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Banking for Boomers—A Field Experiment on Technology Adoption in Financial Services*

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Abstract

Digitalization in banking is leaving elderly clients at risk of losing access to financial services, but little is known about technology adoption at an advanced age. We develop and evaluate training interventions to foster internet banking adoption in a field experiment with more than 25,000 elderly clients of a large German savings bank, of whom we randomize 333 into training. Our administrative banking panel data allows us to account for selection on observables and assess the sustainability of treatment effects. After the interventions, the share of clients who use internet banking increases by 26 percentage points in the treatment group relative to a matched control group. In terms of sustainable usage, the share of online transactions increases by 13 percentage points and remains elevated four months later. An extensive placebo analysis suggests that as much as 85% of the effect can be causally attributed to the training interventions. We find that training boosts non-technical adoption skills and reduces key adoption barriers. Treatment effects are larger for women and those not in charge of household finances. We further estimate intent-to-treat effects and predict dropout along the entire multi-stage adoption process to shed light on practical considerations when rolling out large-scale technology adoption interventions in this age group. Specifically, we show that the type of training (self-guided versus social learning) impacts dropout differentially despite similar treatment effects overall, with the social learning treatment being more inclusive.

Keywords: technology adoption · internet banking · financial inclusion · digitalization · non-cognitive skills

JEL classification: O33 · G21 · I21 · J24 · D12 · D91 · C93

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1 Introduction

In times of rapid innovation, the elderly are inevitably confronted with new technologies such as internet banking. As even brick-and-mortar banks are increasingly shifting their services online—the number of physical bank branches in Germany has almost halved between 2013 and 2023[1]—, data from across the globe consistently show that the elderly lag behind younger clients in the adoption of internet and mobile banking.[2] This digital divide is particularly concerning as older adults often experience declining financial sophistication and cognitive capacity with age (Finke et al., 2017; Gamble et al., 2015; Lusardi and Mitchell, 2014), making access to financial services critical. Besides, the elderly are a highly relevant group from a financial intermediation perspective: Individuals aged 55 and older own 55% of all financial assets in the Eurozone and 71% in the United States.[3] Thus, studying technology adoption in this setting is important as older bank clients who are unwilling or unable to use internet banking are at risk of being left behind.

While existing literature has focused on the determinants of technology adoption (Xue et al., 2011; Bauer and Hein, 2006), the effectiveness of training interventions to increase adoption has not received much attention. In addition, despite the growing importance of digital technology adoption in private life settings, empirical research has so far been primarily concerned with technology adoption *at work* (Autor, 2022; Hampole et al., 2025; Dixon et al., 2021), where employees are often forced to keep up with technological change. In contrast, internet banking offers a private life setting in which technology adoption is convenient but not yet unavoidable, as physical branches still exist. This makes selection into training informative: it reflects voluntary investment into a technology that offers clear benefits but also carries perceived risks. The internet banking setting is also representative of technology adoption more generally as it is a multi-stage adoption process that most of our study participants report as challenging ex ante—primarily due to barriers that are also encountered in other technology adoption domains (such as fear of own mistakes, danger of fraud, and lack of skills, cf. Mitzner et al., 2010).

In this paper, we study the selection into and effectiveness of brief training interventions on internet banking adoption among members of the Baby Boomer generation[4]—a group that

[1] Source: Deutsche Bundesbank.

[2] See American Bankers Association (2023) for US data, Bitkom (2023) for German data, Office for National Statistics (2019) for British data, and Szopiński (2016) for Polish data. See also Figure A1 in the Appendix.

[3] The US figure is based on the 2022 Survey of Consumer Finances and 2022 Census. The Eurozone figure is based on the 2021 wave of the European Central Bank's Household Finance and Consumption Survey and population data from Eurostat.

[4] Specifically, we focus on individuals aged 50-85, which covers the age range of the Baby Boomer generation in Germany who were born in the 1950s and 1960s. While the US definition of Baby Boomers includes earlier years of birth, these would also be covered by our sample. We show that effects of our interventions are not driven by participants at the younger end of the spectrum.

is often considered difficult to train in the context of financial literacy (Clark et al., 2025) and labor market interventions (Berger et al., 2022). Specifically, we conduct a randomized controlled trial in cooperation with one of the largest German savings banks. After inviting more than 25,000 clients randomly sampled from a larger group of Baby Boomer clients who do not use internet banking, we are able to randomize 333 responding clients into two different types of training: A self-guided training program focusing on technical internet banking knowledge; and a training program that additionally addresses the identified adoption barriers and focuses on the formation of non-cognitive skills such as self-efficacy and emotional regulation. The latter emphasizes an in-person social component designed to build non-technical adoption skills—a broad set of abilities that are essential for navigating new technologies effectively. The three main goals in this domain were to help participants build routines and strategies for sustainable and secure internet banking use, to increase confidence by highlighting similarities between traditional and internet banking, and to alleviate fear of fraud by working on fraud detection and self-regulation strategies (e.g., when confronted with a suspicious email). The non-technical component was delivered either via an on-site workshop in small peer groups (social learning I) or (exploratively) an at-home training session with an internet-banking-savvy family member or friend (social learning II).

Our analyses rely on administrative client-level banking data collected at multiple points before and after the interventions that are complemented by three surveys (pre-survey, enrollment survey, post-survey). This set-up allows us to track the entire adoption process from initial intent through enrollment and training to sustained use for transactions. We use a difference-in-differences strategy that assesses changes in adoption measures in various treatment groups relative to a control group which was never contacted during the study period (*silent control group*). To address selection on observables, we apply propensity score matching based on the rich demographic and banking data we observe for both participants and non-participants. To address selection on unobservables, we conduct an extensive placebo analysis relying on the group of clients that have signaled intent but never complete the training.

Several robust main findings emerge from our field experiment. When estimating the average treatment effect on the treated (ATT) for our internet banking training, the share of participants who have set up their internet banking access increases by 26 percentage points relative to the matched control group. In terms of sustainable usage, the share of online transactions increases by 13 percentage points and remains elevated four months later. These effects are both statistically and economically meaningful, especially considering the low effort required—–a two-hour training program offered to prior non-adopters. This strong ATT is the culmination of a series of intent-to-treat (ITT) effects, which we estimate along the multi-stage adoption process: While, as expected given the low response rate of 2%, there is no treatment effect of our initial invite, we document steadily increasing treatment effects from initial intent to participate, through enrollment to training completion. Given the significant effects of training completion (vs. ITT estimates) and the results of the placebo analysis, we attribute approximately 85% of the effect causally to the training interventions.

To shed light on the mechanisms underlying the training effects, we investigate the role of non-technical adoption skills in our post-survey. While the ATTs for internet banking adoption are very similar across training types, the social training interventions—that focused on non-technical adoption skills in addition to technical competences—are indeed more successful in reducing fear of fraud and in helping participants develop strategies and routines for internet banking use. Heterogeneity analyses reveal that the treatment effect on adoption is not driven by younger participants in employment or those with high socio-economic status. Rather, women and those who are not in charge of their household's finances benefit most. Initial technological skills and perceived benefits are also positively related to treatment effectiveness. This latter finding points to spillovers of technological skills and knowledge (of benefits of a technology): If prior skills make internet banking training more productive, those skills conveyed through internet banking training will themselves likely facilitate the adoption of further technologies—adding to the positive effects of training.

Given the success of our training interventions, our last main finding addresses the issue of practical implementation at a larger scale and without an experimental context: We document significant selection at the first stage of the adoption process, the intent stage (cf. Kim et al., 2016). Responding clients are significantly older and richer. However, after this initial hurdle, selection becomes substantially more subdued, although attrition remains high at the enrollment stage. Thus, later-stage selection mainly informs our discussion of the relative attractiveness of the self-guided versus the social learning interventions. In general, dropout is lower and inclusivity is higher for the social training, which must be considered when scaling up such interventions.

This study adds to several strands of literature at the intersection of technology adoption and financial education. Our contribution is threefold: (1) addressing adoption barriers in the context of a mature and widespread technology, (2) focusing on an older demographic often neglected in technology adoption and financial education research, and (3) leveraging administrative banking data in the evaluation of the interventions.

Existing work on technology adoption often focuses on infrastructural and coordination frictions. Prior studies emphasize the role of exogenous shocks and network effects——such as demonetization (Crouzet et al., 2023), debit card rollouts (Higgins, 2024), or ATM closures (Choi and Loh, 2024; Smajlbegovic et al., 2025)——in accelerating digital technology adoption, particularly by shifting perceived norms or reducing behavioral frictions. We complement this work by addressing skill-based constraints and non-technical adoption barriers at the individual level in targeted training interventions, which go beyond purely information-based interventions (Lee et al., 2022).

In line with the broader goal of financial education—to empower people to manage their finances effectively—being able to navigate internet banking platforms and conduct digital transactions is a pre-requisite for financial inclusion. While much of the financial education literature focuses on students and working-age adults[5], we target an elderly population, who are increasingly at risk of being excluded from financial service access. Despite generally positive attitudes toward technology among the elderly, Mitzner et al. (2010) find that security and reliability concerns prevent technology adoption. While we replicate these concerns in the baseline, we show that a well-designed training intervention that addresses non-technical adoption skills can alleviate them. In addition, many financial education studies rely on self-reported financial literacy and behavior as outcome measures (Kaiser et al., 2022). We add to this by leveraging actual transaction and login data collected at multiple points in time. Perhaps surprisingly, we replicate a central finding from a study involving significantly younger participants (Sconti, 2022): We find that our self-guided digital treatment yields similar treatment effects as the in-person treatment. However, treatment *take-up* varies by education level: self-guided training attracts more educated participants, raising questions about the inclusivity and scalability of different delivery modes (List, 2020). Finally, our heterogeneity results are in line with prior work by Lee et al. (2022), as we find stronger treatment effects for women—a particularly financially vulnerable group in the Baby Boomer generation. This finding suggests that training can help bridge gender gaps in digital financial services.

Taken together, we contribute to the understanding of technology adoption and financial education by developing training interventions designed to build non-cognitive skills to overcome fear-based adoption barriers. We demonstrate that these interventions substantially and sustainably increase internet banking adoption in an age group at risk of losing access to financial services and which has previously been proven difficult to train. In addition, our setting allows us to study selection into training, which provides insights for the practical implementation of such interventions.

The remainder of the paper is organized as follows: Section 2 discusses the theoretical background. Section 3 presents our experimental design and section 4 the data and estimation strategy. Section 5 describes findings related to selection into training along the adoption process, while section 6 presents the main ITT and ATT results as well as a placebo analysis. Section 7 presents results using alternative adoption measures and examines treatment heterogeneity. Section 8 discusses practical implications and section 9 concludes.

2 Theoretical Background

Our internet banking interventions for Baby Boomers are grounded in economic theory: The simple human capital model (Becker, 1962) speaks to the difficulties elderly agents face when making education choices. Since they have fewer periods left to reap the returns to education compared to younger agents, any skill acquisition becomes relatively less attractive when

[5] In a recent meta study of 76 financial education studies, only three of the reviewed studies report average sample age above 50 (Kaiser et al., 2022).

other factors, such as time preferences, remain constant. Due to the lower net present value of education benefits, it is rational for Baby Boomer agents to be reluctant about training take-up when they carefully balance costs and benefits of training. This effect is exacerbated by well documented (average) skill depreciation with age (e.g., Finke et al., 2017), making learning even more costly for elderly agents. Thus, standard economic models predict selection into training by those individuals for whom training is less costly because they have lower opportunity costs (e.g., more time, especially among the retirees in the sample) or are more skilled, and by those for whom the expected benefits are higher because they conduct more transactions.

In the case of technology adoption, we argue, however, that there are additional barriers to training take-up. Crucially, these may lead to a misperception of the costs and benefits associated with technology adoption and prevent a rational investment in technological skills: Davis (1989) develops a workhorse technology adoption model centered around, among others, perceived usefulness—which dominates in empirical tests of the model—, perceived ease of use, and attitude toward using. The focus on *perceived* factors already implies scope for misperception and prejudice against new technologies, which may be more severe among the elderly and less likely to self-correct due to the higher adoption costs. Building on this prior work, Kim et al. (2016) show that learning intentions are an important additional step in the adoption process. This view of technology adoption as a multi-stage process starting with a simple intention is the basis of our work, where we follow the adoption process holistically—from interest in training, enrollment and completion to the final adoption outcomes. How our interventions affects each stage of the adoption process remains an empirical question that we tackle in our field experiment, while also examining selection into training and heterogeneous effects of training completion.

Aside from building knowledge needed for successful technology adoption, part of our training focuses on the formation and re-emphasis of non-technical adoption skills—a broad set of abilities that are essential for navigating new technologies effectively. Among these, non-cognitive skills have received substantial attention in economic research over the past decades (Deming and Silliman, 2024) as trainable components of an agent's decision-making toolkit. From a theoretical point of view, several such non-cognitive skills may matter in the technology adoption decision of elderly agents: For instance, Kim et al. (2016) stress the role of self-efficacy in successful mobile technology adoption when comparing elderly adopters to non-adopters. Self-efficacy describes the belief in one's own ability to master a situation and has been found to positively affect financial behavior (Kuhnen and Melzer, 2018). This non-cognitive skill may be particularly important in overcoming the potential cognitive dissonance associated with feeling incompetent in the internet banking world despite having successfully managed one's own finances "offline" for a lifetime. In this context, Pang et al. (2021) highlight the benefits of self-paced training among the elderly, which is reflected in our self-guided learning concept.

Another non-cognitive skill that we deem highly relevant in the context of technology adoption is curiosity. Overcoming the fear factor that dominated our pre-survey of adoption barriers among Baby Boomers by fostering curiosity regarding the new technology is a central theme in the training interventions (see Table A5 in the Appendix). Another non-cognitive skill related to the fear of mistakes and the fear of security breeches expressed in the survey is emotional regulation, which is a sub-concept of self-regulation which has been shown to improve school performance in children (Schunk et al., 2022). A new technology that comes with perceived high stakes and potential traps (i.e., scams) requires agents to stay emotionally regulated in order to make optimal decisions under pressure.

In our understanding of non-technical adoption skills, coping strategies also fall into this category. Although they are specific to a situation that needs to be coped with, they improve economic decision making and may transfer to other settings. For instance, remaining calm and calling a trusted family member may be an effective strategy to avoid internet banking scams. The same strategy may, however, also work for other technological issues, such as a forgotten email password.

Overall, to encourage technology adoption among the elderly despite higher costs and potentially misperceived benefits, we argue that training offers that focus on potential benefits and non-technical adoption skills are worth evaluating empirically. Section 3.3 describes how we target the different components of the technology adoption process (including the correction of misperceptions) and foster non-technical adoption skills in our training concept.

3 Experimental design

3.1 Background

We conducted a field experiment with elderly clients of one of Germany's largest savings banks, which serves over 250,000 clients. The bank had planned to offer internet banking trainings to their clients and could be convinced of the merit of a randomized controlled trial to evaluate the effectiveness of these trainings. It granted the research team control over the training materials and provided the financial and organizational resources to conduct the experiment. The interventions received ethics approval by the joint ethics commission in economics by Johannes Gutenberg University Mainz and Goethe University Frankfurt. We closely follow the pre-registered experimental design and comprehensive analysis plan (AEARCTR-0013985).

3.2 Recruitment process

We employed a three-stage recruitment process for the randomized controlled trial. Figure 1 provides an overview of sample sizes in the various recruitment stages and Figure 2 illustrates the timeline containing the dates of data exports and interaction with bank clients. First, our partner bank provided anonymized demographic and transaction data for all clients aged 40 and older who have personal accounts, excluding legally incompetent individuals and accounts seized for liquidation (153,370 clients). Within this sample, internet banking adopters are younger, more often male, more active, and richer than non-adopters (see Table A1 in the Appendix). These patterns are generally consistent with the results of existing studies on the drivers of internet banking adoption (Xue et al., 2011; Szopiński, 2016). From this group of clients, we pre-selected 27,707 clients (the *target group*) aged between 50 and 85 years who had not logged into internet banking in the past three months, had no third-party account access, resided in the metropolitan area of our partner bank, and had account outflows in May 2024, indicating active banking clients.[6] We restricted the sample of potential experimental participants to limit recruitment costs and avoid sending out unsolicited invitations to clients who are unlikely to participate in the training. We included only clients aged 50 to 85 years as internet banking adoption was already high among younger clients. We set the upper limit at 85 to facilitate content tailored specifically to the target group.

Second, we randomly assigned 1,725 of the 27,707 eligible clients to a silent control group which were never contacted throughout the study.[7] On July 12, 2024, we reached out to the remaining 25,982 clients, contacting 12,482 by letter and 13,500 by email, based on their consent for contact. We also used phone calls as an additional channel at all stages. All clients received identical invitations outlining the planned interventions and requesting preliminary information, including their availability for the social learning treatments and demographic details for randomization. The invitation also included the link to a learning platform containing set-up instructions for the internet banking function at the partner bank in the form of an instructional video (duration: 30 minutes) and a detailed step-by-step guide. Importantly, clients were required to enter their project IDs to obtain access to the platform, which allows us to track whether clients have accessed the learning platform.

By August 5, 2024, we received 550 responses (response rate: 2.1%) indicating intent to participate. Of these, 333 participants met all inclusion criteria and were randomized into treatment groups.[8] They constitute our randomized main sample, balanced in terms of gender, age, educational attainment, and bank account inflows (see Table A4 in the Appendix for balancing tests). The remaining 217 respondents were also assigned to treatments but are not part of the core treatment group.

Third, on September 18, 2024, we sent a second, group-specific invitation to all 550 respondents. Treatment conditions were assigned using stratified randomization at the individual

[6] Table A2 in the Appendix details the sample sizes for the respective filtering steps.

[7] Table A3 in the Appendix presents balance tests for baseline variables. Almost all variables are balanced. The only statistically significant differences we find despite randomization are with respect to age (slightly higher age in the control group, $p < 0.01$) and the number of account inflows (slightly more inflows in the control group, $p < 0.1$).

[8] Inclusion criteria were: availability for at least one social learning treatment, sufficient language skills, and access to the required technology (smartphone and computer).

level based on availability.[9] In accordance with our pre-registered experimental design, we prioritize the on-site workshop and self-guided learning groups. As a result, we invited 200 participants to the on-site workshop, requesting their availability for the intervention dates between October 21 and 28, 2024. 99 participants were assigned the self-guided learning group, receiving access to the online learning platform with the training material, but without a social learning component. 34 individuals received invitations to the social circle support treatment, which required them to provide details on a supporting relative. The deadline for completing the training and for finishing the second survey was November 4, 2024.

In total, 180 participants from the main sample responded to the survey and enrolled in the treatments (self-guided learning: 38 individuals, social learning I: 131 individuals, social learning II: 11 individuals).[10] Of these, 135 participants (self-guided learning: 26 individuals, social learning I: 99 individuals, social learning II: 10 individuals) actively attended the on-site workshop or accessed the online learning platform and are therefore considered as treated (in the ATT specifications).

3.3 Treatment conditions

We employ a self-guided approach and approaches that emphasize non-technical adoption skills in distinct social contexts. There are four experimental groups: i) silent control group, ii) self-guided learning, iii) social learning I (on-site workshop), iv) social learning II (social circle support). We use a silent control group instead of a randomized control group due to the low response rate (see pre-registration) and concerns on our partner bank's side regarding the alienation of interested clients.

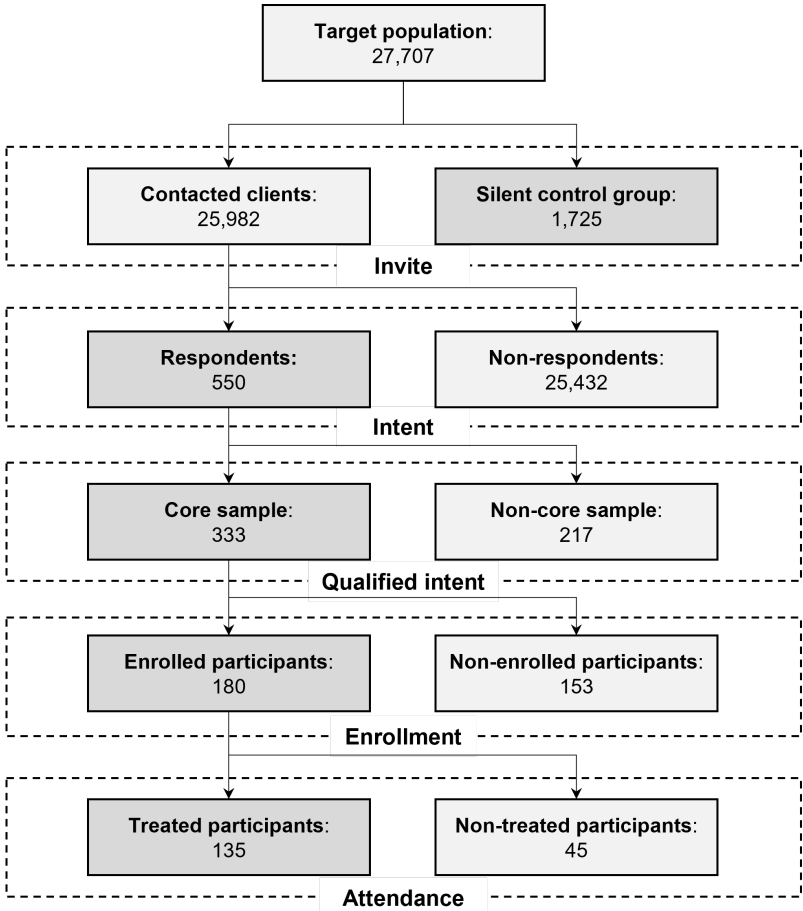
3.3.1 Training content

Participants in all treatment groups were given access to an online learning platform containing instructional slides and a video (duration: one hour), which guides participants through the slides. For in-person participants, it became available after the on-site workshop. Each treatment condition followed the same technical curriculum, structured into three modules. The first module addresses common misconceptions by explicitly outlining the benefits associated with internet banking usage. The second module guides participants through a demo version of the bank's internet banking platform, covering tasks such as logging in, making transfers, and managing recurring transfers. The demo tool allows clients to safely learn about the functions of the real platform and ensures data protection. To accommodate the

[9] Respondents eligible for both social learning treatments were randomly assigned to either the self-guided learning treatment or a social learning treatment. Those eligible for only one social learning treatment were randomly assigned between that treatment and the self-guided learning treatment. We excluded respondents unable to participate in any social learning treatment - those without a supporting relative and unable to attend an on-site workshop - from the main randomized sample.

[10] A detailed analysis of potential self-selection into enrollment and attendance is provided in section 5.

Figure 1: Sample size flow chart



Note: The figure displays the number of bank clients in each step of the recruitment process.

apparent concerns regarding fraud, this part also covers the bank's security architecture (two-factor authentication, transfer and credit limits, etc.) and effective fraud prevention strategies. In the third module, which emphasizes experience-based learning, participants complete five standard internet banking tasks within the demo tool. This approach is preferred over description-based learning, as it produces superior learning outcomes in the financial context (Laudenbach et al., 2023). The tasks include checking account balances, opening the electronic inbox, and setting up a recurring transfer order.

The two social learning treatment groups supplement the knowledge-based modules above by addressing complementary non-technical adoption skills. These groups employ distinct social settings as social networks play a crucial role in the adoption of new technologies (Belo et al., 2016; Choudrie et al., 2018). Compliance was tracked in all groups by tracking participants' access to the learning platforms. All contacted clients received information on setting up their personal internet banking accounts. Although not part of the treatment variation, this aspect is considered in the placebo test in section 6.

3.3.2 Self-guided learning

The self-guided learning group only received knowledge-based training for internet banking adoption. Participants independently accessed the online learning platform, reviewing the slides and video at their own pace. Evidence suggests that on-demand videos are highly effective financial education tools (Lusardi et al., 2017; Litterscheidt and Streich, 2020), though it is unclear whether this is the case in our specific target group. In the context of this study, the on-demand format offers scalability with minimal marginal costs while providing effective visual demonstrations. It also facilitates clients with reduced mobility to participate in the training from home and at their own pace (cf. Pang et al., 2021).

3.3.3 Social learning I: On-site workshop

In addition to access to the instructional slides and video, the social learning I group participated in a two-hour on-site workshop. The workshop took place in small groups of on average 10 peers (min: 5, max: 14) at the bank's educational center. To ensure that the workshops conveyed the intended skills, two of the authors of this study acted as instructors. In each workshop, a bank employee was present to help answer clients' bank-specific questions. Beyond simply providing knowledge about internet banking, both social learning groups focused on the formation of non-technical adoption skills. The three main goals in this domain were to help participants build routines and strategies for sustainable internet banking use, to enhance confidence and self-efficacy by highlighting similarities between traditional and internet banking, and to alleviate fear of mistakes and fraud by working on emotional regulation strategies (e.g., when confronted with a suspicious email). Figure A2 in the Appendix displays exemplary slides.

The workshop specifically addresses the barriers to internet banking adoption identified in our pre-survey. Table A5 in the Appendix illustrates the barriers to internet banking adoption mentioned by pre-survey participants. We focus on managing the fear of mistakes and fraud and provide coping strategies for recognizing and regulating emotions. Through case studies, participants practice reacting to unforeseen situations, such as receiving a phishing email or dealing with technical issues, and are encouraged to remain calm while utilizing help-seeking strategies.

Our teaching strategies emphasize the explicit discussion of the required non-cognitive skills. We address clients' conscientiousness by introducing self-organization strategies, such as developing routines to store learning material and remember login credentials. We promote curiosity and persistence by encouraging participants to practice regularly in the risk-free demo tool environment. To build self-efficacy, we reminded the participants that they already possess the necessary knowledge to conduct bank transfers, with only the environment changing from a physical branch to a virtual one. The workshop is also designed to foster social interaction through a pleasant atmosphere and networking opportunities during coffee breaks. The setting ensures high teaching quality and guidance by an approachable instructor, which helps to reduce feelings of shame associated with failure and allows peers to support each other. We track compliance through attendance lists at the workshop.

3.3.4 Social learning II: Social circle support

In the social learning II group, participants are asked to nominate a relative (alternatively, a friend or neighbor) who is familiar with internet banking to assist them during an at-home training session. This relative guides the participant through the same content covered in social learning group I. To ensure effective training, the relative receives a one-page guide on how to support the participant and to address non-technical adoption skills. In recognition of the opportunity costs (approximately two hours), the relative receives a 100 EUR gift voucher.[11]. To be eligible for the gift vouchers, participants are required to submit a selfie with their relative and responses to the learning tasks they completed together.

The concept behind this treatment is based on the finding that older individuals often adopt technology through younger family members. For example, Belo et al. (2016) show that children's exposure to broadband technology in school increases internet adoption in Portuguese households. They attribute this finding to children learning the value of new technology and complementary skills in school and transmitting this knowledge to adults at home. Similarly, internet banking adoption should be more likely when older individuals can draw on the technological expertise and emotional support of younger relatives who are already using it.

4 Data and estimation strategy

4.1 Data

Our analyses rely on administrative banking data and three separate surveys. We obtain anonymized data on clients' banking activity from the internal systems of our partner bank, which has been exported for all 27,707 target group clients at seven points in time (April 2024, June 2024, September 2024, December 2024, January 2025, February 2025, and March 2025). Figure 2 illustrates the timeline of data exports and client interactions. The data includes demographic characteristics (year of birth, gender), consent to various modes of contact by the bank, the client's history with the bank, the number of active checking and savings accounts[12], detailed banking data referring to the preceding calendar month (including the number of inflows and outflows, the sum of all inflows and outflows, the number of transactions conducted via self-service terminal, transfer slips, and internet banking), information on which

[11] The voucher's face value can be considered nearly equivalent to its cash value as recipients are free to choose among a wide range of online and offline stores.

[12] Checking accounts include foreign exchange accounts and instant access savings accounts (*Tagesgeld*). Savings accounts do not include brokerage accounts and longer-term term deposits.

type of TAN processes have been activated, the number of days since a client has last logged on to their internet or mobile banking, the last time a client has attended a meeting with their bank advisor, and the client's 4-digit zip code. Data on the activation of a TAN process and logins to the internet banking platform are observed as of the data retrieval dates. Data on account activity (including the online transaction share) are observed as of the calendar month preceding the retrieval date.

Table 1 provides summary statistics on target group clients. 60% of the target group are female, reflecting both lower levels of technology adoption (see Table A1 in the Appendix) and higher life expectancy among females. The vast majority of clients in this group (77%) have been long-term clients of the bank (since before 2003). The income distribution of target clients is broadly representative of net salaries of Germans in this age group.[13]

Table 1: Summary statistics for target clients

	Mean	SD	Min	Max	N
Panel A: Demographic information					
Age	67.68	10.2	50	85	27,707
Female	0.60	0.5	0	1	27,707
Panel B: Bank relationship					
No. checking accounts	1.45	0.6	1	8	27,707
No. savings accounts	0.96	1.3	0	36	27,707
Contact in 2023/2024	0.56	0.5	0	1	18,418
Joined before 2003	0.77	0.4	0	1	26,759
Overdraft facility available	0.66	0.5	0	1	27,707
Panel C: Account activity					
Total transactions	2.08	2.7	0	132	27,707
No. inflows	4.20	3.6	0	133	27,707
Inflows EUR 0-1,000	0.12	0.3	0	1	27,707
Inflows EUR 1,000-2,000	0.17	0.4	0	1	27,707
Inflows EUR 2,000-4,000	0.36	0.5	0	1	27,707
Inflows > EUR 4,000	0.36	0.5	0	1	27,707
No. outflows	25.71	21.4	1	228	27,707

Note: The table reports summary statistics for target group clients. Data are as of June 11, 2024. Account activity variables refer to calendar month May 2024. The inflow variables are dummy variables indicating that a client's account inflow was within the respective category. Details on the client selection process are reported in Table A2 in the Appendix.

In addition to this rich administrative banking data, we conduct three surveys with the target client group. The first survey (*pre-survey*) is conducted as part of the initial invitation (which was distributed on July 12, 2024). The survey's goal was to (i) elicit key client charac-

[13] The median net income of Germans aged 55 and older was EUR 3,954 in 2023, with an inter-quartile range between EUR 2,969 and EUR 5,573 (Bundesagentur für Arbeit, 2024). The inflow data suggest that the 29th percentile is EUR 2,000 and the 64th percentile is EUR 4,000 for target group clients as of May 2024.

teristics required for our randomization into treatment groups and (ii) inquire about barriers to internet banking adoption so we could tailor the contents of the training interventions to the most prevalent concerns. All recipients received the same survey. As such, we elicit internet banking adoption barriers as a structured multiple choice question, access to a computer and smartphone, availability for the on-site trainings and social circle support intervention, educational attainment, and German language skills.

The second survey (*enrollment survey*) was distributed among respondents to the initial invitation on September 18, 2024. The survey's goal was (i) for clients who had been randomized into the on-site trainings to book one of 12 available training slots and (ii) to elicit more exhaustive client-level characteristics that we could use to identify treatment heterogeneity. Thus, while the first part of the survey was specific to the treatment arm a client has been randomized into, the questions on client characteristics were identical. We included this more comprehensive list of questions in the enrollment survey as we expected less dropout due to extensive survey questions at this stage. Specifically, we asked questions on clients' tech-savvyness, attitudes toward technology, the perceived utility of internet banking, risk preferences, and whether or not the client is responsible for financial matters in their household ("head of finance").

The third survey (*post-survey*) was distributed to all clients in the target group on December 9, 2024. The goal was to elicit alternative outcome measures and mediators, as well as reasons for non-participation. To ensure high participation rates, survey respondents obtained the chance to win one of 50 gift vouchers worth 50 EUR each.[14] Invitations to participate in the survey were sent via letter and email. Our partner bank additionally conducted phone calls. Data collection was completed on March 18, 2025. There were four versions of the post-survey (one for non-participants, one each for participants in the three treatment arms).

4.2 Estimation strategy

To estimate the effects of the various training interventions on internet banking adoption, we mainly rely on a simple difference-in-differences (DiD) set-up for ITT and ATT effects:

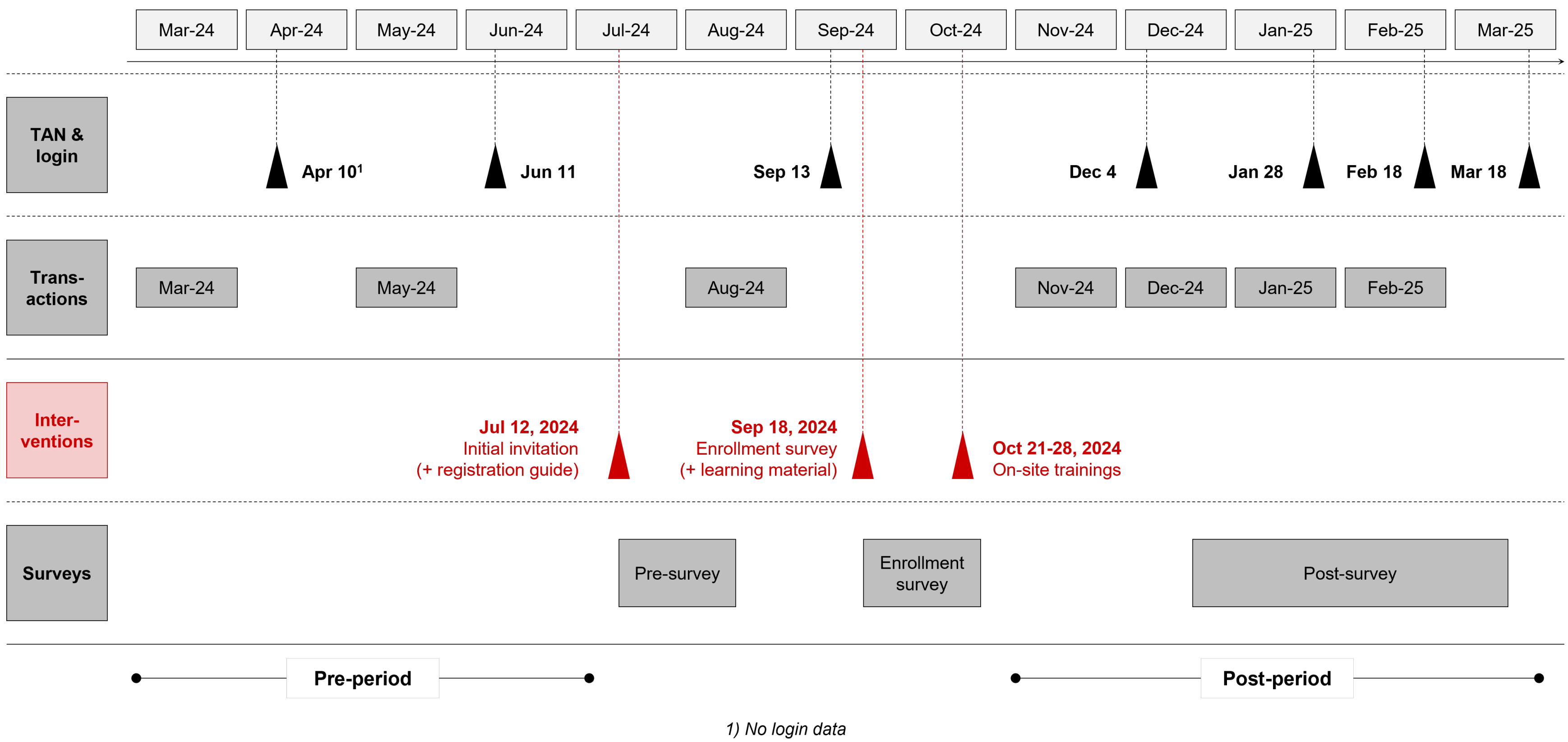
$$\text{Adoption}_{it} = \beta_0 + \beta_1 \text{Post}_t + \beta_2 \text{T}_i + \beta_3 \text{Post}_t \times \text{T}_i + X_{it}\gamma + \epsilon_{it} \quad (1)$$

where Post_t is a dummy variable equal to one after the training interventions, T_i indicates that client i is treated according to the respective treatment definition, and X_{it} is a vector of contemporaneous client-level control variables (age, gender dummy, inflow dummies).[15] Our main coefficient of interest in this setting is β_3. In addition to this simple model, we will include time and client fixed effects, which absorb the $Post_t$ and T_i dummies, in robustness

[14] The voucher's face value can be considered nearly equivalent to its cash value as recipients are free to choose among a wide range of online and offline stores.

[15] Within-client variation in control variables is low.

Figure 2: Timeline of data exports and client interactions



Note: The figure displays the timing of data exports and interventions with bank clients. TAN indicates whether a client has an active TAN process as per the data export date. Login indicates whether the client has logged into their internet banking at least once as per the export date. The login data is not available for the April 10 data export. Transactions refer to the full calendar month preceding the export date (i.e., calendar month March for data exported on April 10).

tests. The former account for generally higher adoption rates over time, while the latter account for the impact of time-invariant unobserved client characteristics on adoption.

To investigate the timing and sustainability of potential treatment effects (and assess the common trend assumption), we also conduct a dynamic version of the pooled DiD estimation according to the following regression equation:

$$\text{Adoption}_{it} = \alpha + \sum_{t} \beta I_t + \gamma T_i + \sum_{t} \delta \left(I_t \times T_i \right) + X_{it}\theta + \epsilon_{it} \tag{2}$$

where I_t are dummy variables indicating month t. In this specification, the vector of δ coefficients are our coefficients of interest as they reflect the effect of being in the treatment group in any given month t relative to the omitted month $t-1$, which directly precedes the interventions. Since we sent out the initial invitation, which contained the link to the internet banking set-up learning platform, on July 12, 2024, we consider data obtained in April and June 2024 as preceding the interventions and data obtained in December 2024, January 2025, February 2025, and March 2025 as succeeding the interventions. Since the data obtained in September 2024 precedes an important part of the interventions (the on-site and online trainings), we will omit this datapoint in our pooled DiD regressions. However, we will use the data in the dynamic DiD regressions to evaluate the timing of potential treatment effects.

We use three main outcome variables (Adoption_{it}):[16] $\text{D(TAN active)}_{it}$ is a dummy variable equal to 1 if a client has activated any TAN verification mode (for instance, push-TAN via smartphone), and 0 otherwise. D(login)_{it} is a dummy variable equal to 1 if the client has ever logged into their internet banking account, and 0 otherwise. Online transaction share_{it} is the share of transactions a client has carried out via internet banking.[17] Transactions include the commissioning of individual bank transfers and setting up or adjusting recurring transfer orders. Importantly, the measure captures whether clients sustainably shift their banking activities from offline modes to internet banking. For instance, setting up a monthly recurring transfer order online only counts as an internet banking transaction in the first month.

As typical in a DiD setting, the central identifying assumption is the common trend assumption: In the absence of internet banking training, internet banking adoption would have followed a parallel trend in treatment and control groups. While, to the best of our knowledge, there is no competing intervention happening at the same time as our treatment, selection into treatment (completion) may be an important concern.

[16] In line with our pre-registered analysis plan, we additionally use a dummy variable indicating any online transaction, the number of online transactions, and the number of days since the last login as adoption measures (see section 7). The results are consistent with the results obtained for our preferred dependent variable specifications in both the statistical and economic sense.

[17] The alternatives are self-service terminals and transfer slips.

We augment the simple version of the DiD set-up in two important ways to mitigate threats to identification: To account for selection on observables and to optimally deal with the small sample size in later stages, we use a matched control group sampled from the 1,725 silent control observations. As we move along the adoption process in a cascade of ITTs, we always pick the control group that is the best matched to each respective treatment group in terms of observable characteristics (age, gender, inflows, activity). We use 5-nearest-neighbor matching based on a propensity score for each treatment definition.[18] Our results are not sensitive to the matching procedure and highly similar to the results obtained when using the unmatched silent control group.

To account for selection based on unobserved client characteristics, such as motivation, we use the group of participants who signaled intent but never access any of the training material as a placebo group. Since the largest share of selection takes place at early stages of the multi-step process (see section 5), we make the claim that this group would be selected following a similar pattern as the eventual main treatment group. To account for later-stage selection, we augment this approach by weighing placebo observations by likelihood of training completion based on observed characteristics. Any "treatment effect" measured for this group then reflects the portion of the estimated treatment effect that is explained by selection based on unobserved heterogeneity rather than the treatment itself (see section 6.4 for results). Combining the randomized field experiment with these additional analyses allows us to estimate causal ITTs as well as the ATT of our internet banking training on internet banking adoption among Baby Boomers.

5 Selection

In our private-life technology adoption setting, studying selection into the interventions is highly informative: As the literature on on-the-job-training has demonstrated (cf. Leuven and Oosterbeek, 2008), selection into training and non-random dropout may be severe when training is not mandatory. However, little is known about training take-up outside of the workplace in a private-life setting in which technology adoption is convenient but ultimately optional, as physical bank branches still exist. In addition, we are looking at a multi-step process between initial contact and training completion. Selection along this training and adoption process reflects voluntary investment into a technology that offers clear—albeit potentially misperceived—benefits but also comes with effort costs. We make use of our rich data structure, which allows us to observe outcomes of all non-responding clients, to study

[18] We use propensity scores fitted from probit regressions of treatment participation in the various stages on age, a gender dummy, a dummy indicating the client has been with the bank since 2022, a dummy variable indicating inflows exceeding EUR 2,000, the number of total transactions, the number of inflows, and the number of outflows. Data are as of June 2024. Table A6 in the Appendix reports the coefficients of the first-stage probit regressions. We use 5-nearest-neighbor matching as our preferred specification, but also report results for 1-nearest-neighbor matching as a robustness test.

selection and its implications on two distinct levels: First, non-random selection phenomena may pose severe threats to the causal identification of our main treatment effect. Section 4.2 describes how we tackle selection-related identification concerns through matching and an extensive placebo analysis. Second, we are interested in selection and dropout beyond these empirical concerns as these issues help us paint a more comprehensive picture of technology adoption—or avoidance—among the Baby Boomer generation. Learning about selection and dropout allows to better predict the real-world response to, say, a large-scale technology adoption policy that offers free training to all those who sign up. Figure 1 summarizes the raw dropout numbers at every stage.

Selection at the very first stage of our invite highlights the potential severity of these implications. Recall that we only invite elderly clients who do not use internet banking and that we use the bank's official communication channels for communication. Out of these 25,982 clients, a mere 550 respond to our invite in the first place. This is despite the use of several (including offline) modes of contact and a generous deadline. The response rate is particularly striking considering that we offered free internet banking training—with a strong emphasis on convenience for participants and without the need to fully commit to a date at this initial stage. Table 2 and Table A7 in the Appendix summarize the most important demographic selection determinants. Column (1) of Appendix Table A7 reports dropout determinants in a simple regression framework showing a significant negative relationship between age and dropout. Coefficients on gender and account inflows are also precisely estimated: Clients signaling the intention to participate in training are more likely to be female. Since socio-economic status is consistently at the core of discussions on inequalities in education (Blanden et al., 2023), we also look at inflows of more than 4,000 EUR per month as a measure of income. We find that those with higher inflows are more likely to signal intent. These results hold both in a simple OLS framework and in a logit specification. To gauge the economic magnitude of early-stage selection, it is useful to look at Table 2 since the low overall response rate deflates the absolute coefficients in Table A7. Looking at univariate dropout determinants reveals that the share of women is 7 percentage points higher among the group of respondents (67 versus 60%). Similarly, respondents are older (by approximately 3 years) and 13 percentage points more likely to belong to the highest category of monthly inflows into their bank account. This finding already points towards a positive selection into training by socio-economic status, although we cannot account for education at this initial stage due to lack of survey data for non-respondents.

At the next stage of the intervention—enrollment into treatment, where we hear back from 180 of the 333 respondents (54%) in the randomized main sample—, the education indicator is highly predictive of drop-out. More educated initial respondents are significantly more likely to enroll into treatment, although the effect is only moderate in its economic magnitude. The education variable is the only significant predictor of dropout at this stage—implying that selection is potentially less dimensional than expected. However, the lack of significance among the other indicators could also be due to the decreasing sample size as we move along the different stages of the process. Education being a significant dropout predictor raises concerns for selection into treatment based on unobservable factors related to education, such as motivation or ability. For this reason, we take additional steps in ensuring our ATT can be estimated reliably, such as an extensive placebo analysis. Interestingly, the education selection effect is only present in the self-guided treatment as Table A7 reveals. We cautiously interpret this as the social learning based treatments being potentially more inclusive and better equipped for motivating participants with less learning experience, as we discuss in section 8.

Table 2: Univariate dropout determinants, by recruitment stage

	(1) Non-respondents		(2) Respondents		(1)-(2)		
	Mean	N	Mean	N	Δ	z score	
Panel A: Intent							
Age	67.56	25,432	70.82	550	-3.26	-7.47	***
D(female)	0.60	25,432	0.67	550	-0.07	-3.12	**
D(inflow $\geq$ 4,000€)	0.35	25,432	0.48	550	-0.13	-6.24	***
Panel B: Enrollment							
Age	71.15	153	71.57	180	-0.42	-0.37	
D(female)	0.73	153	0.67	180	0.05	1.05	
D(inflow $\geq$ 4,000€)	0.48	153	0.46	180	0.02	0.41	
Education	2.48	127	2.81	163	-0.33	-2.53	**
Panel C: Attendance							
Age	72.07	45	71.41	135	0.66	0.52	
D(female)	0.67	45	0.67	135	-0.01	-0.09	
D(inflow $\geq$ 4,000€)	0.33	45	0.50	135	-0.17	-1.98	*
Education	2.70	37	2.84	126	-0.14	-0.75	
Risk tolerance	4.50	40	4.94	135	-0.44	-1.00	

Note: The table reports sample means by response in the various recruitment stages, as well as the between-group difference in means and the test scores of non-parametric Wilcoxon rank tests. Administrative banking data (age, gender, inflows) are as of June 11, 2024. Education is elicited in the pre-survey. Risk tolerance is elicited in the enrollment survey (on an 11-point Likert scale, cf. Dohmen et al., 2011). Asterisks indicate statistical significance of non-parametric Wilcoxon rank tests ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$).

Moving along the selection path into the final stage—the training attendance stage—where 135 participants attend the on-site workshop or access their at-home training, we find that richer participants are more likely to complete the training interventions (see Table 2) although the effect is only weakly significant for the social learning treatments (see Table A7 in the Appendix). Looking at all training arms combined at this stage of the training process, the education-based selection effect subsides, leaving us with no significant dropout predictors when pooling all treatments. In addition, we find no significant difference in risk tolerance, which has been linked to internet banking adoption (Bauer and Hein, 2006), between participants and non-participants at this stage (see Table 2).[19] These null results point towards a dominance of random dropout once participants have committed to the training. The overall dropout rate is considerably lower in the social learning interventions than in the self-guided intervention (47 versus 26%).

Overall, this dropout prediction exercise reveals significant selection into training at the first invitation stage although no single factor seems to dominate. While education predicts dropout at the enrollment stage, we find little evidence on systematic dropout at the attendance stage. We cautiously conclude that even careful and multi-modal communication does not prevent high dropout rates, and that classic demographics, such as socio-economic status including education matter for initial selection into training take-up. Regarding the role of education beyond the initial take-up stage, results reveal that education only predicts drop-out in the self-guided intervention. This finding underlines the higher inclusivity of the interventions that emphasize a social component that was also anecdotally communicated to us by participants and the partner bank team.

6 Main results

In assessing the effectiveness of our training interventions, we estimate treatment effects along the various stages of the recruitment process (see Figure 1). Specifically, we estimate four ITT effects for which participants in the various treatment conditions are pooled and three ATT effects, two of which investigate differences between the treatment conditions. In addition to pooled DiD estimations (equation 1), we run dynamic DiD regressions to explicitly investigate the common trends assumption and assess the timing and sustainability of the treatment effects (equation 2). Finally, to address concerns over selection on unobserved characteristics, we estimate a placebo effect that exploits the fact that selection into treatment occurs mainly at the first stage of the recruitment process.

6.1 ITT estimates

We investigate four distinct ITT effects, which are increasing with respect to their proximity to the actual treatment. First, we estimate an ITT effect among the 25,982 randomly selected participants who received an invitation to the training interventions (*invite ITT*). Second, we estimate an ITT effect among the 550 respondents to the training invitation (*intent ITT*). After completing the brief pre-survey, these respondents were re-directed to a learning platform containing a step-by-step guide to setting up internet banking at the partner bank in the form of a video and instructional slides. Third, we estimate an ITT effect among the 333 respondents who met all inclusion criteria for our core sample (see section 3.2, *qualified*

[19] We elicit risk tolerance in the enrollment survey, which is why we cannot assess selection related to risk preferences at earlier stages. Due to small sample size, we omit risk tolerance as a dropout predictor in the multivariate specification.

intent ITT). Fourth, we estimate an ITT effect among the 180 participants who enrolled in the training in a second survey (*enrollment ITT*).

As a first descriptive glance at our results, Figure 3 displays the evolution of our technology adoption measures for treatment and control groups for the most restrictive ITT classification (enrollment ITT) compared to the matched control group.[20] Note that we do not observe the login variable in April 2024 as it was not part of the original data extraction. The dashed vertical lines reflect the intervention dates: the first line reflects the date at which the invitation was dispatched along with a detailed internet banking set-up instruction (July 12, 2024). The second line reflects the date at which the actual training interventions took place (October, 2024). The descriptive charts suggest parallel trends prior to the interventions (see Table A12 in the Appendix for differences in means per month). We also observe a slight increase in the TAN activation and login variables in September 2024, but no significant increase in the online transaction share in August 2024 (which is the corresponding month for the September data retrieval). This pattern was to be expected as the set-up instructions only provided information on setting up the internet banking platform (including a TAN process), but did not contain any of the actual treatment contents.[21] Since the August/September 2024 data fall between the dates at which the set-up instructions were sent out and the actual training interventions, we will omit this datapoint in the pooled DiD estimations. For the dynamic DiD models, we will include the August/September 2024 data, but we will omit the login variable as there is only one pre-intervention observation per client.

Next, Table 3 reports the DiD coefficients for the various ITT specifications versus the unmatched silent control group (columns 1 through 4) as well as versus matched control groups (columns 5 through 7).[22] There is a slightly positive overall time trend in the TAN and login variables (2 percentage point increase, $p < 0.01$). Since clients rarely deactivate a TAN mechanism once it has been activated and the login dummy retains a value of one once a client has logged in for the first time, this was to be expected. When we use the matched control group, the $Post_t$ coefficients become less precisely estimated. We do not observe a general time trend in the online transaction share measure. Some cross-sectional differences in the outcome measures between treatment and control group diminish when we use the matched control groups.

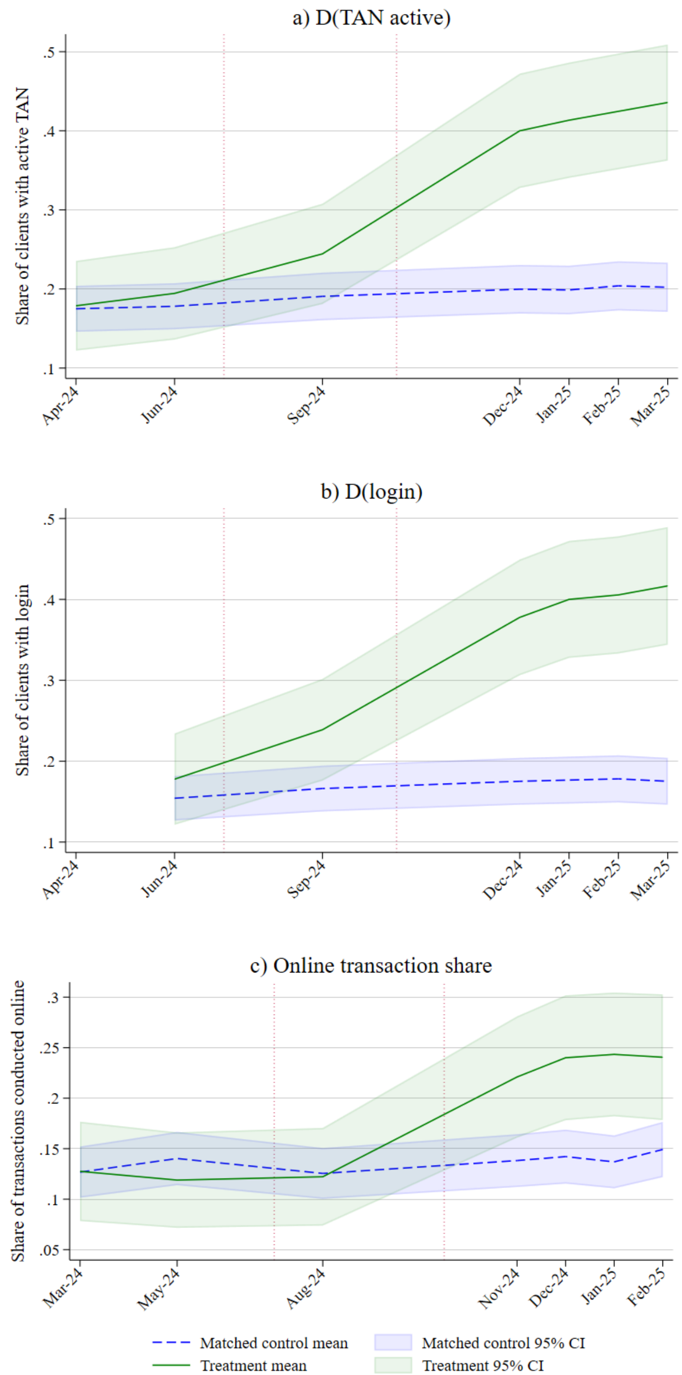
Looking at the DiD coefficients, there is no significant treatment effect in the *invite ITT* specification for either of our three main dependent variables, which was to be expected given the low response rate (2.1%, see column 1).

[20] The corresponding chart using the silent control group is displayed in Figure A3 in the Appendix.

[21] Note that the pattern could also be a consequence of the transaction data referring to a slightly earlier time period (calendar month of August 2024 vs. September 13, 2024; see Figure 2).

[22] We do not use a matched control group for the invite ITT specification as there is no selection into treatment.

Figure 3: Adoption measures, by treatment status (enrollment ITT vs. matched control group)



Note: The figures show monthly averages of the three main dependent variables over time, separately by treatment status. The treatment group here is defined as enrollment in the courses (N = 180, solid green line), the control group is the matched control group (N=668, dashed blue line). The shaded areas indicate 95% confidence intervals. The login variable is not included in the April-24 dataset. The dashed vertical lines reflect the intervention dates: the first line reflects the date at which the invitation was dispatched along with a detailed internet banking set-up instruction (July 12, 2024). The second line reflects the date at which the actual training interventions took place (October, 2024).

Using respondents to the initial survey as the treatment group (*intent ITT*), the results suggest a significant increase in both internet banking setup and logins by 15 percentage points ($p < 0.01$, column 2 of panels A and B). The effect becomes slightly larger when matched control groups are used instead of the unmatched control group ($p < 0.01$, column 5 of panels A and B). The treatment effect represents between 83% and 100% of the control group's pre-treatment average in the internet banking setup measures. Importantly, it also translates into increased use of internet banking for financial transactions: the share of transactions conducted online increases by 7 percentage points compared to both the unmatched and matched control group ($p < 0.01$, columns 2 and 5 of panel C). Again, the effect size represents more than 60% of the respective control group's pre-treatment mean.

All treatment effects increase consistently the more closely our ITT specification resembles actual treatment. Specifically, in the *qualified intent ITT* specification, internet banking setup increases by between 17 and 18 percentage points ($p < 0.01$, columns 3 and 6 of panels A and B), and the share of transactions conducted online increases by 10 percentage points ($p < 0.01$, columns 3 and 6 of panel C). In the *enrollment ITT* specification, internet banking setup increases by between 20 and 21 percentage points ($p < 0.01$, columns 4 and 7 of panels A and B) and the share of transactions conducted online increases by 11 percentage points ($p < 0.01$, columns 4 and 7 of panel C).

The DiD coefficients are virtually identical when we employ 1-nearest-neighbor matching (instead of 5-nearest-neighbor matching, see Table A8 in the Appendix) or when we employ a two-way fixed effects (TWFE) model including month and client fixed effects (which absorb the individual $Post_t$ and T_i coefficients, see Table A9 in the Appendix).

Table 3: ITT estimates

	Unmatched control group				Matched control groups		
	(1) Invite ITT	(2) Intent ITT	(3) Qualified intent ITT	(4) Enroll-ment ITT	(5) Intent ITT	(6) Qualified intent ITT	(7) Enroll-ment ITT
Panel A: D(TAN active)							
$Post_t$	0.023***	0.023***	0.023***	0.023***	0.022**	0.022*	0.025*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.011)	(0.013)
T_i	0.003	0.027*	0.041**	0.034	0.020	0.029	0.011
	(0.007)	(0.014)	(0.017)	(0.022)	(0.015)	(0.018)	(0.024)
$Post_t \times T_i$	0.002	0.145***	0.175***	0.209***	0.146***	0.177***	0.207***
	(0.008)	(0.017)	(0.020)	(0.026)	(0.018)	(0.022)	(0.029)
Obs.	163,249	13,442	12,145	11,230	10,475	7,684	5,017
Adj. R2	0.081	0.078	0.080	0.081	0.078	0.078	0.078
Control pre mean (DV)	0.175	0.175	0.175	0.175	0.175	0.170	0.177
Panel B: D(login)							
$Post_t$	0.024**	0.024**	0.024**	0.024**	0.019	0.020	0.022
	(0.010)	(0.010)	(0.010)	(0.010)	(0.013)	(0.014)	(0.017)
T_i	0.007	0.038**	0.057**	0.047	0.030	0.047*	0.024
	(0.009)	(0.019)	(0.023)	(0.029)	(0.020)	(0.025)	(0.033)
$Post_t \times T_i$	-0.001	0.148***	0.172***	0.199***	0.153***	0.175***	0.200***
	(0.010)	(0.021)	(0.026)	(0.033)	(0.023)	(0.028)	(0.037)
Obs.	138,535	11,375	10,290	9,525	8,865	6,495	4,240
Adj. R2	0.049	0.074	0.077	0.072	0.075	0.080	0.082
Control pre mean (DV)	0.148	0.148	0.148	0.148	0.150	0.144	0.154
Panel C: Online transaction share							
$Post_t$	0.004	0.004	0.004	0.004	0.003	0.001	0.007
	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.009)	(0.011)
T_i	-0.011**	-0.006	-0.007	-0.005	-0.012	-0.020	-0.014
	(0.005)	(0.011)	(0.013)	(0.017)	(0.012)	(0.015)	(0.020)
$Post_t \times T_i$	0.010	0.071***	0.097***	0.109***	0.072***	0.100***	0.106***
	(0.006)	(0.013)	(0.016)	(0.021)	(0.015)	(0.019)	(0.025)
Obs.	163,249	13,442	12,145	11,230	10,475	7,684	5,017
Adj. R2	0.069	0.104	0.108	0.108	0.094	0.094	0.103
Control pre mean (DV)	0.107	0.107	0.107	0.107	0.121	0.133	0.134
Client controls	✓	✓	✓	✓	✓	✓	✓
# treated	25,982	550	333	180	550	333	180
# control	1,725	1,725	1,725	1,725	1,223	966	668

Note: The table reports coefficients of OLS panel regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on a dummy variable which is equal to one after the interventions ($Post_t$), a dummy variable indicating that client i was part of the respective treatment group (T_i), an interaction of $Post_t$ and T_i, and various client-level control variables (age, gender dummy, inflow dummies). Specifications reported in columns (1) through (4) use the full silent control group (N=1,725), while specifications reported in columns (5) through (7) use individually matched control groups obtained from five-nearest-neighbor matching on a propensity score. We use several treatment definitions. Invite ITT refers to all clients invited to the training interventions (N=25,982). Intent ITT refers to all clients that responded to the initial survey (N=550). Qualified intent ITT refers to the subset of respondents that we were able to randomly assign a treatment group based on their survey answers (N=333). Enrollment ITT refers to all clients that have registered for a treatment (N=180). Standard errors are reported in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

6.2 ATT estimates

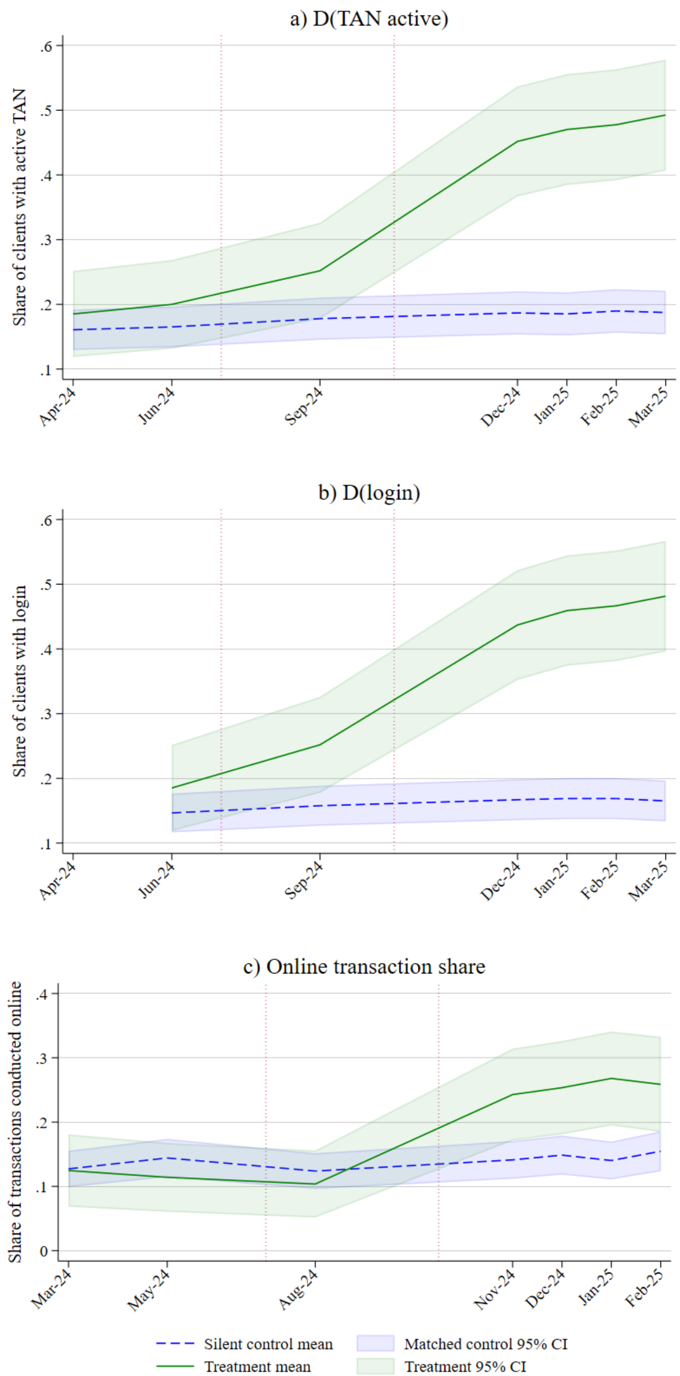
Next, we turn to our main treatment effect on the treated. First, we pool participants in all treatment groups to assess the overall effect of completing our training interventions. Second, we pool participants of the social learning treatments (on-site workshops and social circle support). Third, we only consider participants of the on-site workshop, our main treatment group. Figure 4 displays the evolution of our adoption measures in the pooled ATT specification versus the matched control group. Consistent with Figure 3, TAN activation and logins increase slightly in September, which is likely caused by the setup instructions distributed along with the pre-survey, while the full effect materializes in December. The share of online transactions increases only after the actual training interventions. Compared to Figure 3, the adoption measures in the treatment groups are significantly higher, illustrating that the main treatment effect is the culmination of a series of ITT effects. Specifically, the share of clients who have set up their internet banking increases to almost 50% (compared to less than 20% in the matched control group).

Table 4 reports the DiD coefficients for the ATT specification versus the unmatched control group (columns 1 through 3) as well as matched control groups (columns 4 through 6). We find that internet banking setup and logins increase by 25 to 26 percentage points ($p < 0.01$, columns 1 and 4 of panels A and B). The treatment effect is economically meaningful as it represents approximately 150% of the control group's pre-treatment average in the internet banking setup measures. Sustainable internet banking use as measured by the share of online transactions increases by 13 percentage points ($p < 0.01$, columns 1 and 4 of panel C). This represents a substantial increase from the pre-treatment baseline by more than 100%. As Table A13 in the Appendix shows, treatment effects are significantly more pronounced for participants that have completed the training (ATT) than for participants who have signaled intent to participate or even enrolled in the treatment (ITT), but have not completed training. This is true for both dependent variables and in all post-intervention time periods and corroborates a causal interpretation of our treatment effects.

Our results do not suggest that treatment effects differ systematically across treatment conditions. Specifically, when only social learning treatments (columns 2 and 5) or only on-site trainings (columns 3 and 6) are considered, the treatment effect is no different from the pooled specification.

Again, our results do not change when we use 1-nearest-neighbor matching to define matched control groups (see Table A10 in the Appendix) or when we use a TWFE model (see Table A11 in the Appendix).

Figure 4: Adoption measures, by treatment status (ATT vs. matched control group)



Note: The figures show monthly averages of the three main dependent variables over time, separately by treatment status. The treatment group here is defined as having attended the courses (N = 135, solid green line), the control group is the matched control group (N=539, dashed blue line). The shaded areas indicate 95% confidence intervals. The login variable is not included in the April-24 dataset. The dashed vertical lines reflect the intervention dates: the first line reflects the date at which the invitation was dispatched along with a detailed internet banking set-up instruction (July 12, 2024). The second line reflects the date at which the actual training interventions took place (October, 2024).

Table 4: ATT estimates

	Unmatched control group			Matched control groups		
	(1) All treatments	(2) Social learning treatments	(3) On-site workshop	(4) All treatments	(5) Social learning treatments	(6) On-site workshop
Panel A: D(TAN active)						
$Post_t$	0.023***	0.023***	0.023***	0.024	0.018	0.019
	(0.008)	(0.008)	(0.008)	(0.015)	(0.016)	(0.017)
T_i	0.039	0.025	0.043	0.028	0.011	0.030
	(0.024)	(0.027)	(0.028)	(0.027)	(0.030)	(0.031)
$Post_t \times T_i$	0.258***	0.250***	0.247***	0.257***	0.255***	0.251***
	(0.030)	(0.033)	(0.034)	(0.033)	(0.036)	(0.038)
Obs.	10,961	10,805	10,745	3,990	3,206	2,940
Adj. R2	0.082	0.077	0.079	0.079	0.076	0.083
Control pre mean (DV)	0.175	0.175	0.175	0.163	0.159	0.159
Panel B: D(login)						
$Post_t$	0.024**	0.024**	0.024**	0.021	0.012	0.011
	(0.010)	(0.010)	(0.010)	(0.019)	(0.021)	(0.021)
T_i	0.052	0.044	0.052	0.035	0.022	0.033
	(0.033)	(0.037)	(0.038)	(0.037)	(0.041)	(0.043)
$Post_t \times T_i$	0.252***	0.252***	0.249***	0.255***	0.264***	0.261***
	(0.037)	(0.041)	(0.043)	(0.042)	(0.046)	(0.048)
Obs.	9,300	9,170	9,120	3,370	2,710	2,485
Adj. R2	0.078	0.074	0.073	0.097	0.098	0.100
Control pre mean (DV)	0.148	0.148	0.148	0.147	0.145	0.143
Panel C: Online transaction share						
$Post_t$	0.004	0.004	0.004	0.010	0.005	0.008
	(0.006)	(0.006)	(0.006)	(0.013)	(0.014)	(0.015)
T_i	-0.017	-0.018	-0.022	-0.026	-0.031	-0.029
	(0.019)	(0.021)	(0.022)	(0.023)	(0.026)	(0.027)
$Post_t \times T_i$	0.132***	0.131***	0.132***	0.126***	0.130***	0.127***
	(0.023)	(0.026)	(0.027)	(0.029)	(0.032)	(0.033)
Obs.	10,961	10,805	10,745	3,990	3,206	2,940
Adj. R2	0.106	0.105	0.104	0.092	0.099	0.092
Control pre mean (DV)	0.107	0.107	0.107	0.136	0.140	0.132
Client controls	✓	✓	✓	✓	✓	✓
# treated	135	109	99	135	109	99
# control	1,725	1,725	1,725	539	433	398

Note: The table reports coefficients of OLS regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on a dummy variable which is equal to one after the interventions ($Post_t$), a dummy variable indicating that client i was part of the treatment group (T_i), an interaction of $Post_t$ and T_i, and various client-level control variables (age, gender dummy, inflow dummies). Specifications reported in columns (1) through (3) use the full silent control group (N=1,725), while specifications reported in columns (4) through (6) use individually matched control groups obtained from five-nearest-neighbor matching on a propensity score. Standard errors are reported in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

6.3 Dynamic estimation

Next, we estimate dynamic DiD regressions as specified in equation 2. Figure 5 displays the treatment coefficients of regressions using the TAN activation measure (Panel a)) and the online transaction share (Panel b)) as dependent variables. Each chart plots the coefficients for the three main ITT specifications and the pooled ATT specification. Data obtained in June 2024 acts as the omitted category.

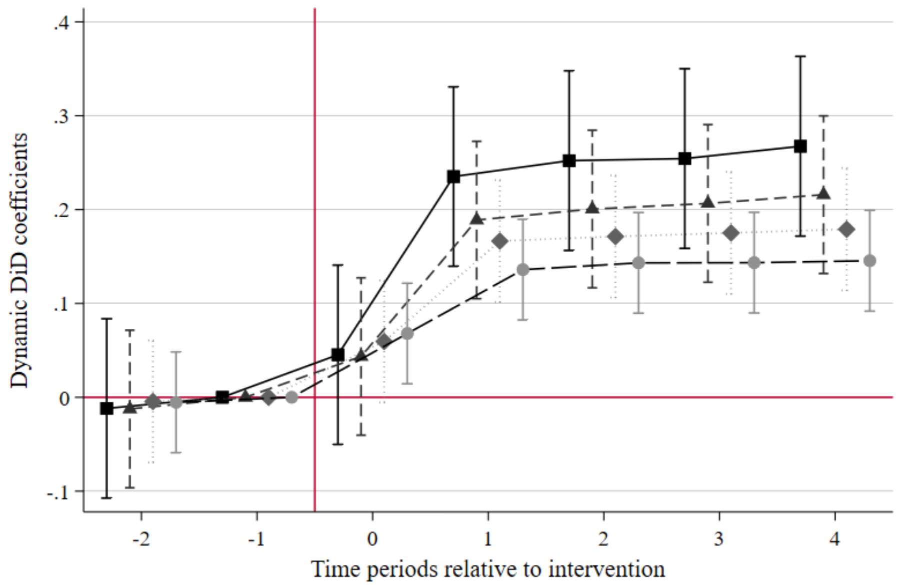
For both dependent variables, the chart provides support for the common trend assumption as there is no significant difference in any of the treatment specifications in month $t = -2$ (i.e., April for the TAN measure, March for the transaction share measure). Table A12 in the Appendix, which reports mean differences by month, shows that average adoption measures do not differ significantly between the treatment and the matched control group in either of the two pre-intervention months. In line with the descriptive evidence presented in Figure 3, the treatment coefficients for the TAN measure are marginally significantly positive in month $t = 0$ (September 2024), but insignificant for the online transaction share measure (August 2024).

The main treatment effect materializes in month $t = 1$ for both dependent variables, with coefficients for all treatment specifications significantly positive. For the TAN measure, the treatment coefficients remain relatively flat throughout the post period, which is intuitive given that TAN de-activation is rare. For the online transaction share, the coefficients peak in $t = 3$ (January 2025), but remain relatively flat, suggesting that the increase is sustainable. In line with the pooled DiD coefficients, the dynamic treatment coefficients are almost linearly increasing, the closer the treatment definition resembles actual training completion.

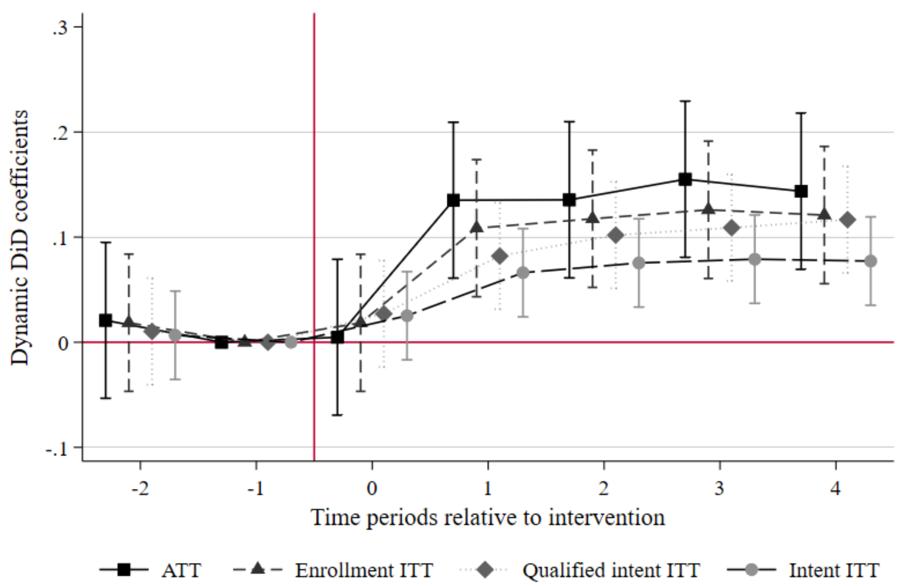
All of our results are replicated when we use matched control groups (see Figure A5 in the Appendix). If anything, none of the treatment coefficients in $t = 0$ are significant in this specification, suggesting that the treatment effects can in fact be attributed to the training interventions (rather than the set-up instructions).

Figure 5: Dynamic DiD coefficients (vs. silent control)

a) DV: D(TAN active)



b) DV: Online transaction share



Note: The figure reports the point estimates and 95% confidence intervals of treatment coefficients obtained from dynamic DiD regressions as specified in equation 2 for various treatment definitions. The dependent variables are a dummy variable indicating an active TAN process (Panel a)) and the share of transactions conducted online (Panel b)). The omitted month ($t = -1$) is June 2024 (calendar month May 2024 for the transaction share measure).

6.4 Placebo test

The evidence reported so far suggests that treated participants increase internet banking adoption relative to the control group. The fact that point estimates are significantly increasing in the proximity to actual participation already makes us confident that we are in fact identifying causal treatment effects. In addition, we can rule out selection on observable characteristics driving our results as results remain unchanged and even become stronger in some specifications when we use matched control groups. However, selection into training based on unobservables may still be a threat to identification, since we cannot force randomly selected clients to participate in the study. To assess if and to which extent selection on unobserved characteristics may be driving our results, we conduct a placebo test, which exploits the variation in our attendance measures. Specifically, we know which clients participate in the on-site sessions (through attendance lists) and which clients access the learning platforms containing the set-up material as well as self-guided and social circle training material.

The results reported in section 5 suggest that selection on observables is most pronounced during the first recruitment stage, i.e., between bank clients that respond to the initial invitation to participate in the training and those that do not (see Table 2). This is plausible since initial sign-up already came with the cognitive burden of completing a survey and signaling availability for each type of training. Selection on observables is more subdued in the later stages (i.e., enrollment and attendance). Thus, we identify the subset of bank clients as a placebo group who have responded to the initial study invitation and fulfill all inclusion criteria, but who have never accessed any of the training material either in-person or online (N= 60). This group is arguably subject to similar unobserved characteristics that potentially co-determine participation and internet banking adoption as the eventual treatment group. Thus, the placebo treatment coefficients allow us to estimate the portion of our treatment effects that can be attributed to selection based on unobservables rather than the treatment itself. Additionally, we account for later-stage selection on observables by augmenting our placebo analyses with weights for the predicted likelihood of enrolling into and completing treatment.

Table 5 reports the DiD coefficients for the placebo specification. In line with a causal interpretation of our main treatment effects, we do not observe a significant placebo effect for either of our three dependent variables. Importantly, while lack of statistical significance could be the consequence of the smaller sample size, the point estimates are negligible compared to our main treatment estimates.[23] When we use a TWFE specification (see Table A15 in the Appendix), point estimates remain negligible, but some coefficients are significantly positive.

[23] Figure A6 in the Appendix displays the dynamic DiD coefficients. None of the post-intervention coefficients is significant, regardless of the control group used. Our results are also robust to using 1-nearest-neighbor matching (instead of 5-nearest neighbor matching) to define matched control groups (see Table A14 in the Appendix).

Finally, to account for the fact that education is related to selection in the enrollment stage (see Table 2), we augment the placebo analysis by weighing observations in the placebo group by their predicted likelihoods of enrolling in and completing the treatment.[24] Specifically, observations within the placebo group with higher predicted treatment likelihoods based on observables are given higher weights in the regressions. Table A16 in the Appendix reports the resulting coefficients. Point estimates increase negligibly and remain statistically insignificant using the propensity-score-weighting specifications.

Table 5: Placebo estimates

	Unmatched control group			Matched control group		
	(1)	(2)	(3)	(4)	(5)	(6)
	D(TAN active)	D(login)	Online transaction share	D(TAN active)	D(login)	Online transaction share
$Post_t$	0.023***	0.024**	0.004	0.020	0.020	-0.026
	(0.008)	(0.010)	(0.006)	(0.020)	(0.025)	(0.017)
P_i	-0.026	0.012	0.024	-0.034	-0.010	-0.019
	(0.035)	(0.048)	(0.028)	(0.038)	(0.052)	(0.033)
$Post_t \times P_i$	0.039	0.031	0.008	0.042	0.034	0.037
	(0.043)	(0.053)	(0.034)	(0.046)	(0.059)	(0.040)
Obs.	10,514	8,925	10,514	1,970	1,670	1,970
Adj. R2	0.068	0.057	0.103	0.037	0.047	0.107
Control pre mean (DV)	0.175	0.148	0.107	0.165	0.150	0.146
Client controls	✓	✓	✓	✓	✓	✓
# treated	60	60	60	60	60	60
# control	1,725	1,725	1,725	274	274	274

Note: The table reports coefficients of OLS regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on a dummy variable which is equal to one after the interventions ($Post_t$), a dummy variable indicating that client i was part of the placebo group (P_i), an interaction of $Post_t$ and P_i, and various client-level control variables (age, gender dummy, inflow dummies). Specifications reported in columns (1) through (3) use the full silent control group (N=1,725), while specifications reported in columns (4) through (6) use individually matched control groups obtained from five-nearest-neighbor matching on a propensity score. Standard errors are reported in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

Thus, assuming that the imprecisely estimated placebo effect captures selection, this selection on unobservables accounts only for a small portion of the treatment effect—around 15%.[25] This allows us to identify a lower bound of the causal treatment effect by subtracting from the treatment effect reported in section 6.2 the estimated placebo effect. Using this

[24] We compute propensity scores as the fitted values from logistical regressions of treatment (enrollment or attendance/completion) on age, a gender dummy, inflow (a dummy indicating inflows exceeded EUR 4,000), and the education level (1: lower secondary, 2: intermediate secondary, 3: grammar school, 4: college degree, 5: PhD). Figure A7 in the Appendix displays the distribution of propensity scores for the placebo and treatment groups. While propensity scores are higher for the treatment group (median is 4 percentage points higher for both specifications), there is a considerable overlap in propensity scores. This suggests that selection on observables cannot fully explain the difference in treatment effects.

[25] The placebo effect accounts for between 15 and 16% of the treatment effect on TAN activation, between 12 and 13% of the treatment effect on logins, and between 6 and 29% of the treatment effect on the online transaction share.

back-of-the-envelope calculation, the majority of the estimated treatment effect (around 85%) can be causally attributed to the training interventions.

7 Alternative outcomes and treatment heterogeneity

7.1 Intentions and non-technical adoption skills

In line with our pre-registered analysis plan, we investigate three additional adoption measures: a dummy variable indicating any online transaction, the number of online transactions, and the number of days since the last login as adoption measures. We find quantitatively similar results using these alternative adoption measures (see Table A18 in the Appendix).

In addition to the objectively measured banking data, we use survey outcomes to gain a deeper understanding of the changes in behavior and attitudes caused by our training. While the following results offer suggestive evidence, they should be interpreted with caution due to limited sample size and potential selection. Observed differences may partly reflect non-random survey participation rather than causal effects. Table 6 summarizes the results from the post-survey. In total, 204 clients have completed the post-survey, of which 93 have at least signaled intent to participate in the trainings. Treatment-related survey measures (e.g., has developed routines for IB) were only collected among the latter group. Panel A reveals that those in the treatment group report a stronger intention to use internet banking more frequently in the future. The effect is economically large at almost half a standard deviation, although the coefficient is only marginally significant. The intention effect seems to be even larger for those in the social learning groups, but the difference is imprecisely measured. Effects on self-reported log-ins go in the expected direction but are insignificant and qualitatively inferior to the results obtained from the administrative banking data. We do not find any effects on practicing internet banking but a stark increase in the probability of seeking help—especially in the self-guided group, which comes with less built-in support than the social learning treatments.

Reassuringly, the social learning settings, which were designed to develop non-technical adoption skills in addition to technical skills, succeed in doing so. The three main goals in the non-technical adoption skill domain were to help participants build routines and strategies for sustainable and secure internet banking use, to increase confidence by highlighting similarities between traditional and internet banking, and to alleviate fear of fraud by working on fraud detection and self-regulation strategies (e.g., when confronted with a suspicious email). These non-technical adoption skills are directly aimed at overcoming the dominant adoption barriers mentioned in the pre-survey. Those in the social learning groups are significantly more likely to have developed routines (by 0.6 standard deviations compared to the self-guided group) and fraud avoidance strategies (by 0.5 standard deviations). The interaction coefficient on similarities between internet banking and offline banking is insignificant but positive. On the other hand, the self-guided independence-fostering training appears to be more successful in fostering openness towards technology. These additional outcomes add to the understanding of the training effects by showcasing mechanisms, such as the removal of adoption barriers and the formation of non-cognitive skills. Despite overall similar treatment effects across training types, we do see some differences in the mechanisms behind these effects. However, compared to the administrative banking data that constitutes the main outcomes, these survey-based outcomes come with two drawbacks: First, survey participation was incentivized through a lottery for multi-retailer gift vouchers, but was entirely voluntary for participants of all groups and control participants—leading to a lower sample size. It is also likely that this selection into survey participation was non-random. Second, survey data is generally more noisy than the administrative data. Thus, we only use these outcomes as supportive evidence, while the banking outcomes remain our main outcomes.

Table 6: Alternative outcomes

	T_i(ATT)	$T_i \times 1$(social learning)	Obs.	Adj. R^2	DV type
Panel A: Intention to adopt IB					
Intends to use IB more frequently	0.482*	0.107	186	0.058	Likert scale (std.)
	(0.288)	(0.300)			
Has logged on in last month	0.098	0.080	193	0.009	Binary
	(0.142)	(0.148)			
Has regularly practiced IB	-0.004	0.018	89	-0.026	Binary
	(0.153)	(0.126)			
Has sought help	0.519**	-0.302	70	0.037	Binary
	(0.235)	(0.236)			
Has sought help from family/friends	0.510**	-0.219	70	0.080	Binary
	(0.207)	(0.208)			
Panel B: Non-technical adoption skills					
Has developed routines for IB	-0.234	0.634*	83	0.013	Likert scale (std.)
	(0.413)	(0.320)			
Knows how to avoid fraud in IB	0.073	0.534*	177	0.054	Likert scale (std.)
	(0.299)	(0.311)			
IB is similar to conventional banking	0.381	0.151	177	0.038	Likert scale (std.)
	(0.302)	(0.313)			
Reacts emotionally to tech. issues	0.195	0.042	177	0.032	Likert scale (std.)
	(0.303)	(0.314)			
Is open toward new technologies	0.536*	-0.289	177	0.001	Likert scale (std.)
	(0.307)	(0.319)			
Is afraid of new technologies	-0.086	0.122	177	0.010	Likert scale (std.)
	(0.306)	(0.318)			

Note: The table reports coefficients of OLS regressions of various outcome measures on a dummy variable indicating treatment completion (T_i(ATT)), an interaction term of treatment completion and social learning assignment ($T_i \times$ 1(social learning)), age, gender, and an income dummy (inflows > EUR 4,000). Dependent variables are either dummy variables or standardized 5-point Likert scales. Standard errors are reported in parentheses ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$).

7.2 Treatment heterogeneity

Our data structure allows us to test for heterogeneous treatment effects along a variety of (pre-registered) dimensions: Based on administrative banking data, we can assess heterogeneity by age, gender, and income (proxied by the volume of account inflows). Based on data from the pre-survey and enrollment survey, we can additionally assess heterogeneity by initial skills and preferences. Results are summarized in Figure 6, while Tables A19 and A20 provide the full underlying regression results. For these analyses, we pool all treatments to maximize statistical power.

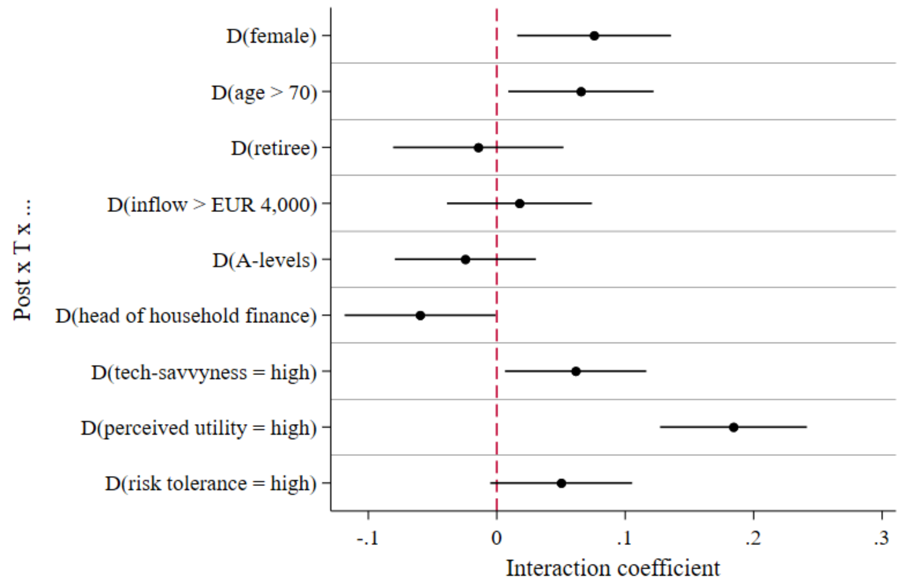
Figure 6 reveals that treatment effects are substantially larger for female participants at the extensive (internet banking activation) and intensive margin (share of online transactions). The interaction is less precisely estimated for the online transaction share—a pattern that we observe for most dimensions of heterogeneity. Looking at age, we find that, if anything, treatment effects are stronger for older participants. Although only weakly significant, this finding reassures us that the training was not only effective for the youngest participants. In addition, treatment effects appear consistent across retirement status. Treatment heterogeneity with respect to income is substantially less pronounced. There may be a slightly larger treatment effect for those with larger account inflows, but it is never significant. Similarly, the treatment effect does not depend on the participants' level of education, which is reassuring with respect to potential selection effects. Among those who participate, the effect is not driven by those with the highest level of education. Notably, the treatment effect is stronger for those who are not the head of finance in their household.[26] This pattern persists when we restrict the sample to women (see Table A21 in the Appendix).

In terms of heterogeneity by initial skills, those with higher initial levels of technological skills—measured through a self-assessment of skills directly related to internet banking, such as the ability to download an app—and higher ex ante perceived value of internet banking usage show the largest treatment effects. This result suggests that—while being effective for all participants (see Table A20 in the Appendix)—an initial level of familiarity with the technology behind internet banking and its benefits augmented the effect of our short training interventions. Finally, we look at risk preferences and find ambiguous results. If anything, those with higher risk tolerance benefit slightly more at the extensive margin, while treatment is most effective for those with lower risk tolerance at the intensive margin. Relating this finding to the effects on non-technical adoption skills, it seems plausible that training reduces concerns related to fraud in internet banking which encourages even the more risk averse participants to use it more intensively. Overall, we find a set of drivers of treatment effectiveness that directly tie into the practical implications of our work, which will be discussed in the subsequent section.

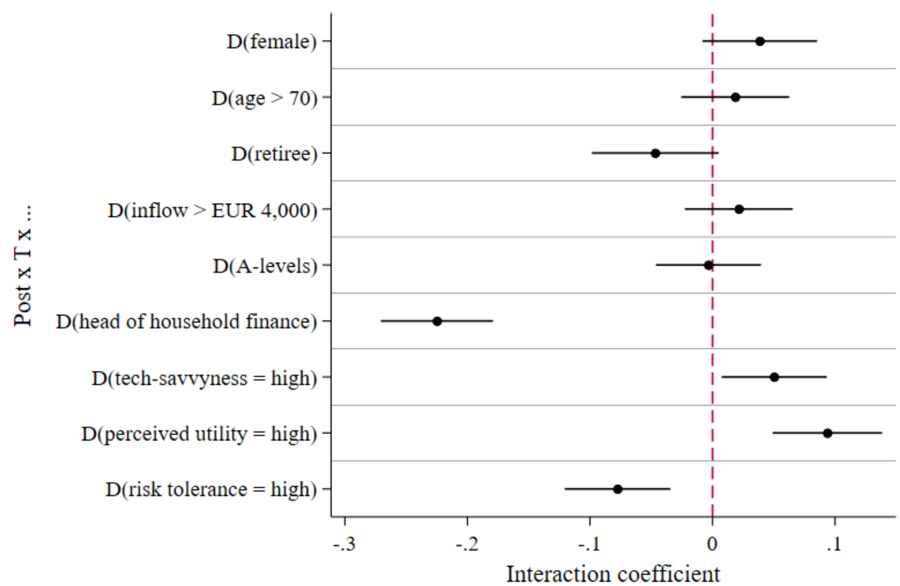
[26] Answer to the question "I am currently mainly in charge of banking issues in my household".

Figure 6: Treatment heterogeneity

a) DV: D(TAN active)



b) DV: Online transaction share



Note: The figure displays the point estimates and 90% confidence intervals for interaction coefficients $Post_t \times T_i \times X_i$, where X_i is the respective heterogeneity dimension. The dependent variable is D(TAN active) in panel a) and the online transaction share in panel b). The full regression coefficients are reported in Table A19 (for the variables based on administrative banking data) and Table A20 (for the variables based on survey measures) in the Appendix. D(tech savvyness= high) is the median split of a standardized average of five standardized sub-indices ("I know how to download apps on my smartphone", "I usually have no issues browsing a website", "I can deal well with unexpected incidents when using internet banking", "I am afraid of new technology, because it could negatively influence my life" (inverted scale used), "I am open towards new technology"), each elicited on a 5-point Likert scale. D(perceived utility = high) is the median split of a standardized average of two sub-indices ("I deem the practical benefits of internet banking as high", "I expect to be able to safely use internet banking on my own following the trainings."), each elicited on a 5-point Likert scale. Head of household finance is equal to one if the client is "currently mainly in charge of banking issues in their household". Risk tolerance is the median split of self-reported risk tolerance on an 11-point Likert scale (Dohmen et al., 2011). All specifications use the ATT treatment definition (N=135) and the silent control group (N=1,725).

8 Practical implications

This section synthesizes the main results in terms of practical recommendations. We make three contributions relating to 1) practical considerations and scaling, 2) inclusiveness of training measures targeted at Baby Boomer participants, and 3) lifelong learning capabilities. Aside from researchers, these practical recommendations hold relevance for banks, who have been shown to benefit from higher internet banking adoption among their clients through increased client retention (Campbell and Frei, 2010) and profitability (DeYoung et al., 2007).

Our findings provide insights into practical challenges when rolling out a large-scale version of this training. In implementing this study, we were confronted with a low initial response rate of roughly 2%. This low response rate is particularly poignant given that we only contacted clients who had not been using internet banking in the months leading up to the invite—our target population. The training was highlighted as free, and several different training types (self-guided and social) were advertised. Letters and emails were sent out by the bank directly using the official letterhead. In subsequent rounds of contact, we also used communication via telephone, which, anecdotally, seemed to work well. We would, thus, recommend the use of multiple communication channels with a focus on direct one-to-one communication whenever possible.

In terms of selection into training along the different stages, we find significant selection based on age, gender, and income at the intent stage, with weaker and less precisely estimated coefficients at the later stages. Selection on education seems to primarily affect the self-guided training. This finding ties in well with the general take-up rates and observations from the post-survey: More than three quarters of on-site workshop participants described the workshop as (very) helpful, with some adding personal comments: "The training was very good, should have done it earlier", "It was special that our problems were targeted precisely and then solved. It is a rarity." Conversely, several post-survey participants who had been in other groups or had not participated in any training expressed a preference for future on-site training: "I am wishing for an in-person training. There, it is easier and faster to ask questions." In line with this, the dropout rate was markedly lower in the social learning interventions than in the self-guided format (47 versus 26%). Moreover, as summarized in Table A17 in the Appendix, participants in the social learning treatment condition rated the usefulness of all five content modules significantly higher than those in the self-guided group. We are inclined to interpret these quantitative and qualitative findings as a general preference for on-site social training in this age group. However, due to the scalability of the self-guided training with negligible marginal cost (List, 2020), we recommend offering a combination of both. In contrast, interest in the family-focused social training was low despite the significant monetary incentive that was absent in the other interventions, highlighting little openness towards this slightly atypical training concept.

The goal of the training interventions was to foster technology adoption in an age group that had previously been struggling to use internet banking. Our heterogeneity analyses reveal that effects are not driven by the youngest participants in our target group. If anything, those older than 70 seem to benefit slightly more from the training. We show that even within an older age group, it is possible to reach the full age range of the target population and facilitate technology adoption. In the context of prevalent female financial dependence and concerns regarding financial literacy (Glass and Kilpatrick, 1998; Bucher-Koenen et al., 2024), it is reassuring to see that simple training interventions may contribute to independence in the use of modern banking channels: Women and those who are not the head of finance in their household benefit most from training completion. Given that we observe higher internet banking adoption among males than females in the baseline (see Table A1 in the Appendix), our results corroborate findings reported by Lee et al. (2022), who show that training can narrow the gender gap in mobile banking adoption.

Further, we cautiously conclude that treatment effects were at the very least not concentrated among the socio-economically most advantaged participants. Instead, at least after the initial selection into responding to the invite, it seems that the training successfully fostered technology adoption among participants from different socioeconomic backgrounds. Treatment effect heterogeneities with respect to income and education are not detectable. Relating back to section 5, education predicts drop out mainly in the self-guided treatment. This finding allows for a cautious interpretation of the social learning interventions as being even more inclusive in this respect. Summing up, the findings highlight that our simple internet banking intervention is highly inclusive: It is most impactful among financially vulnerable populations, such as women and those who are not in charge of household finances.

Finally, our work adds to the understanding of the role of lifelong learning in the education production function at an older age. Our findings relate to Hanushek et al. (2025) who show that skill use can prevent the (otherwise prevalent) skill loss at an older age. Indeed, we show that our elderly target group reacts strongly to training interventions. The initial internet banking activation effect persists months after the interventions when treated participants have shifted a significant share of their transactions online—indicating a persistent use of the newly gained internet banking skills. A recurring theme throughout this paper are the most prevalent barriers to adoption that are summarized in Table A5 in the Appendix. 47% of participants report fear of fraud and 35% report fear of making mistakes as obstacles on the way to adoption. Our training interventions apparently helped participants overcome these fears—more so in the social trainings, which focused more on building non-technical adoption skills, as Table 6 shows. Fostering non-technical adoption skills together with technical skills and offering space for questions and addressing personal concerns makes training more attractive (see above) and more effective at removing fear-based adoption barriers. At the same time, however, training effects are largest for those with higher initial technology skills and perceived utility of internet banking. This indirectly points towards exploitable complementarities between different technology-focused offers for the elderly. Skills built in an internet banking training will likely make labor-market focused trainings more efficient for those in the target group who are still working. While older age groups are often shown to be difficult to train (Berger et al., 2022)—a finding we underline with respect to the low take-up rate in a group that would likely benefit strongly from training—, the strong treatment effects in this study paint a more positive picture of lifelong learning capacities in this age group. Policy-makers and, in our specific setting, banks should weigh the potentially low take-up against the large effects found among those who do participate in training interventions. Following the completion of our field experiment and after all data exports, our partner bank decided to continue offering the on-site social training.

9 Conclusion

A common colloquial yet cynical comment in the context of technology adoption among the elderly is that the issue will resolve itself with time. Naturally, this argument does not stand the test of time in the context of rapid technological change and a changing demographic landscape in many societies. Instead, a significant population group is facing unprecedented threats of being excluded not only from cutting-edge technologies but rather from everyday services—adding to pre-existing inequalities in adoption. To tackle these inequalities in banking access and technology adoption among the elderly, we design and evaluate training interventions that target the barriers identified in a pre-survey as well as building non-technical adoption skills. These interventions turn out to be successful at encouraging sustainable internet banking usage and may even have spillovers to other domains of technology adoption.

Following participants along the entire multi-stage internet adoption process from the first declaration of intent to enrollment, and, finally, training completion, we are able to estimate multiple ITT and selection effects alongside the main ATT of completing the training interventions. We find that the ITTs steadily increase throughout the adoption process, leading to a strong positive ATT of internet banking treatment. The probability of setting up internet banking increases by 26 percentage points in the treatment group relative to the matched control group. The probability to *use* internet banking also increases significantly—as shown by the probability of logging on and by the share of transactions completed online. These positive effects persist four months after the end of the interventions. An extensive placebo analysis indicates that as much as 85% of these effects can be causally attributed to our interventions.

Our training is most impactful among financially vulnerable populations, such as women and those who are not in charge of household finances. When considering the practical challenges of scaling up our interventions, we show that although both training formats (self-guided versus social learning) yield similar effects, social learning is associated with lower dropout and more inclusive. Our post-survey sheds light on the underlying mechanisms by highlighting the positive effects of training—in particular the social learning interventions—on long-term adoption intentions and non-technical adoption skills. We show that members of the Baby Boomer generation are able to successfully complete technology adoption training and build the skills necessary to overcome fear-based adoption barriers.

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Appendix: Supplementary tables

Table A1: Internet banking adoption determinants (pre-treatment)

	(1) Non-adopters		(2) Adopters		(1) - (2)		
	Mean	N	Mean	N	Δ	z score	
Panel A: Demographic information							
Age	68.70	71,483	57.10	81,887	11.60	155.22	***
Female	0.61	71,483	0.51	81,887	0.10	41.21	***
Urban	0.83	71,483	0.74	81,887	0.10	46.43	***
Panel B: Bank relationship							
No. checking accounts	1.34	71,483	1.62	81,887	-0.27	-70.36	***
No. savings accounts	0.82	71,483	0.76	81,887	0.07	17.71	***
Contact in 2023/2024	0.52	44,513	0.56	61,520	-0.04	-12.25	***
Joined before 2003	0.72	68,620	0.63	79,840	0.09	36.93	***
Overdraft facility	0.54	71,483	0.64	81,887	-0.10	-39.19	***
Panel C: Account activity (05/2024)							
Total transactions	1.26	71,483	2.51	81,887	-1.24	-108.61	***
No. Inflows	3.60	71,483	5.12	81,887	-1.51	-80.09	***
Inflows EUR 0-1,000	0.19	71,483	0.09	81,887	0.09	53.14	***
Inflows EUR 1,000-2,000	0.21	71,483	0.11	81,887	0.11	57.37	***
Inflows EUR 2,000-4,000	0.34	71,483	0.31	81,887	0.03	14.27	***
Inflows > EUR 4,000	0.26	71,483	0.49	81,887	-0.23	-94.17	***
No. Outflows	20.20	71,483	39.70	81,887	-19.50	-155.28	***

Note: The table reports sample means by online banking adoption (has conducted an online-banking transaction in the past month) as well as z scores of non-parametric Wilcoxon rank tests. Data are as of June 11, 2024. Account activity variables refer to calendar month May 2024. Asterisks indicated statistical significance ($^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$).

Table A2: Client selection

Criteria	N
Initial bank client sample	**153,370**
Lives in bank's metro area = yes	144,434
Third-party account access = no	132,596
IB or MB login in past 3m = no	61,479
Age $\in$ [50;85]	46,944
# outflows > 0	46,117
E-mail contact = yes	**14,225**
Invited via e-mail	13,500
Silent control group (e-mail)	725
E-mail contact = no & letter contact = yes & # transactions > 0	**13,482**
Invited via letter	12,482
Silent control group (letter)	1,000
Target group	**27,707**

Note: The table reports sample sizes for the respective filtering criteria. Data are as of June 11, 2024. Account activity variables refer to calendar month May 2024. The bank's metro area is defined as the main city including the eponymous county (*Landkreis*), which mostly coincides with the suburban train area. The initial sample comprises bank clients aged 40 and older who have personal accounts, excluding legally incompetent individuals and accounts seized for liquidation.

Table A3: Balancing tests for initial invitation

	(1) Silent control group		(2) Invited		(1) - (2)		
	Mean	N	Mean	N	Δ	z score	
Panel A: Demographic information							
Age	68.48	1,725	67.63	25,982	0.85	3.35	***
Female	0.62	1,725	0.60	25,982	0.02	1.38	
Panel B: Bank relationship							
No. checking accounts	1.44	1,725	1.45	25,982	-0.01	-0.07	
No. savings accounts	0.93	1,725	0.97	25,982	-0.04	-0.89	
Contact in 2023/2024	0.57	1,089	0.56	17,329	0.01	0.45	
Joined before 2003	0.78	1,674	0.77	25,085	0.01	1.26	
Overdraft facility available	0.65	1,725	0.66	25,982	0.00	-0.39	
Panel C: Account activity							
Total transactions	2.17	1,725	2.07	25,982	0.10	3.33	
No. Inflows	4.33	1,725	4.19	25,982	0.13	1.95	*
Inflows > EUR 4,000	0.37	1,725	0.36	25,982	0.01	1.03	
No. Outflows	25.39	1,725	25.73	25,982	-0.33	-0.41	

Note: The table reports sample means for the silent control group (N=1,752) and the group of invited clients (N=25,982), as well as the between-group difference in means and the test scores of non-parametric rank tests. Group assignment was randomized. Stars indicate statistical significance ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$).

Table A4: Balancing tests for treatment assignment

	(1) Self-guided learning		(2) Social learning		(1) - (2)	
	Obs.	Mean	Obs.	Mean	Δ	z score
Age	99	71.69	234	71.25	0.44	-0.601
Female	99	0.70	234	0.70	0.00	-0.007
Education	81	2.74	209	2.64	0.10	-0.622
Inflow > EUR 4,000	99	0.44	234	0.48	-0.04	0.642

Note: The table reports sample means for the self-guided learning group (N = 99) and social learning groups (N = 234), as well as the between-group difference in means and the test scores of non-parametric Wilcoxon rank rank tests. Stars indicate statistical significance ($^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$). Education takes on integers from 1 (indicating the client's highest educational attainment is lower secondary school / *Hauptschule*) to 5 (indicating the client's highest educational attainment is a PhD). Treatments were assigned based on stratified randomization (see section 3.2).

Table A5: Barriers to internet banking adoption (from pre-survey)

Barrier	N	Share
I am afraid of fraud.	257	0.47
I am afraid to make mistakes.	195	0.35
I am unable to use internet banking.	151	0.27
The required support is not always available.	137	0.25
I would miss social interaction at the branch.	86	0.16
The effort to set up internet banking is too high.	71	0.13
I do not have all required devices.	43	0.08
I do not have time to learn about internet banking.	30	0.05
I have no interest in internet banking.	28	0.05

Note: The table reports the number of respondents to our pre-survey (N = 550) that have mentioned each barrier to internet banking adoption. A maximum of three answers were allowed.

Table A6: Propensity score regressions

	ITT			ATT			
	(1) Intent ITT	(2) Qualified intent ITT	(3) Enroll-ment ITT	(4) All treatments	(5) Social learning treatments	(6) On-site workshop	(7) Placebo
Age	0.015***	0.019***	0.020***	0.019***	0.021***	0.020***	0.012*
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Female	0.104*	0.169**	0.101	0.101	0.131	0.115	0.098
	(0.061)	(0.072)	(0.086)	(0.095)	(0.103)	(0.105)	(0.123)
New customer (≥2022)	0.179	0.178	0.181	0.008	0.041	-0.154	0.277
	(0.124)	(0.144)	(0.173)	(0.208)	(0.222)	(0.256)	(0.214)
Inflows ≥ EUR 2,000	0.215***	0.217**	0.167	0.206*	0.191	0.149	0.022
	(0.079)	(0.092)	(0.110)	(0.123)	(0.133)	(0.134)	(0.150)
Total transactions	-0.025*	-0.025*	-0.036**	-0.024	-0.031	-0.015	0.003
	(0.013)	(0.015)	(0.018)	(0.019)	(0.022)	(0.022)	(0.025)
No. inflows	0.033***	0.026**	0.022	0.012	0.014	0.007	0.027
	(0.011)	(0.013)	(0.015)	(0.017)	(0.018)	(0.019)	(0.023)
No. outflows	0.004**	0.004**	0.007***	0.007***	0.007**	0.005*	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Obs.	2,275	2,058	1,905	1,860	1,834	1,824	1,785
Pseudo R2	0.030	0.034	0.035	0.034	0.039	0.032	0.017
# treated	550	333	180	135	109	99	60
# silent control	1,725	1,725	1,725	1,725	1,725	1,725	1,725

Note: The table reports coefficients of probit regressions of a dummy variable indicating the various treatment definitions on a client's age, gender, a dummy variable indicating a client has joined the bank in 2022 or later, a dummy variable indicating a client has had monthly inflow of at least EUR 2,000 (in May 2024), the number of transactions (in May 2024), as well as the average number of inflows and outflows (average of May, November, and December). Based on the predicted treatment probabilities, we define matched control groups for each specification using 5-nearest-neighbor matching (preferred specification) or 1-nearest-neighbor matching (robustness specification).

Table A7: Dropout determinants, by recruitment stage

	All treatments			Social learning treatments		Self-guided learning treatment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV: D(dropout)	Intention	Enrollment	Attendance	Enrollment	Attendance	Enrollment	Attendance
Panel A: Logit regressions							
Age	-0.031***	-0.013	0.030	-0.035**	0.020	0.025	0.050
	(0.004)	(0.014)	(0.024)	(0.017)	(0.029)	(0.029)	(0.045)
D(female)	-0.301***	0.144	-0.019	-0.025	0.066	0.496	-0.277
	(0.092)	(0.261)	(0.405)	(0.316)	(0.480)	(0.519)	(0.895)
D(inflow≥4,000€)	-0.557***	0.181	-0.524	0.041	-0.828*	0.659	0.642
	(0.087)	(0.243)	(0.390)	(0.293)	(0.459)	(0.501)	(0.831)
Education		-0.243**	-0.090	-0.144	-0.103	-0.543***	-0.286
		(0.103)	(0.167)	(0.125)	(0.196)	(0.209)	(0.397)
Obs.	25,982	290	163	209	130	81	33
Pseudo R2	0.019	0.018	0.020	0.021	0.032	0.101	0.067
Panel B: OLS regressions							
Age	-0.001***	-0.003	0.005	-0.008**	0.003	0.005	0.010
	(0.000)	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	(0.009)
D(female)	-0.006***	0.034	-0.002	-0.005	0.012	0.112	-0.048
	(0.002)	(0.063)	(0.070)	(0.073)	(0.077)	(0.113)	(0.184)
D(inflow≥4,000€)	-0.012***	0.044	-0.088	0.010	-0.131*	0.141	0.131
	(0.002)	(0.059)	(0.067)	(0.068)	(0.072)	(0.107)	(0.177)
Education		-0.058**	-0.016	-0.033	-0.017	-0.121***	-0.054
		(0.025)	(0.029)	(0.029)	(0.032)	(0.044)	(0.083)
Obs.	25,982	290	163	209	130	81	33
Adj. R2	0.004	0.011	-0.003	0.009	0.001	0.086	-0.053

Note: The table reports the coefficients resulting from regressions of dropout (dummy variable indicating a contacted client has dropped out at the respective stage) on age, a gender dummy, a dummy indicating inflows of more than 4,000 EUR in May 2024, as well as a categorical education variable (1: lower secondary, 2: intermediate secondary, 3: grammar school, 4: college degree, 5: PhD). Panel A reports the coefficients for logistical regressions, panel B reports the coefficients for OLS regressions. Details on the recruitment stages are provided in section 3.2 and in Figure 1. Descriptive statistics are reported in Table 2 in the Appendix. Standard errors are reported in parentheses ($^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$).

Table A8: ITT estimates (1-nearest-neighbor matching)

	Unmatched control group				Matched control groups		
	(1) Invite ITT	(2) Intent ITT	(3) Qualified intent ITT	(4) Enroll-ment ITT	(5) Intent ITT	(6) Qualified intent ITT	(7) Enroll-ment ITT
DV: D(TAN active)							
$Post_t$	0.023***	0.023***	0.023***	0.023***	0.016	0.016	0.021
	(0.008)	(0.008)	(0.008)	(0.008)	(0.017)	(0.021)	(0.027)
T_i	0.003	0.027*	0.041**	0.034	0.014	0.023	0.057*
	(0.007)	(0.014)	(0.017)	(0.022)	(0.019)	(0.024)	(0.031)
$Post_t \times T_i$	0.002	0.145***	0.175***	0.209***	0.152***	0.183***	0.212***
	(0.008)	(0.017)	(0.020)	(0.026)	(0.023)	(0.029)	(0.038)
Obs.	163,249	13,442	12,145	11,230	5,937	3,711	2,086
Adj. R2	0.081	0.078	0.080	0.081	0.072	0.074	0.114
Control pre mean (DV)	0.175	0.175	0.175	0.175	0.170	0.169	0.124
DV: D(login)							
$Post_t$	0.024**	0.024**	0.024**	0.024**	0.018	0.017	0.015
	(0.010)	(0.010)	(0.010)	(0.010)	(0.022)	(0.028)	(0.037)
T_i	0.007	0.038**	0.057**	0.047	-0.003	0.008	0.004
	(0.009)	(0.019)	(0.023)	(0.029)	(0.027)	(0.035)	(0.046)
$Post_t \times T_i$	-0.001	0.148***	0.172***	0.199***	0.153***	0.178***	0.207***
	(0.010)	(0.021)	(0.026)	(0.033)	(0.030)	(0.039)	(0.051)
Obs.	138,535	11,375	10,290	9,525	4,990	3,120	1,745
Adj. R2	0.049	0.074	0.077	0.072	0.059	0.064	0.082
Control pre mean (DV)	0.148	0.148	0.148	0.148	0.174	0.175	0.166
DV: Online transaction share							
$Post_t$	0.004	0.004	0.004	0.004	-0.006	-0.003	-0.002
	(0.006)	(0.007)	(0.006)	(0.006)	(0.014)	(0.017)	(0.022)
T_i	-0.011**	-0.006	-0.007	-0.005	-0.017	0.004	0.025
	(0.005)	(0.011)	(0.013)	(0.017)	(0.015)	(0.019)	(0.024)
$Post_t \times T_i$	0.010	0.071***	0.097***	0.109***	0.080***	0.104***	0.115***
	(0.006)	(0.013)	(0.016)	(0.021)	(0.019)	(0.023)	(0.030)
Obs.	163,249	13,442	12,145	11,230	5,937	3,711	2,086
Adj. R2	0.069	0.104	0.108	0.108	0.092	0.096	0.127
Control pre mean (DV)	0.107	0.107	0.107	0.107	0.130	0.109	0.086
Client controls	✓	✓	✓	✓	✓	✓	✓
# treated	25,982	550	333	180	550	333	180
# control	1,725	1,725	1,725	1,725	448	291	169

Note: The table reports coefficients of OLS panel regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on a dummy variable which is equal to one after the interventions ($Post_t$), a dummy variable indicating that client i was part of the respective treatment group (T_i), an interaction of $Post_t$ and T_i, and various client-level control variables (age, gender dummy, inflow dummies). Specifications reported in columns (1) through (4) use the full silent control group (N=1,725), while specifications reported in columns (5) through (7) use individually matched control groups obtained from nearest-neighbor matching (n=1) on a propensity score. We use several treatment definitions. Invite ITT refers to all clients invited to the training interventions (N=25,982). Intent ITT refers to all clients that responded to the initial survey (N=550). Qualified intent ITT refers to the subset of respondents that we were able to randomly assign a treatment group based on their survey answers (N=333). Enrollment ITT refers to all clients that have registered for a treatment (N=180). Standard errors are reported in parentheses ($^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$).

Table A9: ITT estimates (TWFE)

	Unmatched control group				Matched control groups		
	(1) Invite ITT	(2) Intent ITT	(3) Qualified intent ITT	(4) Enroll-ment ITT	(5) Intent ITT	(6) Qualified intent ITT	(7) Enroll-ment ITT
DV: D(TAN active)							
$Post_t \times T_i$	0.003	0.145***	0.176***	0.209***	0.146***	0.178***	0.208***
	(0.002)	(0.005)	(0.006)	(0.008)	(0.006)	(0.007)	(0.010)
Obs.	163,239	13,441	12,144	11,229	10,474	7,683	5,016
Adj. R2	0.941	0.902	0.912	0.922	0.892	0.894	0.897
Control pre mean (DV)	0.175	0.175	0.175	0.175	0.175	0.170	0.177
DV: D(login)							
$Post_t \times T_i$	-0.001	0.148***	0.172***	0.199***	0.153***	0.175***	0.200***
	(0.003)	(0.007)	(0.008)	(0.009)	(0.007)	(0.009)	(0.011)
Obs.	138,535	11,375	10,290	9,525	8,865	6,495	4,240
Adj. R2	0.930	0.907	0.915	0.922	0.904	0.908	0.914
Control pre mean (DV)	0.148	0.148	0.148	0.148	0.150	0.144	0.154
DV: Online transaction share							
$Post_t \times T_i$	0.008***	0.068***	0.095***	0.107***	0.068***	0.097***	0.106***
	(0.003)	(0.006)	(0.008)	(0.010)	(0.007)	(0.009)	(0.011)
Obs.	163,239	13,441	12,144	11,229	10,474	7,683	5,016
Adj. R2	0.785	0.795	0.794	0.803	0.790	0.796	0.804
Control pre mean (DV)	0.107	0.107	0.107	0.107	0.121	0.133	0.134
Client controls	✓	✓	✓	✓	✓	✓	✓
# treated	25,982	550	333	180	550	333	180
# control	1,725	1,725	1,725	1,725	1,223	966	668

Note: The table reports coefficients of OLS panel regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on the treatment interaction variable ($Post_t \times T_i$), as well as month and client fixed effects. The individual $Post_t$ dummy is absorbed by the month fixed effects, while the individual T_i dummy is absorbed by the client fixed effects. Specifications reported in columns (1) through (4) use the full silent control group (N=1,725), while specifications reported in columns (5) through (7) use individually matched control groups obtained from five-nearest-neighbor matching on a propensity score. We use several treatment definitions. Invite ITT refers to all clients invited to the training interventions (N=25,982). Intent ITT refers to all clients that responded to the initial survey (N=550). Qualified intent ITT refers to the subset of respondents that we were able to randomly assign a treatment group based on their survey answers (N=333). Enrollment ITT refers to all clients that have registered for a treatment (N=180). Standard errors are reported in parentheses ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$).

Table A10: ATT estimates (1-nearest-neighbor matching)

	Unmatched control group			Matched control groups		
	(1) All treatments	(2) Social learning treatments	(3) On-site workshop	(4) All treatments	(5) Social learning treatments	(6) On-site workshop
DV: D(TAN active)						
$Post_t$	0.023***	0.023***	0.023***	0.024	0.020	0.022
	(0.008)	(0.008)	(0.008)	(0.031)	(0.033)	(0.035)
T_i	0.039	0.025	0.043	0.063*	0.077**	0.081**
	(0.024)	(0.027)	(0.028)	(0.036)	(0.038)	(0.041)
$Post_t \times T_i$	0.258***	0.250***	0.247***	0.257***	0.252***	0.247***
	(0.030)	(0.033)	(0.034)	(0.044)	(0.046)	(0.050)
Obs.	10,961	10,805	10,745	1,577	1,271	1,151
Adj. R2	0.082	0.077	0.079	0.122	0.143	0.148
Control pre mean (DV)	0.175	0.175	0.175	0.124	0.087	0.096
DV: D(login)						
$Post_t$	0.024**	0.024**	0.024**	0.016	0.010	0.011
	(0.010)	(0.010)	(0.010)	(0.042)	(0.046)	(0.048)
T_i	0.052	0.044	0.052	0.010	0.020	0.034
	(0.033)	(0.037)	(0.038)	(0.053)	(0.057)	(0.060)
$Post_t \times T_i$	0.252***	0.252***	0.249***	0.260***	0.266***	0.262***
	(0.037)	(0.041)	(0.043)	(0.059)	(0.064)	(0.067)
Obs.	9,300	9,170	9,120	1,320	1,065	965
Adj. R2	0.078	0.074	0.073	0.103	0.128	0.135
Control pre mean (DV)	0.148	0.148	0.148	0.163	0.135	0.128
DV: Online transaction share						
$Post_t$	0.004	0.004	0.004	0.001	0.006	0.012
	(0.006)	(0.006)	(0.006)	(0.025)	(0.028)	(0.029)
T_i	-0.017	-0.018	-0.022	0.018	0.013	0.033
	(0.019)	(0.021)	(0.022)	(0.029)	(0.033)	(0.033)
$Post_t \times T_i$	0.132***	0.131***	0.132***	0.135***	0.129***	0.124***
	(0.023)	(0.026)	(0.027)	(0.035)	(0.040)	(0.041)
Obs.	10,961	10,805	10,745	1,577	1,271	1,151
Adj. R2	0.106	0.105	0.104	0.115	0.113	0.109
Control pre mean (DV)	0.107	0.107	0.107	0.082	0.087	0.064
Client controls	✓	✓	✓	✓	✓	✓
# treated	135	109	99	135	109	99
# control	1,725	1,725	1,725	129	104	94

Note: The table reports coefficients of OLS regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on a dummy variable which is equal to one after the interventions ($Post_t$), a dummy variable indicating that client i was part of the treatment group (T_i), an interaction of $Post_t$ and T_i, and various client-level control variables (age, gender dummy, inflow dummies). Specifications reported in columns (1) through (3) use the full silent control group (N=1,725), while specifications reported in columns (4) through (6) use individually matched control groups obtained from nearest-neighbor matching (n=1) on a propensity score. Standard errors are reported in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

Table A11: ATT estimates (TWFE)

	Unmatched control group			Matched control groups		
	(1) All treatments	(2) Social learning treatments	(3) On-site workshop	(4) All treatments	(5) Social learning treatments	(6) On-site workshop
DV: D(TAN active)						
$Post_t \times T_i$	0.256***	0.247***	0.245***	0.255***	0.252***	0.247***
	(0.009)	(0.009)	(0.010)	(0.012)	(0.013)	(0.013)
Obs.	10,960	10,804	10,744	3,990	3,206	2,940
Adj. R2	0.925	0.929	0.930	0.889	0.891	0.891
Control pre mean (DV)	0.175	0.175	0.175	0.163	0.159	0.159
DV: D(login)						
$Post_t \times T_i$	0.252***	0.252***	0.249***	0.255***	0.264***	0.261***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.014)	(0.015)
Obs.	9,300	9,170	9,120	3,370	2,710	2,485
Adj. R2	0.923	0.925	0.926	0.908	0.914	0.910
Control pre mean (DV)	0.148	0.148	0.148	0.147	0.145	0.143
DV: Online transaction share						
$Post_t \times T_i$	0.130***	0.128***	0.129***	0.126***	0.129***	0.125***
	(0.011)	(0.012)	(0.013)	(0.013)	(0.015)	(0.015)
Obs.	10,960	10,804	10,744	3,990	3,206	2,940
Adj. R2	0.802	0.805	0.807	0.802	0.803	0.804
Control pre mean (DV)	0.107	0.107	0.107	0.136	0.140	0.132
Client controls	✓	✓	✓	✓	✓	✓
# treated	135	109	99	135	109	99
# control	1,725	1,725	1,725	539	433	398

Note: The table reports coefficients of OLS panel regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on the treatment interaction variable ($Post_t \times T_i$), as well as month and client fixed effects and various client-level control variables (age, gender dummy, inflow dummies). The individual $Post_t$ dummy is absorbed by the month fixed effects, while the individual T_i dummy is absorbed by the client fixed effects. Specifications reported in columns (1) through (3) use the full silent control group (N=1,725), while specifications reported in columns (4) through (6) use individually matched control groups obtained from five-nearest-neighbor matching on a propensity score. Standard errors are reported in parentheses ($^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$).

Table A12: Mean differences in adoption measures by month

	Pre-intervention			Post-intervention			
	t=-2	t=-1	t=0	t=1	t=2	t=3	t=4
DV: D(TAN active)							
Treatment group	0.19	0.20	0.25	0.45	0.47	0.48	0.49
Matched control group	0.16	0.17	0.18	0.19	0.19	0.19	0.19
Delta	0.02	0.03	0.07	0.27	0.28	0.29	0.31
z score	-0.68	-0.96	-1.94*	-6.43***	-6.86***	-6.88***	-7.28***
DV: D(login)							
Treatment group		0.19	0.25	0.44	0.46	0.47	0.48
Matched control group		0.15	0.16	0.17	0.17	0.17	0.17
Delta		0.04	0.09	0.27	0.29	0.30	0.32
z score		-1.11	-2.56**	-6.76***	-7.20***	-7.37***	-7.82***
DV: Online transaction share							
Treatment group	0.12	0.11	0.10	0.24	0.25	0.27	0.26
Matched control group	0.13	0.14	0.12	0.14	0.15	0.14	0.15
Delta	0.00	-0.03	-0.02	0.10	0.10	0.13	0.10
z score	0.11	0.84	0.72	-3.34***	-3.20***	-3.97***	-2.92***

Note: The table reports averages of the three internet banking adoption measures separately for the treatment group (ATT, N=135) and the matched control group (5-NN matching, N=539) and separately for each observation period. We further report the difference between treatment and control average in a given month as well as the z scores of non-parametric rank tests ($^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$).

Table A13: ATT vs. ITT interaction coefficients

	(1) Intent ITT	(2) Qualified intent ITT	(3) Enrollment ITT
DV: D(TAN active)			
$Post_t \times ITT_i$	0.108***	0.119***	0.063
	(0.019)	(0.026)	(0.051)
$Post_t \times ITT_i \times ATT_i$	0.150***	0.139***	0.195***
	(0.034)	(0.038)	(0.058)
Obs.	13,442	12,145	11,230
Adj. R2	0.083	0.083	0.084
DV: D(login)			
$Post_t \times ITT_i$	0.114***	0.117***	0.037
	(0.024)	(0.032)	(0.063)
$Post_t \times ITT_i \times ATT_i$	0.138***	0.136***	0.215***
	(0.043)	(0.047)	(0.072)
Obs.	11,375	10,290	9,525
Adj. R2	0.079	0.080	0.077
DV: Online transaction share			
$Post_t \times ITT_i$	0.051***	0.074***	0.040
	(0.015)	(0.020)	(0.040)
$Post_t \times ITT_i \times ATT_i$	0.080***	0.058*	0.092**
	(0.027)	(0.030)	(0.045)
Obs.	13,442	12,145	11,230
Adj. R2	0.105	0.108	0.108
Client controls	✓	✓	✓

Note: The table reports coefficients of OLS panel regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on the interaction variable of the $Post_t$ dummy and the respective ITT specification ($Post_t \times ITT_i$), the triple interaction variable with the treatment completion variable ($Post_t \times ITT_i \times ATT_i$) as well as various client-level control variables (age, gender dummy, inflow dummies) and the individual ATT_i dummy. Standard errors are reported in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

Table A14: Placebo estimates (1-nearest-neighbor matching)

	Unmatched control group			Matched control group		
	(1)	(2)	(3)	(4)	(5)	(6)
	D(TAN active)	D(login)	Online transaction share	D(TAN active)	D(login)	Online transaction share
$Post_t$	0.023***	0.024**	0.004	0.043	0.051	-0.029
	(0.008)	(0.010)	(0.006)	(0.046)	(0.061)	(0.037)
P_i	-0.026	0.012	0.024	-0.138***	-0.138*	-0.011
	(0.035)	(0.048)	(0.028)	(0.053)	(0.077)	(0.042)
$Post_t \times P_i$	0.039	0.031	0.008	0.020	0.003	0.040
	(0.043)	(0.053)	(0.034)	(0.064)	(0.085)	(0.051)
Obs.	10,514	8,925	10,514	708	595	708
Adj. R2	0.068	0.057	0.103	0.102	0.079	0.117
Control pre mean (DV)	0.175	0.148	0.107	0.271	0.271	0.127
Client controls	✓	✓	✓	✓	✓	✓
# treated	60	60	60	60	60	60
# control	1,725	1,725	1,725	59	59	59

Note: The table reports coefficients of OLS regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on a dummy variable which is equal to one after the interventions ($Post_t$), a dummy variable indicating that client i was part of the Placebo group (P_i), an interaction of $Post_t$ and P_i, and various client-level control variables (age, gender dummy, inflow dummies). Specifications reported in columns (1) through (3) use the full silent control group (N=1,725), while specifications reported in columns (4) through (6) use individually matched control groups obtained from nearest-neighbor matching (n=1) on a propensity score. Standard errors are reported in parentheses ($^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$).

Table A15: Placebo estimates (TWFE)

	Unmatched control group			Matched control group		
	(1)	(2)	(3)	(4)	(5)	(6)
	D(TAN active)	D(login)	Online transaction share	D(TAN active)	D(login)	Online transaction share
$Post_t \times P_i$	0.038***	0.031**	0.006	0.045***	0.034**	0.030*
	(0.011)	(0.014)	(0.015)	(0.011)	(0.014)	(0.016)
Obs.	10,513	8,925	10,513	1,969	1,670	1,969
Adj. R2	0.944	0.938	0.821	0.945	0.944	0.858
Control pre mean (DV)	0.175	0.148	0.107	0.165	0.150	0.146
Client controls	✓	✓	✓	✓	✓	✓
# treated	60	60	60	60	60	60
# control	1,725	1,725	1,725	274	274	274

Note: The table reports coefficients of OLS regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on the treatment interaction variable ($Post_t \times P_i$), as well as month and client fixed effects and various client-level control variables (age, gender dummy, inflow dummies). Specifications reported in columns (1) through (3) use the full silent control group (N=1,725), while specifications reported in columns (4) through (6) use individually matched control groups obtained from nearest-neighbor matching on a propensity score. Standard errors are reported in parentheses ($^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$).

Table A16: Placebo estimates (PSM-weighted)

	Unweighted			Enrollment probability			Attendance probability		
	(1) D(TAN active)	(2) D(login)	(3) Online trans-action share	(4) D(TAN active)	(5) D(login)	(6) Online trans-action share	(7) D(TAN active)	(8) D(login)	(9) Online trans-action share
$Post_t$	0.023***	0.024**	0.004	0.023***	0.024**	0.004	0.023***	0.024**	0.004
	(0.008)	(0.010)	(0.006)	(0.008)	(0.009)	(0.006)	(0.008)	(0.009)	(0.006)
P_i	0.008	0.052	0.033	0.014	0.061	0.025	0.008	0.058	0.029
	(0.040)	(0.054)	(0.031)	(0.039)	(0.060)	(0.036)	(0.038)	(0.060)	(0.038)
$Post_t \times P_i$	0.031	0.020	0.006	0.031	0.021	0.007	0.033	0.023	0.007
	(0.049)	(0.061)	(0.038)	(0.049)	(0.068)	(0.045)	(0.049)	(0.068)	(0.046)
Obs.	10,430	8,855	10,430	10,430	8,855	10,430	10,430	8,855	10,430
Adj. R2	0.068	0.056	0.102	0.069	0.057	0.103	0.068	0.057	0.103
Control pre mean (DV)	0.175	0.148	0.107	0.175	0.148	0.107	0.175	0.148	0.107
Client controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
# treated	46	46	46	46	46	46	46	46	46
# control	1,725	1,725	1,725	1,725	1,725	1,725	1,725	1,725	1,725

Note: The table reports coefficients of OLS regressions of three internet banking adoption measures (a dummy variable indicating an active TAN procedure, a dummy variable indicating some past login in either internet or mobile banking, and the share of bank transactions conducted online) on a dummy variable which is equal to one after the interventions ($Post_t$), a dummy variable indicating that client i was part of the Placebo group (P_i), an interaction of $Post_t$ and P_i, and various client-level control variables (age, gender dummy, inflow dummies). Specifications reported in columns (1) through (3) use all 46 Placebo participants for whom information on educational attainment is available, but do not apply weighting. Specifications reported in columns (4) through (6) use enrollment probability weights for the Placebo participants ($w_i = 1/(1 - p_i^E)$). Specifications reported in columns (7) through (9) use attendance probability weights for the Placebo participants ($w_i = 1/(1 - p_i^A)$). All specifications use the full silent control group (N=1,725), whose probability weights are set to 1 (since we do not observe educational attainment for this group). Standard errors are reported in parentheses ($^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$).

Table A17: Usefulness of modules, by treatment type

	(1) T_i: self-guided		(2) T_i: social learning		(3) Rank test		
Module	Mean	N	Mean	N	Δ	z score	
Setup instructions	2.86	14	3.90	63	-1.05	-3.85	***
Basic functions	3.29	14	4.21	63	-0.92	-3.57	***
Security & fraud	2.79	14	3.94	63	-1.15	-3.46	***
Practice	3.00	14	3.92	63	-0.92	-3.60	***
Concerns	2.93	14	3.75	63	-0.82	-3.15	***

Note: The table reports average reported usefulness of the five intervention modules, separately for the self-guided and social learning treatments. The measure is elicited using a 5-point Likert scale (1 = not helpful at all, 2 = not helpful, 3 = neutral, 4 = helpful, 5 = very helpful) in the post-survey. Column 3 reports the difference in average helpfulness scores as well as the z score for non-parametric Wilcoxon rank tests ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$).

Table A18: ATT estimates (alternative adoption measures)

	(1) D(any online transaction)	(2) No. online transactions	(3) ln(days since last login)
$Post_t$	0.005	0.051	-0.743***
	(0.006)	(0.037)	(0.135)
T_i	-0.018	-0.015	-0.102
	(0.020)	(0.111)	(0.410)
$Post_t \times T_i$	0.151***	0.579***	-2.206***
	(0.024)	(0.136)	(0.431)
Obs.	10,961	10,961	1,712
Adj. R2	0.109	0.085	0.182
Control pre-mean (DV)	0.110	0.436	6.106
Client controls	✓	✓	✓
# treated	135	135	135
# control	1,725	1,725	1,725

Note: The table reports coefficients of OLS regressions of three alternative internet banking adoption measures (a dummy variable indicating any online transaction, the number of online transactions, and the natural logarithm of the number of days since the last login) on a dummy variable which is equal to one after the interventions ($Post_t$), a dummy variable indicating that client i was part of the treatment group (T_i), an interaction of $Post_t$ and T_i, and various client-level control variables (age, gender dummy, inflow dummies). Dependent variables in columns (1) and (2) are missing if no transactions (online or offline) were recorded at all for a given month. The dependent variable in column (3) is missing if no login has ever been registered for a client in a given month. All specifications use the full silent control group (N=1,725). Standard errors are reported in parentheses ($^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$).

Table A19: Treatment heterogeneity: administrative banking data

	(1) D(TAN active)	(2) D(login)	(3) Online transaction share
Panel A: Gender			
$Post_t \times T_i$	0.207***	0.166***	0.106***
	(0.039)	(0.044)	(0.030)
$Post_t \times T_i \times$Female$_i$	0.076**	0.128***	0.039
	(0.036)	(0.035)	(0.028)
Obs.	10,961	9,300	10,961
Adj. R2	0.082	0.079	0.106
Panel B: Age			
$Post_t \times T_i$	0.220***	0.219***	0.121***
	(0.036)	(0.042)	(0.028)
$Post_t \times T_i \times 1(\text{Age}_i > 70)$	0.066*	0.056*	0.019
	(0.034)	(0.033)	(0.027)
Obs.	10,961	9,300	10,961
Adj. R2	0.082	0.078	0.105
Panel C: Income			
$Post_i \times T_i$	0.249***	0.242***	0.121***
	(0.035)	(0.041)	(0.027)
$Post_i \times T_i \times 1(\text{Inflow}_i >\text{EUR } 4{,}000)$	0.018	0.021	0.022
	(0.034)	(0.033)	(0.027)
Obs.	10,961	9,300	10,961
Adj. R2	0.082	0.078	0.106
$Post_t$	✓	✓	✓
T_i	✓	✓	✓
Client controls	✓	✓	✓
# treated		135	
thereof female		91	
thereof age > 70		79	
thereof inflow > EUR 4,000		68	
# control		1,725	
thereof female		1,069	
thereof age > 70		759	
thereof inflow > EUR 4,000		635	

Note: The table investigates heterogeneity in the main treatment effect (ATT) by gender, age, and income. All specifications use the silent control group (N=1,725). Standard errors are reported in parentheses ($^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$).

Table A20: Treatment heterogeneity: enrollment survey constructs

	(1) D(TAN active)	(2) D(login)	(3) Online transaction share
Panel A: Tech-savvyness index			
$Post_t \times T_i$	0.228***	0.247***	0.107***
	(0.034)	(0.040)	(0.027)
$Post_t \times T_i \times$D(tech-savvyness = high)	0.061*	0.010	0.050*
	(0.033)	(0.032)	(0.026)
Obs.	10,961	9,300	10,961
Adj. R2	0.082	0.078	0.106
Panel B: Perceived utility index			
$Post_t \times T_i$	0.192***	0.208***	0.098***
	(0.032)	(0.039)	(0.025)
$Post_t \times T_i \times$D(perceived utility = high)	0.184***	0.123***	0.094***
	(0.035)	(0.033)	(0.027)
Obs.	10,961	9,300	10,961
Adj. R2	0.084	0.079	0.106
Panel C: Head of household finances			
$Post_t \times T_i$	0.298***	0.293***	0.281***
	(0.038)	(0.044)	(0.030)
$Post_t \times T_i \times$D(Head of household finance)	-0.060*	-0.061*	-0.225***
	(0.036)	(0.034)	(0.028)
Obs.	10,961	9,300	10,961
Adj. R2	0.082	0.078	0.111
Panel D: Risk tolerance			
$Post_t \times T_i$	0.236***	0.258***	0.167***
	(0.034)	(0.040)	(0.026)
$Post_t \times T_i \times$D(risk tolerance = high)	0.050	-0.013	-0.077***
	(0.034)	(0.032)	(0.026)
Obs.	10,961	9,300	10,961
Adj. R2	0.082	0.078	0.106
Panel E: Education (at least A levels)			
$Post_t \times T_i$	0.270***	0.255***	0.134***
	(0.034)	(0.040)	(0.027)
$Post_t \times T_i \times$D(A levels)	-0.024	-0.005	-0.003
	(0.033)	(0.032)	(0.026)
Obs.	10,961	9,300	10,961
Adj. R2	0.082	0.078	0.105
Panel F: Retirement status			
$Post_t \times T_i$	0.269***	0.248***	0.168***
	(0.043)	(0.048)	(0.034)
$Post_t \times T_i \times$D(retiree)	-0.014	0.005	-0.047
	(0.040)	(0.039)	(0.031)
Obs.	10,961	9,300	10,961
Adj. R2	0.082	0.078	0.106
$Post_t$	✓	✓	✓
T_i	✓	✓	✓
Client controls	✓	✓	✓

Note: The table investigates heterogeneity in the main treatment effect (ATT) by various characteristics elicited in the enrollment survey. D(tech savvyness= high) (panel A) is the median split of a standardized average of five standardized sub-indices ("I know how to download apps on my smartphone", "I usually have no issues browsing a website", "I can deal well with unexpected incidents when using internet banking", "I am afraid of new technology, because it could negatively influence my life" (inverted scale used), "I am open towards new technology"), each elicited on a 5-point Likert scale. D(perceived utility = high) (panel B) is the median split of a standardized average of two sub-indices ("I deem the practical benefits of internet banking as high", "I expect to be able to safely use internet banking on my own following the trainings."), each elicited on a 5-point Likert scale. Head of household finance (panel C) is equal to one if the client is "currently mainly in charge of banking issues in their household". Risk tolerance (panel D) is the median split of self-reported risk tolerance on an 11-point Likert scale (Dohmen et al., 2011). All specifications use the silent control group (N=1,725). Standard errors are reported in parentheses ($^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$).

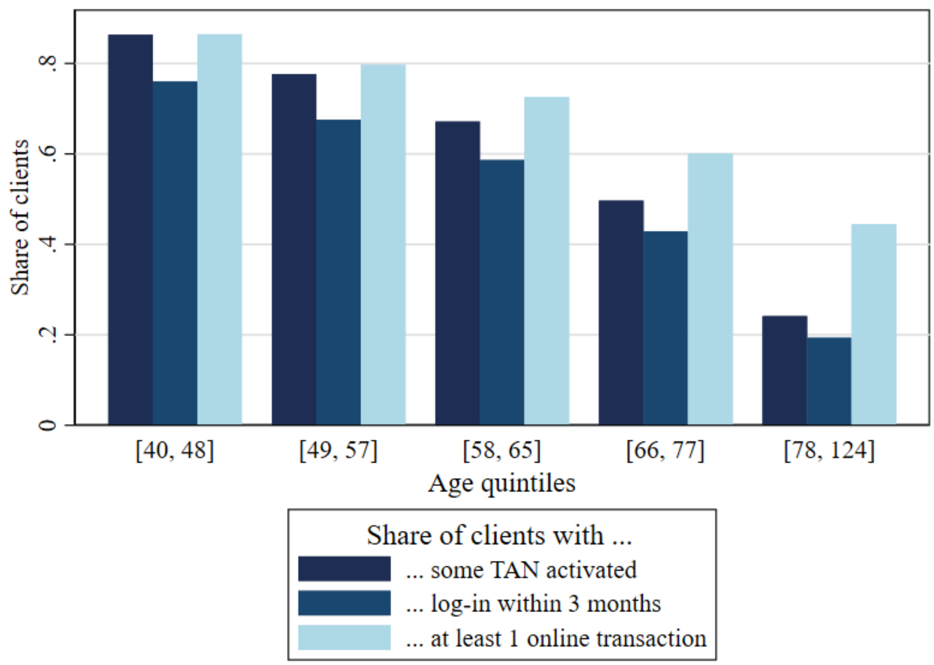
Table A21: Treatment heterogeneity: Head of household finances (female clients only)

	(1) D(TAN active)	(2) D(login)	(3) Online transaction share
$Post_t \times T_i$	0.381***	0.335***	0.319***
	(0.044)	(0.050)	(0.036)
$Post_t \times T_i \times$D(Head of household finance)	-0.166***	-0.103***	-0.256***
	(0.041)	(0.039)	(0.034)
Obs.	6,851	5,800	6,851
Adj. R2	0.091	0.091	0.142
Client controls	✓	✓	✓

Note: The table investigates heterogeneity in the main treatment effect (ATT) by whether the client is the head of household finance ("currently mainly in charge of banking issues in their household"), separately by gender. All specifications use the silent control group (N=1,725). Standard errors are reported in parentheses ($^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$).

Appendix: Supplementary figures

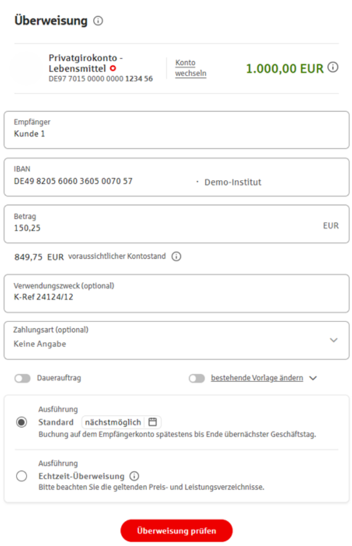
Figure A1: Internet banking adoption, by age groups



Note: The figure displays online-banking adoption and TAN availability by age quintiles. Data is provided by the partner bank and is as of June 11, 2024 for TAN and login and for calendar month May for online transactions. Q1 contains clients aged between 40 and 48 (N=31,250). Q2 contains clients aged between 49 and 57 (N=32,203). Q3 contains clients aged between 58 and 65 (N=29,657). Q4 contains clients aged between 66 and 77 (N=31,156). Q5 contains clients aged between 78 and 124 (N=29,104).

Figure A2: Examples from instructional material (translated from German)

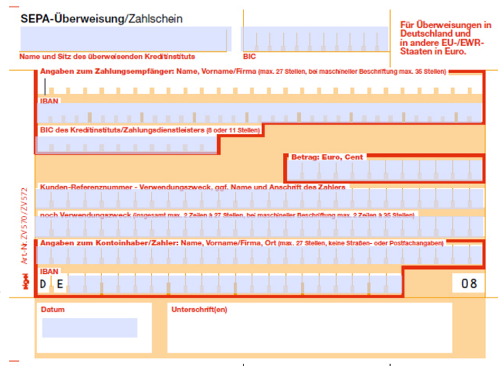
Making transfers



You already know this!

Transfers in online banking require exactly the same information as paper transfers:

- Name of the recipient
- IBAN
- Amount
- Intended use
- Date of the transfer



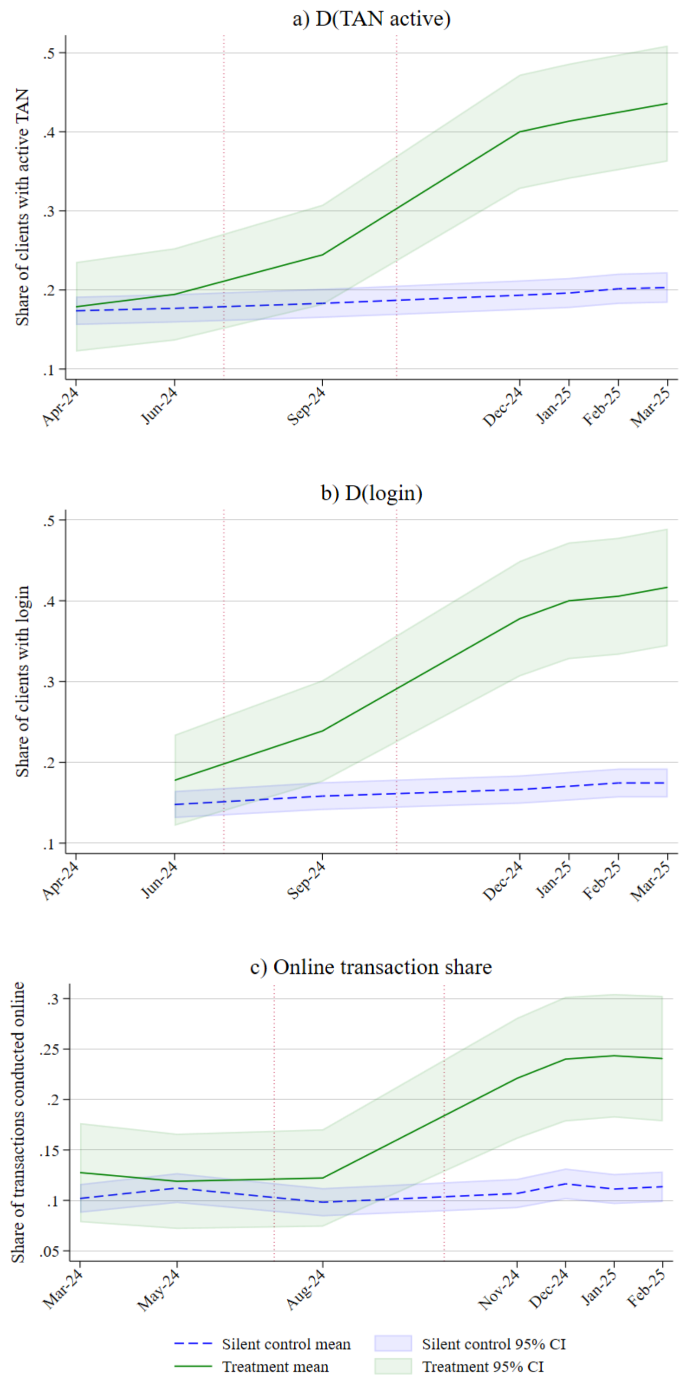
Secure Internet Banking

What can you do if you receive such an e-mail?

1. Many people react emotionally in such a situation. This is completely normal. Don't let your emotions guide you and keep calm.
2. Check thoroughly whether any of the characteristics of phishing emails mentioned apply.
3. Never click on a link or attachment without thinking.
4. Move the e-mail to the spam folder without replying.

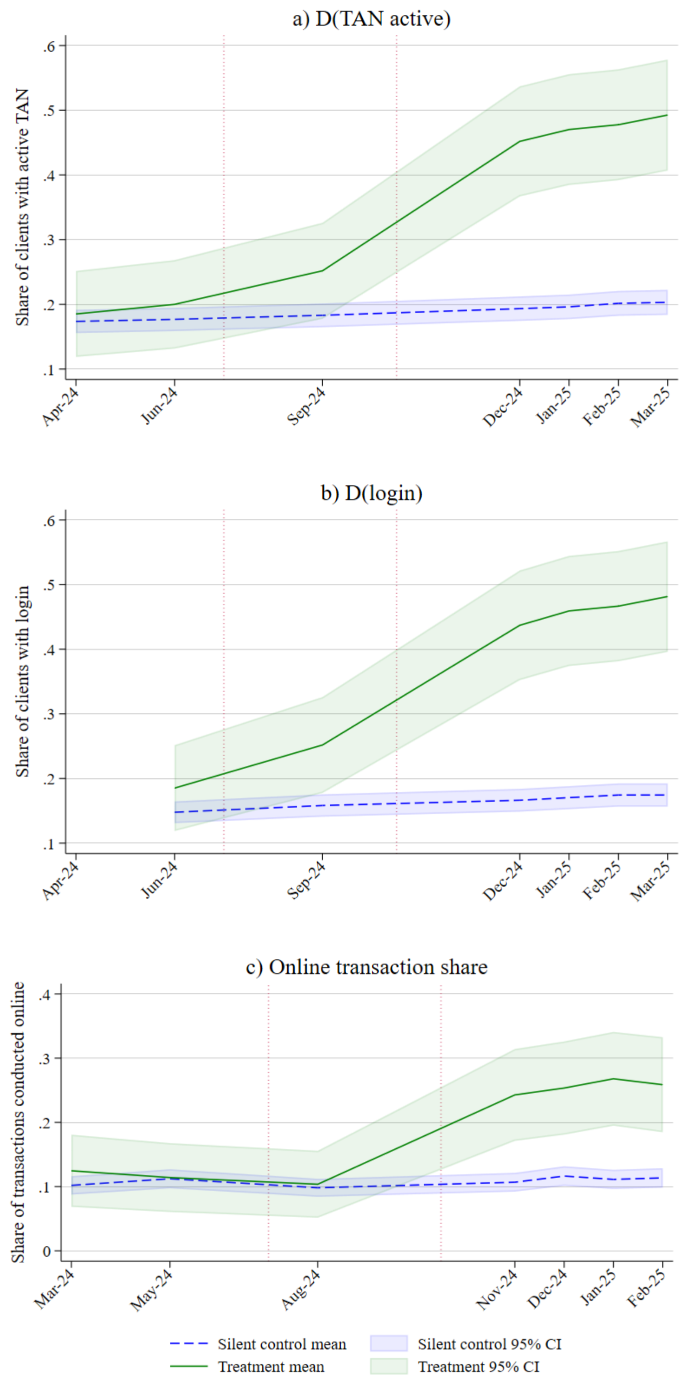
If you are unsure, it is worth taking a look at our website or contacting customer support.

Figure A3: Evolution of adoption measures, by treatment status (enrollment ITT vs. silent control group)



Note: The figures show monthly averages of the three main dependent variables over time, separately by treatment status. The treatment group here is defined as enrolled in the courses (N = 180, solid green line), the control group is the unmatched control group (N=1,725, dashed blue line). The shaded areas indicate 95% confidence intervals. The login variable is not included in the April-24 dataset.

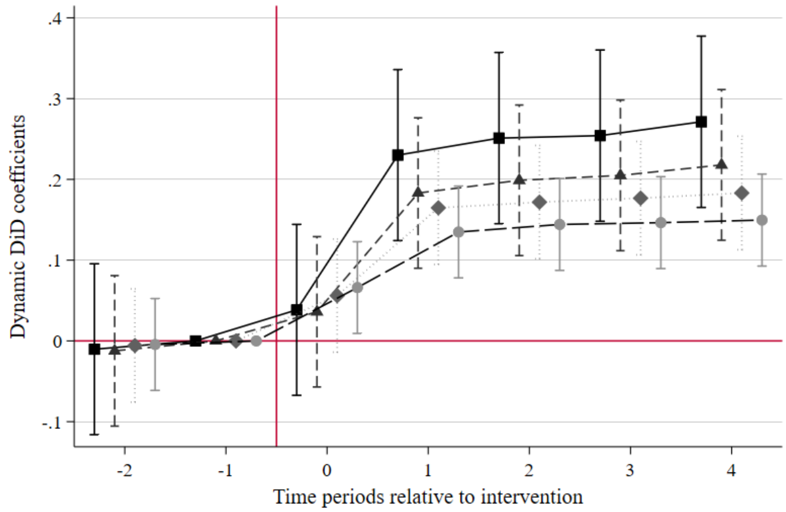
Figure A4: Evolution of adoption measures, by treatment status (ATT vs. silent control group)



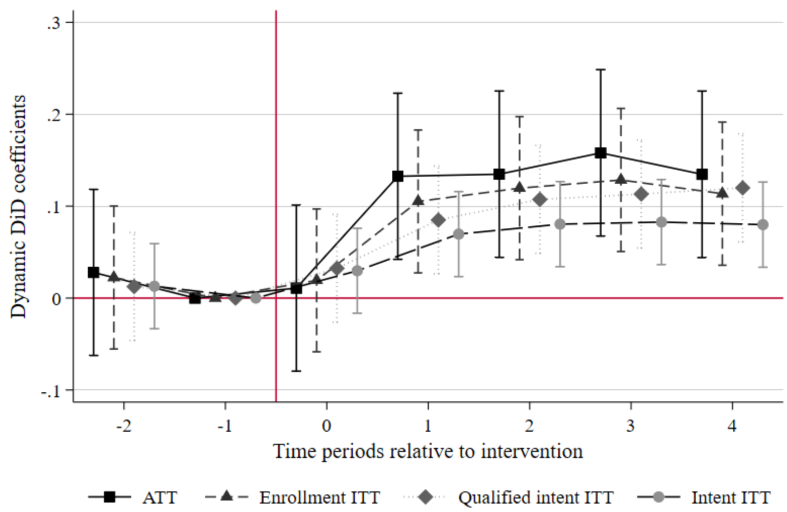
Note: The figures show monthly averages of the three main dependent variables over time, separately by treatment status. The treatment group here is defined as having attended the courses (N = 135, solid green line), the control group is the unmatched control group (N=1,725, dashed blue line). The shaded areas indicate 95% confidence intervals. The login variable is not included in the April-24 dataset.

Figure A5: Dynamic DiD coefficients (vs. matched control groups)

a) DV: D(TAN active)



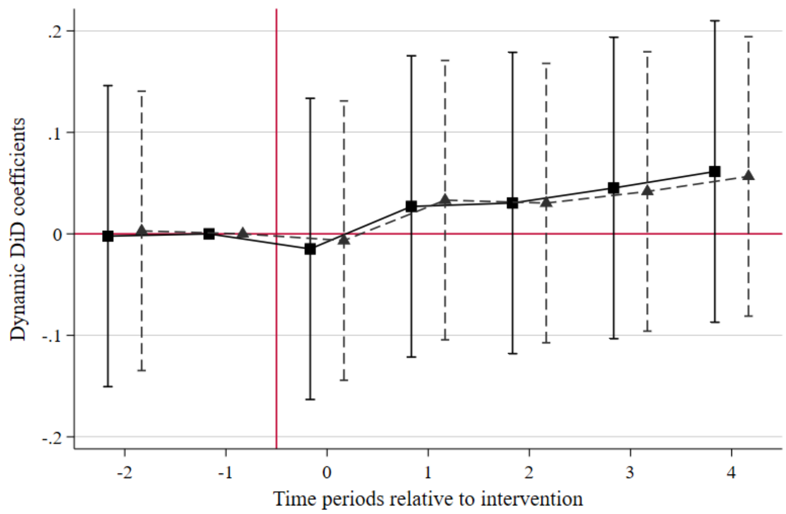
b) DV: Online transaction share



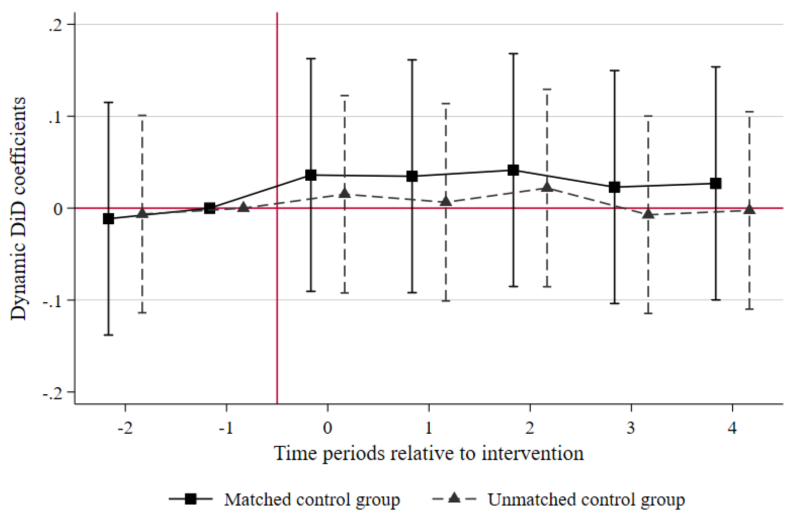
Note: The figure reports the point estimates and 95% confidence intervals of treatment coefficients obtained from dynamic DiD regressions as specified in equation 2 for various treatment definitions. Control groups are matched based on five-nearest-neighbor matching on a propensity score (see Table A6 for the first-stage coefficients). The dependent variables are a dummy variable indicating an active TAN process (panel a)) and the share of transactions conducted online (panel b)). The omitted month ($t = -1$) is June 2024 (calendar month May 2024 for the transaction share measure).

Figure A6: Dynamic DiD coefficients: Placebo

a) DV: D(TAN active)

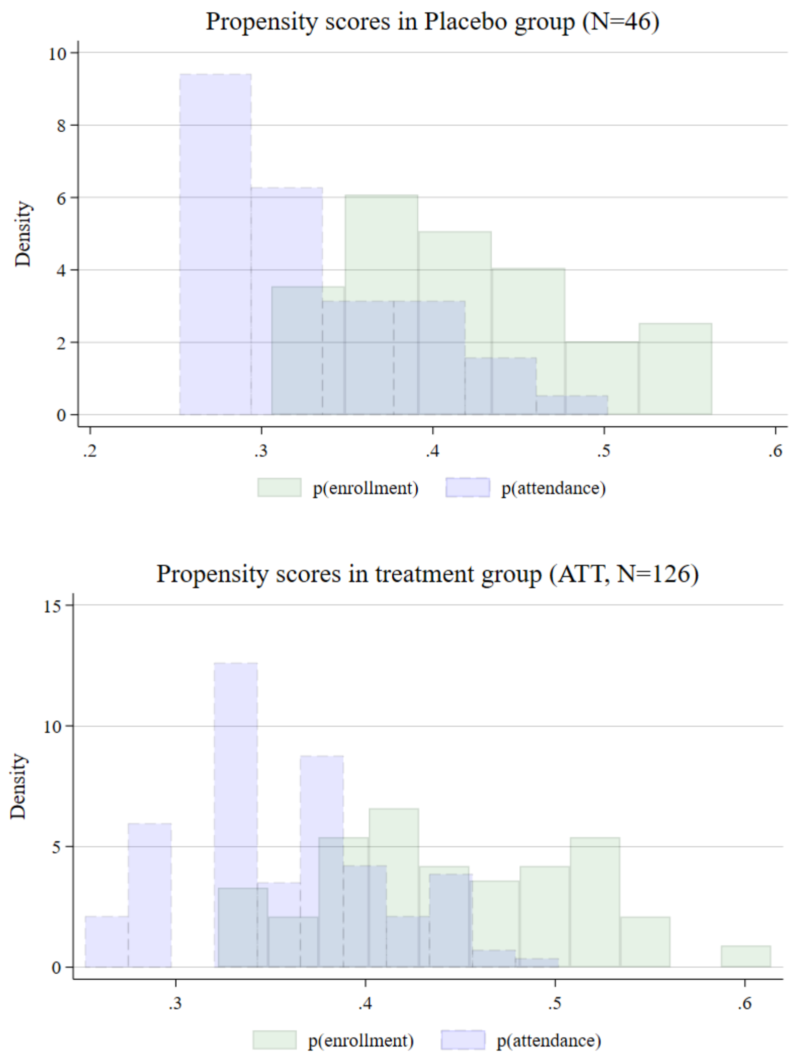


b) DV: Online transaction share



Note: The figure reports the point estimates and 95% confidence intervals of placebo coefficients obtained from dynamic DiD regressions as specified in equation 2 for specifications using the unmatched and matched control groups. Control groups are matched based on five-nearest-neighbor matching on a propensity score (see Table A6 for the first-stage coefficients). The dependent variables are a dummy variable indicating an active TAN process (panel a)) and the share of transactions conducted online (panel b)). The omitted month ($t = -1$) is June 2024 (calendar month May 2024 for the transaction share measure).

Figure A7: Propensity scores in Placebo and treatment groups



Note: The figure displays the distribution of predicted probabilities of participants in the Placebo group (upper panel) and the treatment group (lower panel) to enroll in (green bars, solid outline) and complete (blue bars, dashed outline) training. Probabilities are predicted as the fitted values from logistical regressions of treatment (enrollment or attendance/completion) on age, a gender dummy, inflow (a dummy indicating inflows exceeded EUR 4,000), and the education level (1: lower secondary, 2: intermediate secondary, 3: grammar school, 4: college degree, 5: PhD).