

Who Pays for AI?*

Nikhil Datta

Peter John Lambert

Patrick Schneider

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Abstract

We document who pays for AI tools using anonymized transaction data covering 14 million UK accounts linked to demographics, earnings, and occupations. Identifying AI sellers like ChatGPT and Claude across 8 million weekly transactions, we find that active paid subscriptions roughly doubled every 12 months since early 2024, reaching one in twenty UK adults by mid-2026. Adoption is five times higher for under-30s than over-60s, 27% higher for men, and 78% higher in the top versus bottom fifth of the earnings distribution. While ChatGPT held 74% of subscription spending in December 2025, its share fell to 53% by July 2026 as Claude surged from 7% to 29%, driven by technical and professional workers and power-user plans. High-frequency transactions data are well suited to study the rapidly evolving market for consumer AI products, and we will continue to update our findings in real time.

Keywords: artificial intelligence; technology adoption; subscriptions; transaction data; occupational exposure; product competition

JEL Codes: O33, D12, L86, J24, C81, E21

*Datta: University of Warwick and London School of Economics; Lambert: University of Warwick and London School of Economics (corresponding author, email: Peter.Lambert@warwick.ac.uk); Schneider: Imperial Business School, Imperial College London. We thank seminar and conference participants for helpful comments. All errors are our own. Monthly indices used in this paper can be viewed and downloaded at <https://whopaysfor.ai>

1 Introduction

Within three years of ChatGPT’s public release in November 2022, household surveys in the United States and Europe found that between one-third and three-fifths of adults had tried a generative artificial intelligence (AI) tool (Bick, Blandin, and Deming, 2026; Pew Research Center, 2026; Ofcom, 2026; Bick et al., 2026). Yet because leading developers offer capable free versions and build AI into everyday software, casual experimentation is nearly costless and tells us little about where generative AI delivers enough ongoing value for individuals to pay for it out of pocket. In this paper, we use de-identified UK bank and credit-card records covering 14 million consumer accounts through August 2026 to study the spread of paid consumer AI. By tracking recurring subscription payments across more than three hundred AI products and linking them to salaries, occupations, and demographics, we measure how rapidly paid adoption is growing across the population, how uneven adoption is across income, occupation, and location, and how consumers divide their spending across competing providers.

Measuring paid AI adoption poses fundamental challenges for traditional economic data. Household surveys rely on infrequent self-reports that struggle to separate one-off curiosity from recurring financial commitment, while internal usage logs from a single AI provider (Chatterji et al., 2025; Handa et al., 2025) cannot observe competing sellers, non-adopters, or off-platform earnings and spending. Bank and card transaction records overcome both limitations.¹ Because consumer AI is sold primarily as a monthly subscription priced around £20, card and bank payments record the exact date a consumer crosses the threshold from free use to paid commitment and follow every subsequent renewal, cancellation, and provider switch across the market.

To construct representative national estimates, we reweight active accounts each month to match UK demographic, regional, and income benchmarks, capturing both direct card charges to providers such as OpenAI, Anthropic, Midjourney, Perplexity, and ElevenLabs and mobile app-store subscriptions billed through Apple and Google. Open-banking current accounts further allow us to observe who pays for AI in the labor market. From incoming payroll deposits, we measure each worker’s net take-home salary and link employees to their employer’s industry. Moreover, we overcome a longstanding limitation of financial transaction data—the absence of occupation labels—by using outbound payments to professional regulators, royal colleges, chartered institutes, and occupation-specific trade unions (such as the General Medical Council,

1. Administrative bank and card panels have transformed the real-time measurement of household consumption, income dynamics, and macroeconomic shocks (Ganong and Noel, 2019; Cox et al., 2020; Baker and Kueng, 2022; Chetty et al., 2024). We bring this transaction-based approach to the diffusion of a new general-purpose technology (Griliches, 1957; David, 1990; Bresnahan and Trajtenberg, 1995; Comin and Hobijn, 2004, 2010).

Solicitors Regulation Authority, Royal College of Nursing, and University and College Union), combined with employer payroll records. This approach allows us to measure personal AI adoption across dozens of specific professions and broad occupational groups across the workforce.

Our analysis yields three main sets of findings. First, paid consumer AI has grown rapidly across the adult population, driven overwhelmingly by growth in the number of people paying rather than higher spending per subscriber. Active subscribers roughly doubled every 12 months since early 2024, reaching 5.1% of UK adults (2.8 million people) by June 2026 and an annualized consumer spending run rate exceeding £1.0 billion. General-purpose AI assistants account for roughly nine in ten active subscriptions. By the first half of 2026, more UK adults were signing up for paid AI for the first time than were joining major streaming platforms such as Netflix and Spotify, even though AI subscriptions represent less than 0.5% of subscribers' total monthly card spending. Decomposing total monthly spending growth between January 2024 and July 2026 shows that nearly nine-tenths (88%) of the rise in consumer AI spending comes from an expanding share of adults paying each month, with the remainder reflecting higher average monthly spending per subscriber.

Second, paid AI adoption is highly uneven across age, gender, and income, though the profile of new subscribers has broadened steadily as the technology has spread. Across age groups, cumulative paid adoption is nearly six times higher among adults aged 20–29 than among those aged 60 and over (and nearly five times higher after accounting for income, gender, and region). Men are 27% more likely to hold an active subscription than women and spend 23% more per month when they do, reflecting greater male uptake of expensive power-user plans. Across the earnings distribution, cumulative adoption is 78% higher in the top fifth of earners than in the bottom fifth. However, adding controls step by step reveals that nearly two-thirds of the raw relationship between salary and paid AI adoption is explained by differences in occupation, industry, location, age, and gender; once these characteristics are accounted for, the relationship between salary and AI adoption is no stronger than for mainstream consumer subscriptions such as Netflix and Spotify. At the same time, early demographic and earnings gaps have narrowed among new subscribers: between early 2023 and mid-2026, the male-to-female ratio among first-time adopters fell from 3.0 to 1.2, and the earnings premium of new adopters relative to the average salaried worker fell by more than half.

What people do at work is a central determinant of whether they pay for AI out of pocket. Across professions identified from professional membership and registration payments, active direct subscription rates vary twelvefold—from roughly 20% among

IT professionals and 13%–16% among university lecturers, finance professionals, project managers, and marketers to under 3% among electricians, nurses, and social care workers. Across the workforce, our transaction-based adoption rates align closely with both US survey measures of workplace AI usage ($r = 0.8$ to 0.9 ; Bick, Blandin, and Deming, 2026) and task-based measures of occupational exposure to AI ($r = 0.8$; Eloundou et al., 2024), and occupational AI exposure remains a strong predictor of personal adoption even after accounting for individual take-home pay, age, gender, and region. Geographically, active paid assistant adoption in London (6.8%) is nearly double that in the rest of Great Britain (3.6%), with pronounced local clusters in university and knowledge-economy centers such as Cambridge, Oxford, and Edinburgh.

Third, while OpenAI’s ChatGPT dominated the consumer market through 2024 and most of 2025, competition intensified sharply from late 2025 as Anthropic’s Claude captured a rapidly growing share of both subscribers and consumer AI spending. Between December 2025 and July 2026—following the release of Claude Opus 4.5 and the rapid spread of the coding tool Claude Code—Claude’s share of direct consumer spending on standalone AI subscriptions quadrupled from 7.4% to 29.4%, while ChatGPT’s direct spending share fell by 21 percentage points from 73.5% to 52.5%. ChatGPT still leads by a wide margin in active assistant subscribers (71.2% versus 27.1% in July 2026), and Claude’s spending share exceeds its subscriber share because 6.2% of its subscribers pay for £80+ monthly power-user plans, compared with just 0.3% on ChatGPT—a twenty-to-one gap in power-user plan uptake.

This shift in market share reflects distinct occupational sorting, rising switching between platforms, and strong responses to major model releases. Software and IT workers, engineers, management consultants, finance professionals, and academics disproportionately choose Claude, whereas school teachers, healthcare workers, and human-resources staff strongly favor ChatGPT. Most subscribers pay for only one general-purpose assistant at a time—just 4.2% of assistant subscribers pay two or more assistant providers in the same month—though users of specialized voice, image, and coding tools routinely pair them with a general assistant. Claude’s rapid growth in 2026 reflects both entry by new subscribers—especially users who also pay for standalone AI coding tools, who are more than twice as likely to choose Claude as other assistant buyers (46.8% versus 21.6%)—and rising switching from ChatGPT: the share of cancelling ChatGPT users who switch to Claude within 60 days rose more than eightfold from 1.4% in 2025 to 11.7% in spring 2026, accompanied by sharp two-week surges in first-time sign-ups immediately following major model releases.

Related Literature. Our study contributes to three main areas of research. First,

we build on research measuring technology diffusion (Griliches, 1957; David, 1990; Bresnahan and Trajtenberg, 1995; Caselli and Coleman, 2001; Goolsbee and Klenow, 2002; Rogers, 2003; Comin and Hobijn, 2004, 2010) and the rapidly growing literature on the adoption and labor-market impact of generative AI (Noy and Zhang, 2023; Peng et al., 2023; Dell’Acqua et al., 2023; Bick, Blandin, and Deming, 2026; Eloundou et al., 2024; Brynjolfsson, Li, and Raymond, 2025; Handa et al., 2025; Chatterji et al., 2025; Humlum and Vestergaard, 2025b, 2025a; Yotzov et al., 2026; Brynjolfsson, Chandar, and Chen, 2026; Lambert and Schindler, 2026).² Controlled experiments and field studies have documented substantial productivity gains from generative AI tools in writing, customer support, software engineering, and consulting, while task-exposure studies predict that large language models primarily assist cognitive, white-collar work (Felten, Raj, and Seamans, 2021; Eloundou et al., 2024). Recent empirical studies have tracked AI adoption using household and firm surveys (Bick, Blandin, and Deming, 2026; Humlum and Vestergaard, 2025b, 2025a; Pew Research Center, 2026; Bick et al., 2026; Yotzov et al., 2026) or internal platform logs from a single provider (Chatterji et al., 2025; Handa et al., 2025). We complement survey and single-provider studies by observing out-of-pocket subscription payments continuously across all competing sellers in a representative consumer panel linked to demographics, salaries, and occupations, and by showing that personal consumer spending on AI closely tracks workplace task exposure and survey usage even after accounting for individual income and demographics.

Second, we contribute to household finance and empirical macroeconomics using bank and card transaction records (Ganong and Noel, 2019; Ganong, Noel, and Vavra, 2020; Cox et al., 2020; Hacıoğlu-Hoke, Känzig, and Surico, 2021; Gathergood et al., 2021; Baker and Kueng, 2022; Greene, Perry, and Stavins, 2024; Chetty et al., 2024). Although transaction datasets have transformed the measurement of household spending, income dynamics, and fiscal stimulus, their application to labor-market questions has historically been limited by the lack of occupation and industry identifiers in banking records. We show that payment signals available in open-banking current accounts—outbound membership and registration payments to professional regulators, royal colleges, and trade unions, combined with incoming salary descriptions—can recover individual occupation and employer industry at population scale, linking workplace characteristics directly to household spending decisions.

Third, our study contributes to work in industrial organization studying markets for

2. Related studies examine how generative AI affects search, education, financial advice, and companionship (Bastani et al., 2024; Choukhmane et al., 2025; Padilla et al., 2025; Phang et al., 2025; Zheng et al., 2025; De Freitas et al., 2026; Brynjolfsson et al., 2026; Dillon et al., 2026).

digital goods, subscription pricing, and consumer switching (Mussa and Rosen, 1978; Klemperer, 1995; Chen and Hitt, 2002; DellaVigna and Malmendier, 2006; Goldfarb and Prince, 2008; Einav and Levin, 2014; Grubb and Osborne, 2015; Goldfarb and Tucker, 2019). Unlike traditional software licenses or ad-supported web services, consumer AI is sold simultaneously through capable free versions, standard monthly subscriptions, and high-priced power-user plans. We show how expensive power-user plans (£80+ per month), occupational sorting across platforms, and rapid consumer switching around major model releases can produce large shifts in revenue market shares even when subscriber headcount shares change more gradually.

The remainder of the paper proceeds as follows. Section 2 describes our data and measurement approach; Section 3 examines aggregate growth; Section 4 analyzes how adoption varies across age, gender, income, occupation, and geography; Section 5 studies competition between providers; and Section 6 concludes.

2 Data, Measurement, and Validation

This section describes our transaction dataset and how we use it to measure paid AI adoption and individual worker characteristics across the United Kingdom. We first describe the underlying bank and card records and our sample selection rules, then explain how we identify direct and mobile app-store AI subscriptions and reweight our sample to represent the national adult population. Finally, we detail how we infer salaries, employers, and occupations and validate our measures against external benchmarks.

2.1 Payment Records and Sample Selection

We analyze de-identified UK consumer bank and card records from a financial data aggregator covering 14.2 million accounts and an average of 8 million weekly transactions between January 2022 and August 2026 (Table 1 and Appendix C). The dataset combines open-banking current accounts—which capture debit card purchases, direct debits, bank transfers, and incoming salary deposits—with individual credit and debit card accounts.³ For headline population estimates, we use the combined dataset; for analyses of earnings, employers, and occupations, we use the open-banking current-account sample. For each transaction, we observe an account identifier, the transaction date, amount, currency, payment channel, the business category of the seller (merchant

3. Under UK open-banking regulations, consumers can connect their everyday bank current accounts and credit cards to financial management apps, allowing us to observe anonymized bank statements including incoming salary payments, direct debits, and card purchases; see Appendix C.

category code), and the anonymized text description on the statement, alongside the account holder’s age band, gender, and residential postal area.

As is standard when working with transaction datasets, we distinguish between active main accounts and dormant or secondary cards so that inactive accounts do not artificially lower per-account adoption rates (Ganong and Noel, 2019; Cox et al., 2020; Baker and Kueng, 2022; Chetty et al., 2024). To focus on active main accounts, we require an average of at least 20 non-AI transactions per month and median monthly non-AI spending of at least £100 over the preceding twelve months, yielding 457,072 active accounts in June 2026 (and 390,404 salaried open-banking accounts across 2022–2026; Table 1, Panel C). Because our unit of observation is an individual bank or card account, our estimates measure out-of-pocket consumer and worker subscriptions rather than corporate licenses paid directly by an employer; when translating per-account subscription rates into national adult payer counts, we use a benchmark one-to-one mapping between active main accounts and UK adults and evaluate sensitivity to holding multiple accounts or secondary cards in Appendix C.

2.2 Identifying Direct and Mobile App-Store Subscriptions

We identify direct AI payments across a curated directory of standalone AI products (Appendix A and Appendix Table A1), led by the nine major general-purpose AI assistants (ChatGPT, Claude, Gemini, Microsoft Copilot, Perplexity, DeepSeek, Mistral, Grok, and Poe), while excluding general software packages that later added AI features to existing subscriptions (such as Microsoft 365, Canva, and Adobe). We match transactions to AI sellers using text patterns in the payment description, combined with subscription prices, product launch dates, and merchant category codes (Table 1, Panel A).⁴ We link repeated monthly payments to the same seller into ongoing subscription spells, treating a subscription as cancelled when no renewal payment arrives within one skipped billing cycle (65 days for monthly plans) while the account remains active in our dataset (Appendix A).

Consumers subscribe to AI assistants both directly on provider websites and through mobile apps on iOS and Android, which appear on bank statements under generic billing descriptions (apple.com/bill and google play) rather than naming the AI provider. To account for mobile billing, we estimate mobile AI subscriptions in two steps (Appendix B). First, we track recurring monthly Apple and Google charges at the exact prices of major AI plans (such as £20 for ChatGPT Plus and Claude Pro, or

4. When automated privacy filters replace personal names such as “Claude” with <name>, or when payment processors truncate claude.ai to claud, we identify the payment using the remaining web domain and exact subscription price, and drop any ambiguous transactions.

£7 to £8 for ChatGPT Go) and measure the surge in recurring mobile subscriptions at those price points following AI product launches relative to pre-AI baselines and similar non-AI price points. Second, among users paying those recurring mobile prices, we estimate each user’s likelihood of holding an AI subscription based on their demographics and non-AI spending patterns, trained on the characteristics of users who pay AI providers directly on the web. Incorporating mobile app-store subscriptions alongside direct web billing captures the substantial share of younger, female, and lower-salaried users who subscribe through mobile devices; we report our analyses both across all payment channels combined and on directly billed web subscriptions alone in the Appendix.

2.3 Reweighting to the UK Adult Population

Because the active accounts in our dataset need not mirror the national demographic mix, we reweight the sample each month to represent the 55.5 million adults aged 18 and over in the United Kingdom (Baker and Kueng, 2022; Chetty et al., 2024). Specifically, we adjust account weights each month to match official national benchmarks from the Office for National Statistics (ONS) and HM Revenue and Customs (HMRC) by age, gender, region, after-tax income, and local neighborhood characteristics.⁵ Whenever we analyze a specific subset of accounts—such as current accounts with salary deposits, or the subset of card accounts where privacy filters do not obscure merchant names—we reweight that subsample to match the same national demographic, regional, and neighborhood benchmarks.⁶

2.4 Measuring Salaries, Employers, and Occupations

For open-banking current accounts, we use incoming payroll deposits and outbound professional payments to measure each worker’s net take-home salary, employer industry, and occupation (Table 1, Panel C, and Appendix D). We measure monthly net take-home pay from regular salary credits and assign each worker’s employer to a UK Standard Industrial Classification (SIC 2007) industry across 21 official sections for 319,298 salaried accounts (65% of the salaried sample) by matching employer names on salary deposits to Companies House and public-sector directories (such as National

5. As detailed in Appendix C, we construct these weights in two steps: we first adjust for the probability that an account in the wider dataset meets our monthly activity threshold, and then use iterative proportional fitting to match national population benchmarks.

6. As noted in Section 2.2 and detailed in Appendix A, automated privacy filters at a small number of card issuers replace the personal name “Claude” with <name>; when comparing competing providers or occupations on direct web payments, we exclude those card issuers and reweight the remaining accounts to match national population benchmarks.

Health Service trusts, school registers, and local authorities). We also check whether workers receive separate non-payroll transfers from their employer following an AI subscription charge, finding that personal AI subscriptions are rarely followed by separately identifiable expense reimbursements.

Standard banking records do not record a person’s occupation. To overcome this, we classify workers into occupations in the UK Standard Occupational Classification (SOC 2020) by combining direct professional membership and employer records with a machine-learning model of non-AI spending (Appendix D). First, we compile a directory of 66,000 organizations linked to specific occupations, including 466 statutory professional regulators, royal colleges, chartered institutes, and occupation-specific trade unions—such as the General Medical Council for doctors, the Nursing and Midwifery Council for nurses, the Solicitors Regulation Authority for solicitors, and the University and College Union for university lecturers. Outbound registration fees or membership dues to these bodies directly identify the profession of 46,419 salaried open-banking accounts across 65 specific professions. Second, we match incoming payroll strings to employers whose workforce is concentrated in a single occupation (such as airlines, law firms, or dental practices), identifying the occupation of an additional 24,180 salaried accounts for a combined reference sample of 70,599 workers with directly observed occupations. Third, to extend occupational measurement across the wider workforce, we train a machine-learning model on these 70,599 workers using their employer industry, salary percentile, age, gender, local area, and non-AI consumer spending patterns, and use the trained model to predict occupational probabilities across all 26 broad UK occupational groups for 1.7 million open-banking accounts. We exclude all AI and software transactions when building the model so that our occupation measures never use information about AI adoption.

2.5 Validation using External Benchmarks

Each component of our measurement approach aligns closely with external administrative and survey benchmarks (Table 1, Panel B, and Appendix Figure A2). When we hide merchant names on known direct subscriptions to test our mobile app-store model, this exercise shows that our classifier performs well above random guessing in separating AI subscribers from other subscribers paying the exact same monthly price, with an area-under-the-curve (AUC) classification performance metric of 0.9;⁷ likewise, recurring monthly Apple charges at OpenAI’s entry-level ChatGPT Go price point (£7 to £8) jump thirteenfold immediately upon its UK launch (Appendix Fig-

7. The AUC metric measures how well a model ranks true cases above non-cases on a scale from 0.5 (random guessing) to 1.0 (perfect classification); see Appendix B.

ure A2a). Across the labor market and household sector, our open-banking net salary distribution matches official ONS Annual Survey of Hours and Earnings (ASHE) net pay percentiles almost one-for-one across the 30th to 90th percentiles, captures the January 2024 statutory cut in employee National Insurance contributions within two pounds per month (£31 observed versus £33 predicted by the tax schedule), and tracks official UK household Netflix penetration (Appendix Figure A2b–d). Finally, when we hide a worker’s professional membership payments and predict their occupation solely from their non-AI transactions, demographics, and employer, our occupational model distinguishes a worker’s true profession well above chance, achieving a median AUC classification score of 0.9 across all 65 professions, and our resulting occupational AI adoption rates correlate closely with US workplace survey usage and GPT-4 task-exposure indices (Section 4).

3 Growth of Paid AI Across the Population

3.1 Share of Adults Paying and Total Spending

We begin by examining how rapidly paid consumer AI has spread across the adult population in the United Kingdom.

Figure 1 plots active paid AI subscribers per 1,000 UK adults from January 2023 to June 2026.⁸ From a negligible base at the start of 2023, paid consumer AI has spread rapidly across the British adult population, roughly doubling every 12 months since early 2024. By June 2026, 50.6 per 1,000 UK adults hold an active paid subscription to a standalone AI product—equivalent to 5.1% of the adult population, or 2.8 million people. Roughly three-fifths of active subscriptions (29.0 per 1,000 UK adults, or 1.6 million people) are billed directly to bank accounts or cards on provider websites, while the remaining two-fifths are billed through mobile app stores (20.5 per 1,000) and PayPal or other payment processors (1.1 per 1,000; Appendix Table A2).⁹

In pound terms, UK consumer spending on standalone AI products has grown from almost nothing prior to February 2023 into a billion-pound annual market (Appendix Figure A6a). Across calendar year 2024, UK consumers spent £3,442 per 1,000 adults on paid AI; in calendar year 2025, annual spending more than doubled to £8,387 per 1,000 adults, a 2.4-fold increase. Growth accelerated further in the first half of 2026:

8. As defined in Section 2, our headline series measures standalone AI products (such as ChatGPT, Claude, Midjourney, and Cursor) rather than pre-existing software suites (such as Microsoft 365, Canva, and Adobe) that later added AI features to existing plans.

9. Appendix Table A2 and Appendix Figure A1 show that our national estimates are robust across alternative sample definitions and reweighting methods.

by July 2026, monthly spending reached £1,600 per 1,000 UK adults, equivalent to an annualized spending rate exceeding £1.0 billion across the UK adult population.

Comparing our 5.1% paid subscription rate with population surveys highlights the sharp difference between costless experimentation and paying out of pocket. UK surveys by Ofcom, Deloitte, and the Digital Regulation Cooperation Forum find that 35% to 62% of UK adults have tried a generative AI tool (Digital Regulation Cooperation Forum, 2025; Ofcom, 2026; Deloitte, 2026), similar to the 45% to 50% trial rates reported in US and European surveys (Bick, Blandin, and Deming, 2026; Gambacorta, Jappelli, and Oliviero, 2025; Pew Research Center, 2026; Bick et al., 2026). Because leading providers offer capable free versions, roughly nine in ten users who have tried generative AI do not currently pay for a standalone subscription. Dividing our 5.1% adult subscriber share by the 35% to 62% of UK adults who have ever tried generative AI implies that roughly 8% to 15% of people who have tried AI hold an active paid subscription—in line with OpenAI’s global disclosure of 50 million consumer subscribers out of 900 million weekly active users (5.6%) as well as US bank-statement estimates (OpenAI, 2026; Bank of America Institute, 2026; PNC Financial Services Group, 2026).

3.2 New Subscribers and Drivers of Spending Growth

More than three years after ChatGPT Plus launched in February 2023, the monthly flow of first-time AI subscribers continues to rise. Comparing first-time paid AI subscribers between January and July 2026 against new subscribers to major entertainment streaming services over the same seven-month window (Appendix Figure A6b), directly billed paid AI added 11.8 first-time payers per 1,000 adults, outpacing new direct sign-ups to Netflix (9.2 per 1,000) and Spotify (8.0 per 1,000); when mobile app-store AI sign-ups are included, the seven-month AI inflow reaches 25.8 per 1,000 adults, surpassing Disney+ as well. Unlike mature streaming platforms, where monthly sign-ups are roughly constant over time, first-time paid AI sign-ups accelerated over the first half of 2026 as models improved and workplace use broadened (Griliches, 1957; Bass, 1969; Jovanovic and Lach, 1989).

Total consumer spending on AI can grow either because more adults pay in a given month or because active subscribers spend more per person. Between January 2024 and July 2026, the share of UK adults billed for AI in a given month rose nearly sixfold from 1.0% to 5.8%, whereas average monthly AI spending per active subscriber rose much more modestly from £22 to £28 on direct billing, representing roughly 0.4% to 0.5% of active subscribers’ total monthly card spending—about the price of a single streaming subscription (Appendix Figure A6c). Separating total spending growth

between January 2024 and July 2026 into growth in the number of subscribers versus growth in spending per subscriber shows that nearly nine-tenths (88%) of total market growth comes from more adults paying each month, while the remaining 12% comes from higher average spending per subscriber as some users upgrade to expensive power-user plans or hold multiple subscriptions.¹⁰

4 Who Pays for AI? Age, Gender, Income, Occupation, and Geography

4.1 Differences by Age, Gender, and Income

Who crosses the threshold from free use to paying out of pocket for artificial intelligence? Figures 2 and 3 show how paid adoption varies across age, gender, and net take-home salary, and how the profile of first-time subscribers has broadened over time.

Panel (a) of Figure 2 plots the share of adults who have ever paid for AI since November 2022 across five age bands, comparing raw population-weighted rates (navy bars) with adjusted rates that hold monthly net salary, gender, and UK region constant (orange bars). Paid AI adoption falls nearly sixfold across the adult life cycle, from 17.9% among adults aged 20 to 29 to 3.0% among adults aged 60 and over (a ratio of 5.9 to 1), and remains nearly fivefold higher at ages 20 to 29 than at ages 60 and over after accounting for salary, gender, and region (18.3% versus 3.8%, a ratio of 4.8 to 1). This strong youth pattern mirrors earlier waves of personal computer and internet adoption (Goolsbee and Klenow, 2002; Goldfarb and Prince, 2008; Deming and Noray, 2020).

Panel (b) of Figure 2 tracks monthly active paid AI subscribers per 1,000 UK adults separately for men and women from February 2023 through July 2026. Men subscribe at higher rates throughout the sample, reaching 62.2 active payers per 1,000 men versus 48.6 per 1,000 women in July 2026—a 27% gender gap (a ratio of 1.3 to 1 across all payment channels; the gap is larger on direct web payments alone because women purchase a higher share of subscriptions through mobile app stores). Men also spend 23% more per month when they subscribe (£26 versus £21), reflecting higher male uptake of £80+ power-user plans. Yet the profile of new subscribers has broadened

10. Because total AI spending per adult equals the share of adults paying multiplied by average AI spending per active payer, we decompose the log change in monthly spending per adult into the sum of the log changes in these two components (84% from the share of adults paying on direct web subscriptions alone); see Appendix E.

substantially over time: the male-to-female ratio among first-time monthly adopters fell from 3.0 to 1 in early 2023 to 1.2 to 1 in the first half of 2026 (Aldasoro et al., 2024; Humlum and Vestergaard, 2025b).

Figure 3 examines how paid AI adoption varies with monthly net take-home pay across salaried open-banking accounts. Unlike transaction studies that proxy for income using total card spending—which mixes income with differences in card usage and saving behavior across the income distribution (Dynan, Skinner, and Zeldes, 2004)—our open-banking records measure net salary deposits directly.¹¹ Across monthly net take-home salary brackets (Figure 3a), cumulative paid AI adoption is 88% higher in the top bracket than in the bottom bracket before adding controls, rising from 10.0% among workers taking home under £1,500 per month to 18.8% among those taking home over £4,000 per month (and is 78% higher in the top fifth of earners than in the bottom fifth), and rises by 69% (from 11.1% to 18.8%) after accounting for age, gender, and UK region. As with gender, the earnings gap between new subscribers and the average worker has narrowed as the market has grown: first-time payers in early 2023 earned 1.7 times the average salaried worker’s take-home pay, compared with 1.3 times the average by mid-2026.

Panel (b) of Figure 3 asks how much of this overall relationship with income reflects differences in who works in which jobs and locations versus a direct effect of income, and compares paid AI adoption against everyday consumer streaming subscriptions (Spotify and Netflix). We use linear regressions to relate cumulative adoption to log monthly take-home pay across four specifications that add controls step by step. Before adding controls, a one-unit increase in log monthly take-home pay is associated with a 5.6 percentage point increase in paid AI adoption (or 36.1% of the 15.6% sample mean),¹² which is larger than the corresponding income relationships for both Spotify (4.0 percentage points) and Netflix (3.3 percentage points). Accounting for age and gender reduces the paid AI slope to 5.0 percentage points, and accounting for local authority district reduces it to 4.4 percentage points. Crucially, accounting further for occupation and employer industry cuts the remaining paid AI income slope by more than half to 2.0 percentage points—showing that nearly two-thirds (64%) of the raw income gap in paid AI adoption is explained by occupation, industry, location, and demographics, and leaving a conditional income response slightly smaller than those

11. On the same open-banking accounts, the estimated relationship between paid AI adoption and log card spending is roughly one-third smaller than the relationship with log net salary, showing that proxying for income with card spending understates the true relationship with earnings.

12. A one-unit increase in log pay corresponds to multiplying take-home pay by $e \approx 2.7$; equivalently, doubling a worker’s take-home pay is associated with a $5.6 \times \ln(2) \approx 3.9$ percentage point increase in paid AI adoption before controls, falling to $2.0 \times \ln(2) \approx 1.4$ percentage points after accounting for occupation, industry, location, and demographics.

of Spotify (3.1 percentage points) and Netflix (2.6 percentage points).¹³

4.2 Occupational Differences

Paid AI adoption also varies sharply across occupations (Autor, Levy, and Murnane, 2003; Acemoglu and Restrepo, 2018; Eloundou et al., 2024). Figure 4 reports active June 2026 paid AI adoption across 34 professions identified directly from registration fees and membership dues paid to professional regulators, royal colleges, and trade unions.¹⁴

On directly billed subscriptions (Figure 4), active June 2026 adoption spans a twelve-fold range across the displayed professions (and more than ninefold across professions with at least 150 active accounts). Adoption is highest among IT professionals (20.3%), higher- and further-education lecturers (16.0%), finance and insurance professionals (15.8%), project and procurement managers (13.8%), and marketing specialists (12.8%); intermediate (6% to 9%) across surveyors (8.2%), engineers (7.5%), school teachers (7.5%), medical doctors (7.0%), and human-resource professionals (6.5%); and lowest (under 3%) in manual trades, emergency services, and hands-on care professions such as electricians (2.9%), construction workers (2.9%), nurses and midwives (2.5%), firefighters (2.5%), and social care workers (1.7%). Including mobile app-store subscriptions raises subscription rates across the board while leaving the ranking of occupations almost unchanged (with a rank correlation of 0.9; Appendix Table A9).

Figure 5 compares 12-month active paid assistant adoption across 51 professions against two external benchmarks (Appendix Table A10). In Panel (a), UK paid AI adoption aligns closely with US survey measures of self-reported workplace AI usage from Bick, Blandin, and Deming (2026), explaining $R^2 = 69.4\%$ of the employment-weighted variation across the 51 professions (and $R^2 = 90.0\%$ across all 26 broad UK occupational groups covering the entire workforce). In Panel (b), UK paid AI adoption also aligns closely with the task-based GPT-4 exposure index of Eloundou et al. (2024), which measures the share of an occupation's tasks that can be sped up by large language models ($R^2 = 63.1\%$): moving up by one standard deviation in

13. As shown in Appendix D, this two-thirds reduction is robust both when restricting occupational controls to directly observed professional membership and employer labels and when estimating the regressions on directly billed web subscriptions alone. Within named employers with at least 50 salaried accounts in our dataset (where job seniority and occupation vary across pay grades inside the firm), active direct paid AI adoption rises from 5.9% in the bottom fifth of earners within the firm to 10.0% in the top fifth, whereas Netflix and Spotify adoption are flat across within-firm pay levels.

14. As described in Section 2 and Appendix D, we identify a worker's specific profession when they pay registration fees or membership dues to one of 466 occupation-specific bodies (such as the General Medical Council or Solicitors Regulation Authority). Figure 4 plots the 34 professions meeting our minimum sample-size rules on card accounts where privacy filters do not obscure merchant names; Appendix Tables A8–A10 report full results across all 65 professions and across all payment channels.

occupational task exposure is associated with a 5.1 percentage point higher rate of paid AI adoption. In individual-level regressions across our open-banking sample (Appendix Table A10, Panel C), both workplace survey usage and GPT-4 task exposure remain strong, statistically precise predictors of personal out-of-pocket AI adoption even after accounting for age, gender, region, and individual take-home pay.

4.3 Industry and Geography

Grouping salaried workers by the UK Standard Industrial Classification (SIC 2007) industry of their employer reveals a parallel pattern across sectors (Appendix Figure A5a). Among salaried workers linked to an employer industry (where mean cumulative adoption is 14.2%), adoption across major sectors is highest in software and information technology (27.0%), advertising and market research (26.6%), publishing and broadcasting (24.2%), education (18.2%), and management consulting (16.6%), and lowest in retail (11.8%), human health (12.2%), and public administration and defense (11.6%). Notably, in our open-banking records only 13.8% of consumer AI subscription charges are followed within 30 days by any non-payroll transfer from the account holder's employer—virtually identical to the background rate of employer transfers in random non-AI months on the same accounts (12.6%) and the rate for entertainment streaming (13.8%; Appendix D)—indicating that personal AI subscriptions rarely reflect separately reimbursed employer expenses.

Occupational and industrial sorting also produces stark geographic concentration across the United Kingdom. Mapping cumulative paid AI adoption across 2,533 Great Britain postcode districts (Figure 6) and comparing local-authority adoption across 361 Local Authority Districts (Appendix Figure A7) reveals pronounced clustering in London and major university or technology hubs such as Oxford, Cambridge, Edinburgh, and Reading. Across Great Britain in June 2026, active paid general-purpose assistant adoption in London (6.8%) is nearly twice as high as outside London (3.6%), with a nearly fourfold gap between the top and bottom tenths of local authorities (3.8 to 1). Across local authorities, cumulative adoption correlates strongly with both the local share of residents in managerial and professional occupations ($r = 0.7$) and local disposable household income per head ($r = 0.7$), with a single summary index combining local professional employment, household income, and young-adult population share accounting for nearly two-thirds (64%) of the geographic variation across Britain.¹⁵

15. This summary index is the first principal component of the local managerial and professional employment share, ONS Gross Disposable Household Income per head, and the share of residents aged 20–34 across Great Britain local authorities; see Appendix E.

5 Competition, Pricing Tiers, and Switching Across AI Providers

5.1 Market Shares and Provider Differentiation

Because our transaction dataset follows the same individuals across competing sellers over time, we can measure both how spending shares have shifted across leading AI providers and how different groups of workers choose between them.

For nearly three years after launching ChatGPT Plus in February 2023, OpenAI held a near-monopoly in paid consumer AI. As late as December 2025, ChatGPT captured 73.5% of directly billed consumer AI subscription spending across standalone AI products (Figure 8) and was held by 88.3% of active general-purpose assistant subscribers (Appendix Table A2), whereas Anthropic’s Claude accounted for just 7.4% of standalone subscription spending and 6.5% of active assistant subscribers.

Over the first seven months of 2026—following Anthropic’s release of Claude Opus 4.5 in November 2025 and rapid uptake of its coding and desktop tools (Claude Code)—Claude’s share of direct consumer spending on standalone AI subscriptions quadrupled from 7.4% in December 2025 to 29.4% in July 2026, while ChatGPT’s spending share fell by 21 percentage points from 73.5% to 52.5% (Figure 8).¹⁶ Measured by active general-purpose assistant subscribers (Appendix Table A2), ChatGPT is held by 71.2% of assistant subscribers in July 2026 versus 27.1% for Claude, while Claude generates substantially higher average revenue per subscriber.

Rather than competing for an identical pool of customers, Claude and ChatGPT attract very different occupations and industries. Figure 7 plots each profession’s Claude share among direct subscribers of Claude or ChatGPT minus the 22.6% overall average across the 16 professions with at least 10 direct subscribers to each provider.¹⁷ While ChatGPT retains a majority of cumulative direct subscribers in every profession, technical, financial, and analytical professions lean strongly toward Claude relative to the average across all subscribers—led by finance and insurance professionals (+13.3 percentage points), university and college lecturers (+8.1 percentage points), civil servants (+8.1 percentage points), accountants (+7.4 percentage points), marketing

16. The spending shares in Figure 8 are computed across directly billed standalone AI subscriptions on card accounts where privacy filters do not obscure merchant names, reweighted to match the UK adult population (so ChatGPT and Claude together account for 81.9% of standalone spending in July 2026, with Gemini and specialist tools accounting for the remainder; see Section 2 and Appendix C). When mobile app-store subscriptions are included, Claude’s spending share rises nearly fourfold from 6.1% in December 2025 to 22.8% in July 2026 (Appendix Table A2).

17. As described in Section 2, professions are identified from registration fees and membership dues paid to professional regulators, royal colleges, and trade unions.

specialists (+4.1 percentage points), medical doctors (+3.6 percentage points), and chartered engineers (+2.3 percentage points). Conversely, classroom, clinical, and human-resource professions rely much more heavily on ChatGPT: relative to the overall benchmark, Claude’s share is lower by 9.1 percentage points among school teachers, 8.2 percentage points among allied health professionals, 8.1 percentage points among human-resource specialists, and 6.7 percentage points among nurses and midwives.

Grouping workers by their employer’s industry shows a parallel split (Appendix Figure A5b): relative to the 15.3% salaried average, employees in software and IT lean toward Claude by 11.4 percentage points alongside workers in publishing, advertising, consulting, scientific R&D, and finance, whereas employees in public administration (−6.0 percentage points) and health (−5.6 percentage points) strongly favor ChatGPT. Likewise, linking assistant choice to payments for standalone software-development tools (such as Cursor, GitHub Copilot, Replit, and Lovable) highlights strong sorting among software developers: consumers who pay for standalone coding tools are more than twice as likely to choose Claude for their general assistant subscription as other assistant subscribers (46.8% versus 21.6%; Appendix E).

5.2 Pricing Tiers, Switching, and Model Releases

Why does Claude command a higher share of subscription spending than of active subscribers, and how much of its 2026 surge came from subscriber growth versus expensive power-user plans and switching from ChatGPT? Figure 9 examines four channels: price tiers, entry-level plans, cross-platform switching, and responses to major model releases.

At the standard subscription tier (£20 per month for ChatGPT Plus and £18 to £20 per month for Claude Pro), the average monthly price paid by UK subscribers remained stable at roughly £19 from early 2023 to mid-2026. Rather than competing through price cuts on the £20 tier, OpenAI and Anthropic expanded their product menus at the top and bottom of the price distribution (Mussa and Rosen, 1978). At the top of the menu, both providers introduced high-capacity plans priced at or above £80 per month—ChatGPT Pro at £160–£200 per month in December 2024, and Claude Max at £90 and £180 per month in April 2025—which offer much higher usage limits and integrated coding features such as Claude Code. Figure 9(a) shows that by mid-2026, 6.2% of active Claude subscribers pay £80 or more per month, compared with just 0.3% of active ChatGPT subscribers—a twenty-to-one ratio (and in account-level transitions in Appendix Table A11, 6.2% of Claude Pro accounts upgrade to Max plans versus 0.7% of ChatGPT Plus accounts upgrading to higher-priced plans). As a simple benchmark,

if we replace all £80+ power-user payments in July 2026 with each provider’s standard £20 monthly plan, virtually all of Claude’s spending-per-subscriber premium over ChatGPT disappears (£29 versus £20 falling to roughly £20 for both) and Claude’s July 2026 direct spending share falls from 29.4% to 23.6%. Applying this same £20 cap over time shows that roughly three-quarters (76%) of Claude’s direct spending-share gain between December 2025 and July 2026 comes from growth in its subscriber base, while one-quarter (24%) comes from uptake of £80+ power-user plans (Appendix E.2).

At the bottom of the menu, OpenAI introduced an entry-level plan, ChatGPT Go, priced at £7 to £8 per month, with roughly three-fifths (59%) of its UK subscriptions billed through mobile app stores. Figure 9(b) breaks down UK ChatGPT Go buyers by their prior AI payment history: 70.2% had never previously paid for an AI subscription, 12.2% returned to OpenAI after a previously cancelled subscription, 11.9% moved down from an active higher-priced ChatGPT plan, and 5.8% held or returned from a competing provider. The sub-£10 tier thus primarily brought new mobile users into paid AI rather than cannibalizing existing £20 subscribers.

Growth at Anthropic combined entry by new subscribers with a sharp rise in direct switching from ChatGPT. Tracking the direct payment history of new Claude subscribers shows that two-thirds (66.7%) had no prior direct ChatGPT payments on their account, while roughly one-fifth were former ChatGPT subscribers who had cancelled and one-seventh held an active ChatGPT subscription when starting Claude.¹⁸ At the same time, switching from cancelled ChatGPT subscriptions rose sharply in spring 2026. Figure 9(c) tracks direct ChatGPT subscribers who cancel in each month and plots the percentage who start a paid Claude subscription within 60 days. Throughout 2025, only 1.4% of cancelling ChatGPT subscribers switched to Claude within 60 days; between March and May 2026, that 60-day switching rate rose more than eightfold to 11.7% (10.5% on direct web charges alone).

Finally, Figure 9(d) shows that consumer sign-ups respond very differently across providers to major model releases. Because AI subscriptions were growing rapidly over this period even in weeks without a product launch, we compare first-time paid sign-ups in the 14 days following major model launches against the preceding four weeks and benchmark those changes against randomly chosen dates (Figure 9d; event list in Appendix E.2). Major Anthropic releases are associated with a 39.5% jump in new sign-ups compared with a 10.0% average two-week increase on random comparison dates—a net surge of nearly 30 percentage points above normal trend

18. Within general-purpose assistants, most subscribers pay for only one provider at a time: just 4.2% of active assistant subscribers in a given month pay two or more assistant providers concurrently, whereas users of specialist voice, image, and coding tools frequently pair them with a general assistant (Appendix E.2 and Appendix Figure A8).

growth—whereas OpenAI releases change first-time sign-ups by just 1.9% (versus 3.4% on random dates) and Google releases by 12.2% (versus 4.3% on random dates). For a challenger growing from a smaller customer base, major model releases attract new payers into the market and accelerate market-share gains.

6 Concluding Remarks

Combining UK consumer bank and card records covering 14.2 million accounts with direct and mobile app-store subscription measures and individual demographic, income, and occupational data, this paper provides a comprehensive portrait of who pays for consumer artificial intelligence, how rapidly paid adoption is spreading, and how consumers choose among competing providers. By June 2026, an estimated 5.1% of UK adults (2.8 million people) held an active paid standalone AI subscription, with 88% of total spending growth driven by an expanding share of adults paying rather than higher average spending per subscriber.

Who adopts paid AI varies sharply across the population, even as the profile of new subscribers has broadened over time. Adoption is nearly fivefold higher among adults aged 20–29 than among those aged 60 and over after accounting for income, gender, and region, and 27% higher among men than women, though the male-to-female ratio among first-time payers narrowed from 3.0 to 1.2 between early 2023 and mid-2026. Paid adoption is 78% higher in the top than in the bottom fifth of the salary distribution, while nearly two-thirds of the raw relationship between salary and adoption is explained by differences in occupation, industry, location, and demographics. Across 34 professions identified from professional membership payments, active direct adoption spans a twelvefold range in close alignment with US workplace survey usage and occupational GPT-4 task exposure, while across Great Britain local authorities adoption spans a nearly fourfold range between the top and bottom tenths of areas.

Finally, following individual subscribers across sellers reveals rapid, differentiated competition between OpenAI’s ChatGPT and Anthropic’s Claude. Between December 2025 and July 2026, Claude’s share of direct standalone AI subscription spending rose fourfold from 7.4% to 29.4% while ChatGPT’s spending share declined from 73.5% to 52.5%, as Claude’s share of active assistant subscribers expanded from 6.5% to 27.1% (against 71.2% for ChatGPT). This revenue shift reflects both rapid subscriber growth—supported by strong occupational sorting among technical, financial, and academic workers, an eightfold rise in 60-day switching from cancelling ChatGPT subscribers, and sharp sign-up responses to major model releases—and twenty-to-one

uptake of £80+ power-user plans (6.2% versus 0.3%), which accounts for why Claude's spending share exceeds its subscriber share.

Several limitations of our data suggest fruitful directions for future work. Consumer bank and card records measure personal out-of-pocket spending and renewals across competing providers, but they do not observe unpaid free-tier usage, individual prompts, employer-paid corporate licenses, or account sharing within households, and mobile app-store billing obscures provider identities on bank statements. Extending this transaction-based approach across countries, studying subscription pricing and switching using models of consumer demand (Mussa and Rosen, 1978; Klemperer, 1995; Brynjolfsson et al., 2026), and tracking longer-run labor-market outcomes as AI tools mature remain important priorities for future research.

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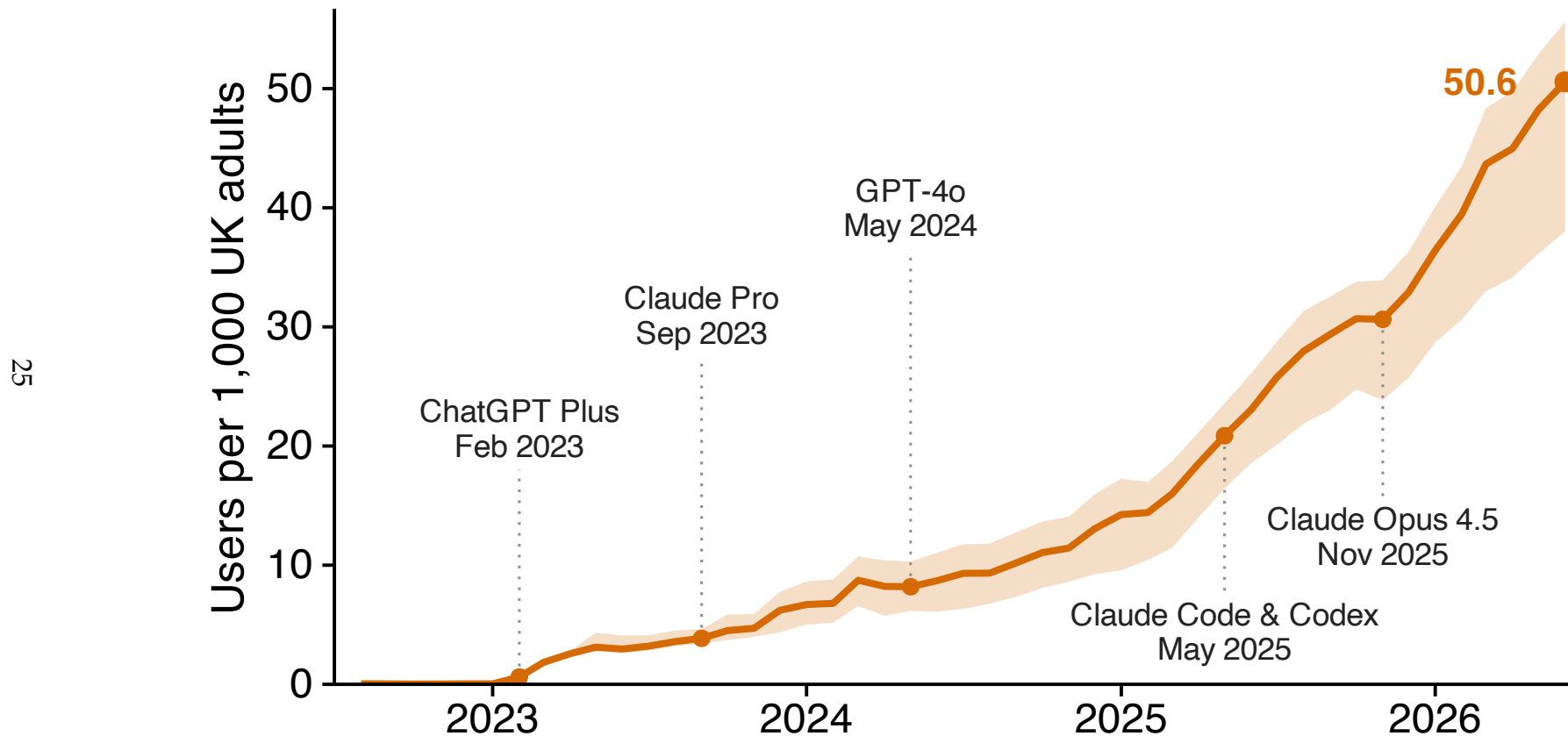
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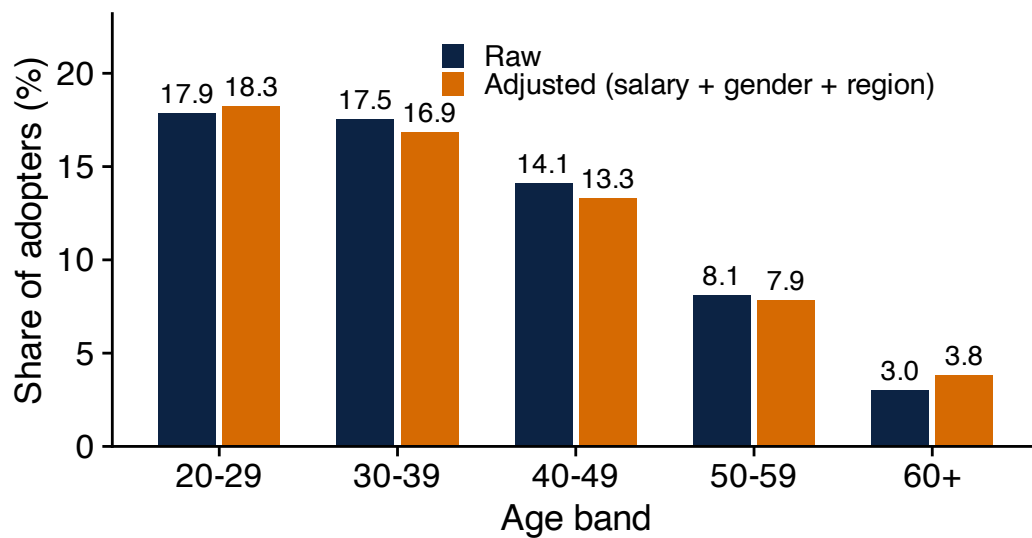
Figure 1: Paid Standalone AI Subscriptions Doubled Annually Since 2024, Reaching 5.1% of UK Adults



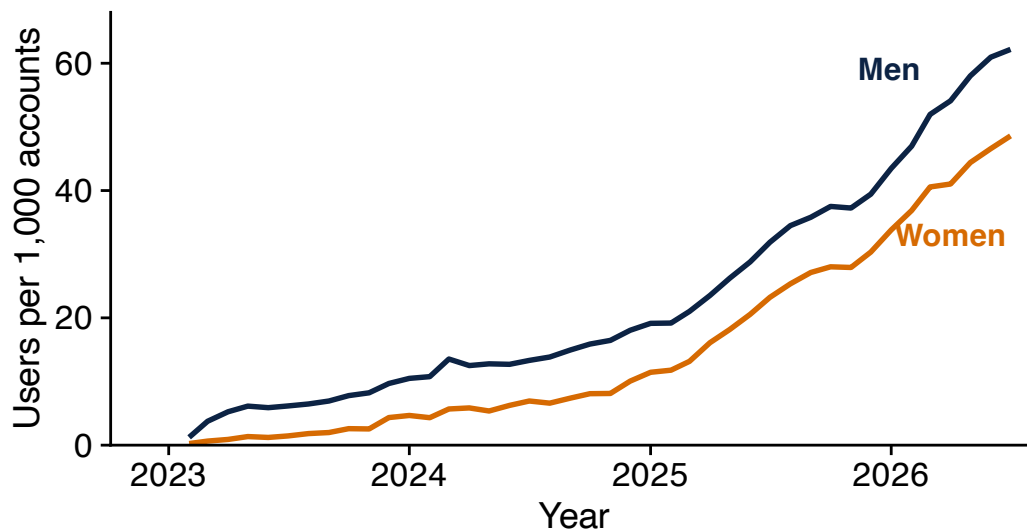
Notes: This figure plots active monthly paid standalone AI subscribers per 1,000 UK adults from January 2023 to June 2026. The series combines direct web subscriptions with mobile app-store subscriptions (described in Section 2 and Appendix B), with the shaded band showing 95% bootstrap confidence intervals. Active accounts are reweighted each month using demographic, regional, and income benchmarks to represent the UK adult population (Appendix C). Vertical dotted lines mark major product and model launches.

Figure 2: Young Adults and Men Adopt Paid AI at Substantially Higher Rates

(a) Raw and Adjusted Cumulative Adoption by Age Band



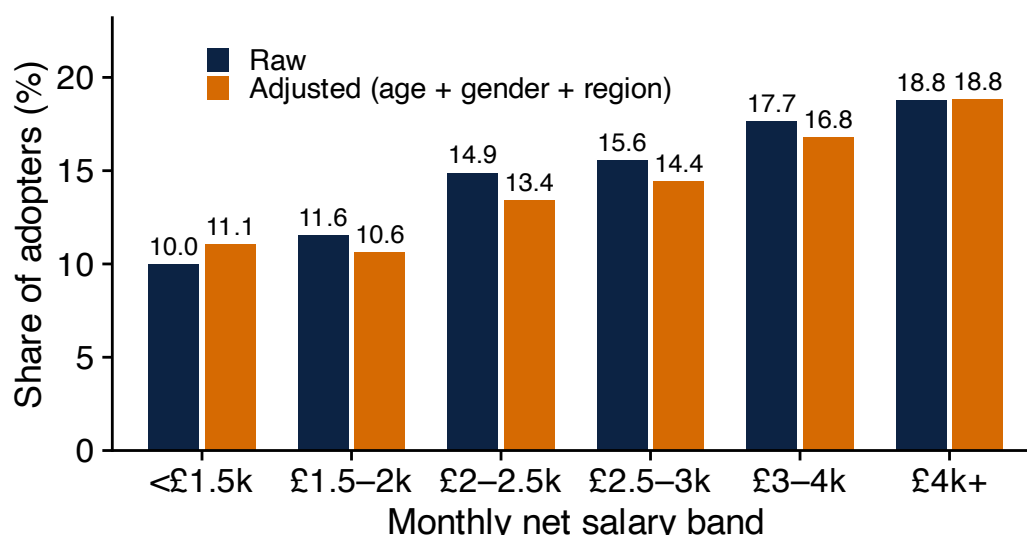
(b) Active Paid AI Subscribers per 1,000 Adults by Gender



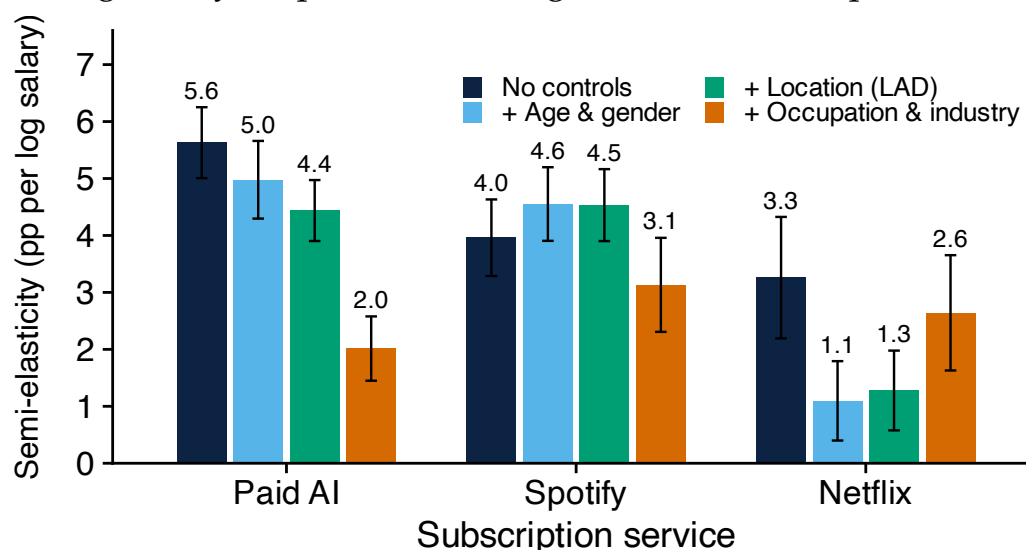
Notes: Panel (a) plots the percentage of adults in each age band who have ever held a paid AI subscription since November 2022, shown before adding controls (navy bars) and after accounting for after-tax income, gender, and UK region (orange bars). Panel (b) plots monthly active paid AI subscribers per 1,000 adults separately for men and women from February 2023 through July 2026. Active accounts are reweighted using demographic and regional benchmarks to represent the UK adult population (Appendix C).

Figure 3: Paid AI Adoption Rises With Earnings, Driven Primarily by Occupation and Industry

(a) Raw and Adjusted Adoption by Monthly Net Salary Band

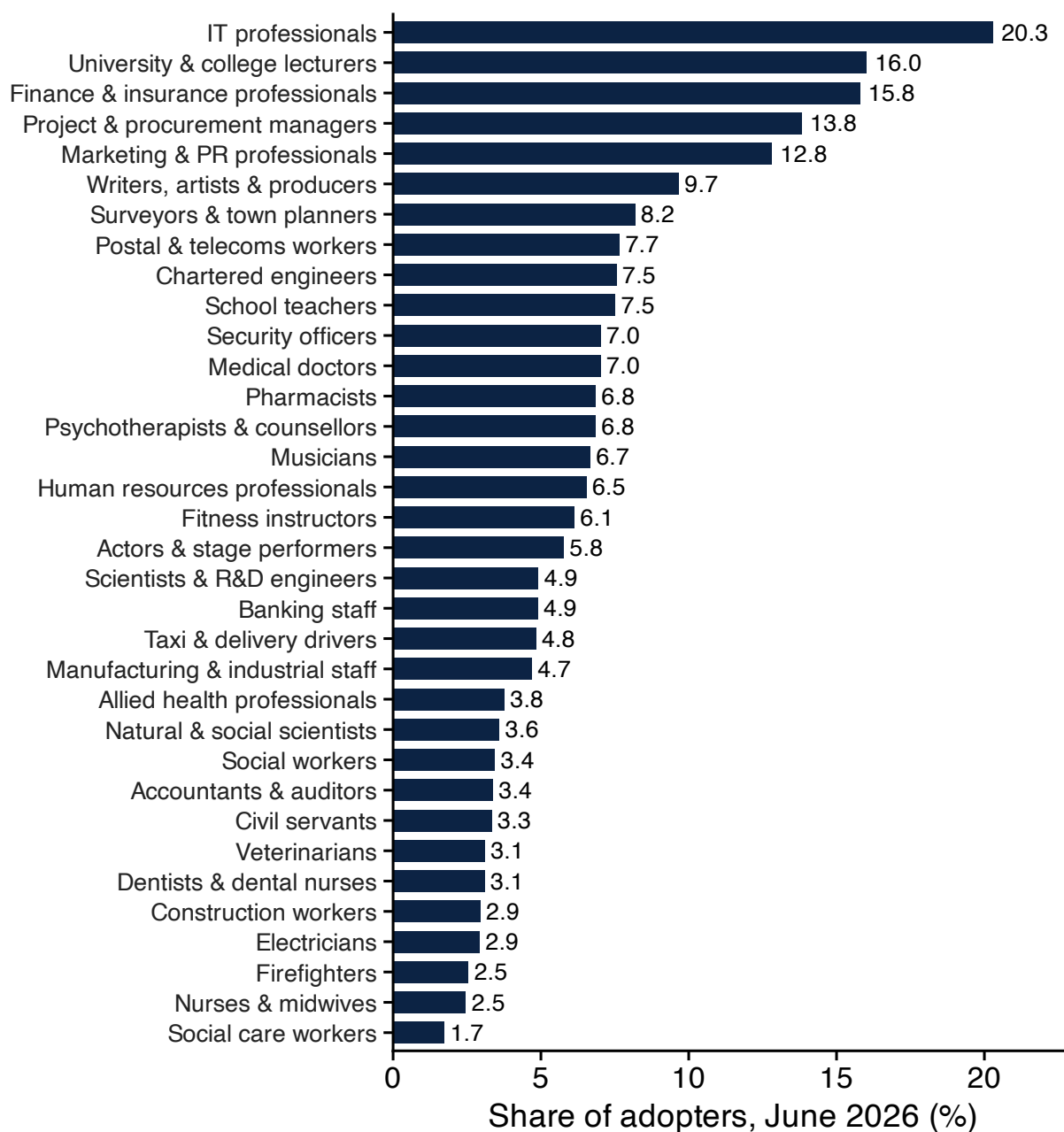


(b) Log-Salary Slopes Across Progressive Control Specifications



Notes: Panel (a) plots the percentage of salaried workers in each monthly net take-home pay band who have ever held a paid AI subscription across 390,404 salaried open-banking accounts, shown before adding controls (navy bars) and after accounting for age, gender, and UK region (orange bars). Panel (b) plots the percentage-point change in cumulative adoption associated with a one-log-point increase in monthly net take-home salary (with 95% confidence intervals clustered by local authority) for Paid AI, Spotify, and Netflix as controls for age and gender, local authority district, and occupation and employer industry are added step by step. Accounts are reweighted to represent the UK adult population; occupational and industry classifications are described in Section 2 and Appendix D.

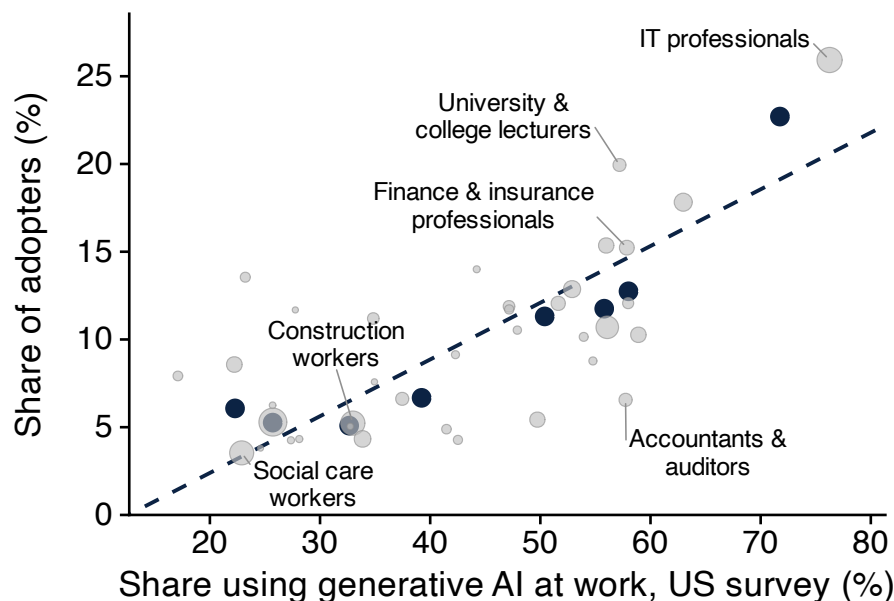
Figure 4: Paid AI Assistant Adoption Varies Twelvefold Across Occupations



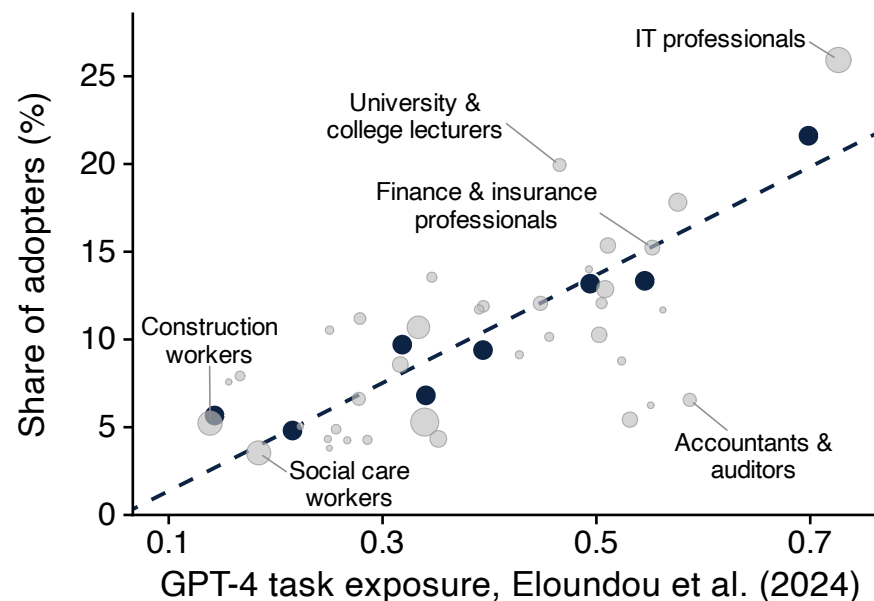
Notes: This figure plots the percentage of workers in each profession holding an active direct paid AI subscription in June 2026 across 34 professions with at least 50 active accounts and at least 10 active June subscribers (results across all 65 professions and across all payment channels are reported in Appendix Table A9). Professions are identified directly from registration fees and membership dues paid to professional regulators, royal colleges, and trade unions (Section 2 and Appendix D), evaluated on card accounts where privacy filters do not obscure merchant names, reweighted to match the UK adult population.

Figure 5: Occupational Paid AI Adoption Closely Tracks Workplace Survey Usage and Task Exposure

(a) UK Paid Adoption vs. US Survey Usage
($R^2 = 69.4\%$)

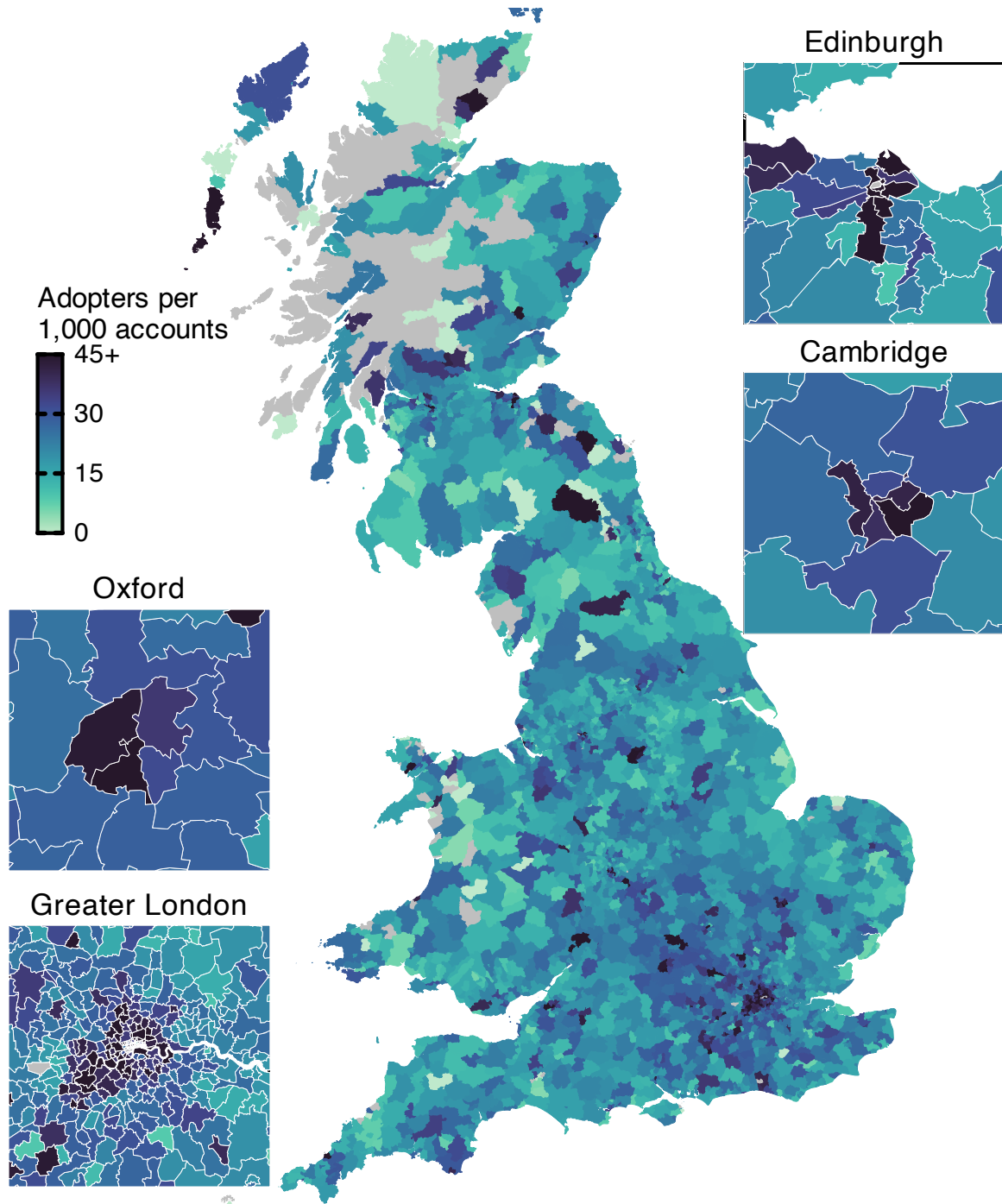


(b) UK Paid Adoption vs. GPT-4 Exposure
($R^2 = 63.1\%$)



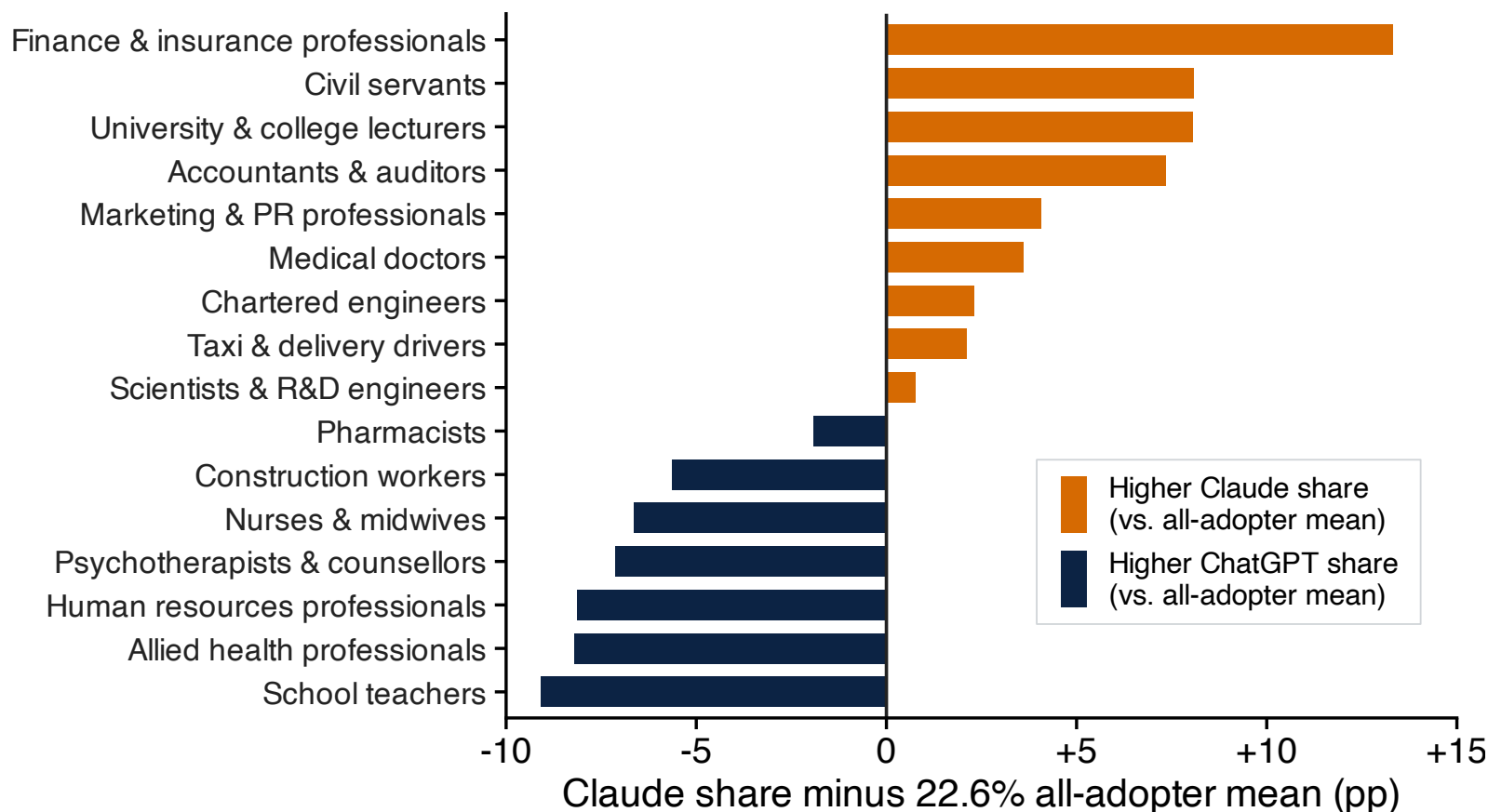
Notes: This figure compares 12-month active paid AI assistant adoption across 51 professions in our UK dataset against US survey self-reported workplace generative AI usage from Bick, Blandin, and Deming (2026) in Panel (a) and the task-based GPT-4 exposure index of Eloundou et al. (2024) in Panel (b). Dark navy circles denote eight equal-employment group averages, grey circles denote individual occupations scaled by UK Annual Population Survey employment, and dashed lines show employment-weighted linear fits. Full regression results and occupational classification details are reported in Appendix D.

Figure 6: Paid AI Adoption Clusters in London and Major University and Tech Hubs



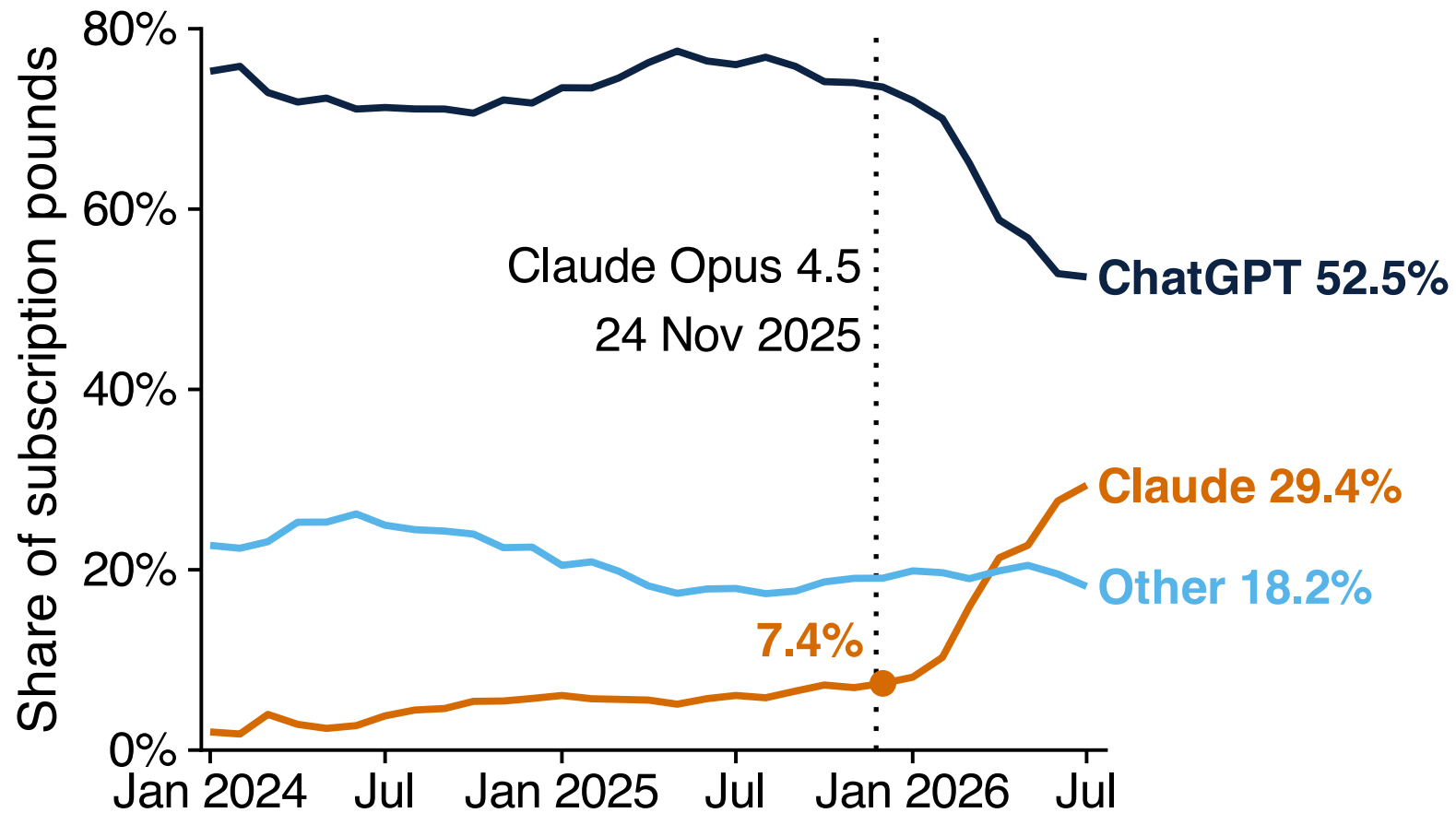
Notes: This figure maps cumulative paid AI adopters per 1,000 accounts across 2,533 Great Britain postcode districts (with districts containing fewer than 50 accounts shaded grey). Surrounding the main map are four urban zoom insets on the same colour scale for Edinburgh, Cambridge, Oxford, and Greater London. Population-reweighted comparisons across Local Authority Districts are reported in Section 4 and Appendix E.

Figure 7: Technical, Financial, and Academic Professions Lean Toward Claude Over ChatGPT



Notes: This figure plots provider choice across the 16 professions with at least 10 cumulative direct subscribers to each provider (Claude and ChatGPT), identified from registration fees and membership dues paid to professional regulators, royal colleges, and trade unions. Each horizontal bar reports the percentage of direct Claude or ChatGPT subscribers in that profession who pay for Anthropic's Claude minus the 22.6% average across all subscribers. While ChatGPT holds a majority of cumulative direct subscribers in every profession, positive values (orange bars) indicate professions that lean toward Claude relative to the overall average and negative values (navy bars) indicate professions that lean toward ChatGPT (Appendices C and D).

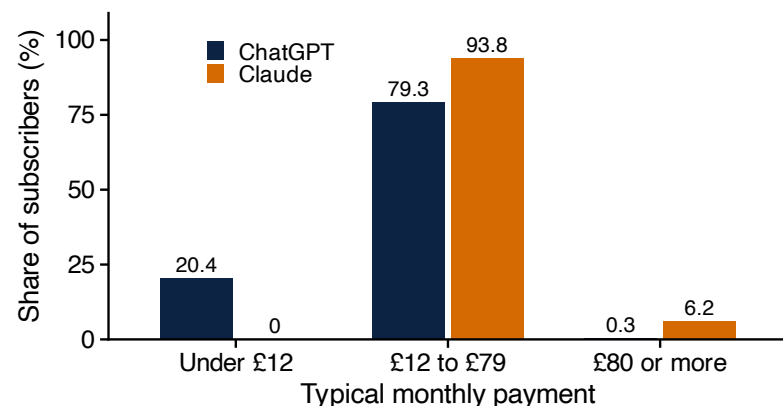
Figure 8: Claude's Share of Consumer AI Spending Quadrupled in Early 2026 as ChatGPT's Fell



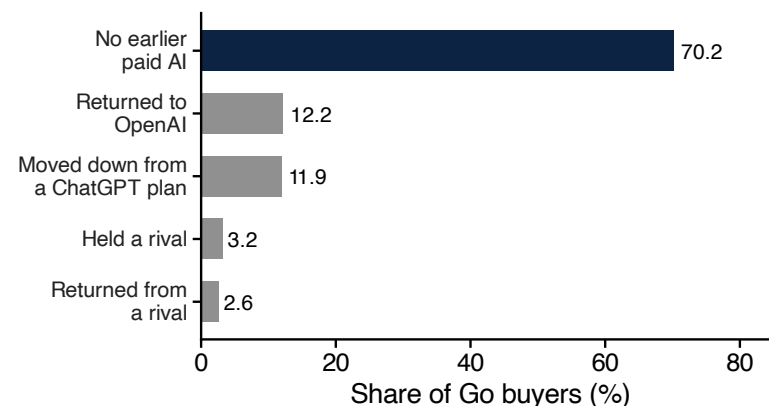
Notes: This figure plots monthly provider shares of directly billed standalone consumer AI subscription spending from January 2023 to July 2026 on card accounts where privacy filters do not obscure merchant names, reweighted to match the UK adult population (Section 2 and Appendix C). Active subscriber shares and supplementary competition analyses are reported in Appendix E.2.

Figure 9: Pricing Tiers, Switching, and Responses to Model Releases

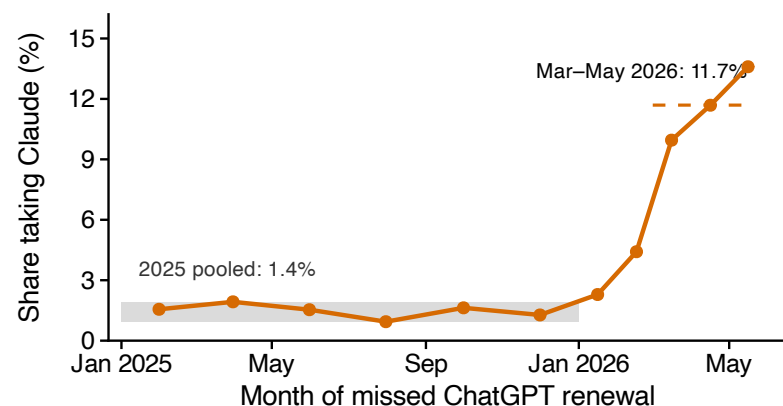
(a) Claude Users Take Up £80+ Plans at 20× ChatGPT



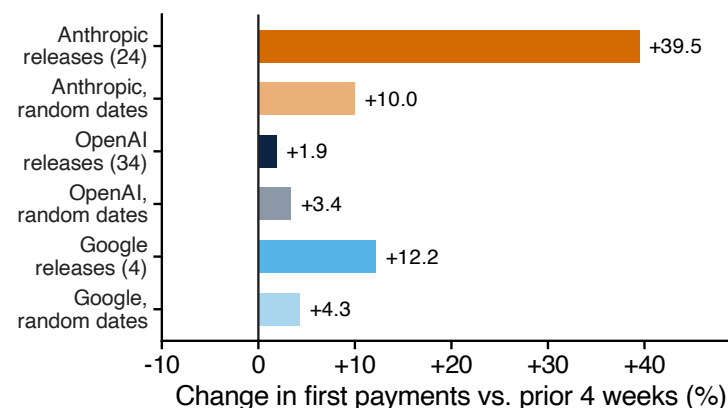
(b) ChatGPT Go Primarily Attracts First-Time Payers



(c) Switching From ChatGPT to Claude Surged in 2026



(d) Anthropic Releases Trigger Sharp Sign-Up Surges



Notes: Panel (a) plots the distribution of active ChatGPT and Claude subscribers across monthly price tiers (under £12, £12 to £79, and £80 or more). Panel (b) breaks down buyers of OpenAI's entry-level ChatGPT Go plan (£7 to £8 per month) by their prior AI payment history. Panel (c) plots the percentage of cancelling ChatGPT subscribers in each month who start a paid Claude subscription within 60 days. Panel (d) compares the percentage change in first-time provider sign-ups in the 14 days following major model launches against pre-release levels and 300 random comparison dates. Accounts are reweighted to represent the UK adult population; see Appendix E.2 for further details.

Table 1: Identifying and Measuring Paid AI in Consumer Transaction Records

Panel A. Examples of Transaction Descriptions and Classification Rules						
Raw description (as received)	Amount	Month	Channel / MCC	Category	Matching rule	
openai *chatgpt subscr san francisco ca	£20.00	Jul 2026	Direct / 5734	Direct AI	Text match openai; ChatGPT Plus £20 plan	
claude.ai subscription san francisco ca	£18.00	May 2026	Direct / 5734	Direct AI	Text match claude.ai; Claude Pro £18 plan	
anthropic* claude sub san francisco ca	£90.00	Jul 2026	Direct / 5734	Direct AI	Text match anthropic; Claude Max £90 plan	
www.perplexit	£15.84	Jun 2026	Direct / 5734	Direct AI	Text match perplexit; \$20 USD plan	
cursor, ai powered ide new york ny	£14.91	Oct 2025	Direct / 5734	Direct AI	Text match cursor; \$20 USD plan	
apple.com/bill	£19.99	Jun 2026	App store / 5735	Mobile AI	Monthly iOS subscription at £19.99 Plus price	
apple.com/bill	£8.00	Jun 2026	App store / 5735	Mobile AI	Monthly iOS subscription at £8.00 Go price	
google *google play	£18.00	Jun 2026	App store / 5817	Mobile AI	Monthly Android subscription at £18.00 Pro price	
Panel B. External Validation Benchmarks						
Validation check		Benchmark / evaluation sample			Validation result	
Mobile app-store model (merchant names hidden)		Known direct AI vs. non-AI £20 subscribers			0.9 AUC; 13× jump at ChatGPT Go launch	
Open-banking net salary distribution (P30–P90)		ONS Annual Survey of Hours and Earnings (ASHE)			Within 1% of official net pay percentiles	
Jan 2024 statutory National Insurance rate cut (12% to 10%)		390,404 salaried open-banking accounts			+£31/mo observed vs. +£33/mo schedule	
Consumer digital subscription penetration (Netflix)		BARB Establishment Survey (2022–2026)			Matches 59% official UK household share	
Out-of-sample accuracy of occupational classification model		70,599 workers with known occupations (65 professions)			0.9 AUC (fee payments hidden)	
Panel C. Analysis Samples and Linked Worker Characteristics (January 2022–August 2026)						
Sample or linked characteristic		Definition / source			Sample size / coverage	
All consumer payment records		All consumer bank and card accounts			14.2M accounts (8M weekly transactions)	
Active main account sample (headline national panel)		≥ 20 non-AI transactions/mo, ≥ £100/mo spend			457,072 active accounts (Jun 2026)	
Open-banking salaried sample		Regular incoming bank salary deposits			390,404 active salaried accounts	
Employer industry (21 UK SIC industry sections)		Companies House & public-sector directories			19,876 employers (65% of salaried)	
Individual occupation (65 professions & 26 broad UK groups)		466 professional bodies/unions + spending model			70,599 directly identified + 1.7M predicted	

Notes: Panel A shows illustrative transaction descriptions from our UK bank and card dataset for direct AI subscriptions and recurring mobile app-store charges (apple.com/bill and google *google play). Panel B summarizes our external validation checks across mobile app-store subscriptions, open-banking salaries, consumer subscriptions, and worker occupations (Appendices B–D). Panel C summarizes our analysis samples and linked worker characteristics (Appendix C).

Who Pays for AI?

Online Appendix

Nikhil Datta Peter John Lambert Patrick Schneider

A Classifying Transactions as AI

This appendix details our direct classification of AI payments from raw bank and card merchant descriptors and our inference of active subscription spells from discrete billing sequences.

A.1 AI Product Directory and Classification Rules

We construct a comprehensive directory of standalone AI products across our bank account and card transaction records between January 2022 and August 2026, identifying 249 sellers. Table A1 lists the top 50 sellers, which account for 89.4% of transactions, and 87.8% of spending. For each product, our directory records the billing-descriptor patterns that identify the seller, its subscription plan prices, and its product launch dates.

For dedicated AI providers (such as OpenAI, Anthropic, Midjourney, ElevenLabs, Suno, Perplexity, xAI, and Cursor), a matching merchant description directly identifies an AI purchase. Where a parent technology company also sells non-AI consumer cloud storage or developer software under the same corporate billing stem (such as Google One, Microsoft Copilot Pro, or GitHub), we require either a charge at the exact registered AI subscription price point or an explicit AI signal in the billing string. Pre-existing software suites that later added AI features to existing subscription plans (such as Microsoft 365, Canva, Adobe, Grammarly, Notion, Google Workspace, and Duolingo) are excluded from our main AI measures.

Table A1: Top 50 Standalone AI Products in Direct UK Bank and Card Billing

#	Product	Accounts	Transactions	Spend (£k)	#	Product	Accounts	Transactions	Spend (£k)
1	OpenAI (ChatGPT)	58,294	329,463	6,285	26	Gamma	924	3,821	69
2	Anthropic (Claude)	14,928	65,728	1,783	27	OpenArt	859	3,177	74
3	Use AI (use.ai)	6,678	18,793	211	28	Pixella.ai	850	1,851	30
4	Midjourney	6,228	35,601	555	29	Motion (usemotion)	842	1,948	141
5	Google (Gemini / One AI)	4,638	19,038	353	30	Kling (Kuaishou)	808	3,479	56
6	QuillBot	4,162	11,801	290	31	Base44 (Wix)	808	2,413	112
7	ElevenLabs	4,119	17,281	213	32	OpusClip	801	3,105	65
8	Suno	2,649	11,034	134	33	Runway	800	2,274	59
9	TeachMate AI	2,482	17,916	147	34	Wordtune	753	2,848	81
10	BitePal	2,011	3,469	82	35	Otter.ai	745	4,661	110
11	JustDone AI	1,921	3,560	48	36	OpenRouter	695	3,259	39
12	GitHub Copilot	1,668	10,252	92	37	ChatBot AI / Chatbot App (Paddle)	651	1,802	37
13	Lovable	1,660	8,177	260	38	VEED.io	562	2,035	63
14	Cursor (Anysphere)	1,582	8,538	248	39	HeyGen	562	1,907	61
15	Remini (Bending Spoons)	1,500	4,266	25	40	Reface	540	1,710	34
16	Looka (AI logo maker)	1,342	2,661	109	41	Lovi (AI skin scanner)	539	772	22
17	Perplexity	1,310	4,254	89	42	GPTZero	538	1,494	32
18	Speechify	1,297	2,343	115	43	Descript	528	2,703	68
19	Higgsfield	1,172	4,105	161	44	AI-Pro.org	518	1,710	25
20	Replit	1,159	7,974	300	45	ScriptGPT	502	578	18
21	InVideo	1,105	3,442	110	46	scite.ai	481	1,627	24
22	Candy.ai	1,060	2,909	38	47	Aigeeny	478	3,160	238
23	xAI (Grok / SuperGrok)	962	3,050	56	48	Google Colab Pro	466	2,163	28
24	Undetectable AI	953	2,765	53	49	Crayo	423	901	17
25	Zing Coach	940	1,941	61	50	Replika (Luka)	422	881	16
Top 50 standalone AI products		110,974	656,640	13,338	<i>Share of all standalone AI</i>		<i>90.1%</i>	<i>89.4%</i>	<i>87.8%</i>
Other 199 standalone AI products		20,619	77,828	1,859	All 249 standalone AI products		123,223	734,468	15,197

Notes: This table lists the top 50 standalone AI products ranked by distinct paying accounts in our UK consumer and business bank and card records between January 2022 and August 2026, alongside summary totals for the remaining 199 standalone AI products with observed payments and all 249 standalone AI products combined. Because some accounts pay more than one standalone AI product over the sample period, distinct accounts across the top 50 products (110,974) and the remaining 199 products (20,619) sum to more than the 123,223 unique accounts across all 249 standalone AI products. General software suites that later added AI features to existing plans (such as Microsoft 365, Canva, Adobe, Grammarly, and Notion) are excluded from standalone AI measures. Classification rules are detailed in Appendix A.

B App-Store Subscription Imputation

Consumers who subscribe to AI assistants through the iOS ChatGPT, Claude, Gemini, Perplexity, or Grok mobile apps, or via Android devices, are billed by Apple or Google rather than directly by the AI provider. On UK bank and card statements, these transactions appear under generic aggregator descriptors, principally `apple.com/bill` (10.9 million charges across 540,735 accounts in 2025) and `google *google play` (3.5 million charges across 190,595 accounts). Ignoring mobile in-app billing undercounts consumer AI adoption. This appendix details our two-track methodology for recovering mobile app-store AI subscriptions.

B.1 Excess-Mass Decomposition

At the aggregate level, mobile AI assistant subscriptions generate sharp, dated structural breaks in the frequency of recurring `apple.com/bill` and `google *google play` charges at the exact price points for AI subscriptions. For example, Apple and Google bill UK consumers at fixed price tiers: £19.99 and £20.00 per month for ChatGPT Plus and Claude Pro iOS subscriptions, £18.99 per month for Google One AI Premium, £18.00 per month for Android Claude Pro, £6.99 to £8.00 per month for ChatGPT Go, and £199.99 per month for high-capacity power-user plans.

To construct our aggregate population best estimate (Table A2 and Figure A1, Panel (a)), we first isolate recurring monthly app-store sequences defined as runs of two or more charges to Apple or Google at the exact same sterling amount separated by 25 to 35 days. For each target AI price tier p active in month t , we normalize active spell counts by the monthly active account base A_t ($r_{p,t} = N_{p,t} / A_t$) and scale the twelve-month pre-May-2023 baseline rate $r_{p,\text{pre}}$ by a non-AI placebo price-tier growth index Γ_t estimated across adjacent non-AI app-store price tiers, yielding the time-varying counterfactual $\hat{N}_{p,\text{pre},t} = A_t \cdot r_{p,\text{pre}} \cdot \Gamma_t$ and the post-launch excess mass:

$$E_{p,t} = \max\{0, N_{p,t} - \hat{N}_{p,\text{pre},t}\}, \quad \pi_{p,t} = \frac{E_{p,t}}{N_{p,t}}, \quad (\text{B.1})$$

with empirical Bayes shrinkage applied across narrow composite tiers where an account's pre-existing iCloud or Google One storage plan is billed on the same invoice date.

Adding these excess-mass estimates across Apple App Store and Google Play recurring runs increases June 2026 active paid standalone AI penetration on the primary sample from the direct lower bound of 29.0 per 1,000 UK adults to 50.6 per 1,000 UK adults with a 95% bootstrap confidence interval of [38.0, 55.6] across 500 draws. Figure A1(a) shows the impact on our time-series estimates.

Across alternative counterfactual baselines for $\hat{N}_{p,\text{pre},t}$, the June 2026 app-store increment varies between +21.8 per 1,000 under a static pre-launch rate ($\Gamma_t \equiv 1$), +20.5 per 1,000 under our baseline placebo-tier growth adjustment, +18.9 per 1,000 under linear tier-neighbor drift, and +16.8 per 1,000 if composite storage-plus-AI invoices are excluded entirely.

B.2 Individual-Account Imputation and Channel Specifications

To incorporate mobile app-store subscribers into individual-level analyses of age, gender, income, industry, and tier choice, we assign each account i in the candidate recurring app-store pool $\mathcal{C}_{p,t}$ at price tier p in month t an imputed AI subscription probability $\hat{p}_{i,t}^{\text{app}}$. To ensure that excess payment runs reconcile one-for-one with unique incremental payers in our composite indicator $Y_{i,t} = D_{i,t}^{\text{direct}} + (1 - D_{i,t}^{\text{direct}})\hat{p}_{i,t}^{\text{app}}$, the candidate pool $\mathcal{C}_{p,t}$ restricts to unique accounts without a concurrent direct standalone AI subscription ($D_{i,t}^{\text{direct}} = 0$, deduplicating the $< 0.4\%$ of accounts with multiple app-store runs in the same month by retaining the highest-tier run, and netting out the empirical cross-channel overlap rate when mapping run-level excess $E_{p,t}$ to unique-account excess mass $E_{p,t}^w = 1,000 \times E_{p,t}^{\text{acct},w} / A_t^w$ evaluated under the specification's weights $w_{i,t}$ so that $\sum_i w_{i,t} = 1,000$, yielding a population-weighted mobile increment of +20.5 per 1,000 adults in June 2026 versus +26.3 per 1,000 unweighted in Table A2). We evaluate three candidate allocation rules:

1. *Rule 1 (Homogeneous excess-mass prior only)*: Assigns every post-May-2023 candidate app-store spell at price tier p in month t the uniform cohort excess-mass share $\pi_{p,t} = E_{p,t}^w / W_{p,t}$, where $W_{p,t} = \sum_{i \in \mathcal{C}_{p,t}} w_{i,t}$.
2. *Rule 2 (Account historical baseline subtraction)*: Excludes accounts whose total monthly Apple or Google spend in 2021–2022 already averaged at least £15 per month, attributing only net new app-store spending above the account's pre-AI baseline.
3. *Rule 3 (Preferred spell-cadence and supervised probability model)*: Restricts candidate spells to post-launch recurring runs with inter-charge intervals strictly between 25 and 35 days at exact AI assistant tiers on accounts with zero pre-May-2023 recurring charges at that tier, and combines the cohort excess-mass target $E_{p,t}^w$ with out-of-fold predictions $\hat{g}(X_i) \in [\epsilon, 1 - \epsilon]$ ($\epsilon = 10^{-4}$) from a gradient-boosted decision tree trained on direct web AI subscribers using exclusively non-AI account features X_i (age band, gender, ITL1 region, log non-AI card spending, count of non-AI digital subscriptions, ONS Output Area Classification supergroup, and urban-rural postal class) via Bayes odds scaling:

$$\hat{p}_{i,t}^{\text{app}} = \frac{\kappa_{p,t} \hat{g}(X_i)}{1 - \hat{g}(X_i) + \kappa_{p,t} \hat{g}(X_i)}, \quad \text{where } \kappa_{p,t} \text{ solves } \sum_{i \in \mathcal{C}_{p,t}} w_{i,t} \hat{p}_{i,t}^{\text{app}} = E_{p,t}^w, \quad (\text{B.2})$$

with boundary conventions $\hat{p}_{i,t}^{\text{app}} = 0$ if $E_{p,t}^w = 0$ (or $\mathcal{C}_{p,t} = \emptyset$) and $\hat{p}_{i,t}^{\text{app}} = 1$ if $E_{p,t}^w \geq W_{p,t}$ (in practice $E_{p,t}^w / W_{p,t} \in [0.18, 0.74]$ is strictly interior in every post-launch month, guaranteeing a unique finite $\kappa_{p,t} > 0$). An account's composite adoption indicator is $Y_{i,t} = D_{i,t}^{\text{direct}} + (1 - D_{i,t}^{\text{direct}})\hat{p}_{i,t}^{\text{app}}$, so $\sum_i w_{i,t} Y_{i,t} = \sum_i w_{i,t} D_{i,t}^{\text{direct}} + \sum_p E_{p,t}^w$.

We validate this imputation approach in three ways shown in Figure A1. First, imputed spells expand steadily after the late-May 2023 UK rollout of the ChatGPT

iOS app and co-move with direct OpenAI subscriptions ($R^2 = 0.84$). Second, on pre-launch placebo cohorts, the excess-mass estimator achieves 95.1% coverage with a six-month error of only 2.0%. Third, to verify that demographic gradients do not depend on transporting web-trained classifier weights $\hat{g}(X_i)$ to mobile users, we compare subgroup ratios across our different imputation rules and against direct non-parametric price-tier excess mass computed separately within each demographic cell. We find little sensitivity, for example the age 20–29 to 60+ adoption ratio ranges tightly from 5.7 to 5.9, the male-to-female active ratio ranges from 1.24 to 1.29, and the top-to-bottom salary-band ratio ranges from 1.84 to 1.90.

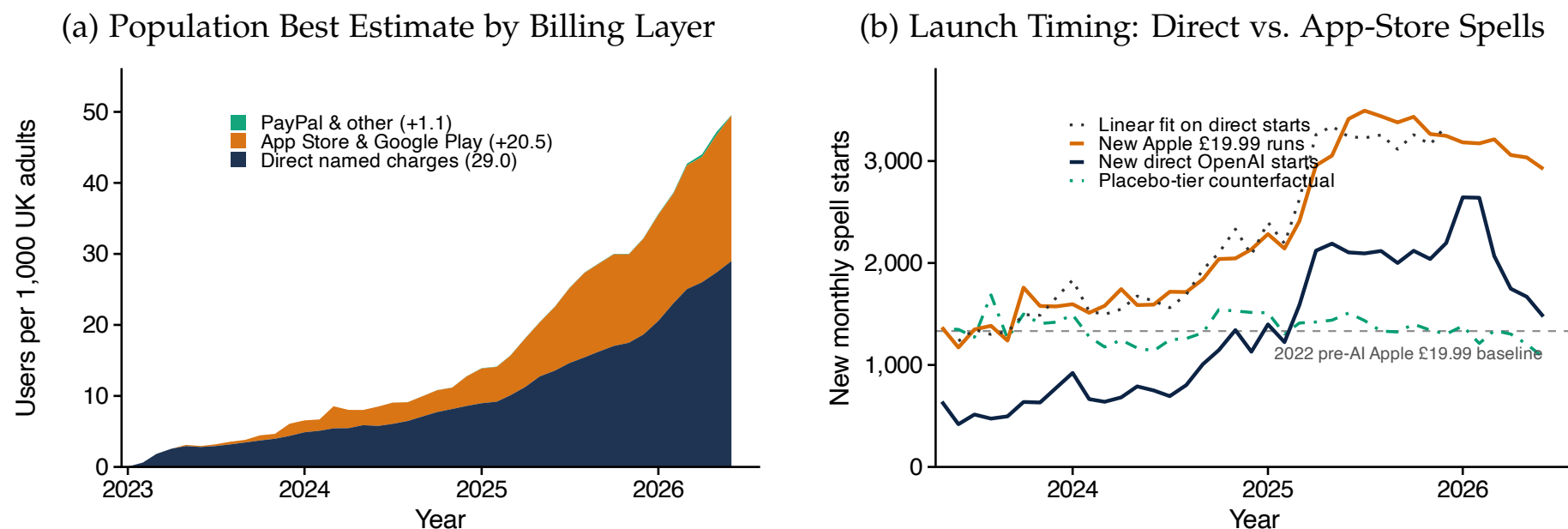
Table A2: Decomposition of Active June 2026 Paid Standalone AI Subscribers and Cross-Design Sensitivity of Headline Paper Moments

Panel A. Active June 2026 Paid Standalone AI Subscribers by Billing Channel, Sample, and Feed Type (per 1,000)						
Population and weighting specification	Accounts	Direct benchmark [95% CI]	+ App store	+ PayPal	Best estimate [95% CI]	Best / Direct
<i>Population-reweighted UK adult estimates</i>						
Rolling primary, pooled feeds (headline)	443,728	29.0 [28.4, 29.6]	+20.5	+1.06	50.6 [38.0, 55.6]	1.74
Rolling primary, 99th-percentile weight cap	443,728	29.8 [29.2, 30.4]	+21.0	+1.08	51.9 [39.0, 57.1]	1.74
Rolling primary, open-banking feeds only	273,418	34.6 [33.8, 35.4]	+20.7	+1.08	56.4 [42.4, 62.0]	1.63
Rolling primary, card-only feeds only	170,310	18.1 [17.3, 18.9]	+19.1	+1.00	38.2 [28.7, 42.1]	2.11
Fixed balanced primary, pooled feeds	172,988	31.1 [30.0, 32.2]	+20.8	+1.32	53.2 [40.3, 58.5]	1.71
<i>Unweighted consumer account panels</i>						
Rolling primary accounts, unweighted	457,072	34.2 [33.7, 34.7]	+26.3	+1.42	61.9 [45.8, 68.3]	1.81
Fixed balanced primary accounts, unweighted	181,939	32.5 [31.7, 33.3]	+23.8	+1.57	57.9 [43.7, 63.7]	1.78
All transacting consumer records, unweighted	1,437,225	15.3 [15.1, 15.5]	+12.4	+0.58	28.3 [21.8, 31.0]	1.85
Panel B. Cross-Design Sensitivity of Headline Diffusion, Heterogeneity, and Competition Moments						
Empirical moment	Unweighted Direct	Weighted Direct	Reweighted Direct (Unmasked)	All-Channel (Direct + Mobile)	Primary exhibit	
Age gradient: 20–29 vs. 60+ raw ratio (adjusted ratio)	5.70 (3.27)	6.08 (4.66)	6.18 (4.66)	5.90 (4.76)	Figure 2a	
Gender gradient: Men vs. women active Jul 2026 per 1,000 (ratio)	44.9 vs. 28.4 (1.58)	39.7 vs. 24.1 (1.65)	38.7 vs. 23.5 (1.65)	62.2 vs. 48.6 (1.28)	Figure 2b	
Salary gradient: > £4,000 vs. < £1,500 ever paid % (ratio)	14.2% vs. 5.0% (2.81)	11.8% vs. 4.6% (2.55)	10.7% vs. 4.1% (2.60)	18.8% vs. 10.0% (1.88)	Figure 3a	
Occupation spread: Top vs. bottom class active Jun 2026 % (ratio)	15.9% vs. 1.8% (8.89)	16.0% vs. 1.8% (8.94)	16.0% vs. 1.7% (9.21)	18.9% vs. 4.3% (4.44)	Figure 4	
External validation r : US survey usage / GPT-4 exposure (β)	0.89 / 0.79	0.88 / 0.77	0.89 / 0.76	0.85 / 0.75	Figure 5	
Industry adoption: Software & IT vs. all salaried ever paid (%)	12.5% vs. 5.2%	19.7% vs. 7.3%	18.6% vs. 6.8%	27.0% vs. 14.2%	Figure A5a	
Claude share of subscription pounds: Dec 2025 → Jul 2026 (%)	7.6% → 30.9%	7.9% → 29.7%	7.4% → 29.3%	5.0% → 22.5%	Figure 8	
Claude share of active subscribers: Dec 2025 → Jul 2026 (%)	6.5% → 27.8%	6.7% → 27.4%	6.5% → 27.0%	4.6% → 20.3%	Section 5.1	
Power-user tier share ($\geq$ £80/mo): Claude vs. ChatGPT (%)	8.74% vs. 0.51%	7.80% vs. 0.46%	7.32% vs. 0.44%	6.21% vs. 0.31%	Figure 9a	
60-day switching to Claude after ChatGPT exit: 2025 → 2026 (%)	1.4% → 9.3%	1.3% → 10.6%	1.3% → 10.5%	1.4% → 11.7%	Figure 9c	

Notes: Panel A decomposes active June 2026 paid standalone AI subscribers per 1,000 across account samples, weighting specifications, and billing channels, with 95% bootstrap confidence intervals in brackets. Panel B compares headline paper moments across four estimation specifications: unweighted direct payments, population-weighted direct payments, reweighted direct payments on accounts with unmasked billing descriptions, and all-channel estimates incorporating mobile app-store subscriptions. In Panel B, the occupation spread row reports the outcome-blind comparison across professions with $N \geq 150$ primary accounts, external validation r reports the unweighted correlation across the 51 professions, and the all-channel Claude pound share row includes the unallocated PayPal layer in the standalone AI spending denominator (corresponding to 6.1% → 22.8% across provider-attributed direct and app-store spending).

Figure A1: App-Store Subscription Imputation: Billing-Layer Decomposition and Launch Timing

42



Notes: Panel (a) decomposes active paid standalone AI subscribers per 1,000 UK adults in June 2026 into directly classified payments, imputed Apple App Store and Google Play subscriptions, and PayPal-routed subscriptions. Panel (b) compares monthly initiation counts of direct web OpenAI Plus subscriptions and new recurring £19.99 Apple App Store spells from May 2023 through June 2026 against the 2022 pre-AI baseline (dashed line) and the non-AI placebo-tier counterfactual (dot-dash line).

C Sample Construction, Population Weighting, and External Validation

Raw administrative bank and card panels contain secondary credit cards and dormant accounts, and their demographic composition skews younger and more urban than the national adult population as they are biased towards fintech providers. This appendix details our sample-screening ladder, our two-stage reweighting to the adult population, our regression adjustment specifications, and our supplementary external validation checks.

C.1 The Account Sample Ladder and Descriptive Statistics

Table A3 shows the count and paid AI subscriptions across progressively stricter sample selection criteria. In the unrestricted universe of 1,424,855 consumer records with at least one transaction in June 2026, direct standalone AI penetration is 15.3 per 1,000 accounts, falling predominantly as the denominator grows for low utilisation cards. Table A4 compares adoption rates across alternative definitions of an ‘active’ account, showing for example that screening cards which have at least six active months since 2022 raises adoption rates to 17.0 per 1,000.

Our analysis focuses on two primary-account samples that isolate consumers whose main day-to-day payment instrument is observed:

1. *Balanced primary panel* ($N = 178,109$ active in June 2026; 201,038 ever-active across 2022H1–2026H1): Consumer accounts that transact in every half-year from 2022H1 through 2026H1, maintain median monthly non-AI expenditure of at least £100, and average at least 20 non-AI transactions per month. Direct June 2026 penetration on this sample is 33.9 per 1,000 accounts. We use this balanced panel when measuring baseline 2022 account characteristics (Tables A5 and A6).
2. *Rolling primary sample* ($N = 457,072$ active in June 2026): Accounts meeting the same primary activity screen (≥ 20 non-AI transactions per month and $\geq$ £100 monthly spend) over a rolling twelve-month window. Because the rolling screen retains younger adults and newly opened fintech accounts that entered the panel after 2022, it captures 71.4% of all active direct AI subscribers in the raw data while yielding a similar direct adoption rate (34.2 per 1,000). Within our open-banking feeds, 390,404 primary salaried accounts have verified recurring payroll deposits for our earnings and industry analyses.

Because de-identified aggregator records do not link accounts held by the same person across different banking institutions, our headline national estimate translates calibrated primary accounts to UK adults one-for-one. Paying for an AI subscription on an unlinked secondary card would cause per-account rates to understate individual adoption, whereas holding multiple accounts that simultaneously clear our monthly activity threshold would expand the account denominator relative to individuals;

allowing the net account-to-person conversion factor to vary by $\pm 15\%$ around one-to-one places individual UK adult payers between 2.4 million (4.4%) and 3.3 million (6.0%).

Table A5 compares the baseline 2022 characteristics of future paid AI adopters ($N = 14,798$) against the balanced primary panel as a whole ($N = 201,038$). Prior to the launch of ChatGPT Plus, future adopters were 3.6 years younger on average, had 23% higher baseline monthly card spending, held more non-AI digital subscriptions, and were more likely to be observed on an open-banking current-account feed.

To verify that demographic and earnings gradients in paid AI adoption are not driven by differences in account feed type or baseline spending intensity, Table A6 estimates linear probability and Poisson regressions of cumulative paid AI adoption on age band, gender, income band, account feed type, baseline 2022 spending tercile, and UK region simultaneously ($N = 201,038$). Holding all other recorded characteristics fixed, the adoption gaps by age, gender, and income remain large, retaining 68% to 90% of their unconditional magnitudes.

Similarly, for the regression-adjusted bars in Figures 2(a) and 3(a), we estimate population-weighted linear probability models on the rolling primary sample incorporating both direct and imputed app-store subscriptions:

$$Y_i = \sum_b \beta_b \mathbf{1}[\text{Group}_i = b] + Z_i' \gamma + \varepsilon_i, \quad (\text{C.1})$$

where Z_i controls for after-tax income band, gender, and UK region when estimating age profiles (Figure 2a), and for age band, gender, and UK region when estimating monthly net salary profiles (Figure 3a), with adjusted bars $\hat{\beta}_b + \bar{Z}' \hat{\gamma}$ evaluated at the weighted sample mean $\bar{Z}$.

C.2 Two-Stage Population Weighting and External Validation

To scale our primary-account samples to the 55.5 million adults aged 18 and over in the United Kingdom, we construct monthly calibration weights $w_{i,t}$ in two stages:

1. *Stage 1 (Within-aggregator selection weight)*: Among accounts with at least six active months in the wider aggregator panel, we estimate a logistic propensity model for selection into the rolling primary sample as a function of age band, region, local area classification, account feed type, and baseline non-AI activity deciles, trimming the resulting inverse-propensity weights at the 1st and 99th percentiles.
2. *Stage 2 (Iterative proportional fitting to UK adult benchmarks)*: In each month t , we rake the trimmed Stage-1 weights to match five official national benchmark distributions from the Office for National Statistics (ONS) and HM Revenue and Customs (HMRC): the joint distribution of Age Band $\times$ ITL1 Region, Gender, five net after-tax income bands, ONS 2021 Census Output Area Classification supergroups, and urban-rural postal classes.

Figures A2 and A3 summarize our external validation and weighting diagnostics. In Figure A2, we benchmark our transaction records against external series, documenting the sharp jump in sub-£10 Apple App Store subscriptions upon the UK launch of ChatGPT Go (Panel a), the close alignment between open-banking net salary deposits and official ONS ASHE net pay percentiles (Panel b), the pass-through of the January 2024 employee National Insurance cut into observed take-home pay (Panel c), and primary-account Netflix adoption relative to BARB household survey benchmarks (Panel d). Figure A3 shows that our aggregate adoption trajectory is stable across weighting schemes with modest design effects (Panels a and b), compares launch-aligned paid AI diffusion against major video streaming services (Panel c), and confirms that total non-AI card spending is flat in event time around paid AI subscription starts, ruling out mechanical entry spikes from newly active cards (Panel d).

Table A3: The Account Sample Ladder: Counts and Direct Standalone AI Penetration in June 2026

Sample layer	Screening rule	Active accounts		Direct AI subscribers		
		Count	Share (%)	Count	Share (%)	Per 1,000
<i>Panel A. Broad transacting bases</i>						
All transacting records	≥ 1 transaction in June 2026	1,424,855	100.0	21,837	100.0	15.3
Wider panel	≥ 6 active months since 2022	1,211,609	85.0	20,571	94.2	17.0
<i>Panel B. Balanced panel screens (2022H1–2026H1)</i>						
Fixed panel (no spend floor)	Active every half-year 2022H1–2026H1	419,652	29.5	7,717	35.3	18.4
Regular accounts	Active every half-year, median spend ≥ £100/mo	357,037	25.1	7,490	34.3	21.0
Balanced primary panel	Regular accounts, ≥ 20 non-AI txns/mo	178,109	12.5	6,029	27.6	33.9
<i>Panel C. Rolling 12-month primary screens</i>						
Rolling primary (threshold 20)	Mean ≥ 20 non-AI txns/mo over prior 12 months	446,429	31.3	15,581	71.4	34.9
Rolling threshold 15	Mean ≥ 15 non-AI txns/mo over prior 12 months	517,714	36.3	16,655	76.3	32.2
Rolling threshold 25	Mean ≥ 25 non-AI txns/mo over prior 12 months	396,766	27.8	14,662	67.1	37.0
Rolling 9-of-12 screen	≥ 20 non-AI txns in ≥ 9 of prior 12 months	321,168	22.5	11,999	54.9	37.4
In-month activity screen	≥ 20 non-AI txns in June 2026	503,831	35.4	16,216	74.3	32.2
Spend, debits, and tags screen	≥ £250 spend, ≥ 10 debits, ≥ 5 tags (9/12 mos)	349,239	24.5	12,574	57.6	36.0
<i>Panel D. Persistence and subscription-active benchmarks</i>						
Continuously active (12 months)	≥ 1 transaction in each of prior 12 months	549,199	38.5	13,657	62.5	24.9
Recurring-subscription payers	≥ 1 non-AI recurring subscription in June 2026	631,614	44.3	17,748	81.3	28.1
<i>Panel E. Breakdown by data feed</i>						
Wider panel: open banking	Current-account open-banking feeds	371,212	26.1	13,646	62.5	36.8
Wider panel: card-only	Credit and debit card feeds	840,397	59.0	6,925	31.7	8.2
Balanced primary: open banking	Primary open-banking current accounts	104,136	7.3	4,674	21.4	44.9
Balanced primary: card-only	Primary credit and debit card accounts	73,973	5.2	1,355	6.2	18.3

Notes: Each row reports the number of consumer accounts active in June 2026, the number holding an active direct paid standalone AI subscription, the share of all transacting accounts and active direct subscribers captured by that sample, and the resulting direct subscription rate per 1,000 accounts. Sample screening criteria are described in Appendix C.

Table A4: Direct Paid AI Adoption Across Sample Definitions and Time Windows

			Share of the stated population (%)			
	Definition	Accounts (Jan–Jun 2026)	June 2026	January– June 2026	July 2025– June 2026	Jul 2025–Jun 2026, age-reweighted
<i>This paper: paid subscriptions to standalone AI products</i>						
All transacting records	every UK consumer record	2,043,430	1.5	1.8	1.9	—
Wider panel	≥6 active months since 2022	1,703,286	1.7	2.0	2.1	1.6
Regular accounts	active every half-year 2022H1–2026H1; median monthly spend ≥ £100	439,616	2.0	2.4	2.8	2.2
Primary accounts	regular accounts averaging ≥20 non-AI transactions a month	201,038	3.3	4.1	4.7	3.6
primary accounts fed by open banking	the whole current account is observed	119,968	4.3	5.3	6.1	4.4

Notes: Share of transacting consumer accounts holding an active direct paid standalone AI subscription during the stated window (June 2026 single month, 2026H1 six-month window, and 12-month window ending June 2026) across progressively stricter activity screens, before and after post-stratification reweighting to the ONS adult age distribution.

Table A5: Baseline 2022 Descriptive Statistics: Paid AI Adopters vs. Balanced Primary Sample

	Group mean or share		Contrast	
	Primary accounts	Paid-AI adopters	Ratio	Std. diff.
Age (band midpoint, years)	39.9	36.3	0.91	-0.29
Total spend 2022 (GBP)	20,624.0	25,283.8	1.23	0.29
Spend percentile within card type	50.0	54.8	1.10	0.17
Online share of spend (%)	46.3	51.0	1.10	0.23
Transactions in 2022	759.4	883.6	1.16	0.27
Active recurring subscriptions (monthly mean)	9.3	11.1	1.19	0.26
Streaming subscriptions (monthly mean)	0.5	0.7	1.29	0.20
<i>Base</i>	192,939–201,038	14,595–14,798		
<i>Age band (% of column)</i>				
<30	22.5	27.3	1.21	0.11
30–39	34.2	41.7	1.22	0.16
40–49	22.4	22.2	0.99	-0.00
50–59	14.2	7.4	0.52	-0.19
60–69	5.3	1.2	0.23	-0.18
≥70	1.3	0.2	0.14	-0.10
<i>Base</i>	192,939	14,595		
<i>Card type (% of column)</i>				
Open-banking feed	59.7	74.5	1.25	0.30
Debit card	21.4	7.4	0.35	-0.34
Credit card	18.9	18.1	0.96	-0.02
<i>Base</i>	201,038	14,798		
<i>Region (% of column)</i>				
South East	14.0	14.7	1.05	0.02
London	12.1	18.4	1.53	0.20
North West	11.8	10.7	0.91	-0.03
Scotland	10.7	9.1	0.84	-0.05
East of England	8.8	8.6	0.98	-0.01
South West	8.7	8.4	0.97	-0.01
Yorkshire and The Humber	8.1	7.0	0.86	-0.04
West Midlands	8.0	7.7	0.96	-0.01
East Midlands	7.2	6.4	0.90	-0.03
Wales	5.0	4.4	0.88	-0.03
North East	3.8	3.0	0.78	-0.04
Northern Ireland	1.9	1.6	0.87	-0.02
<i>Base</i>	199,006	14,647		
<i>ONS supergroup (% of column)</i>				
Multicultural Metropolitans	19.4	20.8	1.07	0.04
Urbanites	16.9	17.4	1.03	0.01
Hard-Pressed Living	15.6	10.1	0.65	-0.15
Suburbanites	14.0	14.0	1.00	-0.00
Ethnicity Central	10.6	14.3	1.35	0.12
Constrained City Dwellers	8.2	6.5	0.79	-0.06
Rural Residents	8.2	6.0	0.73	-0.08
Cosmopolitans	7.0	10.9	1.55	0.15
<i>Base</i>	45,265	2,807		
All primary accounts	201,038	14,798		

Notes: Balanced primary panel ($N = 201,038$ ever-active accounts, including 14,798 cumulative paid AI adopters). All spending, transaction-count, online-share, and recurring-subscription variables are measured in calendar year 2022 prior to the diffusion of consumer generative AI. Standardized differences divide the difference in group means by the full-sample standard deviation.

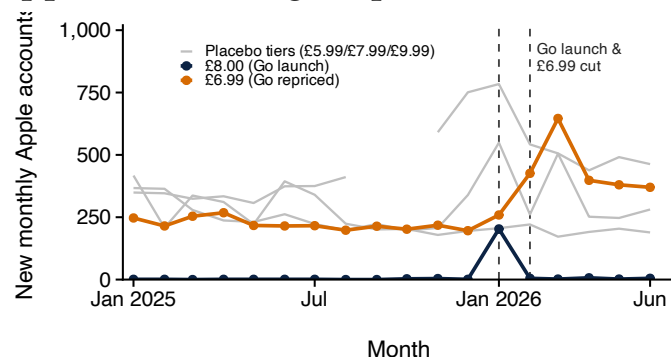
Table A6: Joint Multivariate Linear Probability and Poisson Models of Paid AI Adoption

	Share of accounts, %	Adoption rate, %	Gap from base, pp		Rate ratio to base	
			Alone	Joint	Alone	Joint
<i>Age band</i>						
Under 30	21.6	9.17	7.59 (0.18)	6.08 (0.19)	5.80	4.43
30–39	32.8	9.21	7.63 (0.16)	5.30 (0.17)	5.82	3.98
40–49	21.5	7.50	5.91 (0.17)	3.82 (0.17)	4.74	3.38
50–59	13.6	3.95	2.37 (0.16)	1.29 (0.16)	2.50	2.08
60 and over (base)	6.4	1.58				
Not recorded	4.0	2.51	0.92 (0.21)	1.86 (0.30)	1.58	2.34
<i>Gender</i>						
Women (base)	41.9	6.93				
Men	32.0	10.58	3.64 (0.15)	3.28 (0.16)	1.53	1.45
Not recorded	26.0	4.09	−2.85 (0.12)	2.83 (0.33)	0.59	1.36
<i>Monthly income band</i>						
Under £1,500 (base)	35.9	5.04				
£1,500–2,000	20.2	6.72	1.67 (0.15)	0.19 (0.15)	1.33	1.07
£2,000–2,500	11.4	9.79	4.75 (0.21)	2.60 (0.22)	1.94	1.43
£2,500–3,000	6.7	11.13	6.09 (0.28)	3.62 (0.29)	2.21	1.55
£3,000–4,000	5.9	12.97	7.92 (0.32)	5.05 (0.33)	2.57	1.71
Over £4,000	5.3	14.17	9.12 (0.35)	6.21 (0.36)	2.81	1.86
Not recorded	14.6	5.59	0.54 (0.16)	1.13 (0.24)	1.11	1.20
<i>Record type</i>						
Open banking (base)	59.7	9.18				
Credit card	18.9	7.03	−2.15 (0.16)	−2.34 (0.19)	0.77	0.77
Debit card	21.4	2.56	−6.62 (0.11)	−5.05 (0.34)	0.28	0.39
<i>Spending tercile</i>						
Bottom (base)	33.3	6.26				
Middle	33.3	6.80	0.54 (0.13)	0.53 (0.13)	1.09	1.07
Top	33.3	9.02	2.75 (0.14)	1.93 (0.15)	1.44	1.30
<i>Region</i>						
London (base)	11.9	11.24				
East Midlands	7.1	6.60	−4.64 (0.29)	−3.93 (0.29)	0.59	0.65
East of England	8.7	7.20	−4.05 (0.28)	−3.61 (0.28)	0.64	0.68
North East	3.8	5.72	−5.53 (0.33)	−4.72 (0.33)	0.51	0.57
North West	11.7	6.67	−4.57 (0.26)	−3.72 (0.26)	0.59	0.67
Northern Ireland	1.8	6.43	−4.82 (0.45)	−4.12 (0.45)	0.57	0.63
Scotland	10.6	6.21	−5.03 (0.26)	−4.48 (0.26)	0.55	0.60
South East	13.9	7.72	−3.53 (0.26)	−3.29 (0.26)	0.69	0.72
South West	8.6	7.18	−4.07 (0.28)	−3.46 (0.28)	0.64	0.70
Wales	4.9	6.51	−4.73 (0.32)	−3.99 (0.32)	0.58	0.64
West Midlands	7.9	7.07	−4.18 (0.29)	−3.33 (0.29)	0.63	0.71
Yorkshire and The Humber	8.0	6.34	−4.90 (0.28)	−4.13 (0.28)	0.56	0.63
Not recorded	1.0	7.43	−3.81 (0.62)	−3.52 (0.61)	0.66	0.68
Accounts, every column	201,038					

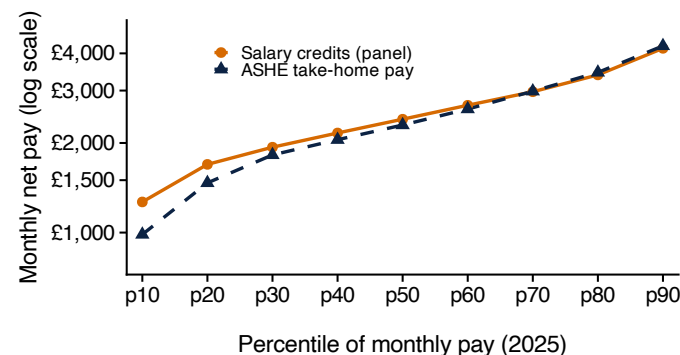
Notes: Balanced primary panel ($N = 201,038$). The dependent variable is an indicator for having held a direct paid AI subscription at a standalone seller by July 2026 (scaled in percentage points for LPM). “Alone” columns report bivariate differences (LPM) or rate ratios (Poisson) relative to each characteristic’s reference category; “Joint” columns include indicators for all six characteristics simultaneously. Heteroskedasticity-robust standard errors are in parentheses.

Figure A2: Validating Transaction Records Against External Benchmarks

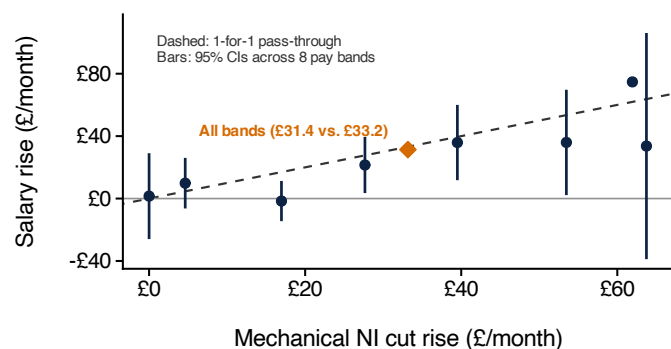
(a) Apple Sub-£10 Sign-Ups Around Go Launch



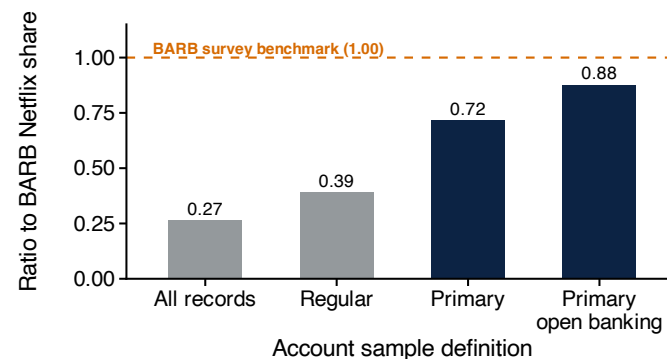
(b) Open-Banking Salary Credits vs. ASHE Net Pay



(c) Jan 2024 National Insurance Cut Pass-Through



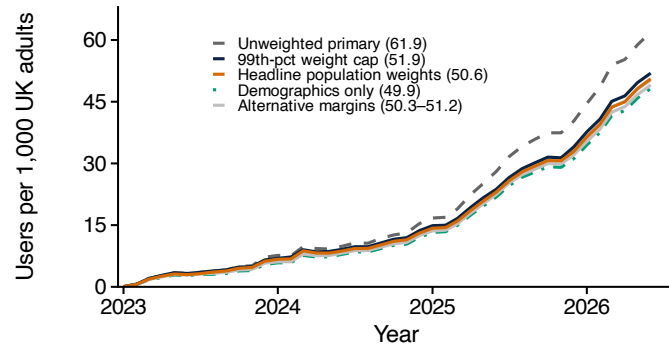
(d) Primary-Account Netflix Share vs. BARB



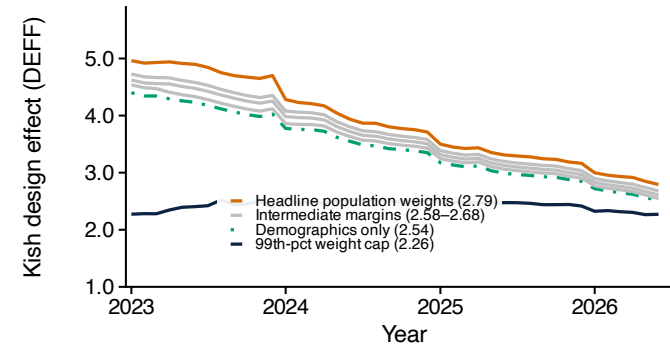
Notes: Panel (a) plots monthly new recurring Apple App Store subscription runs at OpenAI's entry-level ChatGPT Go price tiers (£8.00 at its January 2026 UK launch, jumping from ~49 pre-launch to ~200, and £6.99 after the February 2026 repricing, reaching 658 total runs per month or 410 net of the ~248 pre-launch £6.99 non-AI baseline). Panel (b) compares percentiles of monthly net take-home salary credits in our open-banking panel against net take-home pay percentiles constructed from the official UK Annual Survey of Hours and Earnings (ASHE). Panel (c) plots the event-time change in monthly net salary deposits around the January 2024 two-percentage-point cut in UK employee National Insurance contributions. Panel (d) compares the share of rolling primary accounts paying Netflix against the implied per-adult primary-payer benchmark derived from BARB's quarterly UK household Netflix survey (~59% household penetration scaled across 1.9 adults per UK household to 31%–38% implied per-adult primary payers).

Figure A3: Population Weighting Trajectories, Design Effects, Launch Diffusion, and Event-Time Spending

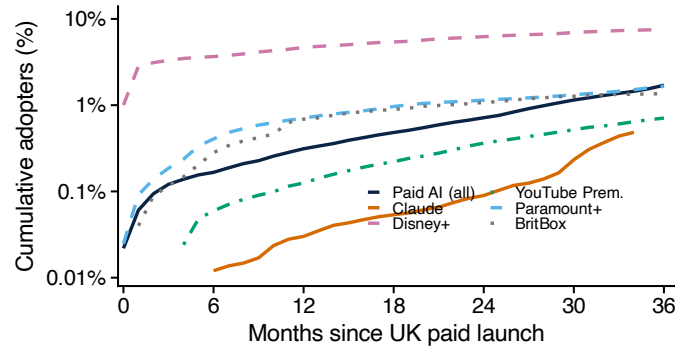
(a) Adoption Trajectories Across Weighting Schemes



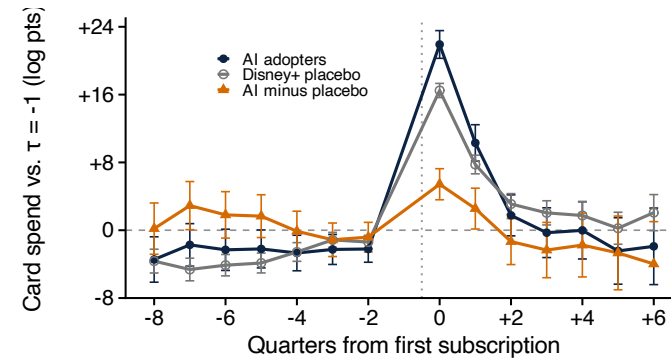
(b) Weighting Design Effect (DEFF) Over Time



(c) Launch-Aligned Diffusion vs. Streaming Services



(d) Event-Time Card Spending Around Adoption



Notes: Panel (a) compares monthly active paid standalone AI subscribers per 1,000 across weighting specifications on the rolling primary sample. Panel (b) plots the monthly Kish design effect ($DEFF = 1 + CV(w)^2$) of the population calibration weights across specifications. Panel (c) compares launch-aligned cumulative direct card adoption trajectories over the first 36 months since UK launch (or panel start for YouTube Premium) for paid AI assistants against major video streaming services, estimated on the unweighted extended 2019–2026 historical card subpanel. Panel (d) plots event-time log total card expenditure around first subscription start for paid AI adopters and a Disney+ adoption placebo.

D Individual Occupation and Employer Industry Classification

Standard bank and card datasets record demographics and geographic location but lack occupation or employer industry. We overcome this limitation by exploiting two administrative signals in open-banking current-account records: incoming salary credits naming the employer, and outbound payments to professional regulators, royal colleges, learned societies, and trade unions. This appendix details our classification pipelines and validation checks for employer industry, expense reimbursement, and individual occupation.

D.1 Employer Resolution, SIC 2007 Industry Classification, and Expense Reimbursement

To classify employer industries across our salaried open-banking accounts, we normalize incoming payroll strings and match them against the UK Companies House corporate register, the NHS Organisation Data Service, the Department for Education register of schools and universities, and central and local government paymasters (Table A7). This procedure assigns an official UK Standard Industrial Classification (SIC 2007) code to 319,298 salaried accounts (65% of our primary salaried sample) and links workers to 19,876 named organizations. In a manual audit of 300 stratified payroll strings, the assigned SIC industry achieves a precision of 96.8% among determinable strings. Figure A5 reports the resulting paid AI adoption rates and provider lean across major employer industries.

To verify that consumer AI subscriptions on personal accounts represent out-of-pocket spending rather than employer-reimbursed expenses, we examine non-payroll incoming transfers from an employee’s matched employer arriving within 30 days after an AI subscription charge. Across our salaried panel, only 13.8% of paid AI subscription charges are followed within 30 days by a non-payroll employer credit. This rate is nearly identical to the pre-adoption baseline on the same accounts 60 days prior to starting AI (12.6%) and to the rate following personal entertainment streaming charges (13.8%), yielding a difference-in-differences excess reimbursement rate of just 0.61 percentage points. Thus, AI subscriptions billed to personal accounts are rarely followed by separate employer expense transfers.

D.2 Hierarchical Occupation Classification and Validation

We classify accounts into 65 occupational groups harmonized with the UK Standard Occupational Classification (SOC 2020)—comprising 51 fee-verified professions and 14 broader SOC sub-major groups (Tables A8 and A9)—using a four-stage priority cascade:

1. *Stage 1: Direct professional fees and statutory registers (46,419 salaried accounts).* Practicing in many UK professions requires or routinely entails annual registration

fees or dues to statutory regulators (such as the General Medical Council, Nursing and Midwifery Council, or Solicitors Regulation Authority), royal colleges, chartered institutes, or occupation-specific unions. Matching outbound payments against our curated directory of 466 professional bodies and unions directly identifies members of these professions with 97.8% audited match precision.

2. *Stage 2: Single-occupation employers (24,180 salaried accounts)*. We match incoming payroll strings to employers whose workforce is concentrated in a single occupational group, such as airlines, accounting partnerships, law firms, dental practices, veterinary clinics, and haulage fleets. Combining Stage 1 fee payers and Stage 2 employers yields 70,599 ground-truth salaried accounts for model training and validation.
3. *Stage 3: Industry $\times$ age $\times$ net-salary cells (248,117 salaried accounts)*. Within multi-occupation employers (such as hospital trusts, universities, local authorities, retail chains, and banks), we combine resolved employer SIC industry with ONS ASHE age-by-gender net pay percentiles to form structured occupational priors, helping separate support, technical, and managerial roles within the same sector.
4. *Stage 4: Behavioral transaction classifier (143,812 salaried accounts; scored out-of-fold across all 1.74 million open-banking accounts)*. For remaining accounts—and to construct consistent SOC 2020 occupational probabilities across the full open-banking panel—we train an out-of-fold gradient-boosted decision tree model on our ground-truth accounts using the Stage 3 priors and non-AI transaction features (merchant categories, workplace location, commuting patterns, and time-of-day activity). All AI and software-suite merchants are excluded from the feature set so that occupational assignments never use information about AI adoption.

Across the salaried panel, this four-stage cascade classifies 94.2% of accounts with 88.4% concordance against a blinded human audit of 29,436 stratified records. When we mask Stage 1 fee payments and predict occupation solely from employer and non-AI transaction features, the out-of-fold classifier achieves a median AUC of 0.874 across anchor professions (Figure A4a–b).

Table A9 reports paid AI adoption across the 34 fee-verified professions meeting our main-text sample-size thresholds, comparing direct web payments against all-channel estimates incorporating mobile app-store subscriptions. The more than ninefold spread in adoption between technical or academic professions and hands-on care or manual roles holds across sample thresholds and when restricting strictly to mandatory statutory regulators (excluding voluntary professional associations and unions).

Finally, Table A10 and Figure A4(c)–(d) validate our UK occupational adoption rates against external workplace AI usage surveys (Bick, Blandin, and Deming, 2026) and task-exposure indices (Eloundou et al., 2024; Felten, Raj, and Seamans, 2021). Paid AI adoption correlates strongly with US survey usage across all 26 broad SOC sub-major groups ($r = 0.95$, Panel A) and across our 51 fee-verified professions (Panel B), aligns closely with generative-AI task-exposure measures while correlating negatively with pre-LLM routine computerization (Frey and Osborne, 2017), and remains a strong

predictor in individual-level regressions controlling for age, gender, region, and take-home pay (Panel C). Likewise, in our earnings regressions (Figure 3b), accounting for occupation, industry, location, and demographics explains roughly two-thirds of the raw income gradient whether we use the full occupational cascade or restrict to directly observed professional membership and employer labels.

Table A7: Employer SIC 2007 Industry Resolution Coverage, Institutional Sectors, and Audit Precision

Panel A. Employer SIC Division and Named-Organization Resolution Coverage						
Sample / unit	<i>N</i>	Any SIC division	Confidence ≥ 0.60	Confidence ≥ 0.80	Named organization	Generic payroll processor
All salary spells	533,958	63.8%	62.3%	59.7%	62.3%	20.0%
Named salary spells (excl. generic BACS)	427,439	79.7%	77.8%	74.6%	77.8%	0.0%
Salaried accounts (longest-duration employer)	390,404	65.0%	63.4%	61.0%	63.5%	19.9%
Salaried open-banking outcome accounts	374,902	64.0%	62.5%	60.2%	62.6%	20.4%
Salaried accounts (any resolved employer)	390,404	68.4%	66.7%	64.2%	66.8%	—
Panel B. Resolved Named Employers by Institutional Sector						
Employer sector / organization type	Distinct organizations		Account–employer links		Share of links (%)	
Private-sector company (Companies House)	15,134		175,624		58.2%	
NHS hospital trust or health board	232		30,505		10.1%	
Local authority or municipal council	373		17,908		5.9%	
Registered charity or non-profit	996		12,320		4.1%	
State school or multi-academy trust	1,576		11,124		3.7%	
University or further-education college	410		9,097		3.0%	
Central government or public body	264		6,606		2.2%	
General medical practice	187		568		0.2%	
Other organization types	741		38,237		12.7%	
All distinct named organizations	19,876		301,989		100.0%	
Panel C. Independent Verification Audit of 300 Stratified Resolved Payroll Strings						
Audit weighting scheme	Audited strings	Organization confirmed	Organization indeterminate	Organization refuted	SIC division confirmed	
Stratified by spell-stratum size	300	87.0%	11.0%	2.0%	80.6%	
Weighted by accounts × stratum size	300	85.5%	13.7%	0.8%	78.2%	

Notes: This table summarizes employer SIC 2007 industry resolution across open-banking salaried accounts ($N = 319,298$ SIC-resolved accounts out of 491,228 salaried accounts, or 65.0%, including 301,989 accounts linked to 19,876 named organizations and 17,309 accounts resolved directly from industry-specific payroll descriptions). Panel A reports coverage across confidence thresholds and payroll processors; Panel B reports resolved named employers and linked accounts by institutional sector; Panel C reports human-audit verification on 300 stratified payroll strings (80.6% confirmed, 16.7% indeterminate from the narration string alone, and 2.7% refuted, yielding 96.8% precision among determinable strings).

Table A8: Hierarchical Occupation Classification Cascade and Professional Fee Anchor Groups

Panel A. Occupational Registry Entities by Discovery Channel and Organization Type							
Discovery channel	Entities	Organization type			Label-producing	On ≥ 10 accounts	Matched in both channels
		Statutory registers	Professional bodies	Trade / employer orgs			
Curated statutory registers and unions	205	37	109	59	146	183	182
Top-down SOC2020 institutional enumeration	55,370	212	2,657	52,501	181	3,465	0
Bottom-up merchant descriptor vocabulary	10,778	52	353	10,373	136	65	0
Residual high-frequency stem scan	39	0	3	36	3	10	0
All occupational entities	66,392	301	3,122	62,969	466	3,723	182
Panel B. Gold-Standard Fee-Paying Accounts Across Major Statutory and Union Families							
Occupation family	Full panel	Salaried OB universe	Other OB accounts	Card-only panel	New entrants	Lapsed / one-off	Professional body / union
Nursing and midwifery (NMC / RCN)	23,535	17,341	[s]	<10	2,044	1,019	6,211
School teachers (NEU / NASUWT / GTCs)	15,338	11,191	4,136	11	1,449	2,245	5,622
Allied health professionals (HCPC)	8,492	6,756	1,736	0	2,015	505	3,640
Social care registers (SSSC / SCW / NISCC)	7,310	5,228	2,047	35	260	1,460	0
Medical doctors (GMC / BMA / Royal Colleges)	4,243	3,293	940	[s]	288	336	3,131
Social workers (SWE)	3,796	2,474	795	527	0	659	469
Dental professionals (GDC / BDA)	2,205	1,417	592	196	147	777	336
Pharmacists and technicians (GPhC / PDA)	1,500	1,151	349	0	25	239	277
Veterinary surgeons and nurses (RCVS)	936	590	163	183	22	290	276
Security operatives (SIA)	897	676	208	13	0	72	0
Rail and transport staff (RMT / ASLEF)	611	468	143	0	56	37	3,239
Registered childminders (Ofsted / PACEY)	510	381	129	0	0	159	273
Commercial pilots (CAA / BALPA)	276	191	[s]	<10	25	23	26
Architects (ARB / RIBA)	263	213	34	16	<10	117	127
Solicitors and barristers (SRA / Law Society)	119	97	22	0	0	40	91
Smaller statutory families (11 groups)	568	329	95	144	<10	225	792
All statutory and union families	70,599	51,796	17,665	1,138	6,341	8,203	24,510

Notes: Panel A summarizes occupational registry entities (66,392 total entities, including 466 professional regulators, royal colleges, and trade unions) by discovery channel and organization type, alongside the 70,599 accounts paying statutory, royal-college, or trade-union fees across all feeds (51,796 salaried open-banking accounts, 17,665 other open-banking accounts, and 1,138 credit-card-only accounts). Panel B summarizes ground-truth accounts across statutory professional regulators, royal colleges, chartered institutes, trade unions, and single-occupation anchor employers (where deduplicating the 51,796 salaried fee-payer rows across overlapping professional bodies yields 46,419 unique salaried Stage 1 fee payers, which combine with 24,180 Stage 2 single-occupation employer anchors to form the 70,599 salaried ground-truth anchors used in supervised training).

Table A9: Ground-Truth Occupational Classes, Source Types, and Paid AI Adoption Across the 34 Primary-Panel Professions

Profession / fee class	Source type	Rolling primary base calibrated to UK adults				All gold-standard members, unweighted		
		Active June 2026 direct [90% CI]	+ App-store in-app	Ever paid since 2022	N	Active June 2026 direct	Ever paid since 2022	N
IT professionals (BCS)	Prof. body / union	20.3 [10.9, 32.2]	22.0	40.0	53	6.7	22.7	163
HE and FE lecturers (UCU)	Prof. body / union	16.0 [12.8, 19.1]	17.7	23.0	684	5.9	13.1	2,019
Insurance and finance (CII)	Prof. body / union	15.8 [10.6, 22.2]	18.9	20.8	290	3.0	7.9	1,171
Project and procurement (APM/CIPS)	Prof. body / union	13.8 [8.7, 22.1]	18.3	22.4	248	4.4	11.2	735
Marketing and PR (CIM/CIPR)	Prof. body / union	12.8 [8.8, 17.2]	18.3	20.4	192	4.2	11.6	662
Artistic and literary occupations (SOC 341)	Prof. body / union	9.7 [4.6, 14.2]	11.0	16.2	109	3.8	9.2	261
Surveyors and planners (RICS/RTPI)	Prof. body / union	8.2 [4.3, 12.9]	11.3	13.0	134	4.1	7.9	340
Postal and telecoms (CWU)	Prof. body / union	7.7 [4.0, 11.4]	10.0	14.1	150	2.8	9.7	507
Chartered engineers	Prof. body / union	7.5 [5.6, 9.4]	10.1	12.8	552	3.6	9.1	1,713
School teachers (NEU/NASUWT/GTCS)	Statutory register	7.5 [6.9, 8.2]	9.9	19.3	5,560	3.1	12.5	15,067
Security operatives (SIA)	Statutory register	7.0 [4.0, 9.7]	10.5	12.0	292	2.0	6.3	889
Medical doctors (GMC/BMA)	Statutory register	7.0 [5.9, 8.4]	11.0	14.9	1,160	2.5	7.9	4,175
Pharmacists and technicians (GPhC)	Statutory register	6.8 [5.1, 8.8]	10.6	13.0	631	3.1	6.7	1,486
Psychotherapy and counselling (BACP)	Prof. body / union	6.8 [5.1, 9.6]	9.9	12.5	798	2.7	7.4	2,394
Musicians (Musicians' Union)	Prof. body / union	6.7 [4.2, 10.2]	10.8	11.1	203	2.9	7.0	647
HR professionals (CIPD)	Prof. body / union	6.5 [5.1, 7.8]	10.9	13.6	1,038	2.5	7.0	3,070
Fitness instructors	Prof. body / union	6.1 [3.9, 8.7]	9.4	10.5	255	2.8	8.3	791
Performing arts (Equity)	Prof. body / union	5.8 [4.2, 7.3]	9.8	11.3	646	2.0	6.5	2,271
Science and engineering union (Prospect)	Prof. body / union	4.9 [3.6, 5.9]	8.3	11.5	1,104	2.2	7.5	3,024
Banking staff	Prof. body / union	4.9 [2.4, 7.2]	8.3	8.2	243	1.3	3.2	950
Taxi and courier drivers	Prof. body / union	4.8 [4.1, 5.6]	7.6	11.6	2,513	1.1	4.1	16,813
Industrial union (Community)	Prof. body / union	4.7 [2.4, 6.9]	6.8	9.3	205	2.5	6.0	635
Allied health professionals (HCPC)	Statutory register	3.8 [3.3, 4.4]	6.3	8.6	3,334	1.7	5.1	8,387
Natural and social scientists	Prof. body / union	3.6 [1.9, 5.9]	4.3	10.9	173	2.7	10.4	594
Social workers (SWE)	Statutory register	3.4 [2.2, 5.1]	7.0	7.9	1,234	1.0	3.5	3,754
Accountancy (ACCA/ICAEW/CIMA)	Prof. body / union	3.4 [2.2, 4.6]	6.0	8.0	844	1.0	4.7	3,449
Civil service unions (PCS/FDA)	Prof. body / union	3.3 [2.5, 4.1]	6.3	7.5	1,722	1.2	4.3	5,129
Veterinary professionals (RCVS)	Statutory register	3.1 [1.4, 4.7]	5.1	6.8	327	1.3	3.9	928
Dental professionals (GDC)	Statutory register	3.1 [1.8, 4.4]	6.4	6.6	759	1.1	3.0	2,180
Construction site operatives (CSCS/CITB)	Prof. body / union	2.9 [2.2, 3.7]	6.3	7.0	1,489	1.4	4.6	3,869
Electricians	Prof. body / union	2.9 [2.2, 5.1]	7.4	6.5	469	1.1	4.0	1,696
Firefighters (FBU)	Prof. body / union	2.5 [1.3, 3.8]	5.6	4.9	434	1.0	3.1	1,197
Nursing and midwifery (NMC/RCN)	Statutory register	2.5 [2.1, 2.8]	5.1	5.7	8,627	1.0	3.3	23,140
Social care registers (SSSC/SCW/NISCC)	Statutory register	1.7 [1.3, 2.3]	4.8	5.2	2,302	0.6	2.8	7,239

Notes: This table reports paid AI adoption across the 34 fee-verified professions with at least 50 primary accounts and at least 10 active June 2026 adopters (drawn from the 51 primary-sample professions with $N \geq 30$). Columns report organization source type, active June 2026 direct (matching Figure 4) and all-channel (including mobile app-store) adoption rates on the rolling primary sample reweighted to UK adults, cumulative ever-adoption rates, and unweighted direct adoption rates across all ground-truth accounts. Across the outcome-blind set of 28 professions with at least 150 primary accounts regardless of adopter count, direct adoption spans 16.0% (university lecturers) to 1.7% (social care workers), a 9.21-fold ratio (18.9% to 4.3%, or 4.44-fold, on the all-channel series).

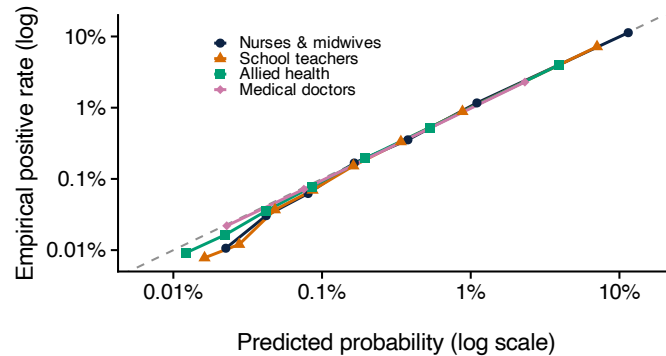
Table A10: Occupational Paid AI Adoption Regressions: Survey Usage, Task Exposure, and Account Controls

Panel A. Occupation-Level Regressions on US Survey AI Usage (Bick, Blandin, and Deming, 2026) (1.74M Open-Banking Universe, Mean 2.1%)					
Occupation partition	Specification	No fixed effects	SOC1 major group FE	Worker controls (pay, age, gender)	SOC1 FE + worker controls
SOC1 major groups (9 groups)	Level-level (pp per SD)	0.627 (0.060) $R^2 = 0.96$	—	—	—
	Log-log (elasticity)	0.765 (0.121) $R^2 = 0.93$	—	—	—
	Rank-rank slope	0.968 (0.121) $R^2 = 0.94$	—	—	—
SOC2 sub-major groups (26 groups)	Level-level (pp per SD)	0.734 (0.034) $R^2 = 0.90$	0.473 (0.130) $R^2 = 0.95$	0.568 (0.113) $R^2 = 0.91$	0.419 (0.212) $R^2 = 0.95$
	Log-log (elasticity)	1.000 (0.054) $R^2 = 0.87$	0.509 (0.171) $R^2 = 0.96$	0.611 (0.199) $R^2 = 0.91$	0.384 (0.229) $R^2 = 0.97$
	Rank-rank slope	0.930 (0.073) $R^2 = 0.86$	0.593 (0.189) $R^2 = 0.95$	0.640 (0.186) $R^2 = 0.91$	0.516 (0.303) $R^2 = 0.95$
Panel B. Occupation-Level Regressions on GPT-4 Task Exposure (Eloundou et al., 2024) (Rolling Primary Base, APS-Weighted Mean 10.4%)					
Occupation partition	Specification	No fixed effects	SOC1 major group FE	Worker controls (pay, age, gender)	SOC1 FE + worker controls
Fee-verified professions (51 classes)	Level-level (pp per SD)	5.122 (1.612) $R^2 = 0.63$	5.812 (2.578) $R^2 = 0.76$	4.422 (1.654) $R^2 = 0.69$	5.021 (2.553) $R^2 = 0.78$
	Log-log (elasticity)	0.931 (0.279) $R^2 = 0.52$	1.016 (0.396) $R^2 = 0.70$	0.780 (0.165) $R^2 = 0.65$	0.661 (0.355) $R^2 = 0.74$
	Rank-rank slope	0.734 (0.134) $R^2 = 0.54$	0.630 (0.229) $R^2 = 0.68$	0.620 (0.164) $R^2 = 0.62$	0.359 (0.281) $R^2 = 0.72$
Panel C. Individual Account-Level Regressions on Rolling Primary Base (Level-Level Slope, pp per SD)					
Regressor and occupational assignment (N accounts; clusters)		No fixed effects	Age $\times$ gender $\times$ region FE	+ Individual income band FE	+ Occupation mean net pay
US survey AI usage across 26 SOC2 groups (191,220 accounts; 26 occupational clusters; mean 6.3%)		3.21 (0.37) $p_{wcb} < 0.001$	2.71 (0.25) $p_{wcb} < 0.001$	2.34 (0.26) $p_{wcb} < 0.001$	3.24 (0.57) $p_{wcb} < 0.001$
US survey AI usage across 9 SOC1 major groups (176,643 accounts; 9 occupational clusters; mean 7.4%)		2.55 (0.25) $p_{wcb} = 0.010$	2.23 (0.25) $p_{wcb} = 0.006$	1.71 (0.27) $p_{wcb} = 0.006$	3.57 (0.85) $p_{wcb} = 0.028$
GPT-4 task exposure (β) across 51 gold-standard professions (27,403 accounts; 51 occupational clusters; mean 7.7%)		1.71 (0.58) $p_{wcb} = 0.003$	1.66 (0.57) $p_{wcb} = 0.003$	1.57 (0.57) $p_{wcb} = 0.005$	1.45 (0.63) $p_{wcb} = 0.010$
Task exposure first principal component (16 indices, 51 professions) (27,403 accounts; 51 occupational clusters; mean 7.7%)		1.81 (0.60) $p_{wcb} = 0.002$	1.96 (0.56) $p_{wcb} < 0.001$	1.87 (0.55) $p_{wcb} < 0.001$	1.78 (0.61) $p_{wcb} < 0.001$

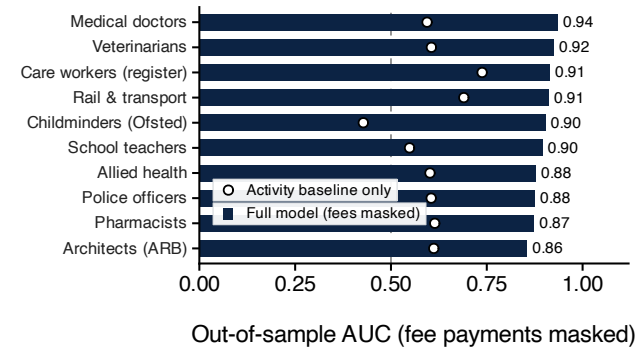
Notes: All panels use 12-month active paid AI assistant adoption (September 2025–August 2026) as the dependent variable. Panel A regresses UK occupational adoption across SOC 2020 major and sub-major groups on US survey workplace AI usage (Bick, Blandin, and Deming, 2026). Panel B regresses UK occupational adoption across the 51 fee-verified professions on GPT-4 task exposure (Eloundou et al., 2024). Panel C reports individual account-level linear probability regressions on the population-weighted rolling primary panel against the first principal component across all 16 external occupational benchmarks (10 task-exposure indices and 6 observed-usage benchmarks; restricting the principal component strictly to the 10 task-exposure indices yields +1.72 pp per SD, $p_{wcb} = 0.002$), controlling progressively for demographics, net income band, and occupational mean pay. Heteroskedasticity-robust standard errors (Panels A–B) and occupational wild-cluster-bootstrap p -values (p_{wcb} , Panel C) are reported.

Figure A4: Occupational Classification Calibration, Out-of-Sample ROC, and External Validation

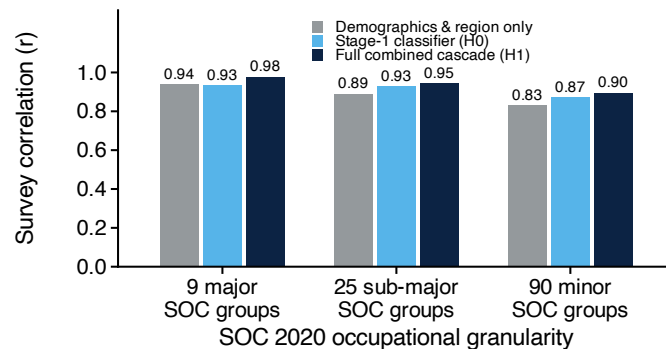
(a) Classifier Probability Calibration vs. Human Audit



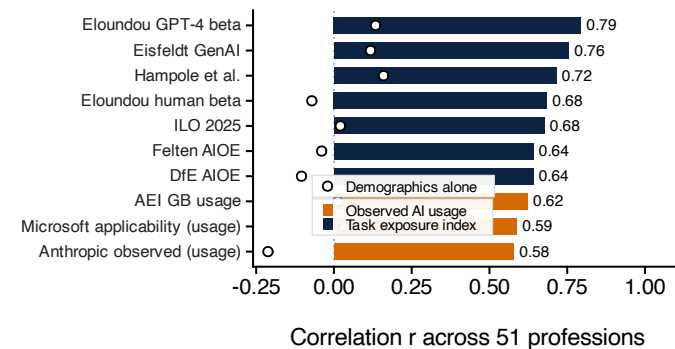
(b) Out-of-Sample ROC Across Anchor Professions



(c) Sub-Major SOC 2020 Adoption vs. Survey Usage



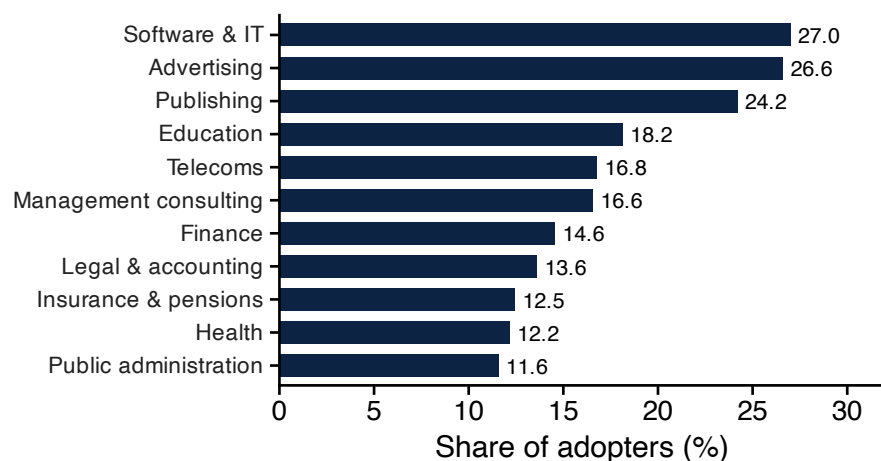
(d) 51 Professions vs. External Exposure Indices



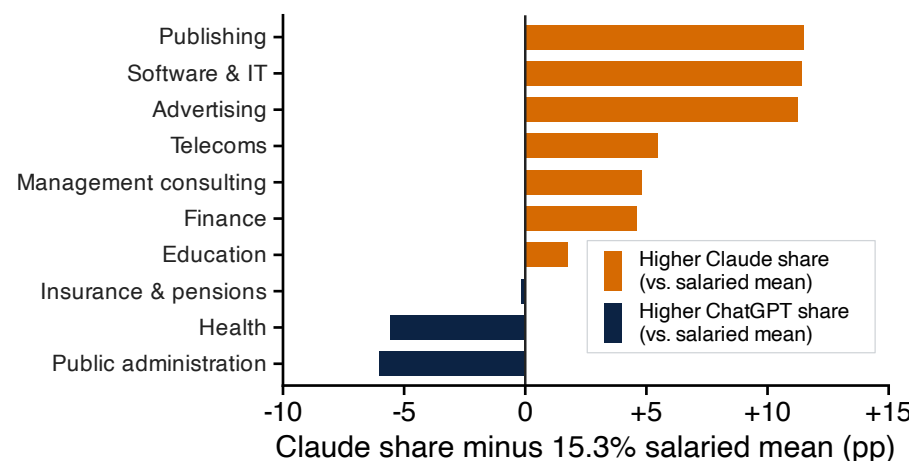
Notes: Panel (a) plots human-audit accuracy across deciles of predicted occupational assignment probability. Panel (b) plots out-of-sample ROC curves when holding out Stage 1 fee labels and predicting occupational membership from employer and non-AI transaction features for the top 10 fee-masked classes with at least 50 held-out members, alongside an activity-visibility baseline (0.562 AUC from account tenure, transaction count, and income). Panel (c) compares occupational adoption across SOC 2020 major, sub-major, and minor groups against US survey usage across alternative classifier specifications. Panel (d) plots employment-weighted correlations across the 51 fee-verified professions against the top 10 of our 13 generative-AI task-exposure and observed-usage benchmarks (out of 16 total occupational benchmarks; navy dots) alongside demography-implied rates (hollow dots).

Figure A5: Paid AI Adoption and Provider Lean Across Major Employer Industries

(a) Paid AI Adoption Across Major Employer Industries



(b) Provider Lean Across Major Employer Industries



Notes: Panels (a) and (b) group salaried open-banking accounts across the 11 largest UK Standard Industrial Classification (SIC 2007) major industry groupings (each with at least 2,500 resolved primary salaried accounts). Panel (a) plots cumulative paid AI adoption by industry. Panel (b) plots each industry's direct Claude share among cumulative salaried payers of Claude or ChatGPT relative to the salaried mean.

E Supplementary Diffusion, Geography, Competition, and Remote-Work Analyses

This final appendix presents supplementary empirical exhibits supporting Sections 3–5 and reports our analysis of paid AI adoption across public-transit commuting schedules.

E.1 Extensive vs. Intensive Spending Margins and Geographic Concentration

Extensive vs. intensive margins. Figure A6 decomposes aggregate UK consumer AI expenditure into the share of adults paying in a given month (extensive margin) and average monthly AI spending per active payer (intensive margin), using the identity $\text{AI Spend per Adult}_t = \text{Active Payer Share}_t \times \text{AI Spend per Active Payer}_t$. Between January 2024 and July 2026, the monthly active payer share rose nearly sixfold (from 1.0% to 5.8% of UK adults), while average monthly spending per active payer rose by roughly one-quarter (from £21.80 to £27.60, or from 0.37% to 0.47% of active payers' total monthly card spending in Panel c), reflecting uptake of power-user tiers and multi-homing. In log terms, expansion in the active payer share accounts for 88% of aggregate spending growth (84% on directly observed payments). Restricting the first-time subscriber inflow series in Figure A6(b) to accounts continuously observed for at least 12 months prior to January 2026 confirms that new sign-ups reflect genuine adoption rather than newly linked accounts.

Geographic concentration across Britain. Figure A7 complements the postcode-district map in the main text (Figure 6) by examining adoption across local authority districts. In June 2026, London's active paid AI assistant adoption rate (6.8%) is nearly double that of Great Britain outside London (3.6%), and the top decile of local authorities records an adoption rate 3.8 times that of the bottom decile. Across Great Britain local authorities, cumulative adoption rises steeply with the Census 2021 share of residents in managerial and professional occupations (Panel a, population-weighted $r = 0.74$) and ONS Gross Disposable Household Income per head (Panel b, $r = 0.68$). A single principal component combining local professional employment share, household income per head, and the share of residents aged 20–34 accounts for 64% of the cross-area variation.

E.2 Multi-Homing, Cross-Provider Switching, Tier Upgrades, and Event Studies

Figure A8 and Table A11 provide supplementary evidence on consumer multi-homing, cross-provider switching, vertical plan transitions, and model release event studies (Section 5).

Multi-homing across product scopes. Within general-purpose assistants, only 4.2% of active subscribers on the rolling primary panel pay two or more assistant providers in the same calendar month, with strong asymmetry by provider (23.7% of active

Claude subscribers vs. 7.9% of active ChatGPT subscribers concurrently pay a second assistant). Over the full life of a subscription spell (Figure A8a), 26.7% of Claude subscribers concurrently pay a rival assistant compared with 7.9% of ChatGPT subscribers, while Figure A8(b) shows the destination providers of cancelled assistant spells within 60 days. When we expand scope from general-purpose assistants to any standalone AI product, cross-seller overlap is much higher for specialist voice, image, and coding tools—reaching 44.3% among ElevenLabs subscribers and 37.9% among Midjourney subscribers, and with payers for standalone coding tools more than twice as likely to choose Claude for their general assistant as other assistant subscribers (46.8% vs. 21.6%).

Vertical tier upgrades. Table A11 tabulates account-level vertical transitions across subscription price tiers for OpenAI and Anthropic. Among Claude Pro subscribers, 6.2% eventually upgrade to higher-priced Claude Max tiers (£90–£180 per month), whereas only 0.74% of ChatGPT Plus subscribers transition to higher-priced Pro or Team plans. In counterfactual accounting on the July 2026 direct-billing cross-section, replacing every £80+ power-user payment with the provider’s standard £20 monthly plan reduces Claude’s average monthly spending per active subscriber from £28.90 to £20.15 (eliminating nearly all of its premium over ChatGPT’s £20.40) and lowers Claude’s direct spending share from 29.4% to 23.6%. Applying the same £20 cap between December 2025 and July 2026 implies that roughly three-quarters (76%) of Claude’s spending-share gain came from growth in its subscriber base and one-quarter (24%) came from uptake of £80+ power-user plans.

Frontier model releases and secular-trend adjustment. For the model release event study in Figure 9(d), we compile major flagship model and consumer product launches between January 2023 and July 2026 across Anthropic (24 releases), OpenAI (34 releases), and Google (4 Gemini releases). For each event, we compare first-time provider sign-ups in the 14 days following the announcement against the average of the two preceding 14-day windows. To account for rapid baseline growth between announcements, we benchmark these post-release changes against 300 randomly drawn non-release dates over the same sample period. Anthropic releases are associated with a +39.5% raw 14-day jump in sign-ups versus +10.0% on random placebo dates—a net surge of +29.5 percentage points ($p < 0.001$)—compared with net changes of +7.9 percentage points for Google and −1.5 percentage points for OpenAI.

E.3 Public-Transit Commuting and Remote-Work Schedules

Finally, we construct a weekday public-transit proxy for in-person commuting frequency on our open-banking salaried panel (Figure A9) by identifying weekday fare payments to Transport for London, National Rail train operating companies, and regional metro and bus operators (Barrero, Bloom, and Davis, 2021; Dillon et al., 2026; Lambert and Schindler, 2026). We focus on 19,959 regular commuters in the rolling primary salaried sample who record weekday transit fares in at least eight weeks of the half-year with at least 70% of transit payments occurring on Monday through Friday, grouped by their mean weekly count of weekday fare-payment days (< 1, 1–2, 2–3, and > 3 days per week). Unadjusted paid AI adoption is slightly lower among

workers commuting less than one day per week (7.8%) than among those commuting more frequently (10.4% to 10.7

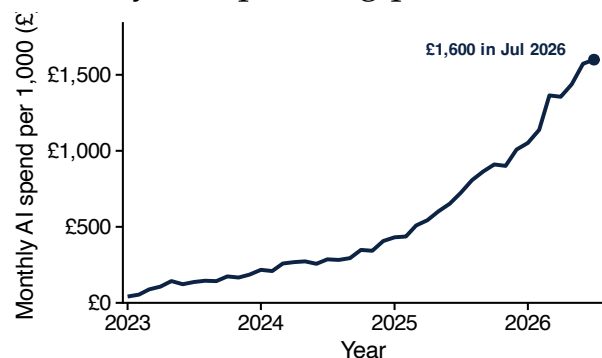
Table A11: Account-Level Subscription Tier Upgrades to Power-User Plans

Plan upgrade transition	Accounts on origin tier	Upgraded accounts	Share of origin (%)	Active at or above tier in Jul 2026
Claude Pro → Max 5× (£18/£20 → £90)	2,242	124	5.53	82
Claude Pro → Max 20× (£18/£20 → £180)	2,242	15	0.67	<10
Claude Max 5× → Max 20× (£90 → £180)	246	31	12.60	23
ChatGPT Plus → Pro (£20 → £160–£200)	8,625	30	0.35	<10
ChatGPT Plus → Pro 5× (£20 → £80–£100)	8,625	21	0.24	19
ChatGPT Plus → Team (£20 → £25+/seat)	8,625	13	0.15	<10
ChatGPT Go → Plus (£6.99/£8 → £20)	1,020	49	4.80	41

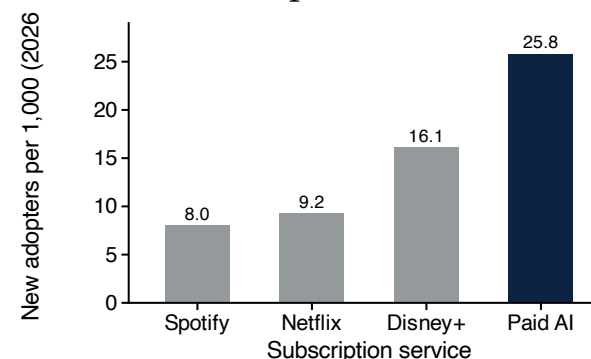
Notes: This table reports account-level vertical upgrade transitions across active subscription price tiers for OpenAI (where 0.59% of ChatGPT Plus subscribers upgrade to £80+ individual Pro plans and 0.15% transition to multi-seat Team plans, totaling 0.74%) and Anthropic (where 6.20% of Claude Pro subscribers upgrade to £90–£180 Claude Max plans). Cells with fewer than 10 underlying accounts are suppressed as < 10.

Figure A6: Aggregate Consumer AI Spending, First-Time Adopter Inflows, and Extensive vs. Intensive Margins

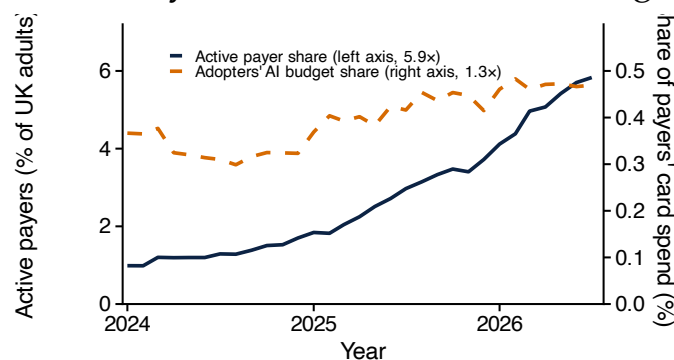
(a) Monthly AI Spending per 1,000 UK Adults



(b) First-Time Adopters vs. Streaming (2026)



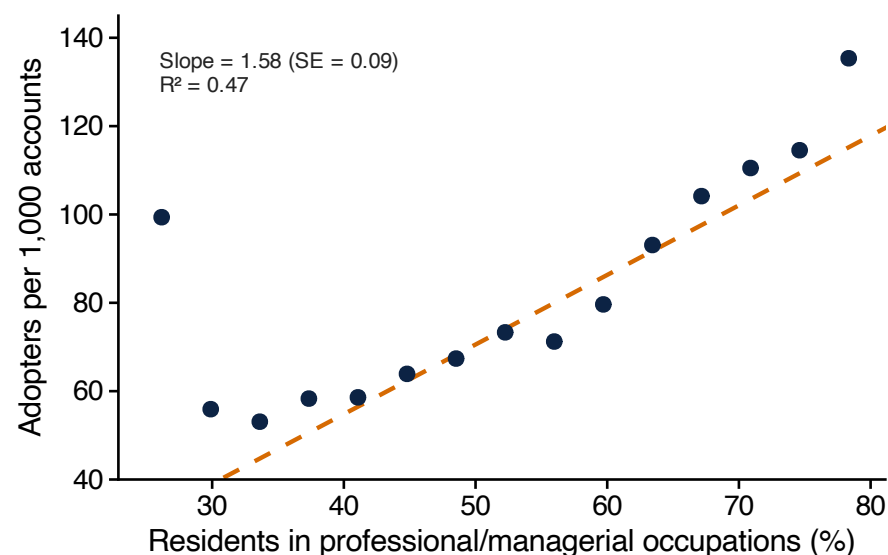
(c) Extensive Payer Share vs. Intensive Budget Share



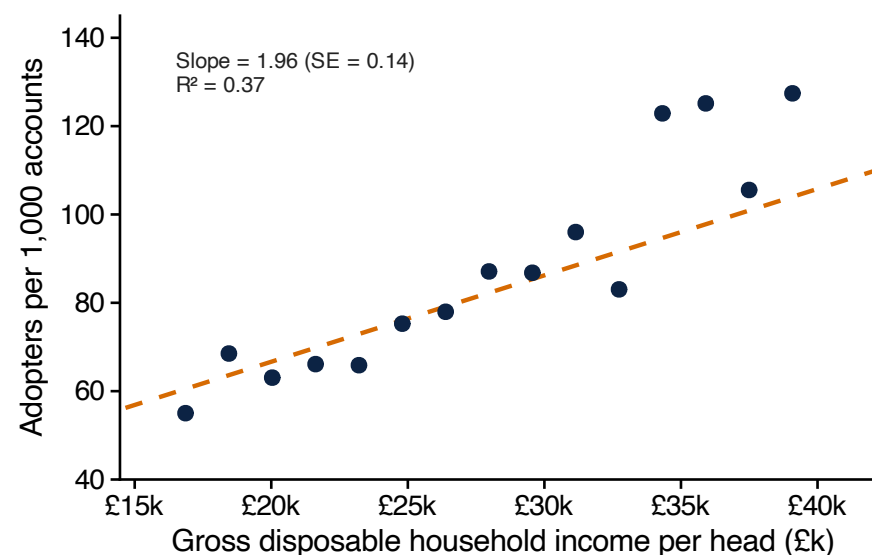
Notes: Panel (a) plots monthly consumer expenditure on standalone AI products in pounds per 1,000 UK adults from January 2023 to July 2026. Panel (b) compares cumulative first-observed paid AI adopters per 1,000 UK adults over January–July 2026 (showing both direct billing and app-store-adjusted series) against directly observed first-time panel entrants to Disney+, Netflix, and Spotify among accounts continuously observed for at least 12 months prior to January 2026. Panel (c) plots the monthly percentage of UK adults billed for AI (left axis) alongside monthly AI spending per active payer expressed as a percentage of active payers' fixed window-average total monthly card spending (£5,890, right axis). Accounts are reweighted to represent UK adults.

Figure A7: Local Authority Paid AI Adoption vs. Occupational Structure and Household Income

(a) Local Authority Adoption vs. Professional Share

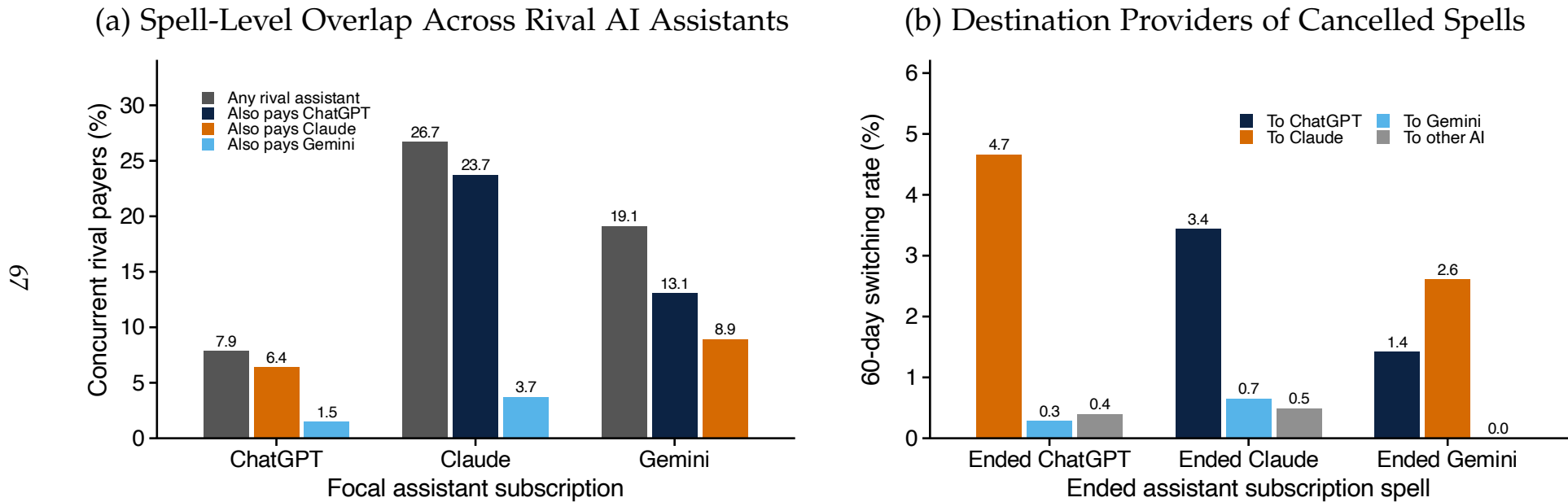


(b) Local Authority Adoption vs. Household Income



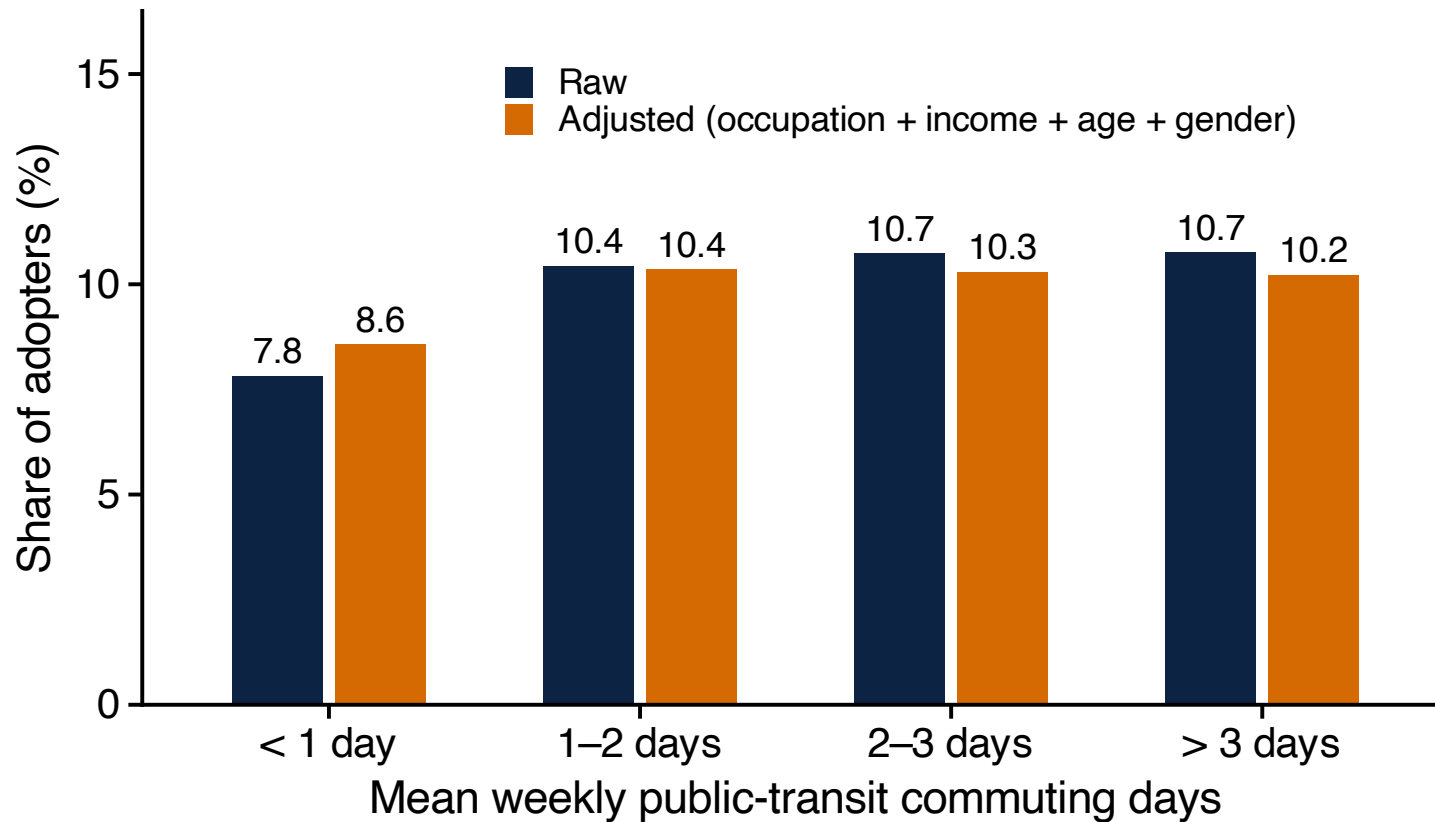
Notes: This figure plots cross-area binscatters of cumulative paid AI adoption per 1,000 accounts across Great Britain local authority districts against the Census 2021 share of residents in managerial and professional occupations (Panel a) and ONS Gross Disposable Household Income per head (Panel b).

Figure A8: Spell-Level Rival-Assistant Multi-Homing and 60-Day Cross-Provider Switching



Notes: Panel (a) reports the percentage of general-purpose assistant subscribers (ChatGPT, Claude, and Gemini on the balanced primary panel) who concurrently hold an active paid subscription with a rival general-purpose assistant during their subscription spell (corresponding to the 6.0% balanced-panel assistant multi-homing rate vs. 4.2% monthly rolling-panel multi-homing rate; cross-product monthly overlap across all standalone AI sellers averages 35.1% at peak and reaches 44.3% at ElevenLabs and 37.9% at Midjourney). Panel (b) tracks ended assistant subscription spells where the account continues transacting and reports the percentage that initiate a subscription with a competing AI provider within 60 days.

Figure A9: Paid AI Adoption by Weekly In-Person Public-Transit Commuting Days



Notes: This figure plots paid AI adoption across mean weekly in-person public-transport commuting frequency bins (< 1 day, 1-2 days, 2-3 days, and > 3 days) among 19,959 salaried regular transit commuters in the rolling primary panel. Navy bars show unadjusted adoption rates; orange bars show adoption rates adjusted for occupation, net take-home salary, age, and gender. Commuting classification and regression specifications are detailed in Appendix [E.3](#).