linked to highly educated individuals (Nakagomi et al., 2025; Shata, 2025). Crucially, our behavioural metric isolates intrinsic barriers from external demands (i.e., motivational or necessity), as all participants were prompted to perform the task.

The linear downward relationship of the role of education with avoidance in the search and CAI groups implies a general technology avoidance from lower educated populations, though the steeper slope for CAI participants suggests an additional mechanism, likely tied to the novelty of the technology, where education may play a larger role in shaping participants' willingness or confidence to engage. While our results show a strong relationship between education and CAI avoidance, the relationship between education and behavioral intention (BI) is only significant in UTAUT2 models that exclude the behavioral path. In other words, once individuals are confronted with a behavioral task, the importance of education on intention appears to be negligible compared to its direct role in the behavior.

We have centered our analysis on education to contribute to a more nuanced and actionable understanding of user diversity in digital adoption. A parallel narrative could have been constructed focusing on age, arriving at similar conclusions to those we reached for education. The role of gender, by contrast, proved more nuanced as we only found it interacted with the CAI condition but not the search condition. Both of them remained significant in both our SEM-UTAUT2 and LASSO analyses. Crucially, the observed patterns for age and gender align with previous findings in digital inequality research, lending additional support to the validity of our analyses.

Overall, our study provides evidence for the role of education by employing a behavioral metric within an experimental design, moving beyond the predominant reliance on self-reported or correlational data in the existing literature. Accordingly, our findings support the inclusion of education as a key variable within the UTAUT2 framework within the genAI context.

The uneven engagement with CAI that we observe raises concerns about a broader societal impact, namely, the risk of exacerbating existing inequalities if certain groups systematically opt-out and are underrepresented in CAI use and research. Studies involving CAI or similar technologies may be susceptible to self-selection bias in which those in an already advantageous position are more likely to participate, leading to conclusions that overlook the perspectives and needs of disadvantaged groups. Recognizing and addressing this dynamic is crucial for developing equitable and inclusive digital systems.

4.1. Limitations

The analysis and results presented here are based on an analysis conducted due to high attrition rates in the CAI treatment observed in the context of another research project. The panel agency informed us about the issue early in the data collection, prompting us to remove the mandatory dwell time for this group to enhance participation. This adjustment resulted in a heterogeneous CAI treatment, where some participants completed the task with a mandatory dwell time while others did not. While our analyses reveal that removing the timer did not reduce avoidance, this should be considered when interpreting the results.

Secondly, though all treatment groups were concurrently and randomly filled as participants entered the study over time, they were not perfectly balanced regarding demographics. This imbalance may have arisen either by chance or due to a complex interaction between socio-demographic differences in the timing of survey participation, higher duration in the CAI and search tasks, and higher CAI and search abandonment of the survey during the task. To address the imbalances, we applied weighting procedures to align our sample distributions with the German general population, which has been shown to help mitigate biases when attempting to represent an entire population with an online sample (Grewenig et al., 2023). This, together with the consistency of results across weighing strategies, provides a fair degree of confidence. Still, we note that weights were calculated using only three socio-demographic variables and caution against generalizations beyond the corresponding context of the study, i.e., avoidance of a single CAI-related task with a German online sample. Regarding generalizations of online panelists, they tend to be more tech-savvy and financially motivated than the general population, and their behavior may not reflect that of less digitally engaged or less incentivized individuals. Given that the study was conducted in Germany, a Western, Educated, Industrialized, Rich, and Democratic (WEIRD) context, the transferability of results to other countries and cultures remains uncertain (Henrich et al., 2010) and could be explored in the future.

Finally, although the CAI task was designed to be simpler than the search task, we did not measure perceived or experienced task difficulty, usability, or frustration directly in relation to the avoidance, which could help disentangle avoidance due to UTAUT factors, low motivation, or other user experience issues; that said, technical feasibility was pre-tested and regularly checked throughout the study duration, and users had the opportunity to contact the researchers or Bilendi about technical issues, and we did not receive any reports.

5. Conclusion

This study examined how educational attainment relates to avoidance of conversational AI in an experimental setting. Across multiple analytical approaches, we observed that lower education was associated with a higher likelihood of avoiding a task involving CAI, supported by associations across UTAUT and other affective factors such as optimism/pessimism about AI and trust. The consistency of this association across methods suggests that educational differences may play a role in shaping initial engagement with emerging AI tools. These findings highlight the value of including education in theoretical frameworks of technology adoption and raise considerations for designing inclusive digital systems.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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RU: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Project administration. CK: Conceptualization, Methodology, Investigation, Writing – review & editing, Project administration. JK: Investigation, Resources, Funding acquisition.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tele.2025.102346.

Data availability

Data and analysis scripts are available at: https://osf.io/4ksw6.

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