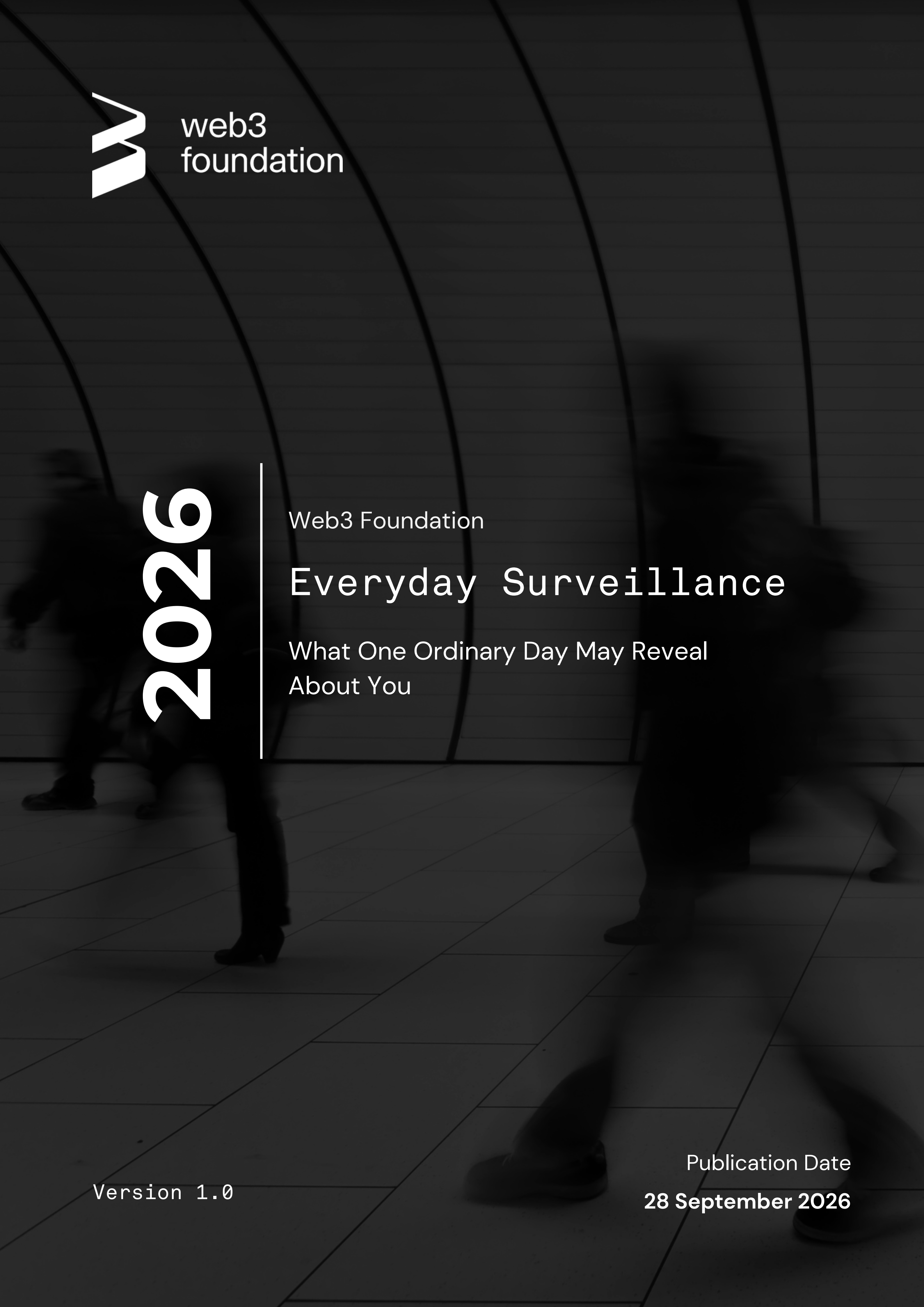

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Web3 Foundation

# Everyday Surveillance

## What One Ordinary Day May Reveal About You

Version 1.0

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# Contents

# 1. Foreword

Web3 Foundation supports a fairer internet built on systems that are more distributed and give people greater control over their data and identity. This is the second White Paper in a series about the data that modern digital services may collect, generate or infer during ordinary use. The first paper, which was titled *The Hidden Price of Free: What Your Data Is Really Worth* (https://web3.foundation/insights/), examined the economic value created from personal data. This paper asks a more immediate question: what do published policies, technical materials and other evidence indicate could be collected, generated or inferred about a model person or model household during one ordinary day, not only through the products and services they choose to use, but also through the systems operating around them, including those they do not directly choose or sign up to, such as cameras, number-plate readers and public or institutional systems?

The modelled scenarios indicate that the potential data footprint is extensive. A model person can wake, travel, work, shop, exercise, watch television, speak to family and go to sleep while devices, services and surrounding systems may create a trail of records about their body, home, money, movements, relationships, children, health, interests and likely future behaviour.

### Working Definition

In this paper, 'surveillance' means the systematic generation, observation, recording or inference of information about a model person or model household. The term describes an information process, not a legal conclusion or an allegation of wrongdoing. It includes records that may be created for safety, public services, administration, commerce and security as well as potential advertising or behavioural monitoring.

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### Version and Corrections

This White Paper reflects the evidence and source material reviewed during the research period. Web3 Foundation welcomes factual corrections or relevant updates to the evidence cited. To report a potential factual error, provide updated source material or raise a question about the research, please contact us at hello@web3.foundation or via post at Web 3.0 Technologies Foundation, Gotthardstrasse 3, 6300 Zug, Switzerland. Where appropriate and confirmed, material corrections will be reflected in subsequent versions of the White Paper, with the version number and publication date updated accordingly.

# 2. Definitions and Counting Rules

| Term | Meaning in this paper |
|---|---|
| ACR screen capture | A screen observation captured by an Automatic Content Recognition system and used to generate a content signature or fingerprint identifying what is showing on the television. |
| Additional documented use | A documented way in which data associated with a primary use may be processed beyond what the study defines as the primary use. |
| Camera capture | An image or video clip in which a model person or model household may be recorded by CCTV, doorbells, school cameras, dashcams or similar systems. |
| Collected data | Information received from a model person or model household or their respective device, from another organisation or from a public source. |
| Commercial-partner sharing | A study-defined tier of onward data sharing with commercial third parties. It excludes processors acting solely on the organisation's instructions, transfers arising from mergers or bankruptcy, data received rather than sent and sponsored arrangements. Processor sharing remains included in the broader sharing measure. |
| Countable observation | One separately countable machine measurement, fingerprint, image or other recorded observation about a model person or model household within a documented stream. It is used to calculate the conservative daily observation floorand is a counting unit, not a legal or severity judgment. |
| Generated data | A new record made automatically by a system because of an activity, sensor, transaction or interaction with a model person or a model household. |
| High-volume data stream | A fast repeated series of machine-made observations, such as heart-rate readings, ACR screen captures or smart-meter readings. These are kept separate from the modelled processing-event figure. |

| Term | Meaning in this paper |
|---|---|
| Inferred data | A guess, category, score or prediction worked out from other information rather than directly supplied by a model person or a model household. |
| Model household or model person (depends on the context) | An evidence-based model person or model household built from common features, routines and product / services use. It is not a real person. |
| Modelled processing event | A particular occasion in the modelled day when a model person's or model household's data is collected, generated or inferred as part of a specific interaction or processing episode. |
| Open-ended retention | Retention described in an organisation's documents without a fixed retention period |
| Organisation | One organisation linked to one modelled household's modelled day. |
| Periodic overlay | An activity that is plausible in the model but does not happen every day, such as an insurance renewal, occasional takeaway, dating-app use or age check. Periodic overlays are excluded from the conservative daily observation floor. |
| Primary use | A modelled occasion on which a model household uses a product or service for the immediate purpose for which it appears in the modelled day. |

# 3. Executive Summary

This White Paper asks a simple question: what do published policies, technical materials and other evidence indicate could be collected, generated or inferred about a model person or model household during one ordinary day, both through the products and services they choose to use and through the wider systems operating around them, including systems they never actively signed up to?

To answer it, Web3 Foundation built six evidence-based model households, three in the United Kingdom and three in the United States, and followed them through a modelled 24-hour period.

This White Paper mapped the products and services model persons used, the systems operating around them and the information those systems say they collect, generate or infer. It draws on company privacy notices and terms, technical documentation, regulator records, academic research and published measurement studies.

The permissions described by organisations that provide these products and services are detailed in their privacy policies, notices and supporting documents. This study examined that fine print to establish what organisations themselves say they may collect, generate, infer and do with information about a model person. A documented permission shows what an organisation says it may do; it does not establish that every permitted action occurred in a modelled scenario or occurs for every (or any) actual user.

The modelled scenarios show the potential scale of everyday surveillance (as the term is defined in Foreword above). In all four single-adult models, more than 20,000 countable observations can each be generated in a modelled day.[1] These headline counts do not represent the full potential footprint. Many background network calls, advertising auctions, device messages, cloud syncs and camera encounters cannot be given a stable daily number and are therefore excluded from the totals. The figures in this White Paper are merely documented minimums or reasonable ranges that can be clearly evidenced, rather than a complete tally of every digital observation made around a model household. The potential footprint may, therefore, be higher.

In the UK model, a 34-year-old working single adult is linked to 68 organisations across the modelled 24-hour period through products and services appearing in his day and associated data flows. The study identified around 271 modelled processing moments, more than 1,100 possible body readings, about 21,600 modelled ACR screen captures and an estimated 60 to 190 potential camera captures. The modelled UK family is linked to 88 organisations, 25 of which have documents indicating that they may collect information relating to the children. Their two children could generate around 100 school-camera captures in a day and 11,400 logged keystrokes in a school week, including keystrokes that may be recorded even when text is immediately deleted or never sent.

The same pattern appears in the United States model households. The modelled day of an ordinary 34-year-old single man involves 62 organisations, about 219 modelled processing events, roughly 1,000 heart-rate samples and an estimated 20 to 80 private camera clips. A US model household with children combines about 2,000 potential daily heart-rate readings with the possibility of minute-by-minute school-device monitoring, child location modelled as being available around the clock and two to six roadside number-plate reads a day. For a

[1] This headline figure is driven principally by the study's ACR modelling assumption, under which Samsung Viewing Information Services is assumed to be enabled and screen observations are modelled at approximately 500-millisecond intervals during the relevant viewing period. If ACR observations are excluded entirely, the corresponding daily floors fall to approximately 1,100 for Sam and 1,000 for Bob, being their modelled wearable readings alone, and to zero for Margaret and Carol, whose floors consist of ACR observations only. Camera captures, smart-meter intervals and plate-reader records are reported separately as ranges or intervals and are not part of these floors. The headline figures should therefore be read as assumption-dependent modelled estimates, rather than measured observation counts for typical users

retired 75-year-old the model assumes her location is available to family 24 hours a day and daily scans are made of her incoming mail envelopes.

Television illustrates how an activity that feels entirely ordinary can produce a large volume of behavioural information. Where the model assumes that Automatic Content Recognition is enabled, a smart television can recognise what is appearing on the screen and can decide that information is to be linked to an identifier associated with the model household. This means, for example, it could notice that at 8:03 pm the screen showed a particular football match, at 8:27 pm it switched to Netflix and later displayed a particular advert. Over time, this can create a detailed profile of viewing habits, including which news, sport, programmes and advertisements are regularly watched. Applying the stated modelling assumption, the study concludes that even a retiree in the United Kingdom with limited overall technological exposure can still generate about 40,000 such television scans during five to six hours of viewing over a 24-hour period, while for a retiree in the United States the number of scans is 36,000.

Much of what can be captured is deeply personal. The modelled data includes sleep, heart rate, medication, reproductive health, financial circumstances, browsing, messages, photographs, contacts, location, driving, school activity, household occupancy and political or religious behaviour. The organisations' documents also describe circumstances in which systems may also then use this data to infer further information about people, including possible health concerns, financial stress, political leanings, sexuality, personality, interests and likely future behaviour. By bedtime during the modelled day, different organisations therefore have the potential to hold fragments which, when linked, can produce a remarkably detailed picture of a model person's life.

The organisations generally describe these practices in their own terms, privacy notices and supporting documents. Across the six household reading-time rosters, the study counted 1,195 document entries containing more than 5.38 million words after applying the reading-time inclusion and exclusion rules. Depending on the model household, reading the material governing just one modelled day would require 37 to 83 hours, or 4.6 to 10.4 full working days. For the model Leeds family alone, 257 documents contain almost 1.19 million words and would take about 83 hours to read. These figures measure reading burden. The study did not measure whether users read or understood the documents.

What those documents permit is equally important. Across the 143 organisations examined, 118 (83%) have documents describing use of data for marketing, 114 (80%) combining data across sources, 109 (76%) inference or profiling, 102 (71%) sharing with commercial partners and 95 (66%) no fixed retention period stated. Separately, the documents of at least 35 organisations (24%) contain an affirmative statement that user data may be used to train or improve AI or machine-learning systems. Across 1,280 primary uses, the five practices used in the per-use calculation — marketing, combination across sources, inference, commercial-partner sharing and no fixed retention period stated — produce 4,283 documented claims, an average of 3.4 per primary use.

The UK and US achieve this through different institutional structures. The UK model households in the study linked to more separately counted organisations than their US equivalents, while the US models show wider involvement of some commercial location, insurance and data systems. This reflects the modelled involvement in the UK of several public or quasi-public systems that are counted separately, including smart-metering, health, transport and police infrastructure, while in the US models some comparable functions are bundled within broader commercial providers. This illustrates how regulation impacts who may collect and reuse information, what rules apply and what rights people have once the data exists. It does not remove the underlying reality that modern life continuously generates personal data which has the potential to be used and stored.

The modelled days consist of the ordinary activities: waking up, travelling, working, shopping, communicating, caring for children, watching television and going to sleep. The study concludes that the systems surrounding those activities may generate measurements, identifiers, images, location traces, financial records and behavioural signals. This matters to Web3 Foundation. That is why we will be publishing an open dataset and will examine the primary questions raised by this study in the next White Papers produced in this series.

We recognise that the answer is not stopping all data collection. Cameras, smart meters, medical systems, schools and connected services have legitimate functions. The more important question is whether digital systems can be designed so that people disclose less information by default, fewer permanent copies are made by default, permissions are structured in a way that it’s easy to make informed choices clearer and to withdraw, and proving something about yourself (e.g. age) does not always require surrendering the underlying data (e.g. date of birth). Only once those steps have been taken will we be on the way to a fairer and safer internet.

**Important note on limitations**: This White Paper presents evidence-led model scenarios rather than observations of real individuals or statistically representative national averages. References to information that “may”, “could” or “can” be collected, generated, inferred or processed describe documented capabilities, permissions or supported modelling assumptions and do not establish that every such action occurred, occurs for every (or any) user, or occurs every (or any) day. The findings are sensitive to product choice, configuration, settings and opt-outs, and exclude background activity for which no reliable daily count could be established. Numerical results are therefore documented minimums, modelled estimates or reasonable ranges and should not be treated as a complete tally of the data associated with any real person or household. Full limitations are set out in the Methodology section under “Limitations” and a full detail of the method used for calculating results in Appendix E Technological Methodology.

# 4. Methodology

## Study design

The study follows six matched model households through one ordinary 24-hour weekday period. In both the US and UK there is a working adult living alone, a family with two children and an older adult living independently. The models are designed to be evidence-led and recognisably ordinary, not statistically representative of every person in the US or UK. They are modelled scenarios, not diaries of real people.

## Archetype and product selection

The research built each model household from common demographic features and common patterns of product use. It used market data, academic research and other evidence about ordinary routines. The model includes things a person chooses to do, such as opening an app, and background systems that become involved because the person travels, pays, works, watches television, manages health, drives or uses a public service. Appendix C lists the product and service research set and explains why each item is included.

For example, a Samsung Smart TV was selected following research that examined television ownership, purchasing and product-prevalence evidence. Samsung smart televisions include Automatic Content Recognition (ACR), which operates through the relevant Viewing Information Services. For the purposes of the model, ACR is assumed to be enabled. No public data was identified showing the proportion of users who enable or disable it. Omdia, the independent market research firm, has found that Samsung was the world's largest television brand by revenue for the last 20 years, and in March 2026 reported it accounted for 29.1% of global television revenue the previous year. Appendix B2 provides full details of the analysis, evidence and modelling assumption underpinning the findings on Automatic Content Recognition.[2]

## Evidence hierarchy

Evidence sources perform different roles in the study. The analysis of what organisations say policies, terms and related documentation. Laws, regulator and government materials are used to establish legal or institutional context and to report regulatory or judicial findings. Academic and market research is used principally to establish prevalence, product choice and ordinary routines. Reputable reporting is used as supporting background where appropriate. A company policy establishes what the company says it may do; it does not establish that every permitted action occurred.

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[2] Samsung Electronics (2026), 'Samsung Electronics Marks 20 Consecutive Years as the World's No.1 TV Brand', 8 March 2026, citing Omdia 2025 market data showing a 29.1% global TV revenue share. Available at: https://news.samsung.com/global/samsung-electronics-marks-20-consecutive-years-as-the-worlds-no-1-tv-brand; Samsung Electronics, 'Samsung Smart TV Automatic Content Recognition (ACR) Feature'. Available at: https://www.samsung.com/us/support/answer/ANS10010616/.

For the purposes of the model, we assume an Automatic Content Recognition (ACR) sampling interval of approximately 500 milliseconds, equivalent to about two observations per second. This figure is solely taken from allegations in the Texas Attorney General's December 2025 petition against Samsung, which alleged that Samsung's ACR system captures audio and video information at approximately 500-millisecond intervals and operates across native apps, built-in channels and external inputs. Samsung's own current materials describe ACR differently, stating that the system generates unique content signatures to identify viewing information and that Samsung does not record or watch the content displayed on the television. We identified no public Samsung statement specifically confirming or denying the alleged 500-millisecond interval. The February 2026 agreement between Samsung and the Texas Attorney General required clearer disclosures and express consent for ACR collection but did not establish the accuracy of the alleged sampling interval. We therefore use the 500-millisecond figure solely as a modelling assumption for the arithmetic and do not take a position on whether the allegation is correct.

## Countable surveillance observation

A countable observation is one separately countable machine measurement, fingerprint, image or other recorded observation about a model person or model household within a documented stream. It is used to calculate the conservative daily observation floor and is a counting unit, not a legal or severity judgement. To calculate the daily floor, the study separates the daily baseline from periodic activities, such as using a dating app or ordering a takeaway. These periodic overlays are excluded from the conservative daily observation floor because they are occasional rather than everyday events.

## Counting framework

The study distinguishes four kinds of data relationship: direct use, where the model household uses a product; data flows, where another organisation receives or records data because of something happening in the day; standing records, where an institution holds an ongoing file independently of that day's activity; and ambient capture, such as cameras and number-plate readers. Headline organisation counts include organisations appearing in the modelled days and associated data flows. Standing records are reported separately.

The model uses several measures because one number cannot fairly describe every kind of data activity. Organisation counts show how many organisations are involved. Modelled processing events show specific moments of collection, access or processing that the research can support. High-volume data streams, such as heart-rate readings, smart-meter readings and television viewing scans, are kept in their own units. Camera exposure is shown as a range when the evidence supports a minimum and maximum. The same organisation can appear in more than one model household, but each model household is reported separately. Several products from one organisation do not automatically become several organisations.

## Treatment of time and continuous systems

For systems that run continuously, the study uses the clearest unit supported by the evidence instead of inventing an event count. A smart meter is shown by its reading interval. A television ACR system is shown using the documented capture interval applied over the modelled viewing period. Wearables are shown by supported physiological sampling rates. Continuous location availability is described as 24/7 where no defensible event count exists. Annual plate-reader records remain annual unless the source supports a fair daily conversion.

Each modelled day is divided into 13 episodes. Every day includes at least one money or administrative moment, such as a credit check, insurance renewal, contract switch, mortgage payment or buy-now-pay-later checkout, because such activities can trigger background reporting or inquiries involving lenders, insurers and credit-reference agencies.

## Numbers, ranges and uncertainty

Numbers are used only where the research supports a repeatable calculation. Ranges stay as ranges. The paper deliberately leaves many background network calls, advertising auctions, device communications, cloud synchronisations and camera encounters uncounted because the available material does not support a stable daily number. The numbers in this White

Paper should therefore be read as documented minimums or reasonable ranges, not as every (or any) single digital message produced by a real household.

## Collected, generated and inferred data

The study separates three kinds of information. Collected data is information a person or another source gives to a system, such as a name. Generated data is a new record created by an activity or sensor, such as a heart-rate reading or smart-meter reading. Inferred data is a guess, score or prediction worked out from other information, such as a likely political view or risk score.

## Limitations

These findings are based on evidence-led model households, not real people or statistically representative national averages. Company policies show what services may collect or process, not that every (or any) action happens to every (or any) user every (or any) day. Results also depend on the products and settings used in each model, including whether optional data-collection features are enabled or disabled (our model assumes enabled where those features are included) and whether settings, opt-outs or account configuration apply (our model applies the settings, opt-outs and account configuration specified for each model). The study does not establish that the feature is enabled for every(or any) real user or by default. The numerical findings should be read as documented modelled minimums, modelled estimates or reasonable ranges. Many background processes cannot be reliably counted and are excluded. Different observations also vary greatly in sensitivity and significance, so the headline figure measures frequency, not severity.

The archived document corpus used for the reading-time and classification analysis is dated 1–2 September 2026. Legal, regulatory and other contextual material was checked separately up to 18 September 2026. Documents, product settings and functionality can change frequently. Recent examples within the study include Amazon's withdrawal of Alexa's local voice-processing option in March 2025, meaning those requests are instead processed through Amazon's cloud services, and changes introduced to the use of interactions with WhatsApp's Meta AI for advertising personalisation effective from December 2025. The findings should therefore be read as reflecting the documented position during the study period rather than as a permanent account of how any product or service included in the study operates.[3]

This White Paper has not been independently reviewed by an external reviewer. The methodology, assumptions and supporting data are published as part of the study so that the calculations, source choices and analytical approach can be scrutinised, challenged and rerun by others. Because model-assisted steps use live search and no fixed seed, an independent rerun should reproduce the rules and settings but may not reproduce identical model outputs.

[3] TechCrunch (15 March 2025), 'Amazon's Echo is ending its "Do Not Send Voice Recordings" feature, starting March 28', reporting Amazon's notice that supported Echo devices would no longer offer local processing of Alexa voice recordings; Amazon, 'Alexa and Alexa Device FAQs'. Available at: https://digprjsurvey.amazon.com/csad/help/node/201602230; Meta (2025), 'Improving Your Recommendations on Our Apps With AI at Meta', effective 16 December 2025. Available at: https://about.fb.com/news/2025/10/improving-your-recommendations-apps-ai-meta/.

**Aggregate profiles**

The illustrative profiles show what separate pieces of information could reveal when they are linked by a stable detail such as a name, address, phone number, account, device or vehicle. They are reconstructions made for this study, not files bought from one data broker.

# 5. Who the Six Model Households Are

The six people and families in this paper are construed models, but they were not chosen at random. Each was built from extensive publicly available data about how an ordinary person at that stage of life is likely to behave. The research looked at age, family size, whether people rent or own their home, work, transport, health and care needs, devices, media habits, banking, shopping, schools and how common particular products are in order to establish an appropriate 'everyman' suite of products and services used. Official statistics, academic research, market evidence and published usage patterns were used to construct realistic routines based on common behaviours and services, and product use.

The objective was to create model households that are evidence-led and hence feel recognisably ordinary and can be fairly compared between the UK and US. They do not suggest that everyone of the same age behaves in the same way nor what any real person did at a particular time. The model households are evidence-backed models built mainly from common demographic, behavioural and product-use characteristics. Where the study deliberately departs from the most common value, that choice and its rationale are identified in Appendix E.

Appendix A gives the full modelled 24-hour routines and Appendix C explains why each product, service or system was included. In addition a Technological Methodology is provided in Appendix E to further explain the process behind this study. That research resulted in the following archetypes:

| Archetype | Evidenced-based model profile & model product environment |
| --- | --- |
| **Sam – 34, Manchester, United Kingdom** | Single male renter in a one-bedroom flat: full-time office administrator in a hybrid role; one car; no stated health conditions. Uses an iPhone and Apple Watch, home broadband, Samsung smart TV, Alexa, mainstream social and messaging apps, streaming, online banking, credit checking, food delivery, connected-car services and a smart meter. |
| **Bob – 34, Columbus, Ohio, United States** | Matched single working adult: never married, renting an apartment, full-time hybrid office work and one car. Uses an iPhone and Apple Watch, home broadband, Samsung/Roku television, Alexa, Chase and Venmo, social and dating apps, online shopping, a connected Ford, navigation, credit services and a 15-minute smart meter. |

| Archetype | Evidenced-based model profile & model product environment |
|---|---|
| **Priya and Tom – 40 and 43, Leeds, United Kingdom** | Married couple with children aged 8 and 11 in a mortgaged semi-detached home: Tom works full-time and Priya part-time; one car. The household combines adult phones and wearables, children's devices and school systems, Samsung TV, Alexa, Ring, online groceries and banking, ParentPay, health services, a connected vehicle and smart metering. |
| **Maria and David – 37 and 39, Charlotte, North Carolina, United States** | Married suburban homeowners with children aged 8 and 11; both work full-time and David works remotely; two cars. The family uses Apple/Fitbit wearables, school-device monitoring, Life360, Ring, Samsung TV, Alexa, online banking and shopping, a connected Toyota, private plate-reader infrastructure and smart metering. |
| **Margaret – 75, Yorkshire, United Kingdom** | Widowed, retired homeowner living independently in a small Yorkshire town: owns her home outright, receives State Pension plus a small occupational pension and still drives. Uses a smartphone and tablet, television, Alexa, online banking and NHS services, a smart meter, a medical-alert pendant, video doorbell and location sharing with her daughter. |
| **Carol – 75, Tucson, Arizona, United States** | Widowed, retired and mortgage-free; lives independently on Social Security and retirement savings and drives one car. Uses an iPhone/iPad ecosystem, television plus Roku, Alexa, Ring, Medicare and patient portals, pharmacy apps, smart metering, a medical-alert pendant and 24/7 location sharing with her daughter. |

Data collection comes from much more than apps a model person chooses to open. A home brings utilities and connected devices. Work brings workplace software. Children bring school and safety systems. Driving brings automatic vehicle data and number-plate cameras. Older age can bring health, pharmacy, benefits and emergency-care systems. That is why the study looks at the whole modelled day and what data the evidence indicates may be collected, generated or inferred across each model scenario.

# 6. One Ordinary Modelled Day in Numbers: Six Separate Scenarios

## Summary

| Model Household | Organisation/event scale | High-volume datastreams | Other quantified modelled (potential) exposure |
|---|---|---|---|
| **Sam, 34 – Manchester, UK** | 68 organisations; ~271 modelled processing events; 522 described information items in the illustrative profile | 1,100+ biometric/physiological readings; ~21,600 ACR TV screen captures | ~60-190 camera captures; 48 half-hour meter intervals; 1,847 uploaded contacts; 11 group chats; AI-use review: at least 22/68 assessed products |
| **Bob, 34 – Columbus, Ohio, US** | 62 organisations; ~219 modelled processing events; 485 described information items | ~1,000 heart-rate samples plus four overnight metrics; ~21,600 TV screen captures | 96 quarter-hour meter intervals; 1,284 plate reads/12 months; one linked financial connection can expose up to 24 months of transactions; ~20-80 private camera clips; 12 companies holding voice recordings; AI-use review: at least 20/62 assessed products |
| **Priya and Tom, 40/43 – Leeds, UK** | 88 organisations; 25 may collect from the children | ~2,000 combined body readings; four TV viewer profiles | ~100 child school-camera captures/day; ~90-260 whole-family recordings/day; 11,400 school keystrokes/week; 45 min in-cabin footage; 48-meter intervals; AI-use review: at least 26/88 assessed products |
| **Maria and David, 37/39 – Charlotte, NC, US** | 81 organisations | ~2,000 daily heart-rate readings | ~79 child camera captures/day; minute-by-minute school-device monitoring; child location 24/7; 2-6 plate reads/day; 24-96 meter intervals; AI-use review: at least 28/81 assessed products |
| **Margaret, 75 – Yorkshire, UK** | 49 organisations | ~40,000 TV ACR screen captures during 5-6 hours of viewing | ~16-45 quantified doorbell clips; 48-meter intervals; 312 plate reads/12 months; telecare and health-service records |
| **Carol, 75 – Tucson, Arizona, US** | 44 organisations; 173 modelled processing events including 156 product touchpoints | ~36,000 Samsung ACR screen captures from about five hours of viewing | ~25-65 camera captures; 24-96 meter intervals; 186 commercial plate reads/12 months; 24/7 location; daily mail-envelope scans |

## Detailed Findings

### Sam, 34, single working adult – Manchester, United Kingdom

| Daily indicator | Estimated exposure / model output |
|---|---|
| **Organisations** | 68 separate organisations are associated with his modelled day. |
| **Modelled processing events** | Approximately 271 modelled processing events. |
| **Described information** | 522 described information items. |
| **Body and health** | More than 1,100 biometric and physiological measurements: roughly 1,000 heart-rate samples plus sleep, respiratory, wrist-temperature, blood-oxygen and facial measurements. |
| **Television** | Approximately 21,600 modelled ACR viewing screen captures in one day. |
| **Physical cameras** | Estimated 60-190 recordings: roughly 30-110 residential doorbells, 20-50 tram CCTV captures and 10-30 shop, gym and office recordings. |
| **Finance** | Documents for 45 organisations in the source analysis list his home address as potentially held and 35 list financial or payment information as potentially collected. |
| **Home** | 48 half-hour smart-meter intervals across 24 hours. |
| **Movement** | Maps, tram CCTV and connected-vehicle systems add route, journey and vehicle-health records. |
| **Communications** | 1,847 uploaded contacts, 11 group chats and 6 daily ties. |
| **AI training/model improvement** | At least 22 products say they may use Sam's data to train or improve AI. |

Nothing unusual happens in Sam's modelled day. He checks messages, travels to work, pays for things, shops, exercises, watches television and sleeps. Yet the model links that day to 68 organisations and about 271 modelled processing events, alongside more than 1,100 body readings, around 21,600 ACR screen capture and an estimated 60 to 190 camera captures. His modelled routine may create records about health, movement, finances, contacts, viewing, work and likely interests even before any attempt is made to combine them into a profile.

### Bob, 34, single working adult – Columbus, Ohio, United States

| Daily indicator | Estimated exposure / model output |
|---|---|
| **Organisations** | 62 organisations are associated with the day. |
| **Modelled processing events** | Approximately 219 modelled processing events. |
| **Described information** | 485 described information items, reported separately from event counts. |
| **Body and health** | About 1,000 daily heart-rate samples plus four overnight metrics. |
| **Television** | About 21,600 modelled daily Samsung ACR screen captures from roughly three hours of viewing; Roku-related viewing/device data is separate and not added to the headline floor. |
| **Finance** | One linked financial-data connection can expose up to 24 months of transaction history in a single action. |
| **Home** | 96 quarter-hour smart-meter intervals across 24 hours. |
| **Vehicle and movement** | 1,284 licence-plate reads over 12 months, alongside connected-car location, speed, route and vehicle-health telemetry. |
| **Mail** | USPS Informed Delivery can provide grayscale images of the address side of eligible incoming letter-sized mail processed through USPS automated equipment and can record engagement with Informed Delivery. |
| **Background location** | Mobile-network, maps and connected-vehicle systems can create overlapping location records during the same journey. |
| **Private cameras** | 20-80 clips from private doorbell and yard cameras during his ordinary movements. This is separate from public or workplace cameras. |
| **Voice recordings** | 12 companies holding voice recordings, including smart-assistant and voice-authentication uses. |
| **AI training/model improvement** | At least 20 products say they may use Bob's data to train or improve AI. |

Bob's modelled day shows how a routine that feels simple can be observed through overlapping systems. One drive can create connected-car data, map history, mobile-network location and number-plate records. His modelled day includes 62 organisations and about 219 modelled processing events, while separate high-volume data streams add roughly 1,000 heart-rate samples and around 21,600 TV viewing scans. A supplementary estimate of 20 to 80 potential private camera clips shows how quickly physical observation can sit beside app and location activity.

**Priya and Tom, 40 and 43, family with children aged 8 and 11 – Leeds, United Kingdom**

| Daily indicator | Estimated exposure / model output |
|---|---|
| **Organisations** | 88 organisations may obtain data about the household; 25 may collect information from the children. |
| **Body and health** | Around 2,000 combined daily health readings from the two adults' wearables. |
| **Children at school** | About 62 camera captures/day for the daughter and 38/day for the son – roughly 100 between them. |
| **School typing** | 11,400 keystrokes are logged in a week in the illustrative school record, including messages typed and deleted but retained by the monitoring system. |
| **Vehicle** | Approximately 45 minutes of in-cabin footage on a normal day, plus GPS and telemetry covering speed, acceleration, braking, mileage, gear, battery state and seat occupancy. |
| **Finance** | 57 organisations may hold the family address and 47 may collect financial or payment information. |
| **Home** | 48 half-hour smart-meter intervals in 24 hours. |
| **Health history** | Priya's illustrative profile would contain 31 months of menstrual-cycle data. |
| **Location and safety** | Family location tools and school, transport and model household systems create additional records around children's movements. |
| **Television** | The household creates four separate viewer profiles meaning a defensible daily ACR count cannot be assigned to this family television. |
| **Whole-family filming estimate** | About 90-260 times the family may be filmed in one day across school CCTV, school-gate cameras, police number-plate cameras, shop and street cameras, their own Ring doorbell and continuous in-cabin filming. |
| **AI training/model improvement** | At least 26 products say they may use household data to train or improve AI. The review includes children's data; for example, Roblox voice recordings used for safety systems and Snapchat My AI conversations that are retained. |

For a family, the potential surveillance surface expands beyond the parents' phones. The Leeds model household is linked to 88 organisations and documents of 25 of them indicate that they may collect information from children. In this scenario, the two children could generate about 100 school-camera captures in a modelled day and 11,400 logged keystrokes in a school week. The model household also produces around 2,000 body readings, 45 minutes of in-cabin vehicle footage and an estimated 90 to 260 recordings across the family in a day.

### Maria & David, 37 and 39, family, children aged 8 and 11 – Charlotte, North Carolina, US

| Daily indicator | Estimated exposure / model output |
|---|---|
| **Organisations** | 81 organisations may obtain data about the household. |
| **Body and health** | Approximately 2,000 daily heart-rate readings from the adults' Apple Watch and Fitbit. |
| **School screens** | Classroom monitoring records what appears on school devices and which tabs are open on a minute-by-minute basis, together with device location. |
| **School cameras** | About 48 captures/day for the daughter and 31/day for the son – roughly 79 combined; the narrative range is 40-120 depending on movement through the building. |
| **Child location** | The family-location service is available 24 hours a day. |
| **Vehicle** | The family car may be recorded 2-6 times in a day by roadside plate readers, in addition to connected-vehicle location and driving data. |
| **Identity and money** | 55 of the 81 organisations collect the home address and 45 collect financial or payment information. |
| **Home** | Smart-meter readings at 15-minute to one-hour intervals create approximately 24-96 readings per day. |
| **Television** | The household creates four separate viewer profiles meaning a defensible daily ACR count cannot be assigned to this family television. |
| **AI training/model improvement** | At least 28 products say they may use household data to train or improve AI. This includes financial-data modelling, children's gaming/safety systems and the parents' work AI tools. |

The Charlotte model household combines several systems designed for convenience, safety, education and transport. The model includes about 2,000 daily heart-rate readings, around 79 child camera captures, minute-by-minute school-device monitoring, child location available around the clock and two to six roadside plate reads a day. Depending on settings and service use, the parents can see where the children are, while schools, vehicles, utilities, cameras and commercial services create parallel records of the same family's movements and routines.

### Margaret, 75, widowed retired homeowner – Yorkshire, United Kingdom

| Daily indicator | Estimated exposure / model output |
| --- | --- |
| **Organisations** | 49 organisations may obtain data about Margaret during the modelled day. |
| **Television** | Five to six hours of viewing is modelled as producing approximately 40,000 ACR screen captures – the largest quantified stream in her day. |
| **Cameras** | About 10-30 doorbell clips while walking to the shops plus 6-15 clips from her own Ring: roughly 16–45 quantified doorbell recordings before other cameras are counted. |
| **Home** | 48 half-hour smart-meter intervals can reveal regular occupancy and waking patterns. |
| **Vehicle and movement** | 312 plate reads over 12 months, linking recurring journeys to places such as the surgery, supermarket and church hall. |
| **Health** | NHS App, Patient Access/EMIS, pharmacy and optical services create separate health and appointment records. |
| **Care** | Her medical-alert service holds health conditions, medications, keyholder and next-of-kin details and logs every activation and self-test. |
| **Location sharing** | Device location can remain available to her daughter as part of the post-fall safety arrangement. |
| **Retail and identity** | Loyalty, pharmacy and payment systems add item-level purchases and identity-linked transactions to the day. |

Margaret's model scenario shows that potential extensive surveillance does not depend on heavy app use or a wearable. She owns no fitness tracker, yet her modelled day is linked to 49 organisations and multiple health, telecare, financial, utility, transport and home-safety systems. Five to six hours of television can create about 40,000 ACR viewing screen scans and her doorbell can create around 16 to 45 quantified clips. The model shows that her home and routines can reveal patterns even when she is not actively using a screen.

### Carol, 75, widowed retired homeowner – Tucson, Arizona, United States

| Daily indicator | Estimated exposure / model output |
|---|---|
| **Organisations** | 44 organisations may be associated with the day. |
| **Modelled processing events** | 173 data-collection events are modelled, including 156 product touchpoints. |
| **Television** | The model produces approximately 36,000 Samsung ACR screen captures during about five hours of viewing. Other Roku viewing/device data is kept separate. |
| **Cameras** | Estimated 25-65 recordings over a day from her own doorbell, neighbours, shops and community locations. |
| **Home** | Smart-meter readings every 15 minutes to one hour produce about 24-96 intervals per day. |
| **Location** | Under the model assumption that Carol has enabled ongoing location sharing with her daughter, her daughter can view Carol's shared location through Find My until Carol stops or pauses sharing. |
| **Vehicle and movement** | 186 commercial plate reads over 12 months, separate from connected-device and map location. |
| **Mail** | USPS Informed Delivery can provide grayscale images of the address side of eligible incoming letter-sized mail processed through USPS automated equipment. |
| **Identity and money** | 32 organisations collect her home address and 21 collect financial or payment information. |
| **Health and care** | Medicare/patient portals, pharmacy systems and a medical-alert pendant hold health, medication, identity, emergency-contact and usage records. |

Carol's model scenario shows the same point in the United States as Margaret's one in the UK. With ACR assumed to be enabled, the model estimates that her television alone can generate about 36,000 ACR viewing scans in roughly five hours. The broader model includes 44 organisations, 173 modelled events, smart-meter intervals, cameras, location sharing, mail-envelope scans, health and benefits systems.

# 7. The T&Cs

The potential scale of surveillance of the model households is described in documents, which are in principle available to these model households. The problem is the volume. For each of the six model households, this paper gathered the terms, privacy policies, notices and related documents attached to the products and services involved in one modelled day. For the reading-time calculation, the six model household rosters together contain 1,195 countable document entries after the study's inclusion and exclusion rules were applied. The study then calculated how long an adult would need to read them at 238 words per minute, the average silent reading rate for non-fiction identified in Brysbaert's 2019 meta-analysis.[4]

Reading the terms attached to a single day of such model households would itself require days of concentrated reading. Sam, the 34-year-old model person in Manchester, is linked to 224 documents containing more than 1.05 million words. Reading them would take about 74 hours, or just over 9 eight-hour working days. For Priya and Tom's model household in Leeds, the burden rises to 257 documents and almost 1.19 million words: around 83 hours of reading, equivalent to 10.4 working days. Even the two retired model households, which use fewer services, face 37 to 45 hours of reading.

| Model household | Documents | Words | Reading Hours | Reading time in 8-hour working days |
|---|---|---|---|---|
| **Sam, 34 – Manchester, UK** | 224 | 1,055,153 | 73.9 | 9.2 |
| **Bob, 34 – Columbus, Ohio, US** | 188 | 848,062 | 59.4 | 7.4 |
| **Priya and Tom – Leeds, UK** | 257 | 1,184,835 | 83 | 10.4 |
| **Maria and David – Charlotte, US** | 233 | 1,118,224 | 78.3 | 9.8 |
| **Margaret, 75 – Yorkshire, UK** | 156 | 645,118 | 45.2 | 5.6 |
| **Carol, 75 – Tucson, US** | 137 | 530,031 | 37.1 | 4.6 |

[4] Brysbaert, M. (2019), 'How many words do we read per minute? A review and meta-analysis of reading rate', Journal of Memory and Language, 109, 104047.

The six modelled household reading-time rosters together contain more than 5.38 million words. Some material, however, could not even be included in this because it was presented as a large bundle of legal documents rather than as a discrete document applicable to the model person. Plaid's legal hub, for example, contained 141,904 words spanning its full set of legal documents on a single page. Counting the entire bundle would have attributed substantial material to Bob and Maria that did not necessarily govern their particular use of Plaid, so it was excluded rather than risk overstating the reading burden. The reading-time figures should therefore be treated as a floor.

The study divides the material into three tiers. Tier A covers services the model household is modelled as actually using. Tier B covers workplace tools whose terms are accepted by an employer rather than by an individual model person. Tier C covers records held about the model person without any sign-up by them. For Sam, for example, 59.8 of the 73.9 reading hours come from services he uses directly, but another 3.7 hours come from workplace systems and 10.5 hours from records held about him without sign-up. For Margaret, who has no workplace tier, nine of her 45.2 hours come from this third category alone.

Assuming the study's reading rate, the longest single document identified in the study is Roblox's Terms of Use at 36,966 words, requiring around 155 minutes to read. While Microsoft's Privacy Statement would take about 139 minutes, Deliveroo's terms 101 minutes, the Disney+ UK legal page 97 minutes and Lloyds Personal Banking Terms around 95 minutes.

The policies contain information about potential collection and use, but the study did not measure whether users read, understood or recalled those terms. It instead quantified the reading burden: in the six modelled households, simply reading the relevant documents for one day would consume between roughly one and a half and three and a half days without sleep, or between 4.6 and 10.4 full working days.

# 8. Primary Use and Additional Documented Uses

In this analysis, each time a product appears in one model household's modelled day counts as one primary use. The primary use is the immediate purpose for which the product or service appears in the modelled day, such as getting directions, buying groceries, banking, reading news or messaging a friend. This is the primary function modelled in these scenarios, for which the product or service is used, and the information handed over enables it to work. A study of the organisations' own privacy documents indicates, however, that information collected to fulfil a primary use may be further retained, combined with other information, used to draw inferences, disclosed to others or used in automated systems, which is the additional use permitted by organisations' privacy documents.

Those mentioned privacy documents describe what the organisation says they may do based on the permissions, however, neither the privacy documents themselves nor this study establish that every permitted use occurred in a modelled interaction or occurred for every (or any) real user. Nor does this study determine whether or not any such use is in line with necessity, proportionality and lawfulness principles. This study shows only that such documented permissions extend beyond the primary use the model household was seeking to address in each modelled scenario.

The gap between the primary use and the additional permitted use can be measured. The six modelled daily schedules record 1,280 primary uses of products and services, reaching 143 distinct organisations. Reading each organisation's own documents against the specific primary service or product,

- The documents of 118 out of 143 organisations (83%) describe being able to use the data for marketing or advertising, whether their own or their partners'.
- The documents of 114 organisations (80%) describe the right to combine it with data from other services, devices, group companies or outside sources.
- The documents of 109 organisations (76%) detail the right to draw inferences from it such as about interests, characteristics, predictions or audience segments.
- The documents of 102 (71%) describe commercial-partner sharing, a study-defined category that includes relationships such as advertisers, advertising networks, marketing and measurement firms, publishers and data brokers, but excludes processors acting solely on an organisation's instructions.
- The documents of 95 organisations (66%) state retention with no fixed period at all.
- The documents of 35 organisations (24%) affirmatively describe that they can train AI or machine-learning systems on user data.

For the per-use calculation, the study applies five documented permissions for: (1) using data for marketing, (2) combining it with data from other sources, (3) drawing inferences about the model person, (4) sharing it with commercial partners and (5) retaining it with no fixed retention period stated. AI or machine-learning training is not one of the five practices in the 4,283 per-use calculation; it is analysed separately and forms the sixth criterion in the organisation-level analysisAcross the 1,280 primary uses, these five documented practices produce 4,283 documented claims, an average of 3.4 per primary use. In 214 primary uses, the organisation's documents permit all five practices. On this five-use basis, counting each organisation's documented practices once per recorded use, the modelled day's 1,280 primary uses carry 4,283 additional potential documented uses beyond what the study defines as the primary use.. Each time a model household used a primary product or service, the data associated with that primary use, on average, had the potential of between three and four further uses for it, described in the provider's own documents.

The potential exchange is also not confined to the organisations the model household directly uses. The modelled schedules record 75 additional moments in which privacy documents permit data to reach an organisation the model household was not modelled to use at all . This is distinct from the organisation-level finding that 102 of 143 organisations (71%) describe potentially sharing data with commercial partners. Here, the modelled schedules identify 75 specific additional moments in the six modelled days where the documents indicate that data could reach an organisation the household was not itself modelled as using. Separate from these product-related data flows, the model also identifies 42 pre-existing records held by credit-reference agencies, registers and public authorities. These records exist independently of the model household's use of the products and services modelled during the day.

### i. Potential additional data collection described in organisations' documents

The organisations' documents also describe a wide range of data categories that may be collected in connection with the products and services in the modelled days. Across the 143 organisations, 96 (67%) list device, cookie or advertising identifiers, 77 (54%) payment or financial details, and 66 (46%) location, including precise location as potentially collected. 46 (32%) may collect browsing, search or viewing history, 30 (21%) the content of messages or communications, 22 (15%) voice recordings, 15 (10%) contact lists or social connections, and 11 (8%) employment or income details.

The pattern is easiest to see in one product at a time. The table below takes seven products from the model households' schedules, as examples rather than a ranking. Each was selected because (i) its published privacy documents describe the potential for collection and use beyond the immediate function for which the product was modelled as being used, and (ii) together they cover very different kinds of everyday products including a map, a television, a voice assistant, a fitness app, an electricity meter and a video app. The middle column identifies the primary use the model household was modelled as using the product or the service for. The right-hand column summarises additional data collection or uses described in the organisations' own privacy documents in connection with that primary use of a product or service. Each entry is based either on the organisation's own policies and notices, or on documented regulatory action against it. Where the table relies on company documents, the wording describes what the organisation itself says it may do. Where regulatory or legal action is cited, settlements and adjudicated or regulatory findings are identified separately and are not treated as equivalent.  An investigation or settlement is not presented as establishing a breach or other wrongdoing unless the cited material itself records such a finding.

| Modelled product | The primary use | Potential additional data collection described in its documents and additional detail |
|---|---|---|
| **Google Maps** | Directions | Location logging could continue even after users switched off "Location History" in case a separate Web & App Activity account setting was enabled by default. In November 2022, Google agreed to a $391.5 million settlement with 40 US states resolving an investigation into its location-tracking practices. Google did not admit the states' findings, any violation of law or liability. The participating attorneys general described it at the time as the largest multistate privacy settlement in US history. In May 2025, Texas separately announced a $1.375 billion settlement with Google |

| Product | The primary use | Potential additional data collection described in its documents and additional detail |
|---|---|---|
| | | resolving claims involving geolocation, incognito browsing and biometric data. Location information can be precise enough to reveal home, workplace, health visits and religious or political activity. Google Maps' privacy materials describe that they may combine activity across its services and use information to personalise advertising and develop or improve its products, including AI systems.[5] |
| **Samsung Smart TV** | Watching television | Samsung describes ACR coverage across linear television, OTT, set-top boxes and gaming environments, while external HDMI sources can also be recognised. Samsung states that these viewing signals can be used for audience measurement and targeted advertising. In litigation filed in 2025, the Texas Attorney General alleged that Samsung's consent design made broad opt-in substantially easier than later opt-out. In February 2026, following that action, Samsung agreed in Texas to clearer disclosures and express consent before ACR viewing data is collected. This agreement is not described here as an adjudicated finding of wrongdoing. Samsung's privacy policy also states that, where voice recognition is enabled, voice data may be transmitted to a third-party service provider.[6] |
| **Amazon Alexa** | Setting timers, asking questions | Amazon withdrew the option for supported Echo devices to process Alexa voice requests locally in March 2025. Amazon's current privacy materials describe voice requests being processed through its cloud services and allow users to choose not to save voice recordings; in case that setting is used, text transcripts may still be retained for up to 30 days. Amazon also states that deleting recordings and transcripts may not delete other records of the actions Alexa took in response to a request, and that data already used to improve its systems may continue to be reflected in those trained systems.[7] |

[5] Massachusetts Office of the Attorney General (2022), 'AG Healey Joins Nationwide Settlement With Google Over Location Tracking Practices'; Texas Office of the Attorney General (2025), 'Attorney General Ken Paxton Secures Historic $1.375 Billion Settlement with Google Related to Texans' Data Privacy Rights'. Available at: https://www.mass.gov/news/ag-healey-joins-nationwide-settlement-with-google-over-location-tracking-practices and https://www.texasattorneygeneral.gov/news/releases/attorney-general-ken-paxton-secures-historic-1375-billion-settlement-google-related-texans-data.
[6] Samsung Electronics, 'Samsung Smart TV Automatic Content Recognition (ACR) Feature' and 'SmartTV Privacy Supplement'; Texas Office of the Attorney General, Samsung action filed 15 December 2025 and agreement announced 26 February 2026. Available at: https://www.samsung.com/us/support/answer/ANS10010616/; https://www.samsung.com/us/info/privacy/smarttv/; https://www.texasattorneygeneral.gov/sites/default/files/images/press/Samsung%20TV%20Petition%20Filed.pdf.
[7] TechCrunch (15 March 2025), 'Amazon's Echo is ending its "Do Not Send Voice Recordings" feature, starting March 28'; Amazon, 'Alexa and Alexa Device FAQs'. Available at: https://techcrunch.com/2025/03/15/amazons-echo-will-send-all-voice-recordings-to-the-cloud-starting-march-28/ and https://digprjsurvey.amazon.com/csad/help/node/201602230.

| Product | The primary use | Potential additional data collection described in its documents and additional detail |
|---|---|---|
| **Strava** | Recording a run | Strava states that new adult accounts default profiles and activities to 'Everyone', although the first and last 200 metres of future activity maps are hidden by default. Its privacy controls also default *Product Improvements* and *Personal Information Sharing* to enabled. Strava's documents describe public activity potentially contributing to products such as its heatmap and Strava Metro, the use of health and location information to potentially develop features, including AI-enabled features, and potential disclosures to advertising partners, subject to the user's settings and available opt-outs.[8] |
| **AEP Ohio smart meter account** | Electricity supply | AEP's privacy notice states that it may share name, contact and usage information with vendors marketing services such as relocation information and home warranties, may receive monetary value when customers purchase those services and AEP's privacy policy itself treats some such transactions as a potential 'sale' under applicable state privacy laws.[9] |
| **Tinder** | Dating | Tinder's current privacy policy describes processing categories including sexual orientation, message content and Face Data, including face geometry used in certain verification features. It also states that use of the service generates insights and inferences drawn from users' interactions and the information and content they provide, reflecting matters such as preferences, characteristics, predispositions, behaviour and attitudes. Tinder states that data may be shared with other Match Group companies for purposes including safety, service provision and improvement, marketing and targeted advertising and recommendation systems, and that users may in some circumstances be made visible on other Match Group services. Its current policy also states that transaction data may be retained for ten years to comply with tax and accounting legal requirements.[10] |
| **TikTok** | Watching short videos | TikTok's policies describe potential collection of information including contacts, device and usage information and, in relevant jurisdictions, biometric information. In April 2025, the Irish Data Protection Commission fined TikTok €530 million after finding GDPR infringements relating to transfers of EEA user data to China through remote access and transparency requirements; the decision is under appeal. TikTok subsequently informed the DPC that limited EEA user data had also been stored on servers in China, contrary to evidence it had previously provided. The DPC opened a separate inquiry into that issue in July 2025.[11] |

[8] Strava Help Center, 'What Are My Privacy Defaults When I Create a Strava Account?', setting out the default 'Everyone' profile and activity settings, the first/last 200-metre map hiding, Product Improvements enabled and Personal Information Sharing opted in. Available at: https://support.strava.com/en-us/articles/15401763-what-are-my-privacy-defaults-when-i-create-a-strava-account. See also Strava privacy materials archived in the study dataset.
[9] American Electric Power, Privacy Notice, 'Sale or Sharing of Data', stating that name, contact information and usage data may be shared with vendors marketing services including relocation information and home warranties, and that AEP may receive monetary value where customers purchase those services. Available at: https://www.aep.com/privacy/.
[10] Tinder, Privacy Policy, including protected-classification and Face Data categories and retention provisions stating that transaction data may be kept for 10 years for tax and accounting requirements. Available at: https://policies.tinder.com/privacy/intl/en-gb/. See also the archived Tinder policy analysed in the study dataset.
[11] Irish Data Protection Commission (2 May 2025), 'Irish Data Protection Commission fines TikTok €530 million and orders corrective measures following Inquiry into transfers of EEA User Data to China', concerning the DPC decision of 30 April 2025; DPC (10 July 2025), inquiry into transfers of EEA user data to servers located in China. Available at: https://www.dataprotection.ie/en/news-media/latest-news/irish-data-protection-commission-fines-tiktok-eu530-million-and-orders-corrective-measures-following and https://dataprotection.ie/en/news-media/press-releases/dpc-announces-inquiry-tiktok-technology-limiteds-transfers-eea-users-personal-data-servers-located.

Within all the 143 organisations that emerged from the modelling exercise, every organisation's documents were tested for six categories of potential use that may extend beyond the primary function for which the service was modelled as used by the model household: (i) potential use of the data for marketing or advertising, (ii) potentially combining it with data from other services or outside sources, (iii) potentially drawing inferences from it, (iv) passing it to commercial partners, (v) potentially keeping it on open-ended terms, and (vi) potentially training AI or machine-learning systems on it. Scored this way, 16 organisations document permissions for all six categories of potential use, a further 55 organisations document five, and 30 document four. This six-criterion organisation-level analysis consists of the five permitted practices used in the per-use calculation — marketing, combination, inference, commercial-partner sharing and open-ended retention — plus AI or machine-learning training as a sixth criterion. At the far end of potentialcollection sit the categories the law treats as needing special protection. Fifty five of the 143 organisations (38%) list special category data among what they could collect: health, biometrics, sexual orientation, political opinions, ethnicity or religion. For instance, where users supply them, political views may be potentially collected by Instagram, Tinder and BBC Studios; sexual orientation may be potentially additionally collected by DoorDash, CVS and Banner Health. [12]

A breakdown of this analysis per company examined with full results is detailed in Appendix D.

### ii. Building the new profile: combination and inference

In our modelled interaction, a model person gave one organisation one kind of information for one purpose. As per their privacy documents, the organisation can put that information together with information from elsewhere and works out what the combination implies. The documented routes for combining information include group companies, tracking tools on other firms' websites and third-party data sources, including data obtained from data providers and brokers.

The mechanics are described in the organisations' own documents. Meta states that it may receive activity information from businesses and other partners through tools including its Pixel, SDKs and related business tools, as well as information from third-party data providers. Roku's privacy policy states that it may obtain information from data providers, ad networks and other advertising partners and may combine information to derive interests and other inferences. BBC Studios states that it may use data from brokers including Experian Mosaic. Mail Online's privacy materials state it may use of identifiers and behavioural information to create interest and audience segments for advertising.[13]

In our model scenarios, the resulting information may include facts the model household did not directly provide. Spotify's documents describe potential for deriving information about interests and context from usage and device information. Tinder's policy describes it may In our model scenarios, the resulting information may include facts the model household did

[12] Information Commissioner's Office, 'What is special category data?', setting out UK GDPR Article 9 special categories. Available at: https://ico.org.uk/for-organisations/uk-gdpr-guidance-and-resources/lawful-basis/special-category-data/what-is-special-category-data/. Organisation-level coding in this paragraph is from the study dataset; see Appendix D.
[13] Company privacy and advertising materials reviewed and archived in the study dataset, including Meta, Roku, BBC Studios and Mail Online; see Appendix D for the organisation-level analysis.

not directly provide. Spotify’s documents describe potential for deriving information about interests and context from usage and device information. Tinder’s policy describes it may derive insights and inferences from user data. Aviva’s privacy materials describe it may perform automated profiling that can be relevant to eligibility, terms or pricing.[14]

### iii. The data leaves: disclosure and sale

For 48 of the 143 organisations (34%), the organisation's own documents describe selling personal data, or passing it to advertisers or other third parties in return for money or other value, including disclosures treated as a sale under applicable US state privacy laws. Separately, 20 of the 143 organisations (14%) have documents describing sharing with data brokers.

For example, Equifax’s privacy materials describe categories of personal information that may be potentially sold or shared with third parties, subject to applicable rights. TransUnion’s documents describe potential sales and sharing for specified commercial purposes, including targeted advertising. Digital Recognition Network’s materials describe potentially providing vehicle-location information to customers including lenders, insurers, collections and repossession businesses and investigators. In April 2024, the FCC fined AT&T, Sprint, T-Mobile and Verizon nearly $200 million after concluding that they had unlawfully shared access to customers’ location information with third parties without consent or adequate safeguards. The carriers challenged those orders. Appellate outcomes initially differed in 2025, but in June 2026 the US Supreme Court reversed the Fifth Circuit’s ruling in AT&T’s favour on the constitutional issue and affirmed the Second Circuit ruling concerning Verizon; the D.C. Circuit had separately upheld the T-Mobile and Sprint penalties.[15]

Hulu and Disney+ say they can potentially share across the Walt Disney family of companies acting as independent controllers; Strava's documents say that its corporate affiliates “may process under their own policies”; the payment processor behind Manchester's tram network details how it applies its own policy, which allows potential broad onward sharing. Each such handover would move the data one step further from the organisation the model household was modelled as using.[16]

### iv. Training automated systems

OpenAI states that conversations in personal ChatGPT workspaces may be used to improve its models unless the user opts out. X states that it may share public X data and interactions with Grok with xAI for training and fine-tuning, with users able to opt out through their privacy settings. Meta states that it may use certain public content from adults, including posts, comments, photos and captions, to improve its generative AI models, with objection rights available in the UK and EU. Snapchat states that My AI conversations are retained until the user deletes them and that content shared with My AI is used to improve Snap’s

[14] Company privacy materials reviewed and archived in the study dataset, including Spotify, Tinder and Aviva; see Appendix D for the organisation-level analysis.
[15] Digital Recognition Network states that its vehicle-location data and analytics are used across lending, insurance, collections and recovery. Available at: https://drndata.com/. FCC (29 April 2024), ‘FCC Fines AT&T, Sprint, T-Mobile, and Verizon Nearly $200 Million for Illegally Sharing Access to Customers’ Location Data’. Available at: https://docs.fcc.gov/public/attachments/DOC-402213A1.pdf. Sprint Corporation v. FCC, No. 24-1224 (D.C. Cir. 15 August 2025), denying the Sprint/T-Mobile petitions; Supreme Court of the United States, FCC v. AT&T, Inc., Nos. 25-406 and 25-567, decided 4 June 2026. Available at: https://law.justia.com/cases/federal/appellate-courts/cadc/24-1224/24-1224-2025-08-15.html and https://www.supremecourt.gov/opinions/25pdf/25-406_nmip.pdf.
[16] Company privacy materials reviewed and archived in the study dataset, including Walt Disney, Strava and the payment processor used in the Manchester tram scenario; see Appendix D.

products and personalise the user experience, including advertising. Nextdoor says it may use members' posts in developing its LocalGPT system. For the older consumer Copilot version, Microsoft states that signed-in users can control whether conversation activity is used to train generative AI models and can opt out; for the updated Copilot app released from 18 August 2026, Microsoft says prompts, responses and file contents are not used to train foundation models. In a 2023 complaint, the FTC alleged that Ring used customer videos to train algorithms without consent. Ring settled the case under a stipulated federal-court order requiring $5.8 million for consumer refunds and other remedies, while denying that it had violated the law. Toyota's connected-car documents describe circumstances in which driving data may be used to develop or improve automated systems, while materials reviewed for licence-plate camera systems describe captured images being used to develop or improve recognition models.[17]

The practice also extends beyond technology companies. Aviva says personal data may be used to develop AI and third-party algorithms, including in some circumstances sensitive data. TransUnion states that, where it acts as a controller under applicable state privacy law, it does not use personal data to train large language models itself, but customers purchasing data may use it to customise large language models for internal purposes or to provide products and services.[18]

### v. Data-sharing defaults

Fifty-two of the 143 organisations (36%) were coded as having at least one data-sharing default switched on.

Verizon's "Custom Experience" advertising profiling is detailed in its documents as being on by default. Microsoft consumer accounts are said in its materials that they may have data disclosed to third-party advertising platforms unless the user opts out. Amazon states that Kindle Sync is switch on marketing sharing with affiliates and outside companies unless the customer opts out. [19]

Meta states that from 16 December 2025 interactions with its AI features can be potentially used to personalise content and advertising in most regions. For WhatsApp, Meta says this cross-service personalisation potentially applies where the WhatsApp account is connected to other Meta accounts through Accounts Center. Apple Pay's financial-privacy notice states that customers cannot opt out of sharing for Apple Payments' own business purposes. PayPal's US privacy materials state that, except where applicable law requires prior consent, personal information collected after 27 November 2024 may be shared with participating partners and merchants for personalised shopping unless the user opts out. PayPal states that customers in California, North Dakota and Vermont must instead opt in to this sharing.[20]

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[17] Product and company privacy materials reviewed and archived in the study dataset; see Appendix D. For Microsoft Copilot, Microsoft Support distinguishes the older consumer Copilot version, in which signed-in users can control whether conversation activity is used for model training, from the updated Copilot app released from 18 August 2026, for which Microsoft says prompts, responses and file contents are not used to train foundation models. Available at: https://support.microsoft.com/en-us/microsoft-copilot/microsoft-copilot-privacy-controls and https://support.microsoft.com/en-gb/privacy/microsoft-copilot/activity-history. For Ring, see Federal Trade Commission (2023/2024), including the allegation that customer videos were used to train algorithms without consent and the stipulated order requiring $5.8 million for refunds and other remedies: https://www.ftc.gov/news-events/news/press-releases/2024/04/ftc-sends-refunds-ring-customers-stemming-2023-settlement-over-charges-company-failed-block.
[18] Aviva and TransUnion privacy and AI materials reviewed and archived in the study dataset; see Appendix D.
[19] Verizon, Microsoft, Amazon and Chase privacy/advertising materials reviewed and archived in the study dataset; see Appendix D.
[20] Meta (2025), 'Improving Your Recommendations on Our Apps With AI at Meta', effective 16 December 2025, including the Accounts Center qualification for WhatsApp. Available at: https://about.fb.com/news/2025/10/improving-your-recommendations-apps-ai-meta/. Apple Pay and PayPal privacy materials are archived in the study dataset; see Appendix D.

### vi. Seventeen organisations document all five per-use practices

Using the five practices applied in the 4,283 per-use calculation, 17 of the 143 organisations (12%) document all five: marketing, combining data with other sources, drawing inferences, commercial-partner sharing and open-ended retention. AI or machine-learning training is the separate sixth criterion in the organisation-level analysis.

| Organisation | Primary feature | Potential additional collection as described in the privacy documents |
|---|---|---|
| Facebook (Meta) | Staying in touch | Meta states that it may receive activity information from other businesses and third-party data providers and may combine it with information from its own services. |
| YouTube | Watching videos | Google's materials describe potential sharing with advertising and measurement partners using their own technologies alongside Google's services. |
| Instagram | Photos and messaging | Meta's materials describe potentially using information across Meta services to build interests and personalise content and advertising. |
| TikTok | Short videos | TikTok's privacy materials state that it may supplement its information with data received from third-party sources. |
| X (formerly Twitter) | News and posts | X's privacy materials describe potentially using and sharing behavioural information for personalised advertising and measurement. |
| Spotify | Music | Spotify's materials describe potentially using service and interaction data to develop and improve AI-enabled features. |
| LinkedIn | Professional profile | LinkedIn's privacy materials describe potentially drawing inferences from usage and sharing specified information within the Microsoft group. |
| Nextdoor | Neighbourhood updates | Nextdoor's documents describe potentially combining member activity with information from advertising and data partners for interest-based advertising. |
| Google News | Headlines | Google states that activity across Google services may contribute to account-level personalisation and advertising. |
| Octopus Energy | Gas and electricity | Octopus Energy Group describes the Krakenplatform as potentially using historical customer interactions to develop AI-enabled services. |
| Roblox | Children's games | Roblox's privacy notice states that some potential disclosures for targeted advertising may constitute a 'sale' or 'sharing' under applicable US state privacy laws. |
| Amazon Music | Music | Amazon's privacy materials describe potential disclosures of advertising identifiers and measurement information to advertising partners. |

| Organisation | Primary feature | Potential additional collection as described in the privacy documents |
|---|---|---|
| Plaid | Connecting bank accounts to apps | Settled a $58 million class action in 2022 over allegations that it obtained more financial data than users authorised or apps needed; Plaid denied wrongdoing and no court made a finding that it violated the law. |
| TransUnion | The credit file | TransUnion states that it does not itself use personal information to train LLMs where it acts as controller under applicable state privacy law, but that customers purchasing data may use it to customise LLMs for specified purposes. |
| Aviva | Home and motor insurance | Aviva's privacy materials state that personal data may be used to develop AI and third-party algorithms, including sensitive data in specified circumstances. |
| Direct Line | Car insurance | Direct Line's privacy materials describe the potential use of automated fraud-detection models that may process sensitive and criminal-conviction data. |
| Strava | Runs and rides | Strava's materials describe potentially licensing aggregated data to commercial partners for specified analytical purposes. |

# 9. Where the Volume Comes From

This section explains from which activities the modelled scenarios derive the volumes of data.

### i. The body becomes a continuous sensor

Wearables turn the body of a model person into a continuous data stream. A model person may see one sleep score or fitness summary, while the underlying device may have made hundreds or thousands of measurements to produce it. What the model person experiences as one result can therefore hide a much larger machine-generated stream.

### ii. Watching television can generate tens of thousands of observations

Automatic Content Recognition, or ACR, is technology built into smart televisions to identify what appears on the screen. Anselmi et al. (IMC 2024) report that Samsung's own documentation describes ACR frame capture at intervals of approximately 500 milliseconds, equivalent to about two potential screen scans per second. Their network measurements found that transmission behaviour differs according to the type of viewing. Samsung Ads separately states that its ACR data is derived from glass-level content recognition across linear television, OTT, set-top boxes and gaming environments. For this study, where Viewing Information Services is assumed to be enabled, the documented 500 millisecond capture interval is applied across the modelled Samsung viewing period. Appendix B2 provides the full research basis and modelling assumption for these figures.[21]

Where Viewing Information Services is enabled, ACR generates unique signatures and can associate viewing history, time spent, the TV's Personalised Service ID (PSID) and IP address with the Smart TV. Third-party content or app providers may receive information such as IP address, device identifiers, the requested transaction and use of the application or service. In addition voice commands may be transmitted with device identifiers to a speech-to-text provider when voice recognition is enabled. A model person experiences a few hours of television; the enabled ACR system can experience that period as tens of thousands of repeated observations.

For Margaret and Carol's model household, television is the biggest stream that the study can count. They are doing something passive: watching news or entertainment. Yet the television can potentially keep making records while the picture is on the screen. Under the model's counting assumptions, a quiet evening may be busier than an hour of active social-media use.

### iii. A journey can be recorded several different ways

One journey of a model person can leave several different records. A phone can create mobile-network and map location. A connected car can send location, speed, braking and vehicle-condition data. Roadside cameras can record the number plate. Public transport, shops, schools and doorbells can create images. Turning off one app therefore does not necessarily prevent every movement record. Different systems may watch different parts of the same journey for different reasons. That is why one privacy setting cannot remove the whole movement trail.

### iv. Cameras record people who never pressed 'accept'

Camera exposure is equally revealing because much of it happens without a direct relationship between the model person being recorded and the owner of the camera. Many of these images are created by devices the model person does not own. A model person does not press 'accept' before walking past a neighbour's video doorbell. A child from model household does not negotiate the school's camera policy each time they walk down a corridor. Data is therefore being created in places where the model person has little practical control.

### vi. Financial and insurance activity can expose long histories

Financial and insurance activity of a model person can open access to information covering far more than the transaction taking place at that moment. A credit-score check, insurance assessment or linked financial-data connection can draw on identity, credit, transaction and risk information accumulated over months or years. In Bob's model, for example, one linked

[21] Anselmi, G. et al. (2024), 'Watching TV with the Second-Party: A First Look at Automatic Content Recognition Tracking in Smart TVs', Proceedings of the ACM Internet Measurement Conference 2024, DOI: 10.1145/3646547.3689013; Samsung Electronics, ACR support materials; Texas Office of the Attorney General, State of Texas v. Samsung Electronics America, Inc. et al., filed 15 December 2025. Available at: https://www.samsung.com/us/support/answer/ANS10010616/ and https://www.texasattorneygeneral.gov/sites/default/files/images/press/Samsung%20TV%20Petition%20Filed.pdf.

financial-data connection can expose up to 24 months of transaction history in a single action. Some activities, such as insurance renewals or refinancing, are periodic rather than everyday events. The important point is therefore the depth and reach of the information that a single activity of a model person can expose, rather than the number of separate accesses attributed to one modelled day.

### vii. Children generate records before they can make independent privacy choices

Children can generate create records before they can make independent privacy choices. In Leeds, 25 of the 88 organisations can collect from the children of the model person. In Charlotte, school-device activity can be monitored minute-by-minute and of the model household location can be available around the clock. These systems may exist for education or safety, but they also mean that a detailed digital history can begin years before a child can make an informed choice about it. The point is not that any record is misused. It is that a child's digital history can be built across school, home, transport, entertainment and safety systems.

### viii. Some products use personal data to train or improve AI

A separate product-level review that counts individual products modelled as used within each model household adds another type of secondary use: data that companies say may be used to train or improve AI systems. The review finds at least 22 of 68 assessed products for Sam, 20 of 62 for Bob, 26 of 88 for Priya and Tom and 28 of 81 for Maria and David. These are minimum figures because only clear affirmative statements were counted. The type of data matters as much as the count. Bob's set includes financial data used to train Plaid's transaction model, while the family sets include children's gaming, voice data and adults' work AI tools.

### ix. The day begins before the model person wakes

Potential data collection can start before a model person wakes. In four of the modelled households, wearables measure the model person during sleep. Smart meters record energy use through the night. Doorbells and security cameras remain active. Phones stay attached to mobile networks and sync in the background. Voice assistants wait for a wake word. Cloud services and connected devices exchange information while the model household is asleep. The modelled day can therefore begin with hundreds of measurements already made before the model person deliberately shares a single piece of information.

Some of these records exist without the modelled person ever signing up to a service. The Tier C material in Section 6 covers records held about a model person without any sign-up by them. Reading the documents attached to those records would take 10.5 hours for Sam, 6.5 hours for Bob, 8.6 hours for Priya and Tom, 5.4 hours for Maria and David, 9 hours for Margaret and 7.9 hours for Carol. Section 7 also identifies 42 standing institutional records that can exist before any product is used.

There is therefore a gap between how a model people experience digital life and how data systems experience it. A model person may think they checked one sleep score, watched one television programme, drove one journey or paid for one item. The surrounding systems can potentially turn each of those simple acts into repeated measurements, identifiers, timestamps, location traces, behavioural signals and inferences. Other records can potentially exist without the model person ever having pressed ‘accept’ at all.

# 10. What the Data Says About a Model Person

The six model days do not merely produce technical logs. They can create or expose fragments about identity, body, health, home, money, movement, relationships, children, beliefs and behaviour. A model person can therefore potentially become highly legible to digital systems.

### i. Identity and household

Names, dates of birth, addresses, old addresses, phone numbers, email addresses, who lives in the home, vehicle details, accounts and device identifiers can help connect records from different places.

### ii. Body and health

Heart rate, sleep, breathing, wrist temperature, weight, diet, medication, period-tracking, health apps, eye-care records and emergency-care information can all describe the body of a model person. In the UK, many of these signals sit under the same broad data-protection rules. In the US, protection can depend more on who holds the data. A hospital record and a consumer-app record may describe the same body but fall under different rules.

### iii. Voice and face

Voice assistants, calls, voice-authentication systems and age checks can create voice or face records. Whether the law treats a voice recording as sensitive biometric data can depend on where a model person lives and how the recording is used.

### iv. Movement and routine

Phone location, maps, connected-car data, number-plate reads, transport CCTV, doorbells, school cameras and repeated journey times can show where a model person goes and when. Over time, a routine becomes information in its own right.

### v. Home life

Smart-meter readings, visitor logs, television viewing, broadband activity, voice-assistant use and security events can show when a model person is home, awake, watching, cooking or receiving visitors.

### vi. Money and financial circumstances

Bank transactions, credit files, insurance checks, income clues, shopping baskets, loyalty cards mortgage data and payment timing can build a picture of the modelled person's financial position.

### vii. Relationships and communications

Contact lists, message details such as time and sender, group memberships, call patterns, dating activity and how often a model person interacts can show the shape of the model person's social life even when the message itself is encrypted.

### viii. Interests, beliefs and private life

What the model person watches, reads, searches for, buys and spends time looking at can feed interest and audience models. The research includes examples of systems that can infer political views, religion, sexual orientation and health interests even when the model person did not state those facts directly.

### ix. Predictions

Existing data can also be used to make predictions: what a modelled person may buy, whether they may leave a service, how risky or persuadable they may be and what they may do next.

# 11. The Same Day, Different Systems: What Changes Between the UK and US

The comparison of the situation in the model households in the US and the UK shows that potential extensive surveillance is not confined to one legal system. Each UK model household in this study is linked to more organisations than its US match. The US cases, however, show wider use of some commercial location, insurance and data systems. The key distinction is therefore not whether data may be produced, but how it is governed, reused, shared and challenged after it exists.

The matched pairs help separate the amount of data from the rules around that data. Sam and Bob are the same age and have similar working lives. Both family model households have children aged 8 and 11. Margaret and Carol are both 75, widowed and living independently. Their modelled routines are similar enough to show how the surrounding country can change the data environment even when the day itself looks familiar.

In every pair, the UK model household is linked to more organisations: Sam 68 against Bob 62 Priya and Tom 88 against Maria and David 81, and Margaret 49 against Carol 44. These are model-household figures, not national totals or statistics. They show that one broad privacy law does not make ordinary life data-light. The bigger differences appear in how data may be reused, scored, priced, watched and combined.

| Model Household Comparison | UK model | US model |
|---|---|---|
| **Working-age adult** | Sam: 68 organisations; 271 modelled processing events | Bob: 62 organisations; 219 modelled processing events |
| **Family household** | Priya and Tom: 88 organisations; 25 may be collected from children | Maria and David: 81 organisations; child location available 24/7 |
| **Older adult** | Margaret: 49 organisations; ~40,000 TV ACR screen captures | Carol: 44 organisations; 173 modelled processing events; ~36,000 TV ACR screen captures |
| **General consumer-data framework** | Cross-sector UK GDPR and the Data Protection Act 2018, as amended by the Data (Use and Access) Act 2025 | Federal sectoral rules plus a state-by-state patchwork |
| **Selected state context** | One general framework across all three UK archetypes | Ohio, North Carolina and Arizona do not have comprehensive consumer privacy statutes in force |

### i. The UK has one broad privacy framework; the US separate sector and state rules

In the UK, the same broad data-protection rules apply to personal information in many different settings. Organisations need a lawful reason to use the data and must explain what they are doing. They are also expected to collect only what they need, use it for clear purposes and avoid keeping it for longer than necessary. Consent is only one possible legal reason. This matters because some data is created or collected in the background, even when a person has no direct relationship with the organisation. The rules do not stop all collection, but they provide one common set of duties thatcollection can be tested.[22]

The US system is more divided. Federal laws provide protections in particular areas, including credit, healthcare, children's data and finance, while wider consumer privacy often depends on state law. As of September 2026, the US does not have a single comprehensive federal consumer privacy law. Comprehensive privacy laws are now in force in a growing number of states but Ohio, North Carolina and Arizona, where the three US model households in this study are based, do not have comprehensive consumer privacy statutes. They instead rely on narrower state protections alongside the federal rules. In practice, the protection that applies can therefore depend on who holds the data, which state the person lives in and what the data is being used for.[23]

[22] Information Commissioner's Office, UK GDPR data-protection principles, including purpose limitation, data minimisation and storage limitation. Available at: https://ico.org.uk/for-organisations/uk-gdpr-guidance-and-resources/data-protection-principles/.

[23] Congressional Research Service (2026), Preemption and Privacy Law, R48667; International Association of Privacy Professionals (2026), US State Privacy Legislation Tracker. The latter is used to check which states had comprehensive consumer privacy statutes in force during the study period. Available at: https://www.congress.gov/crs_external_products/R/PDF/R48667/R48667.2.pdf and https://iapp.org/resources/article/us-state-privacy-legislation-tracker.

### ii. Credit and insurance are more deeply coupled in the US examples

In the US cases, credit information can enter activities that are not loan applications. Bob's Ohio car-insurance renewal can use a credit-based insurance score and Carol's Arizona renewal can use a similar check. Bob's linked financial-data connection can also make up to 24 months of transactions available through one action. The UK model households' cases involve credit-reference information too, including for identity and insurance processes, but the US model households connect financial history more directly to some everyday prices and risk decisions.

### iii. Potential public and private surveillance have different rules and responsibilities

Both countries can record movement on a very large scale. The Home Office's 2026 National ANPR Service: data protection impact assessment states that 12,076 camera sets and 1,878 mobile ANPR cameras nationally submit, on average, more than 100 million ANPR read records to national ANPR systems each day. Data held in the national systems can be retained for 12 months and is then automatically deleted unless it is preserved for an investigation or another continuing policing purpose. The system therefore operates on a very large scale, but within a defined law-enforcement structure with rules covering purpose, access, retention and data protection.[24]

The US examples are more mixed. Bob and the Charlotte family meet private automatic number-plate cameras as well as connected-car data, map history and mobile-network location. Flock Safety says its platform connects thousands of agencies and communities. Other commercial plate-reading networks can be used by lenders, insurers and investigators. Rules about access and how long data is kept can vary by customer and by state. While the UK example is often centred on public systems, the US examples can layer publicand private systems over the same journey.[25]

### iv. The same health information can have different legal protection in the US

The model household data also shows why the legal boundary around health information matters. A smartwatch can create about a thousand heart-rate readings in a day. Sleep, weight, diet, breathing, period-tracking and medication records add more detail. In the UK, identifiable health information falls under the broad data-protection framework and gets extra protection as special category data. That protection can also apply to consumer services outside the NHS.

In the US, HIPAA protects health information when it is handled by healthcare organisations covered by that law and by certain companies working for them. It does not automatically protect every health detail stored in a consumer app or personal device. US government

[24] Home Office (updated 29 July 2026), 'National ANPR Service: data protection impact assessment', reporting 12,076 camera sets, 1,878 mobile ANPR cameras, more than 100 million reads per day and a 12-month national retention period unless preserved. Available at: https://www.gov.uk/government/publications/national-anpr-service-data-protection-impact-assessment/national-anpr-service-data-protection-impact-assessment-accessible.
[25] Flock Safety, product/network materials; Digital Recognition Network, vehicle-location data and LPR analytics for lending, insurance, collections and recovery. Available at: https://www.flocksafety.com/products/flock-os and https://drndata.com/.

guidance says that information a person enters into an unrelated consumer app can fall outside HIPAA, although other laws may still apply. The same heart rate or symptom can therefore have different legal protection depending on who holds it.[26]

### v. The families have different mixes of public, school and commercial monitoring

The Leeds model household is linked to 88 organisations and 25 may collect information from the children. School systems can record keystrokes, screen activity and CCTV images. The Charlotte model household is linked to 81 organisations, and the children can be watched minute by minute on school devices, tracked by a family-location service and recorded by school cameras. Their journeys can also enter private number-plate databases.

The comparison does not show that only one country may monitor children. Both may do so. The difference is who is doing the monitoring and which rules apply. The UK example relies more on schools, public systems and model household services that sit under one broad data-protection framework. The US example adds more commercial safety, education and location platforms, which can be covered by different federal and state rules. In both countries, the child may experience the collection as a normal part of school and family life.

### vi. Stronger regulation does not remove the scale of everyday collection

The UK is not a low-data environment. Sam's broader modelled day includes about 271 modelled processing events, but the more conservative headline is stronger because it does not depend on those event assumptions: his wearable and television alone exceed 22,700 observations. Margaret's television alone produces about 40,000. UK privacy rules change the conditions around collection and use, but they do not stop connected products, public systems and household services from creating high-volume records.

The US is not completely unregulated either. Federal and state rules cover important areas such as credit, healthcare, children's information, finance and unfair or misleading business practices, but protection is less uniform across sectors and states.

### vii. What the comparison means

The model households' lives create data in both countries but geography helps decide who may collect it, what rules follow it, how easily it can be reused and how a person can challenge its use. In these modelled scenarios, the UK combines very high modelled data volume with one more consistent legal framework. The US combines similarly high modelled data volume with more separate legal and commercial systems, especially around credit, insurance, location and consumer health data.

A model person can meet fewer organisations but still may face more scoring or secondary use. Another model person can meet more organisations under stronger rights and still may create tens of thousands of observations.

[26] US Department of Health and Human Services, HIPAA guidance on consumer apps: information entered into an app that is not offered by or on behalf of a HIPAA-regulated entity is generally outside the HIPAA Rules, although other law may apply. Available at: https://www.hhs.gov/hipaa/for-professionals/privacy/guidance/hipaa-online-tracking/index.html and https://www.hhs.gov/hipaa/for-professionals/privacy/guidance/cell-phone-hipaa/index.html.

### viii. Enforcement and remedies

The difference also appears when rules are broken. In the UK, people have a general route to complain about data protection through the Information Commissioner's Office, which can investigate organisations and impose penalties. The EU operates a similar regulator-led system through national data protection authorities. In April 2025, for example, Ireland's Data Protection Commission fined TikTok €530 million over infringements relating to transfers of EEA user data to China and transparency requirements; that decision is under appeal.[27]

The US has no single equivalent privacy regulator or general complaints route covering all consumer data. Enforcement can instead come through different channels depending on the law involved. The FTC can bring cases and agree consent orders, state Attorneys General can bring enforcement actions and some disputes can be pursued through private class actions. The practical route to a remedy can therefore depend much more heavily on the type of data, the law that applies and the state in which the person lives.[28]

# 12. What This Means for the Architecture of the Internet

Web3 Foundation's aim is to give users greater control over data and identity. Wider adoption of Web3 approaches could address several aspects of the problems identified by this White Paper by giving users greater control over how identity and personal information are disclosed, copied and linked. But it would not resolve all problems highlighted in this study. Web3 cannot stop a school camera, a smart meter or a neighbour's doorbell from creating a record. But where digital services need to establish identity, entitlement or trust, a different question becomes possible: can they do so while revealing less data, copying it fewer times and giving the user more meaningful control?

### Web3 Foundation's White Paper Design Principles

This Web3 Foundation's White Paper proposes six design principles. Implemented effectively, these principles could reduce how often a useful service requires a full identity, raw dataset or durable cross-service identifier to be copied into another system. They cannot promise total protection, but they could make unnecessary disclosure less routine.

### 1. Reveal only what is needed

An age check may only need to establish that a person is over 18, not reveal a full date of birth, identity document or reusable face scan. Selective disclosure and zero-knowledge proofs can allow a system to verify the necessary fact(e.g. that a person is over 18) while exposing less of the underlying data.

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[27] Information Commissioner's Office, complaints and enforcement framework; Irish Data Protection Commission (2 May 2025), TikTok €530 million decision concerning EEA data transfers to China and transparency requirements. Available at: https://www.dataprotection.ie/en/news-media/latest-news/irish-data-protection-commission-fines-tiktok-eu530-million-and-orders-corrective-measures-following.

[28] Massachusetts Office of the Attorney General (2022), Google multistate location settlement; Texas Office of the Attorney General (2025), $1.375 billion Google settlement; In re Plaid Inc. Privacy Litigation, court-approved $58 million settlement fund. Available at: https://www.mass.gov/news/ag-healey-joins-nationwide-settlement-with-google-over-location-tracking-practices; https://www.texasattorneygeneral.gov/news/releases/attorney-general-ken-paxton-secures-historic-1375-billion-settlement-google-related-texans-data; https://plaidsettlement.com/.

### 2. Let people hold reusable digital proofs

The modelled profiles in this study become powerful because the same identity facts may becopied into many services. A user-controlled credential offers another pattern: a trusted issuer confirms a fact, the person holds the proof and another service checks it when needed. This does not eliminate governance or misuse, but it can reduce the number of databases that need full copies of identity documents.

### 3. Make permissions clear, specific and easy to cancel

Permissions should be narrow, visible and revocable. A person should not have to search through a chain of privacy notices to discover who still has access. The aim is not to put sensitive personal data on a public blockchain. Cryptographic systems can instead help manage proofs and permissions while sensitive information remains off the public record.

### 4. Answer the question without copying all the data

Where possible, a service should answer a question without taking a full copy of the underlying information. A bank may only need to know that income is above a threshold rather than receive records from years of transactions. A health or identity service may only need a yes-or-no answer. The technical methods differ but the principle is simple: move less personal information into new hands.

### 5. Make systems work together without making profiles easier to join

Interoperability can improve convenience while also making records easier to link. Good design can allow a person to reuse a trusted proof without forcing one permanent identifier to follow them everywhere. The test is whether systems working together make privacy stronger or simply make one joined-up profile easier to build.

### 6. Give extra protection to people with less practical choice

Children cannot negotiate school monitoring and older people may depend on health or safety systems they cannot realistically avoid. In those settings, privacy should not depend on finding an opt-out button. The safer design is to collect less information by default where people have the least practical bargaining power.

# 13. Conclusion

The modelled day consists of ordinary activities: waking up, checking a phone, getting children to school, driving, working, buying groceries, collecting medicine, watching television and going to sleep. The evidence reviewed indicates that systems around those modelled activities may potentially produce measurements, identifiers, images, location traces, financial checks, communications records and behavioural signals.

Much of this potential data processing is described in the terms, privacy notices and supporting documents of the organisations included in the study. The study did not measure user awareness or understanding. It found that reading the documents relevant to one modelled day would take between 4.6 and 10.4 full working days, quantifying the practical volume of the material rather than whether any particular user read or understood it.

By bedtime in the modelled scenarios, different systems may hold or infer information about a model person's body, home, money, relationships, movements, children, health, beliefs and likely future behaviour. Repetition, sensitivity and linkability can turn those fragments into a detailed picture of a model person’s lifestyle, interests and likely behaviour. The model shows how watching television, driving to work or sending a message may be associated with thousands of potential observations capable of contributing to a profile; it does not measure whether users are aware of those observations.

### Next Stage

The findings also raise questions that require deeper investigation. Future stages of the Web3 Foundation’s white papers series will therefore examine:

1. Government Observation: In the US and UK, observation by government is subject to legal safeguards. But what happens if governments can obtain detailed information about individuals from data already collected by private companies? Could commercial access to movements, communications and behaviour weaken or bypass protections designed to limit state surveillance?
2. Watched Children: This study shows how early extensive data collection can begin. In the UK model, 11,400 keystrokes can be logged in a school week, while in the US school-device activity and location can be monitored throughout the day. How much of a child’s life is being recorded, by whom and what happens to that data before they can make independent privacy choices or provide legally effective consent?
3. Women’s Safety: Location can be recorded through phones, apps, vehicles, cameras and commercial services, sometimes without a direct user-initiated interaction or choice. For women trying to hide their whereabouts from an abusive partner or former partner, that can become a safety risk. Which systems create the greatest vulnerability and how can users identify and stop location sharing?
4. Personal Sexuality: Systems can infer highly private characteristics from patterns in browsing, location, purchases and behaviour, including sexuality. If someone has chosen not to disclose their sexuality, what does it mean if a commercial system has already inferred and recorded it? Could data analysis effectively ‘out’ someone without their choice?
5. Buried in the Fine Print: The relevant terms and privacy documents for one ordinary day can take between 4.6 and 10.4 full working days to read. The question is therefore not only whether companies disclose their practices but whether disclosures are practically accessible and usable at this volume. How can the most important permissions, particularly around sensitive data, sharing, inference and AI, be made clear so people know what they agree to?

These questions go to the heart of the Web3 Foundation’s mission to give people greater control over the data that increasingly defines them.

The answer is not to stop technology collecting information. It is to stop potential collection of additional data (beyond the primary use of service or product) becoming the default. Less data should be taken by default, less should be copied by default, permissions should be structured to support informed choices and people should have far greater power over how fragments of their lives are connected.

# APPENDIX A

# Appendix A: Full 24-Hour Routines

The modelled routines below reproduce the detailed model days used in the research so that readers can trace statistical findings back to ordinary activities. They combine direct use, passive infrastructure and indirect data relationships. Routine actions are model assumptions, not records of real people. Where a statement is based on a policy, notice or terms, it describes what may occur and does not establish that the action occurred in every modelled interaction. Where a particular optional feature is expressly included in a modelled routine, the relevant assumption is stated in that routine or supporting analysis.This is a modelling assumption and does not mean that the feature is enabled for every real user or enabled by default. Some activities are explicitly described as occurring only a few times a week, monthly or at renewal. Those periodic overlays illustrate the wider potential surveillance surface

## A1. Sam, 34, single working adult – Manchester, United Kingdom

Sam is a 34-year-old male living in Manchester. He is a full-time administrator in an office-based role, working from home part of the week. He has never been married and lives alone in a privately rented one-bedroom flat with one car and no health conditions.

He uses 4G/5G mobile data sessions and keeps a BT Group Broadband at home which allows him to stream Netflix on a Samsung TV, keep an Amazon Alexa smart speaker online, and work from home part of the week. The model assumes he wears an Apple Watch all of the time, which constantly samples his heart rate and motion, logs his overnight sleep results, and mirrors every notification on his iPhone.

### 06:45–07:30 – Wake-up and first phone check

Sam wakes and reaches straight for his iPhone in bed, clearing overnight WhatsApp messages and iMessage notifications, scanning BBC news headlines using Safari, checking the Apple weather, as well as his sleep score (logged on the Apple Health app which aggregates data from his iPhone, Apple Watch and apps such as Strava and MyFitnessPal). He then scrolls on Instagram, Reddit, X, and TikTok for a few minutes, showers, dresses and makes a quick breakfast, which he logs on MyFitnessPal, listening to a Spotify podcast playing through Alexa.

### 07:30–08:00 – Coffee, money and admin

Over coffee, Sam checks his Monzo and Lloyds banking apps to see what has cleared before payday. He reads a few work emails on Microsoft 365 and uses Microsoft Authenticator to prove it is really him. He adds items to a Tesco online basket and checks his credit score through an app such as ClearScore. Periodic overlay: an insurance or mobile-contract renewal reminder may also occur, but this is not treated as part of the daily headline floor.

On office days Sam travels into the city, usually by Metrolink tram, paying using Apple Pay.

Whilst walking to the tram stop, Sam passes Ring doorbells (one in five UK homes has one; a market led by Amazon's Ring). These record motion-triggered video and audio of passers-by to their owners' cloud accounts, from where footage can be shared with neighbours or police.

Whilst on the tram, he listens to a Spotify playlist or a podcast on his Apple Wireless Headphones and checks Google Maps for live travel updates; on work-from-home days he reclaims this hour. Sam is recorded on CCTV at the Metrolink platform and on board the tram; Transport for Greater Manchester (TfGM) control rooms operate 24/7 monitoring feeds from more than 3,800 CCTV cameras across the network. As Sam walks near roads, other people's dashcams may record him. Nextbase alone has a large share of UK dashcam sales. Drivers can keep this footage and may send it to insurers or police.

### 09:00–12:30 – Morning at work

Sam works at a Windows Laptop through the morning – taking Zoom calls and using Outlook and Teams messaging – with his phone beside him for personal notifications he checks between tasks.

### 12:30–13:30 – Lunch break and personal phone use

He takes a lunch break, logging what he eats on MyFitnessPal, and then scrolls on his phone - WhatsApp, Instagram, a quick news catch-up and some browsing or online shopping. Periodic overlay: a couple of times a week he opens a dating app, such as Tinder or Hinge, to reply to matches.

### 13:30–17:00 – Afternoon at work

He works on tasks and meetings run until the end of the working day, using tools such as ChatGPT. He takes a mid-afternoon coffee break, where he uses the Starbucks app to order ahead and skip the queue. During this coffee break, he messages some of his friends on Snapchat and flicks through Facebook, YouTube, and Instagram.

### 17:00–17:45 – Commute home/log off

Sam heads home, messaging friends on WhatsApp or Snapchat to firm up evening plans whilst listening to music or a podcast on the journey. He, in a similar way to how he commutes into work, takes the Metrolink Tram home, passing multiple Ring doorbells and dashcams, and listens to a Spotify podcast or music using his Apple headphones.

### 17:45–18:45 – Gym or evening run

Sam fits in a gym session, often messaging a friend on WhatsApp or Snapchat to meet there, or goes on a run, tracking it on Strava and his Apple Watch. Before heading out for an evening run in Manchester (a statistically wet city), he checks Apple Weather. On gym nights, Sam drives his Ford Fiesta the short distance with his kit; his car transmits location, journey and vehicle-health automatic vehicle data to Ford even if he never opens the FordPass app.

### 18:45–19:45 – Dinner – cooking or a takeaway

Sam cooks a simple dinner while listening to a podcast via his Alexa Speaker. He is likely to watch something on Netflix on his Samsung TV while he eats. Electricity and gas use is recorded by his smart meter and transmitted through the national smart-metering network. Periodic overlay: a couple of nights a week he orders a Deliveroo and pays via Apple Pay.

### 19:45–20:30 – Catching up with friends

Sam WhatsApp-calls or iMessages friends and family on his iPhone, keeps up with group chats about the weekend, and scrolls through Instagram, TikTok, Facebook, Snapchat, Reddit, and YouTube.

### 20:30–22:30 – TV streaming and second-screening

Sam relaxes with Netflix, Amazon Prime Video, or YouTube for a couple of hours on his Samsung TV, frequently 'double-screening' on his iPhone and messaging his friends on WhatsApp or using Safari to look up information about what's on screen (e.g. actors/plot). On some evenings he plays on his Nintendo Switch or Xbox instead.

### 22:30–23:15 – Wind-down and bedtime scrolling

Before bed, Sam sets his alarm, checks tomorrow's weather, scrolls through social media and sends final messages. He may also check a dating app before going to sleep.
Periodic overlay: Sam may on some days visit an adult website. UK age-check rules can require proof that he is over 18 and some verification methods can involve a credit-file company. This example shows how a private activity can trigger additional background processing.

### 23:15–06:45 – Sleep

Sam sleeps overnight, typically getting seven to eight hours before the next working day. Alexa remains powered and listening for its wake word all night. His iPhone runs its automatic iCloud backup, uploading messages, photos and app data to Apple's cloud – the canonical overnight data event.

The smart meter keeps taking half-hourly electricity and gas readings through the night; overnight baseload is itself revealing. Each overnight half-hourly reading travels over the DCC smart-metering communications network while he sleeps. Octopus receives and stores the night's half-hourly consumption profile, extending its picture of when the flat is occupied and what runs overnight.

## A2. Bob, 34, single working adult – Columbus, Ohio, United States

Bob is a 34-year-old man living in Columbus, Ohio. He is a full-time office worker in a hybrid role, never married, and lives alone in a rented apartment with one car. He uses 4G/5G mobile data sessions almost all of the time, and his rented apartment runs on fixed home broadband which he uses to stream from, keep his Alexa online, and work from home part of the week.

He wears an Apple Watch all of the time, which constantly samples his heart rate and motion, logs his overnight sleep results, and mirrors every notification on his iPhone.

### 06:45–07:30 – Wake-up and first phone check

Bob wakes and immediately checks his iPhone in bed – overnight iMessages, emails, and WhatsApp messages, the NBC News headlines via Safari, Apple Weather, and then has a scroll through Instagram, TikTok, and YouTube Shorts. Afterwards, he showers whilst listening to a Spotify podcast, dresses and grabs a quick breakfast, which he logs on MyFitnessPal.

### 07:30–08:00 – Coffee and money check

Over coffee, Bob checks his Chase Mobile banking app and Venmo, skims work email on Microsoft 365 and adds items to an Amazon cart. He also checks a free credit-score app such as Experian. Periodic overlay: an auto-insurance or apartment-lease renewal can add further credit and identity processing.

The free credit-score app shows Bob a score based on the credit information Experian holds about him. Behind the scenes, his credit file is regularly updated and may also be accessed when his car insurance is renewed. The insurer can use his credit information to create a credit-based insurance score, often through a soft credit check, without Bob necessarily realising that his data is being used in this way.

If Progressive is Bob's insurer, it can combine a credit-based insurance score with information about his car and driving. In Ohio, insurers are allowed to use credit-based insurance scores when setting some prices. Bob's credit history can therefore affect what he pays for car insurance.

### 08:00–08:45 – Drive to the office

Bob drives to work in his Ford F-150 using Google Maps or Waze on his iPhone for traffic, with a podcast or Spotify playing; on some days he works from home instead. His car is fitted with FordPass Connect, an embedded modem that can send data to Ford’s cloud over the mobile network even when Bob is not using the app. As he drives to work, it can generate information such as his location, route, speed and vehicle-health data.

Ohio also uses roadside Automatic Licence Plate Recognition (ALPR) cameras, including systems supplied by Flock. These cameras photograph number plates and can also record details such as the make and model of the car, stickers or visible damage. The images can be placed in a searchable database used by participating organisations.

If Bob’s motor policy is with Progressive and he is enrolled in their Progressive Snapshot app, it will record his commute and upload it to Progressive to derive a driver score used in pricing.

### 08:45–12:00 – Morning at work

Bob works at his Windows Laptop throughout the morning – involving Zoom calls, Microsoft

365, and Slack – with his iPhone nearby for personal notifications from Gmail, Instagram, WhatsApp, Facebook, YouTube, TikTok, Reddit, and LinkedIn. He wears his headphones whilst he sits in on Zoom calls and has ChatGPT and Google Chrome open for research purposes.

### 12:00–13:00 – Lunch and personal phone use

Bob eats lunch while scrolling on his iPhone, using iMessage, WhatsApp, Instagram, Facebook, and YouTube, whilst also catching up on NBC News. A few times a week he will open a dating app such as Tinder or Hinge to reply to matches. He remembers to log his lunch on MyFitnessPal.

### 13:00–17:00 – Afternoon at work

Meetings and focused tasks fill the afternoon, with continuous digital communication on his iPhone and Windows Laptop until the end of the workday. He might have an afternoon coffee break, paying for it using his Apple-Pay.

### 17:00–17:45 – Commute home and errands

Bob drives home in his Ford, sometimes stopping at Kroger or Target to buy groceries, paying with Apple Pay, and iMessages friends to make plans as he goes. He listens to Spotify music through his Ford's sound system on the way home. The drive home is logged as journeys and dwell locations in Ford's automatic vehicle data and is also picked up by Flock ALPR.

### 17:45–18:45 – Gym or workout

Bob heads to the gym or goes for a run, tracking the session on his Apple Watch. Before heading out for an evening run (or the drive to the gym), Bob would plausibly check conditions on Apple Weather. Bob drives himself in his Ford to the gym and he uses Google Maps navigation for the trip. He uses his iPhone to play Spotify music, which he listens to from his Apple Headphones. Whilst taking breaks from running or in the gym, Bob scrolls on Instagram and TikTok and replies to WhatsApp messages on his phone. Whilst running through residential streets, Bob passes Ring doorbells and outdoor smart cameras.

### 18:45–19:45 – Dinner – cooking or delivery

Bob cooks a simple dinner or, a couple of nights a week, uses his iPhone to order in through DoorDash, paying with Apple Pay. Whilst he eats his dinner, he watches Netflix or Amazon Prime Video on his Samsung Smart TV, sometimes double-screening and watching YouTube on his phone. If he cooks, he asks his Amazon Alexa device to set timers and play Spotify music whilst he is at the hob. The evening cooking/dinner load is captured interval-by-interval on the AEP Ohio advanced meter and reported to the utility. Once he has eaten his meal, he logs it on MyFitnessPal, which syncs with his Apple Health.

### 19:45–20:30 – Catching up with friends

Bob texts and FaceTimes friends and family on his iPhone, keeps up WhatsApp group chats and scrolls Facebook, TikTok, and Instagram.

### 20:30–22:30 – Streaming and second-screening

Bob relaxes with Netflix, Hulu, Roku, or YouTube on his Samsung TV for a couple of hours, iPhone in hand for second-screening, or plays a game some nights on his Nintendo Switch or Xbox to play some Minecraft. Sometimes he might purchase household items on Amazon, paying with ApplePay.

### 22:30–23:15 – Wind-down and bedtime scrolling

Bob winds down, sets an alarm on his iPhone and does a final scroll through Facebook's news headlines and messages before sleep. Bob also might have a last-minute scroll on Tinder to check his matches, as well as visit Pornhub.

### 23:15–06:45 – Sleep

Bob goes to sleep for about seven to eight hours. His smart meter keeps taking readings every 15 minutes, so the utility can still see patterns of electricity use while he sleeps. His Echo stays powered and waits for a wake word. His phone and other connected devices also keep making background network connections.

## A3. Priya and Tom, 40 and 43, family with children aged 8 and 11 – Leeds, United Kingdom

Priya and Tom, aged 40 and 43, live in Leeds with their son and daughter, aged 8 and 11. They are a married couple in a mortgaged semi-detached house in outer Leeds with one car. Tom works full-time; Priya part-time. The eleven-year-old has just started secondary school and has her first smartphone; Ofcom reports that smartphone ownership rises from 56% at age 10 to 83% at age 11. The eight-year-old is at primary school. The family's home runs on fixed home broadband, supporting the two parents' devices, two children's devices, a smart TV, an Echo and working from home. They also regularly use 4G and 5G mobile data. Priya wears an Apple Watch all of the time.[29]

### 06:30–07:30 – Household wake-up and school prep

Priya and Tom are up first, making breakfast and packing school bags while the two children get dressed. Priya uses her iPhone to check the BBC Weather, the Daily Mail, BBC News, and the school-parents WhatsApp group, with Alexa playing in the background. Tom asks Gemini, his voice assistant, for the time and the weather during breakfast. The 11-year-old daughter checks Snapchat while getting dressed. The 8-year-old son has no smartphone but watches short videos during breakfast on an iPad.

### 07:30–08:45 – School run and commute

A Ring doorbell is passively active as Tom and the two children leave the house on the school

[29] Ofcom (21 May 2026), 'Younger phone owners, the rise of AI, and consumption over creation – our latest look at UK children's media lives': smartphone ownership rises from 56% of 10-year-olds to 83% of 11-year-olds. Available at: https://www.ofcom.org.uk/online-safety/protecting-children/younger-phone-owners-the-rise-of-ai-and-consumption-over-creation-our-latest-look-at-uk-childrens-media-lives.

run, sending door alerts to both the parents' phones. Tom drops the children at school using their long-term leased BYD car, using Google Maps on his Android for the directions. The 11-year-old, who has just started secondary school and has her first iPhone, is the most likely to watch YouTube and TikTok using her mobile data while being driven to school.

When Tom drops the kids off at school, they are recorded by CCTV cameras at the school gate and in the playground. The journey is also recorded by police ANPR cameras. The Home Office’s 2026 National ANPR Service assessment states that more than 100 million ANPR read records are submitted to national ANPR systems on an average day, where national data can be retained for up to 12 months.[30]

Tom listens to Spotify during his commute. BYD documents say the car has cameras inside and outside, a voice assistant and automatic vehicle data. This can include speed, mileage, battery level, whether doors are open and which seats are occupied. The school run can therefore create location, driving and in-car records about Tom and the children.

### 08:45–12:30 – Work – full-time and part-time

Tom physically enters his office by swiping a HID Global workplace access card. Priya and Tom start their working day by checking their Gmails and logging into Microsoft 365, using Microsoft Authenticator, on their Windows Laptops. Priya’s browser of preference is Safari, and Tom’s is Chrome. During a morning break, both check BBC News. One parent will manage the weekly online grocery order through Tesco’s online delivery and order household items from Amazon.

Tom, iPhone-primary, uses Google Wallet for a mid-morning coffee/lunch. In a brief WFH micro-break, Priya scrolls Instagram and Facebook. She also uses this break to pay bills, check her Lloyds and Monzo bank balance, and her direct debits.

With Priya at home mid-morning, an Amazon Alexa Device is a plausible background radio, music, timers and quick queries. Priya uses ChatGPT to draft messages and emails on her Windows Laptop. Priya takes part in video call catch-ups during the work morning and uses Google Workspace for work correspondence. She squeezes in school-related admin, using ParentPay to send payment for meals, and household admin, adding items to her weekly Tesco order and Amazon shopping bag. Both parents use WhatsApp in the morning to coordinate the school run and read school parent groups.

School monitoring software such as Smoothwall Monitor can watch pupils' school devices and accounts. It can flag words that pupils type, take screenshots when it detects a possible risk and send alerts for review by staff or moderators. This means school typing and screen activity can be recorded even when a child deletes something quickly.

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[30] Home Office (updated 29 July 2026), ‘National ANPR Service: data protection impact assessment’, reporting more than 100 million ANPR reads on an average day and national retention of 12 months unless preserved. Available at: https://www.gov.uk/government/publications/national-anpr-service-data-protection-impact-assessment/national-anpr-service-data-protection-impact-assessment-accessible.

### 12:30–13:15 – Lunch

Over a quick lunch, Priya messages family on WhatsApp, checks ParentPay, and glances at an online Tesco shopping basket, all using her iPhone on 4G mobile data. She also has a lunchtime scroll on Facebook.

### 13:15–15:15 – Afternoon work and household admin

Priya handles a Tesco click and collect as well as an Amazon order around her work, whilst Tom continues at the office. Priya uses her Windows PC to book a doctor's appointment via the NHS App, pay an Octopus Energy bill via their website, request an insurance renewal quote on Aviva, and check a credit report from Experian via the ClearScore app before a remortgage.

When the household asks Aviva for an insurance quote, the insurer may run a credit-file check to confirm identity, check for fraud and help assess risk. This is usually a 'soft' check, meaning it appears on the credit file but does not normally lower the credit score. Aviva's privacy documents say it can use credit-reference information during the quote process.

### 15:15–16:15 – School pick-up and snack

Priya uses WhatsApp to coordinate pick-up via the year-group WhatsApp group. She and her two children are filmed on the school playground's CCTV. The children are collected from school and have a snack; they get some screen time on an Amazon Fire Kids tablet - watching YouTube Kids and playing games such as Roblox or Minecraft - while starting homework. Priya supervises and time-limits the children's screen time and gaming via Google Family Link. The 11-year-old goes onto her iPhone to go on TikTok and Snapchat before using an iPad to visit BBC Bitesize as she starts her homework.

### 16:15–17:30 – After-school clubs and play

The 11-year-old messages friends over WhatsApp and iMessage, and watches videos on YouTube, Instagram, and TikTok on her iPhone; the 8-year-old plays games on the Amazon Fire Kids Tablet, his Nintendo Switch, and watches YouTube Kids. Tom coordinates clubs and lifts over WhatsApp, using Google-Maps to plan the pick-ups and drop-offs. Priya uses Apple Find My to keep tabs on the 11-year-old's location while coordinating clubs and lifts. She uses ParentPay to book and pay for breakfast/after-school clubs and trips.

### 17:30–18:30 – Cooking the family dinner

One parent cooks dinner from scratch while the other helps the 11-year-old child with their homework, using BBC Bitesize, ChatGPT, and the family iPad. The 8-year-old is most likely occupied with an Amazon Fire Kids tablet watching YouTube while both parents are busy. On a Friday, the family sometimes orders a Deliveroo takeaway together, paying via Apple Pay.

The parent that is cooking might use an Amazon Alexa Device as a timer, for unit conversions, for music, or quick recipe prompts while hands are busy. After homework, the children watch Netflix or BBC iPlayer together on the Samsung television.

### 18:30–19:15 – Family dinner together

All phones are put aside over dinner. The one device that realistically operates over dinner is an Amazon Alexa Device, most likely for a background dinner music, plus the odd timer or general question during the meal. In the background, the Ring doorbell, the DCC Smart meter, and the broadband are all functioning during this period.

### 19:15–20:00 – Children's bath and bedtime

The 11-year-old WhatsApps her friends goodnight and watches a few videos on YouTube. The children's screens go off; they then have a bath, a bedtime story, sometimes read from an audiobook read aloud by Amazon Alexa, and lights out for the 8-year-old. The 11-year-olds' bedtime is a little later.

### 20:00–22:00 – Parents' downtime

Priya and Tom watch Netflix on their Samsung TV. They also go on their iPhone and Android, shopping for groceries on Tesco and homeware on Amazon and checking their bank via the Lloyds and Monzo apps. As mortgaged owner-occupiers, their mortgage lender routinely reports account-performance data to the credit reference agencies each month, and Experian continuously holds their credit file. If a 'spread the cost' Amazon purchase uses a Buy Now, Pay Later instalments facility, that lender may also report the agreement to Experian.

Priya and Tom scroll through their social media, including YouTube, Facebook, and Instagram, and catch up on the BBC News and Daily Mail headlines. The 11-year-old is plausibly messaging friends on Snapchat in her room in the earlier part of this window before sleep.

### 22:00–23:00 – Wind-down

Final messages are sent on WhatsApp and iMessage, a last scroll through Instagram, Facebook, and YouTube, and the setting of alarms via Amazon Alexa before bed. Priya will log her menstrual cycle symptoms on her Flo app, and then will read a book on her Amazon Kindle. Both will have a last flick through BBC News and the Daily Mail, as well as check the weather forecast for the following day using BBC Weather. As a wind-down couple, Tom and Priya are likely watching a shared episode to fall asleep to.

### 23:00–06:30 – Sleep

The household sleeps overnight before the next school and workday. The video Ring camera is the one product here that is genuinely 'in use' overnight, recording and motion-monitoring the property continuously while everyone sleeps, with alerts pushed to the parents' phones. Priya continues to wear her Apple Watch at night for overnight sleep tracking; Tom wears his Fitbit. Tom may also fall asleep listening to a Calm sleep meditation. The Amazon Alexa will stay active throughout the night, waiting to be called and ready to sound its alarm at 6.30 am.

The family's smart meter keeps recording energy use every half hour while everyone sleeps.

It sends those readings through the national smart-meter communications network to the energy supplier. The home broadband router also stays on, carrying background traffic from connected devices, backups and any late-night phone use.

## A4. Maria and David, 37 and 39, family with children aged 8 and 11 – Charlotte, North Carolina, United States

Maria and David, aged 37 and 39, live in Charlotte, North Carolina, with their son and daughter, aged 8 and 11. They are a married couple in a mortgaged house in the suburbs with two cars; both work full-time, David fully remotely. The children are in middle and elementary school respectively. Maria wears an Apple Watch all of the time; David wears a FitBit. The family's house runs on fixed home broadband, which supports two parents' devices, two children's devices, a smart TV, an Echo, a Ring doorbell, and remote working. The phone owners in the house use 4G and 5G mobile data even when they are in range of Wi-Fi.

### 06:30–07:30 – Household wake-up and school prep

Maria and David are up first, making breakfast and packing bags while the two children get ready. Maria checks her iPhone for Apple Weather, Fox News, and Facebook’s news, and replies to school messages from her Gmail. Alexa plays Spotify music in the background. David checks his Android, scanning NBC News, and opens the school app - Canvas Parent - to see if there are any activity alerts.

### 07:30–08:45 – School run and commute

As Maria and the children leave for the school run and David remains at home, the household's Ring video doorbell captures the departure and pushes motion alerts to Maria's phone. Maria drops the children at school, where they are filmed on the school’s CCTV, and drives the family Toyota RAV4 to work, using Google Maps or Waze on her iPhone. Toyota Connected Services collects the vehicle's location, driving data and vehicle-health data via the embedded modem, whether or not she opens the app. Whilst on this morning journey, the car is tracked by Flock ALPR cameras, which logs vehicle description and location for every passing car.

David starts his day at home and uses Life360 to keep tabs on the kids as they go to school. Both parents begin their working day by checking their Gmail, and Maria also does a quick Facebook scroll.

### 08:45–12:00 – Work – full-time and part-time

David uses Microsoft365, Gmail, Zoom, and Google Chrome on his Windows laptop. Both parents use ChatGPT throughout the working day for their work. For David's back-to-back video calls and background audio at home, he uses Beats (by Dr. Dre) headphones. Every now and again, he might switch to the household Apple MacBook to oversee household admin.

The household's video doorbell delivers concurrent package notifications to his phone during the 08:45–12:00 delivery window.

Both children are monitored by the school's software throughout the day. Classroom-monitoring software such as GoGuardian can record and analyse student web activity on school-managed devices and provide authorised school staff with browsing history, screenshots and safety alerts. GoGuardian says its products support more than 25 million students across more than 10,000 schools.[31]

### 12:00–13:00 – Lunch

Over lunch, Maria catches up on her family WhatsApp, checks Canvas Parent (the school app), scrolls through Facebook, and places an Amazon order, all on her iPhone. For every one of Maria's lunch-break phone actions, she uses her 4G or 5G mobile data.

### 13:00–15:00 – Afternoon work and household admin

Maria fits groceries (an Instacart order or a Target stop) and life admin (including Amazon orders) into breaks at the office. She pays for this shopping using Apple Pay. Maria uses Chase Mobile banking to move money and pay bills and the Duke Energy app to view her energy bills and usage.

David, working from home, handles the chores between meetings. He makes the mortgage payment via the Chase mobile app, obtains an insurance renewal quote using the Progressive software, and checks a credit score through Experian before refinancing.

The mortgage company sends account information such as the balance and payment status to Experian each month. An insurance renewal can also cause a soft credit check. In the model, State Farm can use credit information as one factor when setting an insurance price.

### 15:00–16:15 – School pick-up and screen time

Both parents keep an eye on their children's location using Life360. The children are picked up from school and have a snack. During the pickup, the parent and two children are filmed on the school security cameras, which are used in 93% of US public schools.[32]
The children get iPad and Amazon Fire Kids tablet time, where they play on YouTube, Roblox, and Minecraft, before starting homework. For their homework, they use Google Chrome and Google Drive. Whilst they do this, Maria checks their assignments via Canvas Parent.

### 16:15–17:30 – After-school activities

The 11-year-old messages friends and watches TikTok[33] and YouTube videos, listening through her Apple Wireless Headphones, and then messages friends using Snapchat on her

[31] GoGuardian (14 August 2026), company announcement stating that its products support more than 25 million students across more than 10,000 schools; GoGuardian product materials describe browsing-history, screenshot and safety-monitoring functions. Available at: https://www.goguardian.com/newsroom/goguardian-announces-ai-powered-recommendation-engine-in-goguardian-admin-turning-student-online-behavior-patterns-into-proactive-policy-recommendations and https://www.goguardian.com/product-update/beacon-additional-screenshots-and-browsing-history.
[32] US Department of Education, National Center for Education Statistics, School Survey on Crime and Safety 2021–22: 92.6% of public schools reported using security cameras to monitor the school (rounded to 93%). Available at: https://nces.ed.gov/programs/digest/d23/tables/dt23_233.60.asp.
[33] Where Snapchat or TikTok appears in a child scenario below the service's normal minimum age, this is expressly modelled as underage use contrary to the ordinary account terms, rather than compliant use. The analysis therefore treats it as a specific exception and applies evidence relevant to underage use and the protections or enforcement measures described by the platform. Snap requires users to be at least 13, or the applicable higher minimum age in their jurisdiction, and states that accounts identified as belonging to younger users may be suspended or deleted. TikTok states that its minimum age is generally 13 and that users below that age may not use the standard platform, although in the United States it offers a separate restricted "Under 13 Experience". TikTok also states that it monitors for underage use and may remove or restrict accounts that do not meet its age requirements. See Snap Terms of Service and Snapchat Privacy for Teens; TikTok Terms of Service and TikTok, "Updates to how we enforce age appropriate experiences in Europe"

iPhone. The 8-year-old plays games on his Amazon Fire Kids tablet. As the children arrive home, David receives a Ring doorbell notification on their phone while coordinating activities.

### 17:30–18:30 – Cooking dinner

One parent cooks dinner while the other helps with homework. The parent who is cooking listen to Spotify music on the Amazon Alexa Device.

A couple of nights a week, the family orders DoorDash on their iPhone, paying with Apple Pay. On these nights, a Ring notification view is used to see the driver drop the food at the door.
The 11-year-old middle-schooler does homework, with the help of a parent, on a school laptop that runs Google Workspace. The parent helping with homework uses ChatGPT to explain and checks off the homework assignments on Canvas Parent.

The 8-year-old boy is kept occupied on an Amazon Fire Kids tablet while the parents cook and help his sister with homework. The 8-year-old also watches YouTube on the Samsung Smart TV in the family room while dinner is prepared.

### 18:30–19:15 – Family dinner together

When the family eats together, their Samsung Smart TV will likely be on in the background, possibly streaming Netflix or Hulu & Disney+. If the TV is not playing, the Amazon Alexa Device would likely be playing music or at least waiting on standby to be asked questions. It is also likely that the 8-year-old will be watching content on YouTube on the household iPad.

David and Maria glance at their phones respectively and check their social media accounts.

### 19:15–20:00 – Children's bedtime routine

The family wind down and the kids have a bath. Maria or David use Alexa to play a lullaby playlist or white noise and set a sleep timer for the 8-year-old's wind-down after his bath and story, then again, a little later for the 11-year-old.

### 20:00–22:00 – Parents' downtime

Maria and David watch a streaming series together on Netflix or Hulu on their Samsung Smart TV. Whilst they do this, they go on their phones to shop on Amazon, check their Chase Mobile app, and plan for tomorrow by checking their weather apps. They both catch up on Instagram and Facebook, and message people on WhatsApp and iMessage.

If either parent chooses Affirm while shopping on Amazon, Affirm can run a soft credit check to decide the available amount and terms. From April 2025, Affirm also reports its pay-over-time loans to Experian, so the loan and payment history can become part of the credit file.[34]

[34] Affirm states that eligibility can involve a soft credit check that does not affect the consumer's credit score. See Affirm investor/merchant materials, including https://investors.affirm.com/news-releases/news-release-details/affirm-data-flexible-payment-options. Experian (19 March 2025) states that Affirm would report all pay-over-time loans issued from 1 April 2025 onward, including Pay-in-4, with the information visible on Experian credit files. Available at: https://www.experian.com/blogs/news/2025/03/19/affirm-expands-credit-reporting-with-experian/.

### 22:00–23:00 – Wind-down

Both Maria and David have a final look through their messages and a last scroll on their phones looking at Instagram, YouTube, Facebook, and Apple Weather. David does a last security check on the Ring app, viewing the doorbell camera and locking up. Maria logs her menstrual symptoms on her Flo app (period and ovulation tracker). They set a wake-up alarm using Amazon Alexa.

### 23:00–06:30 – Sleep

The household sleeps overnight before the next school and workday. One adult – most plausibly Maria, given Calm's strongly female-skewed user base – uses Calm's Sleep Stories/soundscapes as a bedtime wind-down at lights-out. The one product that is 'in use' throughout the night is the household's smart-home security. Ring cameras run passively overnight, performing motion detection and 24-hour real-time alerts while everyone sleeps.

The Charlotte smart meter keeps measuring the home's electricity use overnight. Depending on the utility setup, it can send readings every 15 minutes to every hour. Phones and other devices also keep making background connections, checking for updates and syncing data while the family sleeps. Maria's Apple Watch and David's Fitbit the Amazon Alexa Device remain powered and listening for its wake word all night. This tracks their sleep stages, heart rate and breathing rate through the night.

## A5. Margaret, 75, widowed retired homeowner – Yorkshire, United Kingdom

Margaret is 75 and lives in a small-town Yorkshire. She is widowed, owns her house outright in a small Yorkshire town, retired on the State Pension and a small occupational pension, and still drives her one car, like the two-thirds of women over 70 who hold a full licence. She is online daily on an iPad and Android. Her daughter Claire, who lives forty miles away, has become involved in her day-to-day arrangements. Her phone uses mobile data session even when in range of Wi-Fi household.

### 07:00–08:00 – Wake and slow start

Margaret wakes without an alarm and checks her Android for WhatsApp from her daughter Claire. She takes her morning medication and makes breakfast, watching BBC News on her Samsung TV. Sometimes she has BBC Studios radio on her Amazon Alexa radio. She checks BBC Weather on her iPad and then has a look on her Facebook in order to see updates from her distant family.

She has a pendant alarm with 24/7 monitoring as her safety arrangement. The monitoring service holds her health conditions, medications, keyholder and next-of-kin details (Claire), and logs every activation and self-test. She puts the pendant on as part of the morning routine.

### 08:00–09:00 – Medication and health admin

Margaret manages her regular medicines and appointments on her iPad. She may use the NHS

App, Patient Access or Accurx to order repeat prescriptions or book a GP appointment. These services create health, identity and appointment records. She may then message her daughter Claire to let her know what has been arranged. Alongside her health admin, she deals with routine household life-admin, which can include a home or Aviva car insurance renewal letter, an Octopus Energy direct-debit statement, or a Lloyds bank letter. She also checks her Lloyds online banking to see her direct debits and balance.

If an insurer such as Aviva prepares Margaret's renewal, it may reassess the risk and check credit-file and public information. A company such as Experian or LexisNexis can supply some of this information. The check may be a soft credit check, which normally does not lower the person's credit score.

### 09:00–10:00 – Chores and radio

Housework and laundry with the Alexa playing the radio; she reads BBC News and the Daily Mail on her iPad over a cup of tea.

When Margaret reads Mail Online, the page can take part in automated online advertising. Experian is not only a credit-file company; it also runs a marketing-data business. The Information Commissioner's Office has taken enforcement action against Experian over parts of its direct-marketing data-broking activity.

Experian's marketing business holds profiles on many UK adults and supplies audience information to advertisers. This means ordinary reading and browsing can contribute to a marketing profile even when a person did not open a credit app or ask Experian for a service.

### 10:00–11:00 – Out to the shops

Margaret walks to the local shops, carrying her Android in her pocket, for a few groceries in Tesco Express, not forgetting to use her Tesco Clubcard, and stops to chat with neighbours and pay with her Lloyds contactless card. Since her fall, she uses Google Maps location-sharing with her daughter.

The walk to the shops includes the pharmacy: with two long-term conditions and repeat prescriptions, Boots is her regular stop, and the Advantage Card records her purchases and prescription-collection visits.

Her own video doorbell – which her daughter installed after her fall as a security measure - records her departure and return and any deliveries while she is out, with clips stored in the cloud account Claire can also view.

As Margaret walks along familiar streets, neighbours' video doorbells can record her. The clips are saved in other people's cloud accounts. Repeating the same walk can therefore create a regular visual record of her routine.

### 11:00–12:00 – Video call with family

Margaret video-calls her daughter and grandchildren on her iPad over WhatsApp, catching up on the week. The call is carried over her home fixed broadband.

### 12:00–13:00 – Lunch and daytime TV

She has a light lunch in front of BBC News or BBC iPlayer watched on her Samsung TV and has a scroll on her iPad through Facebook, checking BBC Weather. She prepares a light lunch using the kettle, hob, or microwave. Whenever Margaret's smart meter reports her lunchtime consumption, it does so over the DCC's national smart-metering communications network, which relays readings between every GB smart meter and its energy supplier.

### 13:00–15:00 – Afternoon activity or appointment

Some afternoons Margaret goes to a community or church group or a craft class, carrying her Android with her. On the afternoons Margaret has a health appointment, the NHS App is used to help her manage her appointments. Margaret still drives (like two-thirds of women over 70 who hold a licence) and on 'appointment' afternoons she will drive to a health appointment or craft class, using Google Maps on her Android. Margaret parks in a town-centre or hospital car park, paying for her parking using RingGo.

At 75, Margaret is entitled to a free NHS sight test every two years, which she uses through Specsavers. The appointment creates a clinical optical record - including images of the retina and conditions such as glaucoma or macular degeneration - held by the opticians.

When Margaret drives into town, police number-plate cameras may record her car. Parking operators can also photograph the plate when she enters and leaves a car park. A single trip can therefore create several separate location records.

On afternoons where Margaret chooses to garden, she checks the forecast on BBC Weather before deciding whether to go out.

### 15:00–16:30 – Reading, puzzles and tablet

Margaret reads on her Kindle, does a crossword or puzzle, and browses YouTube, Facebook, BBC Weather, and BBC News on her iPad - occasionally some online shopping on Amazon and Tesco, paying via PayPal. She also browses Nextdoor – the social media platform – for local recommendations and neighbourhood news. Amazon Music is streaming through her Amazon Echo during the reading and puzzle session.

### 16:30–17:30 – Preparing the evening meal

Margaret cooks a simple evening meal, sometimes a ready meal on a quieter day. She has her Samsung Television playing BBC iPlayer in the background. During idle moments while food cooks, a quick phone scroll is the realistic behaviour for Margaret. Alexa is on standby, either playing music, setting cooking timers, or ready to answer Margaret's questions without her having to handle her phone with wet hands.

### 17:30–18:30 – Evening meal and news

She eats her evening meal with the early-evening BBC News on her Samsung TV.

### 18:30–21:00 – Television

Margaret settles in for her main television viewing of the day, watching either ITVX, BBC News, Amazon Prime Video, or BBC iPlayer. Margaret is likely to have her iPad next to her as a second screen, glancing at Facebook and her emails.

### 21:00–22:00 – Wind-down and medication

Margaret takes a last check of her Android for BBC Weather, BBC News, and the Daily Mail, and then sends a goodnight WhatsApp message to her daughter before bed. Margaret's Alexa gives her a bedtime medication reminder.

### 22:00–07:00 – Sleep

Margaret sleeps overnight. The Ring doorbell runs continuously as passive background security. Her smart meter continuously records consumption in half-hourly intervals (overnight fridge, heating/boiler cycling, standby loads) and transmits readings automatically without her involvement. Octopus continues to supply Margaret's home with gas and electricity overnight. Her smart-meter readings are sent through the national communications system to the supplier, creating a record of energy use while she sleeps.

If Margaret shares her iPad location through Find My, her daughter can check that she is safely at home without Margaret doing anything at that moment. Her medical-alert pendant also remains available through the night.

## A6. Carol, 75, widowed retired homeowner – Tucson, Arizona, United States

Carol is a 75-year-old female, living in Tucson, Arizona. She is widowed, owns a mortgage-free home (like 64% of owners her age), is retired on Social Security and has retirement savings, and is a smartphone user with one car.

Her out-of-state daughter has become involved in her day-to-day arrangements. On an Apple/iPhone ecosystem, Apple Find My is the native family location/wellbeing-sharing tool, running passively 24/7 so the daughter can confirm her mother is up and about at home during the morning. She also wears a medical alert pendant with 24/7 monitoring. The monitoring service holds her health conditions, medications and emergency contacts (her out-of-state daughter), and logs every activation and test. Carol's home runs on fixed broadband: the iPad, smart TV, Roku, Echo, Ring doorbell and telecare base unit all ride home Wi-Fi. Her smartphone maintains a live cellular data session, even at home.

### 07:00–08:00 – Wake and slow start

Carol wakes without an alarm, takes her morning medication, and makes breakfast while Fox News, the Roku Channel, or NBC News plays on her Samsung TV, checking her iPhone for iMessages from family. Carol checks her phone for Apple Weather and takes a glance at her Facebook. During breakfast and taking morning medication, she asks Alexa for the weather, the news headlines or a medication reminder.

### 08:00–09:00 – Medication and health admin

Carol manages her health - morning medication and using a patient portal such as MyChart to check results and request a refill via the myWalgreens app. At 75, Carol is a Medicare beneficiary (near universal for US over-65s).[35]

Alongside her health admin, she deals with routine household life-admin. This can include a home or auto insurance renewal notice from State Farm, a utility statement or a Medicare and Chase bank letter.

In this model, Carol's insurer may use credit-related information when setting a price or checking risk, as Arizona law allows in some circumstances. The scenario therefore includes a soft credit-file or insurance-score check alongside the insurer's other records.

Carol is retired on Social Security, and since June 2025 the only way to sign in is via Login.gov or ID.me, meaning any access to her benefits information is mediated by a Login.gov or ID.me credential.[36]

### 09:00–10:00 – Chores and radio

Housework and laundry with the radio playing through Amazon Alexa or a morning show from her Samsung; she reads the Fox News or NBC News on her iPad, whilst also scrolling through Facebook, Nextdoor, and Gmail. Carol receives a Daily Digest email from USPS Informed Delivery informing her of the day's incoming mail.

Carol's news reading and browsing can feed the online advertising system. Experian's marketing business is separate from its regulated credit-file business, but the same brand operates in both areas. Experian's own notices say it collects website and app information and identifies itself as a data broker.

### 10:00–11:00 – Errands

Carol drives to Costco for groceries, chatting with neighbours and paying by Chase banking card. As she drives herself, she is reliant on Google Maps for navigation. Every Costco shopping basket is tied to the membership number at the till, so her shop is recorded at item level against her identity.

Carol's errand run includes going to CVS ExtraCare to visit the pharmacy counter and to buy general household goods. Carol is recorded by her neighbours' Ring doorbells when she stops to chat. South Tucson ended its Flock contract in February 2026, but private and commercial number-plate systems still exist. The Digital Recognition Network, for example, builds a commercial database from cameras and vehicles that scan streets and car parks. DRN markets its LPR data and analytics to organisations including lenders, insurers, collections

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[35] US Census Bureau, Health Insurance Coverage in the United States: 2024, reporting that 94.0% of adults aged 65 and over had Medicare coverage in 2024 and describing health-insurance coverage in that age group as nearly universal. Available at: https://www2.census.gov/library/publications/2025/demo/p60-288.pdf. See also CMS Medicare enrollment data: https://data.cms.gov/summary-statistics-on-beneficiary-enrollment/medicare-and-medicaid-reports/medicare-monthly-enrollment.
[36] Social Security Administration, 'Account FAQs & Help': effective 7 June 2025, Login.gov and ID.me are the only sign-in options for Social Security online services. Available at: https://www.ssa.gov/myaccount/account-faqs-and-help.html.

teams and recovery providers. This is separate from a police system.[37]

### 11:00–12:00 – Video call with family

Carol FaceTimes her daughter and grandchildren on her iPad, catching up on the week.

### 12:00–13:00 – Lunch and daytime TV

Carol watches Fox News, NBC News, or some Netflix on her Samsung TV over a light lunch. She is most likely to pick up her iPhone to catch up on her Facebook or YouTube feed while eating in front of the TV. During her lunch, Carol might use Alexa for background music, news, weather or a timer.
Where enabled, Samsung TVs use automatic content recognition to track what households watch. Through the Samsung Ads–Experian partnership, that viewing data is combined with Experian's consumer data to create detailed household profiles, which can then be used for targeted advertising.[38]

### 13:00–15:00 – Afternoon activity or appointment

Some afternoons, Carol attends a community meeting, church group, or health appointment, while on other days she tends to her yard.

For health appointments or church groups, Carol drives herself and uses Google Maps for navigation.

On afternoons when Carol has a health appointment, she uses her Medicare account and Banner – her healthcare provider. She uses the Patient Account (MyChart) app to check in, view test results, message her providers, and manage appointments. The app allows her out-of-state daughter to participate as a proxy when needed. If Carol needs to pick up a prescription after an appointment, she stops at Walgreens pharmacy.

On days when Carol works in her yard, she checks the forecast in Apple Weather before going outside. For a 75-year-old in Tucson's heat, checking the weather is an important safety habit.

### 15:00–16:30 – Reading, puzzles and tablet

Carol reads, does a puzzle from Safari, and browses on her iPad - sometimes on Facebook to view family photos, or to do a little online shopping on Amazon or Costco, paying with PayPal. She also might watch YouTube, open Nextdoor to see some updates from the community, or read the news, using NBC News or Fox News. Carol's Facebook activity and Amazon purchases can contribute to a marketing profile linked to her identity. She may not realise

[37] Tucson Spotlight (19 February 2026), 'South Tucson ends Flock camera contract', reporting the City Council's vote to cancel the contract. Available at: https://www.tucsonspotlight.org/south-tucson-ends-flock-camera-contract/. Digital Recognition Network describes LPR data and analytics for lenders, insurers, collections teams and recovery providers. Available at: https://drndata.com/.
[38] Experian Marketing Services (5 December 2023), 'Experian and Samsung Ads partnership makes Experian identity and syndicated audiences available directly within Samsung's demand-side platform', describing the integration of Samsung Ads viewership data with Experian data and the use of Samsung ACR data and Experian audiences for targeting. Available at: https://www.experian.com/blogs/marketing-forward/experian-identity-and-syndicated-audiences-available-within-samsung-dsp/page/75/.

that the Experian name she knows from credit reporting also belongs to a separate marketing and audience business

### 16:30–17:30 – Preparing the evening meal

Carol cooks a simple supper, sometimes a convenience meal on a quieter day. She has her Samsung TV on whilst she is cooking, watching Fox News, NBC News, or Netflix. She also might play the radio through Alexa whilst she cooks.

### 17:30–18:30 – Supper and news

She eats supper with the Fox News, Roku Channel, or NBC News streaming from her Samsung TV. She might also scroll through her iPad to catch up on her Facebook feed. Again, as earlier outlined, Samsung's automatic content recognition viewing data can be fed into the connected-TV advertising ecosystem, where Experian uses identity graphs to link TV viewers and viewing behaviour to households and individuals.[39]

### 18:30–21:00 – Television

Carol settles in for her main television viewing on her Samsung - watching Fox News, Roku Channel, NBC News, Netflix, or Amazon Prime.

### 21:00–22:00 – Wind-down and medication

Alexa reminds her to message her family before bed and to take her medication. Carol takes her evening medication and has a last look at her iPhone to check Facebook, Nextdoor, Fox News, and also Apple Weather. She receives a reminder from her Walgreens app to take her medication before bed. She sends a goodnight iMessage to family before bed.

### 22:00–07:00 – Sleep

Carol sleeps while her Ring doorbell stays active in the background. It can detect movement, record night-time clips and send an alert if someone approaches. The system can therefore create records while she is asleep.

Alexa also operates in her bedroom, used to set a bedtime reminder and to sound the morning wake alarm. Carol's smart meter runs day and night. It records electricity use every 15 minutes to every hour, depending on the utility setup. These readings can show patterns such as heating or air-conditioning use even while she sleeps. Carol's medical-alert pendant also stays active overnight. The service holds details about her health, medicines and emergency contacts and records each test or activation.

Carol's home runs on fixed broadband: the iPad, smart TV, Roku, Echo, Ring doorbell and telecare base unit all ride home Wi-Fi. Overnight, the router stays up: iCloud backups, the Echo, the Ring doorbell and the medical-alert base unit keep exchanging data with Cox's

[39] Experian Marketing Services, 'Advanced TV advertising', describing Digital Graph as linking consented devices and digital identifiers to a persistent person and household; Experian/Samsung Ads partnership materials describe use of Samsung ACR data with Experian audiences. Available at: https://www.experian.com/marketing/industries/advanced-tv-advertising and https://www.experian.com/blogs/marketing-forward/experian-identity-and-syndicated-audiences-available-within-samsung-dsp/page/75/.

network while she sleeps. Her iPhone stays registered to the mobile network all night – periodic paging and background refresh log network events and coarse location at the carrier around the clock. Find My keeps reporting her devices' location passively overnight, giving her daughter the ability to check that all is well.

# APPENDIX B

# Appendix B: Quantified Daily Exposure Ledger

This appendix consolidates the principal numerical findings regarding the modelled scenarios used in the White Paper. A dash means that the underlying research did not provide a separate daily count for that measure. It should not be read as zero. Counts are scenario-based and should be interpreted using the definitions, counting rules and uncertainty treatment set out in the Methodology section (Appendix E) of this White Paper.

| Model household | Organisations | Modelled processing events | Body readings | TV screen scans | Camera captures |
|---|---|---|---|---|---|
| Sam | 68 | ~271 | 1,100+ | ~21,600 | ~60–190 |
| Bob | 62 | ~219 | ~1,000 + 4 overnight metrics | ~21,600 | – |
| Priya & Tom | 89 | – | ~2,000 | Not separately quantified | ~100 children |
| Maria & David | 81 | – | ~2,000 | Not separately quantified | ~79 children (40–120 narrative range) |
| Margaret | 48 | – | No wearable count | ~40,000 | ~16–45 quantified doorbell clips |
| Carol | 45 | 173 | – | ~36,000 | ~25–65 |

### Additional quantified streams

| Model household | Smart-meter intervals/day | Vehicle or location scale | Other quantified finding |
|---|---|---|---|
| Sam | 48 half-hour intervals | Movement additionally recorded through maps, tram CCTV and vehicle systems | 1,847 uploaded contacts; 11 group chats in illustrative profile |

| Model household | Smart-meter intervals/day | Vehicle or location scale | Other quantified finding |
|---|---|---|---|
| Bob | 96 quarter-hour intervals | 1,284 plate reads over 12 months | A linked financial connection can pull up to 24 months of transaction history |
| Priya & Tom | 48 half-hour intervals | 45 minutes in-cabin footage/day; national ANPR journey records | 25 organisations collect from children; 11,400 school keystrokes/week in child file |
| Maria & David | 24-96 intervals | 2-6 roadside plate reads/day; child location available 24/7 | School-device monitoring minute by minute |
| Margaret | 48 half-hour intervals | 312 plate reads over 12 months | 5-6 TV hours/day generate the largest quantified stream in her model |
| Carol | 24-96 intervals | 186 commercial plate reads over 12 months; location sharing 24/7 | 156 product touchpoints within 173 counted daily events |

## B1. Supplementary AI, camera and voice findings

These findings come from a supplementary product-level review. They count individual products rather than organisations and are kept separate from the pooled organisation-level dataset used for Table 4, which combines the six modelled household days into 143 distinct organisations, 1,280 primary uses and 75 data flows.. They should therefore not be compared directly with the 35 of 143 organisation-level AI finding: the unit of analysis and denominator are different. 'At least' means that only products with a clear affirmative statement were counted.

| Model household | Products which terms permit AI training or model improvement | Other added detail |
|---|---|---|
| Sam, 34 – Manchester, UK | At least 22 of 68 assessed products | 30-110 recordings by strangers' doorbell cameras; about 30 minutes continuously filmed on public transport; two commute journeys may also be recorded by strangers' dashcams. |

| Model household | Products which terms permit AI training or model improvement | Other added detail |
|---|---|---|
| Bob, 34 – Columbus, Ohio, US | At least 20 of 62 assessed products | About 20-80 private doorbell/yard-camera clips; 12 companies holding voice recordings. The supporting review includes Plaid's transaction model trained on financial data from 150m+ consumers. |
| Priya and Tom, 40/43 – Leeds, UK | At least 26 of 88 assessed products | About 90-260 times the family may be filmed in one day; the supporting review includes children's Roblox voice data used for safety systems and retained Snapchat My AI conversations. |
| Maria and David, 37/39 – Charlotte, NC, US | At least 28 of 81 assessed products | The supporting review highlights financial-data modelling, children's gaming/safety systems and adults' work AI tools. |

### B2. Supplementary on ACR findings

For the purposes of the model, we assume an Automatic Content Recognition (ACR) sampling interval of approximately 500 milliseconds, equivalent to about two observations per second. This figure is solely taken from allegations in the Texas Attorney General's December 2025 petition against Samsung, which alleged that Samsung's ACR system captures audio and video information at approximately 500-millisecond intervals and operates across native apps, built-in channels and external inputs. Samsung's own current materials describe ACR differently, stating that the system generates unique content signatures to identify viewing information and that Samsung does not record or watch the content displayed on the television. We identified no public Samsung statement specifically confirming or denying the alleged 500-millisecond interval. The February 2026 agreement between Samsung and the Texas Attorney General required clearer disclosures and express consent for ACR collection but did not establish the accuracy of the alleged sampling interval. We therefore use the 500-millisecond figure solely as a modelling assumption for the arithmetic and do not take a position on whether the allegation is correct.

Separately, Samsung states that, where Viewing Information Services is enabled, ACR runs to generate unique signatures about viewing on the Smart TV. Anselmi et al. (IMC 2024) also identifies Samsung's proprietary ACR system and cites Samsung advertising material describing the technology. Samsung Ads also states that its proprietary ACR data may be derived from glass-level content recognition across linear television, OTT, set-top boxes and gaming environments.[40]

[40] Anselmi, G. et al. (2024), 'Watching TV with the Second-Party: A First Look at Automatic Content Recognition Tracking in Smart TVs', DOI: 10.1145/3646547.3689013; Samsung Electronics ACR materials; Texas Office of the Attorney General, State of Texas v. Samsung Electronics America, Inc. et al., filed 15 December 2025. Available at: https://www.samsung.com/us/support/answer/ANS10010616/ and https://www.texasattorneygeneral.gov/sites/default/files/images/press/Samsung%20TV%20Petition%20Filed.pdf.

There is an important distinction between ACR capture and the network traffic observed in a particular test. Anselmi et al. directly measured traffic between televisions and ACR servers. In their controlled tests they observed ACR network traffic for linear television and HDMI input, but did not observe corresponding ACR traffic while Netflix or YouTube were streamed through third-party apps. That result does not establish a two-per-second network transmission rate and the White Paper does not treat it as potentially doing so. It is also not a direct measurement of every internal frame-capture operation occurring inside the television. The later Texas filing [41] (which is under appeal by Samsung) describes a potential broader implementation across apps and inputs[1]. The evidence therefore does not show one identical network behaviour in every viewing mode, model, jurisdiction or software configuration.

For the purpose of the model, the White Paper makes an explicit and consistent assumption that, where Samsung Viewing Information Services is enabled, the modelled approximately 500 millisecond ACR capture interval is treated as the potential observation rate throughout the modelled Samsung viewing period, including streaming through television apps. Each such capture is counted as one countable observation. This is a modelling assumption used to quantify potential exposure, rather than a claim that Anselmi et al. directly observed two ACR transmissions per second in every app. It is consistent with the White Paper's wider methodology, which models documented technical capability and stated practice where direct user-level measurement is unavailable.

| **Model** | **Counted daily stream(s)** | **Arithmetic** | **Conservative daily observation floor** |
|---|---|---|---|
| Sam, Manchester | Samsung ACR + wearable | 3 h TV × 3,600 sec × 2 = 21,600; plus 1,100+ body/health readings | 22,700+ |
| Bob, Columbus | Samsung ACR + wearable | 3 h TV × 3,600 sec × 2 = 21,600; plus ~1,000 heart-rate samples | ~22,600 |
| Margaret, Yorkshire | Samsung ACR | 5-6 h TV × 3,600 sec × 2 = 36,000-43,200; rounded model finding | ~40,000 |
| Carol, Tucson | Samsung ACR | 5 h TV × 3,600 sec × 2 = 36,000 | ~36,000 |

As a sensitivity check, halving the assumed ACR observation rate from two to one observation per second would reduce the four single-adult daily floors to approximately 11,900 for Sam, 11,800 for Bob, 20,000 for Margaret and 18,000 for Carol.

[41] Texas Attorney General, State of Texas v. Samsung Electronics America, Inc. and Samsung Electronics Co., Ltd., Original Verified Petition, December 2025, paras. 41–43. The petition alleges that Samsung ACR captured audio and video information at approximately 500-millisecond intervals and operated across native streaming apps, built-in channels and external inputs including cable, satellite, HDMI devices and gaming consoles. These statements are allegations in the State's filing rather than independently established technical findings. In February 2026, Samsung and the Texas Attorney General subsequently reached an agreement requiring express consent and clearer disclosures before ACR viewing data is collected or processed. texasattorneygeneral.gov/sites/default/files/images/press/Samsung%20TV%20Petition%20Filed.pdf?utm_source=chatgpt.com

# APPENDIX C

# Appendix C: Organisations, Services and Systems Included in the Study

This appendix lists the products, services and systems examined in the White Paper's research. The explanation beside each entry says why it is included in the modelled day of a model household: because the model person uses it directly, because it operates in the background or because another ordinary activity brings it into the data chain. The column "Why it is included in the study" does not state that any particular collection occurred for a real person. Where the column describes information that may be collected, generated, inferred, retained or shared, that description is based on the evidence reviewed for the study, principally the organisation's own privacy policies, terms or technical documentation and, where relevant, regulator, government, academic or other published sources. Such material establishes a documented permission; it does not establish that every permitted or technically possible action occurred in the modelled scenario or occurs for every actual user. [42]

## C1. Core product and service research universe

| Organisation / service / system | Category | Why it is included in the study | Interaction basis |
|---|---|---|---|
| Experian | Credit bureau / data broker | Included because credit, insurance and marketing processes in the scenarios can consult or enrich an Experian file even when the individual does not deliberately open Experian; the file can contain identity, address, credit and inferred audience data. | Indirect / background |
| Instagram | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |
| TransUnion | Credit bureau / data broker | Included as one of the major credit bureaux represented in the underlying financial and insurance analysis, where identity, credit and risk information can be consulted indirectly during routine financial activity. | Indirect / background |
| Equifax | Credit bureau / data broker | Included as one of the major credit bureaux represented in the underlying financial and insurance analysis, where identity, credit and risk information can be consulted indirectly during routine financial activity. | Indirect / background |

[42] See Methodology, "Evidence hierarchy" and "Limitations". The analysis of what organisations say they may collect, use, retain or share is based principally on their published privacy policies, terms and related documentation. Technical documentation, regulator and government materials, academic research and market evidence are used where relevant to establish product capability, legal or institutional context, prevalence and ordinary use. A company policy establishes what an organisation says it may do; it does not establish that every permitted action occurred in a modelled scenario or occurs for every actual user.

| Organisation / service / system | Category | Why it is included in the study | Interaction basis |
|---|---|---|---|
| X (formerly Twitter) | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |
| The Roku Channel | Streaming / connected television | Included because Roku is used for ordinary television viewing in US scenarios and adds a second connected-TV layer capable of generating viewing and device data. | Direct use; some background processing |
| Facebook (Meta) | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |
| Life360 | Social / messaging / location platform | Included because the US family scenario uses a family-location service to keep track of children, creating continuous location and household-movement data in the background. | Passive + active |
| NBC News | News / media | Included because reading or watching news/weather is a repeated ordinary activity in the scenarios, generating browsing/viewing, device, account and advertising-related signals. | Direct use; some background processing |
| TikTok | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |
| PornHub | Digital service / platform | Included because the working-age scenarios include late-evening adult-site use and, in the UK case, age verification adds an additional identity/biometric step. | Direct use; some background processing |
| Amazon Alexa Device | Digital service / platform | Included because Alexa/Echo devices operate throughout several model households for music, timers, news, reminders and voice queries, creating voice, account, device and usage records, including background activations. | Passive + active |
| Samsung Smart TV | Streaming / connected television | Included because every household model uses a Samsung television and the research examines Automatic Content Recognition and viewing ACR screen captures generated during ordinary television use. | Passive + active |
| Fox News | News / media | Included because reading or watching news/weather is a repeated ordinary activity in the scenarios, generating browsing/viewing, device, account and advertising-related signals. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study | Interaction basis |
|---|---|---|---|
| Instacart | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| Mail Online (Daily Mail) | News / media | Included because reading or watching news/weather is a repeated ordinary activity in the scenarios, generating browsing/viewing, device, account and advertising-related signals. | Direct use; some background processing |
| Medical alert system (PERS pendant with 24/7 monitoring) | Health / fitness / care | Included because the US older-adult scenario uses a monitored safety pendant that holds health conditions, medications, emergency contacts and activation/test logs continuously. | Passive + active |
| 5G/4G mobile data sessions | Connectivity / utility infrastructure | Included because adult smartphones remain connected to cellular networks through much of the day, generating network, device and location-related records even when no app is actively being opened. | Passive / background |
| CVS ExtraCare | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| DoorDash | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| Ford F-150 (FordPass Connect) | Vehicle / transport | Included because the US single-adult scenario drives a connected Ford during the commute and errands, generating location, route, speed and vehicle-health telemetry through the embedded modem. | Passive + active |
| Hulu & Disney+ | Streaming / connected television | Included because ordinary home entertainment uses this service or device, generating viewing history, device/account identifiers and, for connected TVs, potentially high-frequency viewing ACR screen captures. | Direct use; some background processing |
| Nextdoor | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Target Circle and the Target app | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| Amazon Prime Video | Streaming / connected television | Included because ordinary home entertainment uses this service or device, generating viewing history, device/account identifiers and, for connected TVs, potentially high-frequency viewing ACR screen captures. | Direct use; some background processing |
| Ring (video doorbell / cameras) | Digital service / platform | Included because Ring cameras either protect the modelled homes or record subjects as they pass other homes, generating video, audio, motion, timestamps and household-routine data passively. | Mostly passive |
| Google Search | Browser / search | Included in the underlying browsing review as the default search layer behind ordinary information seeking, where search terms, device and account context can become part of a behavioural profile. | Direct use; some background processing |
| My McDonald's app (MyMcDonald's Rewards) | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| WhatsApp | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |
| YouTube | Streaming / connected television | Included because ordinary home entertainment uses this service or device, generating viewing history, device/account identifiers and, for connected TVs, potentially high-frequency viewing ACR screen captures. | Direct use; some background processing |
| LinkedIn | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |
| Sky News website/app | News / media | Included because reading or watching news/weather is a repeated ordinary activity in the scenarios, generating browsing/viewing, device, account and advertising-related signals. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Amazon Kindle | Digital service / platform | Included because reading is part of several modelled evenings and afternoons; synced reading creates title, position, notes/highlights and reading-behaviour records. | Direct use; some background processing |
| Amazon Music | Audio / connected accessory | Included because music, radio or podcasts accompany commuting, work or household activity, creating listening, device and account-usage records. | Direct use; some background processing |
| Android Phone | Digital service / platform | Included because Android phones are core devices in several households, mediating navigation, messaging, browsing, authentication and background network/location activity. | Direct use; some background processing |
| BBC Studios Limited | Digital service / platform | Included because the research distinguishes the BBC public-service environment from BBC Studios commercial services, including circumstances where a commercial registration can create a separate data relationship. | Direct use; some background processing |
| Calm | Health / fitness / care | Included because health, fitness, care, medication or appointment activity is part of the modelled day, creating sensitive physiological, clinical, medication, identity or wellbeing data. | Direct use; some background processing |
| Google Chrome | Browser / search | Included because Chrome is a routine browser in several work and household scenarios, adding browsing, search, device and advertising-related signals. | Direct use; some background processing |
| Google Maps | Digital service / platform | Included because navigation and family routines repeatedly rely on Maps for commuting, school runs, errands and appointments, generating location, route, destination and device data. | Direct use; some background processing |
| MyFitnessPal | Health / fitness / care | Included because health, fitness, care, medication or appointment activity is part of the modelled day, creating sensitive physiological, clinical, medication, identity or wellbeing data. | Direct use; some background processing |
| PayPal | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Progressive | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct use; some background processing |
| Tesco (Tesco Grocery & Clubcard) | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| Tinder | Digital service / platform | Included because dating-app use appears in the working-age scenarios, bringing relationship, preference, communication, location and potentially sensitive profile data into the daily footprint. | Direct use; some background processing |
| Walgreens | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| Toyota RAV4 (Toyota Connected Services) | Vehicle / transport | Included because commuting, school runs or errands use this transport/vehicle system, creating journey, payment, location, vehicle or behavioural telemetry. | Passive + active |
| Amazon (Amazon Shopping) | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| bt group tv broadband phone/mobile | Connectivity / utility infrastructure | Included because the service or infrastructure operates continuously behind ordinary household/device use, generating network, location, connection or time-stamped utility-consumption records. | Passive + active |
| Direct Line | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct use; some background processing |
| Google Assistant / Gemini | Digital service / platform | Included because the family scenario uses a Google voice/AI assistant for everyday queries, adding voice, prompt, device and account data to an otherwise ordinary morning. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Spotify | Audio / connected accessory | Included because music, radio or podcasts accompany commuting, work or household activity, creating listening, device and account-usage records. | Direct use; some background processing |
| Windows Laptop | Work / productivity / identity | Included because working-age archetypes use Windows laptops for work, calls, email and AI tools, creating device, identity, communications and productivity telemetry. | Direct use; some background processing |
| Netflix | Streaming / connected television | Included because ordinary home entertainment uses this service or device, generating viewing history, device/account identifiers and, for connected TVs, potentially high-frequency viewing ACR screen captures. | Direct use; some background processing |
| Reddit | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |
| Boots Advantage Card | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| ITVX | Streaming / connected television | Included because ordinary home entertainment uses this service or device, generating viewing history, device/account identifiers and, for connected TVs, potentially high-frequency viewing ACR screen captures. | Direct use; some background processing |
| Amazon Fire Kids tablet (Amazon Kids) | Child / education / gaming | Included because children use the tablet for entertainment in the family scenarios, bringing child account, app, viewing and device-usage data into the household footprint. | Direct use; some background processing |
| Aviva | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct use; some background processing |
| ChatGPT | Work / productivity / identity | Included because working-age and family scenarios use an AI assistant during ordinary work or household tasks, making prompts, account and device interactions part of the daily footprint. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Ford Fiesta (FordPass Connect) | Vehicle / transport | Included because commuting, school runs or errands use this transport/vehicle system, creating journey, payment, location, vehicle or behavioural telemetry. | Passive + active |
| Google News | News / media | Included because reading or watching news/weather is a repeated ordinary activity in the scenarios, generating browsing/viewing, device, account and advertising-related signals. | Direct use; some background processing |
| Minecraft | Child / education / gaming | Included because children use or are administered through this service for learning, gaming, device supervision or school payments, adding child identity, activity, device, payment or educational data to the household footprint. | Direct use; some background processing |
| Roblox | Child / education / gaming | Included because children use or are administered through this service for learning, gaming, device supervision or school payments, adding child identity, activity, device, payment or educational data to the | Direct use; some background processing |
| Telecare personal alarm (pendant with 24/7 monitoring) | Health / fitness / care | Included because the UK older-adult scenario uses a telecare pendant continuously, exposing health conditions, medications, emergency contacts and alarm/test history. | Passive + active |
| AEP Ohio advanced meter interval usage data | Connectivity / utility infrastructure | Included because the service or infrastructure operates continuously behind ordinary household/device use, generating network, location, connection or time-stamped utility-consumption records. | Passive / background |
| BYD Seal U DM-i (BYD connected car & app) | Vehicle / transport | Included because the UK family uses a connected BYD for the school run and commute; the model includes location, speed, acceleration, braking, mileage, seat/door status, battery data and in-cabin/exterior cameras. | Passive + active |
| Chase Total Checking / Chase Mobile | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct use; some background processing |
| Costco | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Cox Internet (Cox Communications) | Connectivity / utility infrastructure | Included because the service or infrastructure operates continuously behind ordinary household/device use, generating network, location, connection or time-stamped utility-consumption records. | Passive / background |
| Deliveroo | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| Duke Energy online account and app | Connectivity / utility infrastructure | Included because the service or infrastructure operates continuously behind ordinary household/device use, generating network, location, connection or time-stamped utility-consumption records. | Passive + active |
| Google Wallet (Google Pay) | Digital service / platform | Included because the UK family uses Google Wallet for an everyday purchase, turning a coffee/lunch payment into a device-linked transaction record. | Direct use; some background processing |
| Nintendo Switch / Switch 2 | Child / education / gaming | Included because children use or are administered through this service for learning, gaming, device supervision or school payments, adding child identity, activity, device, payment or educational data to the household footprint. | Direct use; some background processing |
| Plaid (embedded in Venmo, Chime, Credit Karma, budgeting apps) | Banking / insurance / financial service | Included because the US financial scenario uses services in which Plaid can sit behind the interface, allowing an ordinary account link to expose a long transaction history and ongoing financial signals. | Indirect / embedded |
| RingGo | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| Starbucks | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Xbox / Microsoft Account | Child / education / gaming | Included because children use or are administered through this service for learning, gaming, device supervision or school payments, adding child identity, activity, device, payment or educational data to the household footprint. | Direct use; some background processing |
| Dropbox | Work / productivity / identity | Included in the underlying cloud-storage product review as a representative file-sync service used in everyday work/personal computing, where filenames, sharing, account and device activity can be recorded. | Direct use; some background processing |
| Gmail | Work / productivity / identity | Included because several scenarios check personal or school/work email during the day, generating communications content, contacts, timestamps, device and account metadata. | Direct use; some background processing |
| ParentPay | Child / education / gaming | Included because the UK family uses it for school meals, clubs and trips, generating child identity, school, payment and household-administration data. | Direct use; some background processing |
| Patient Access (EMIS) | Health / fitness / care | Included because health, fitness, care, medication or appointment activity is part of the modelled day, creating sensitive physiological, clinical, medication, identity or wellbeing data. | Direct use; some background processing |
| Snapchat | Social / messaging / location platform | Included because routine social, messaging or family-location activity forms part of the modelled day, generating account, engagement, relationship/social-graph, device and sometimes location data. | Direct use; some background processing |
| State Farm | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct use; some background processing |
| Strava Limited / Strava, Inc. | Fitness / location tracking | Included because Sam records exercise and runs through Strava, creating route, location, distance, pace, activity and device-linked fitness data during an ordinary workout. | Direct use + background sensors |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Chick-fil-A | Retail / loyalty / delivery / payments | Included because shopping, groceries, loyalty, food delivery or parking appear in the daily routines, generating basket/order, merchant, payment, location, identity and preference data. | Direct use; some background processing |
| Fitbit | Health / fitness / care | Included because health, fitness, care, medication or appointment activity is part of the modelled day, creating sensitive physiological, clinical, medication, identity or wellbeing data. | Direct use; some background processing |
| Google Drive | Work / productivity / identity | Included because cloud files are part of ordinary work and household administration in the underlying scenarios, creating file, sharing, account and device records. | Direct use; some background processing |
| Google Family Link | Child / education / gaming | Included because the underlying family-device review includes parental supervision and child-device management, which can expose device, app, location and family-account information. | Direct use; some background processing |
| Microsoft 365 (Microsoft Office) | Work / productivity / identity | Included because the working-age scenarios use Microsoft 365 for everyday work email, documents and collaboration, creating login, communications, file and usage records. | Direct use; some background processing |
| my Social Security online account | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct / public service |
| Yoti Ltd | Digital service / platform | Included because the UK adult-site scenario uses Yoti for age verification, making identity or biometric verification part of a routine web interaction. | Direct use; some background processing |
| Banner Health Patient Account / Family Profiles | Health / fitness / care | Included because health, fitness, care, medication or appointment activity is part of the modelled day, creating sensitive physiological, clinical, medication, identity or wellbeing data. | Direct use; some background processing |
| Canvas Parent | Child / education / gaming | Included because the US family checks the school platform for child activity and alerts, creating parent, child, school and engagement records. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Lloyds Bank | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct use; some background processing |
| Spectrum Internet (Charter Communications) | Connectivity / utility infrastructure | Included because the service or infrastructure operates continuously behind ordinary household/device use, generating network, location, connection or time-stamped utility-consumption records. | Passive / background |
| USPS Informed Delivery | Mail / postal data service | Included because Carol receives daily digital scans of incoming envelopes; the service turns ordinary postal delivery into image records and can also record whether notification emails are opened or clicked. | Passive + direct viewing |
| YouTube Kids | Streaming / connected television | Included because ordinary home entertainment uses this service or device, generating viewing history, device/account identifiers and, for connected TVs, potentially high-frequency viewing ACR screen captures. | Direct use; some background processing |
| Zoom Workplace | Work / productivity / identity | Included because ordinary workdays include video calls, creating participant, meeting, device, audio/video and usage metadata. | Direct use; some background processing |
| Monzo | Banking / insurance / financial service | Included because routine banking, payment, insurance or benefits administration occurs in the modelled day, creating identity, financial, transaction, credit/risk, device and fraud-prevention records. | Direct use; some background processing |
| Octopus Energy domestic gas and electricity | Connectivity / utility infrastructure | Included because the service or infrastructure operates continuously behind ordinary household/device use, generating network, location, connection or time-stamped utility-consumption records. | Passive + active |
| Specsavers optician | Health / fitness / care | Included because health, fitness, care, medication or appointment activity is part of the modelled day, creating sensitive physiological, clinical, medication, identity or wellbeing data. | Direct use; some background processing |
| Google Messages (RCS) | Messaging | Included in the Android communications review because routine text/RCS messaging can create message, contact, timestamp, device and account metadata across the day. | Direct use + background sync |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Apple Mail (iCloud Mail) | Apple device / account service | Included in the Apple ecosystem review as a routine email service on personal devices, where communications, contacts and device/account metadata can be processed. | Active + background sync |
| Bee Network Tap and Go (Metrolink tram and bus) | Vehicle / transport | Included because the Manchester commuting scenario pays for public transport digitally, linking routine travel with time, location and payment/account data. | Passive + active |
| Flo (Period & Ovulation Tracker) | Health / fitness / care | Included because the family scenario includes routine menstrual-cycle logging, introducing highly sensitive reproductive-health data into the daily information footprint. | Direct use; some background processing |
| HID Global (access cards, badges & readers) | Work / productivity / identity | Included because an office worker enters the workplace using an access card, turning a physical arrival at work into a time-stamped identity and access event. | Direct physical access |
| Microsoft Authenticator | Work / productivity / identity | Included because workplace logins use multi-factor authentication, creating security, device, identity and timestamped access events. | Direct use; some background processing |
| BBC Bitesize | Child / education / gaming | Included because the UK child uses Bitesize for homework, making educational browsing and learning activity part of the modelled day. | Direct use; some background processing |
| DCC smart metering communications network | Connectivity / utility infrastructure | Included because UK smart-meter readings are transmitted over the national DCC infrastructure, making energy use a background data stream independent of deliberate screen use. | Passive / infrastructure |
| Smart meter | Connectivity / utility infrastructure | Included because every household uses metered energy and the scenarios model 15-minute, half-hourly or hourly readings that can reveal time-stamped consumption and patterns of occupancy. | Passive / background |
| BBC iPlayer | Streaming / connected television | Included because television viewing in UK households includes iPlayer, generating account, viewing, device and programme-history data. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| BBC News | News / media | Included because UK archetypes repeatedly read or watch BBC News during morning, lunch and evening routines, making news consumption part of the daily browsing/viewing footprint. | Direct use; some background processing |
| BBC Weather | News / media | Included because checking the weather is a repeated everyday action in UK households, creating routine browsing, device and location-context signals. | Direct use; some background processing |
| Login.gov (USA) | Digital service / platform | Included because the US older-adult scenario accesses federal benefits through Login.gov, adding identity, device and fraud-risk telemetry to routine benefits administration. | Direct / mandatory gateway |
| Apple Wireless Headphones | Audio / connected accessory | Included because personal audio is used during commuting/exercise, linking an accessory and its device/account usage to the daily routine. | Direct use; some background processing |
| Google Workspace (Gmail, Docs, Drive, Meet) | Work / productivity / identity | Included because work and household administration use Google productivity tools, generating account, file, meeting, communication and device metadata. | Direct use; some background processing |
| iCloud Drive | Apple device / account service | Included in the Apple ecosystem review because cloud synchronisation persists in the background and can hold files, device/account metadata and backups beyond moments of active use. | Active + background sync |
| Beats (by Dr. Dre) | Audio / connected accessory | Included because the US family uses Beats headphones during remote work, adding a connected accessory to the device ecosystem supporting the workday. | Direct use; some background processing |
| Apple Laptop | Work / productivity / identity | Included because the US family scenario uses a household MacBook for administration and work, adding account, browser, file and device telemetry. | Direct use; some background processing |
| Apple Messages (iMessage) | Apple device / account service | Included because family and friends are contacted throughout the day by iMessage/FaceTime, creating communications metadata and, depending on service configuration, content/back-up records. | Active + background sync |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Apple Pay | Apple device / account service | Included because several scenarios use contactless/mobile payment during commuting, errands and food purchases, creating transaction, device and merchant records. | Active + background sync |
| Apple Weather | Apple device / account service | Included because iPhone users check weather during morning and evening routines, creating app, device and location-context usage signals. | Active + background sync |
| iPad (Apple) | Apple device / account service | Included because family and older-adult scenarios use iPads for news, health administration, video calls, reading and entertainment, consolidating multiple kinds of activity on one device. | Active + background sync |
| iPhone | Apple device / account service | Included because the iPhone is the main personal device for several archetypes and mediates messaging, payments, browsing, health, location and app activity across the entire day. | Active + background sync |
| Medicare account (Medicare.gov / MyMedicare) | Health / fitness / care | Included because the US older-adult scenario manages Medicare-related health administration online, creating health, identity, account and browsing records. | Direct / public service |
| Safari (Apple) | Browser / search | Included because Apple-device users browse news, shopping, search and services through Safari throughout the day, creating browsing and device-context records. | Direct use; some background processing |
| Accurx | Health / fitness / care | Included because the UK older-adult scenario uses digital GP access/communication tools, adding appointment, message and healthcare-interaction data to an ordinary day. | Direct use; some background processing |
| Apple Watch (watchOS) | Health / fitness / care | Included because wearables remain active across sleep, exercise and ordinary movement, generating repeated heart-rate, motion, sleep and other physiological measurements throughout the day. | Passive + active |
| NHS App | Health / fitness / care | Included because the UK older-adult and family scenarios use NHS digital services for appointments and healthcare administration, creating sensitive health, identity and usage records. | Direct use; some background processing |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Microsoft Entra ID (formerly Azure Active Directory) | Work / productivity / identity | Included in the underlying workplace-identity review because ordinary employment access is mediated by enterprise identity infrastructure, producing login, device and security records. | Indirect / workplace infrastructure |
| Apple Find My | Apple device / account service | Included because family and older-adult scenarios use Apple location sharing to reassure relatives or track children/devices, creating a passive location relationship that persists beyond active app use. | Passive + active |
| Apple Health (iOS Health app) | Health / fitness / care | Included because Apple Health aggregates wearable and phone-generated physiological records, helping quantify the high-volume body-data stream in the model. | Passive + active |
| Apple Passwords app / iCloud Keychain, with credentials shared with family | Apple device / account service | Included in the underlying Apple ecosystem review because credential storage and family sharing connect multiple accounts and devices even when the password manager is not consciously used during every hour of the modelled day. | Background / on demand |

## C2. Additional ambient and indirect systems represented in the daily scenarios

The systems below appear in the daily routines or supporting analysis. They are included here so the reader can see the wider set of background and indirect systems used in the study and understand why they matter.

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis |
|---|---|---|---|
| Flock Safety ALPR | Private licence-plate recognition | Included because US driving scenarios pass Flock cameras; the model uses plate, vehicle-description, location and timestamp records to show how an ordinary journey creates a searchable movement trail. | Passive / ambient |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| Flock Safety ALPR | Private licence-plate recognition | Included because US driving scenarios pass Flock cameras; the model uses plate, vehicle-description, location and timestamp records to show how an ordinary journey creates a searchable movement trail. | Passive / ambient |
| UK National ANPR Data Centre / police ANPR | Public licence-plate recognition | Included because UK school runs, errands and appointments pass police ANPR cameras, creating time-stamped vehicle-location records without a deliberate interaction by the driver. | Passive / public infrastructure |
| School CCTV / security cameras | Physical surveillance | Included because children are recorded at school gates, corridors and playgrounds during an ordinary school day, adding repeated images and timestamps to their data footprint. | Passive / mandatory environment |
| Smoothwall Monitor | School device monitoring | Included because the UK child scenario models school safeguarding software that can monitor keystrokes, typed/deleted text, screenshots and device activity during lessons. | Passive / school-mandated |
| GoGuardian | School device monitoring | Included because the US child scenario models minute-by-minute monitoring of school-device screens, tabs and device location as part of the normal school day. | Passive / school-mandated |
| Transport for Greater Manchester CCTV | Public-transport surveillance | Included because Sam is recorded on Metrolink platforms and vehicles during the commute, adding repeated visual records to a journey that already creates payment and mobile-location data. | Passive / transport infrastructure |
| Nextbase / third-party vehicle dashcams | Roadside/vehicle video | Included because the Manchester walking/commuting model accounts for incidental recording by privately owned dashcams, showing that data can be created by devices the subject does not own or control. | Passive / ambient |

| **Organisation / service / system** | **Category** | **Why it is included in the study for a model household** | **Interaction basis (incl. a potential permitted background processing)** |
|---|---|---|---|
| ClearScore | Credit-score interface | Included because the UK working-age scenario checks a free credit-score app; the action surfaces bureau data and demonstrates how a seemingly simple check connects the user to a wider credit-data ecosystem. | Direct + indirect |
| Waze | Navigation service | Included because US driving scenarios use Waze as an alternative to Google Maps, creating route, location, traffic and device data during ordinary commuting. | Direct use + background location |
| Venmo | Peer-to-peer payments | Included because the US single-adult scenario checks or uses Venmo; it also provides the context for embedded financial-data access through services such as Plaid. | Direct use; embedded third parties |
| Slack | Workplace messaging | Included because the US working-age scenario uses Slack during the workday, adding workplace communications, contacts, timestamps, device and usage metadata. | Direct workplace use |
| Kroger | Retail / grocery | Included because the US single-adult routine includes grocery errands at Kroger, creating purchase, payment, loyalty and location-context records. | Direct use |
| ID.me | Digital identity / public-service gateway | Included because the US older-adult benefits scenario identifies ID.me as an identity gateway used for federal-account access, adding identity-verification and device/fraud signals. | Direct / gateway |
| LexisNexis Risk Solutions | Insurance / identity data intermediary | Included because the UK insurance-renewal analysis identifies bureau/identity checks that can be supplied through LexisNexis, illustrating an indirect data relationship created by routine insurance administration. | Indirect / background |

| Organisation / service / system | Category | Why it is included in the study for a model household | Interaction basis (incl. a potential permitted background processing) |
|---|---|---|---|
| MyChart | Patient portal | Included because the US older-adult scenario checks results and manages care through a patient portal, creating health, appointment, message, identity and device records. | Direct / health service |
| Parking / car-park ANPR systems | Physical-location infrastructure | Included because appointment and town-centre parking in the UK older-adult scenario can create entry/exit plate records in addition to national ANPR and navigation data. | Passive / ambient |
| Public voter-registration files / electoral registers | Public-record data source | Included in the supporting aggregate-profile analysis because political registration and address history can be lawfully combined with commercial data even though the individual does not create a new account or app interaction that day. | Indirect / public record |

# APPENDIX D

# Appendix D: Full Analysis of Documented Collection and Additional Uses

The grids below summarise what the organisations' applicable policies, notices and other documentation say they may collect or do with personal data. A tick means that the documentation describes circumstances in which the relevant use may occur. It does not mean that the use occurs for every (or any) user, product, data category or interaction, nor is it a finding that the collection or use is unnecessary, disproportionate, unlawful or contrary to data-minimisation requirements.

For this purpose, "applicable" means documentation relevant to the modelled product or service and, where an organisation publishes different terms or notices by jurisdiction or user or account type, the documentation relevant to the model household and use being analysed during the study period.

References in this Appendix to a "permission" or "permitted" mean that the organisation's documentation states that it may carry out the relevant use. A dash means that the study found no affirmative permission to that use. In several cases it reflects a stated fixed retention period rather than silence. The grid uses six organisation-level criteria. Five of these — marketing and advertising, combining data across sources, inference or profiling, commercial-partner sharing and open-ended retention — are the five permitted potential practices used in the 4,283 per-use calculation. AI or machine-learning training is the sixth organisation-level criterion. For sixteen organisations, the applicable documentation describes the potential for all six categories considered in this analysis:

| Organisation | May use for marketing / ads | May combine sources | Permits inferring traits | May disclose to commercial partners | Policy permits open-ended retention | May use data to train AI | Described information items listed as potentially collected |
|---|---|---|---|---|---|---|---|
| Roblox (children's games) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 10 |
| Instagram | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 9 |
| TikTok | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 9 |
| Spotify | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |
| Strava | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |
| Octopus Energy | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 8 |

| Organisation | May use for marketing / ads | May combine sources | Permits inferring traits | May disclose to commercial partners | Policy permits open-ended retention | May use data to train AI | Described information items listed as potentially collected |
|---|---|---|---|---|---|---|---|
| Nextdoor | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 7 |
| Direct Line (insurance) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 7 |
| Aviva (insurance) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 7 |
| TransUnion (credit bureau) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 6 |
| LinkedIn | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 6 |
| Google News | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 6 |
| X (formerly Twitter) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 5 |
| Facebook (Meta) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 5 |
| YouTube | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 4 |
| Amazon Music | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | 4 |

A further 55 organisations document permissions for five of the six organisation-level criteria:

| Organisation | May use for marketing / ads | May combines sources | Permits inferring traits | May disclose to commercial partners | Policy permits open-ended retention | May use data to train AI | Data categories[43] listed as potentially collected (of 16) |
|---|---|---|---|---|---|---|---|
| DoorDash | ✓ | ✓ | ✓ | ✓ | ✓ | – | 11 |
| PayPal | ✓ | ✓ | ✓ | ✓ | ✓ | – | 10 |
| Instacart | ✓ | – | ✓ | ✓ | ✓ | ✓ | 9 |
| Medical alert pendant (US PERS) | ✓ | ✓ | ✓ | ✓ | ✓ | – | 9 |

[43] The "16 categories" refer to the study's internal coding taxonomy for types of personal data that an organisation's documents say may be collected. These categories were used consistently across the organisation-level analysis to provide a comparable measure of collection breadth. Examples include device/cookie/advertising identifiers, payment or financial information, location data, browsing/search/viewing history, message or communications content, voice recordings, contact lists or social connections and employment or income information. The complete coding taxonomy is contained in the underlying study dataset.

| Organisation | May use for marketing / ads | May combines sources | Permits inferring traits | May disclose to commercial partners | Policy permits open-ended retention | May use data to train AI | Data categories listed as potentially collected (of 16) |
|---|---|---|---|---|---|---|---|
| Tinder | ✓ | ✓ | ✓ | ✓ | – | ✓ | 9 |
| BBC Studios | ✓ | ✓ | ✓ | ✓ | ✓ | – | 9 |
| Costco | ✓ | ✓ | ✓ | ✓ | ✓ | – | 9 |
| Nintendo Switch | ✓ | ✓ | ✓ | ✓ | ✓ | – | 9 |
| Chase | ✓ | ✓ | ✓ | ✓ | ✓ | – | 9 |
| The Roku Channel | ✓ | ✓ | ✓ | ✓ | ✓ | – | 8 |
| NBC News | ✓ | ✓ | ✓ | ✓ | ✓ | – | 8 |
| Life360 (family location) | ✓ | ✓ | ✓ | ✓ | ✓ | – | 8 |
| MyFitnessPal | ✓ | ✓ | ✓ | ✓ | ✓ | – | 8 |
| Spectrum Internet | ✓ | ✓ | ✓ | ✓ | ✓ | – | 8 |
| iPhone | ✓ | ✓ | ✓ | ✓ | ✓ | – | 8 |
| Experian | ✓ | ✓ | ✓ | ✓ | ✓ | – | 7 |
| Mobile carriers (4G/5G data) | ✓ | ✓ | ✓ | ✓ | ✓ | – | 7 |
| Walgreens | ✓ | ✓ | ✓ | ✓ | ✓ | – | 7 |
| Toyota RAV4 (connected services) | ✓ | ✓ | – | ✓ | ✓ | ✓ | 7 |
| Amazon Shopping | ✓ | ✓ | ✓ | ✓ | ✓ | – | 7 |

| Organisation | May use for marketing / ads | May combines sources | Permits inferring traits | May disclose to commercial partners | Policy permits open-ended retention | May use data to train AI | Data categories listed as potentially collected (of 16) |
|---|---|---|---|---|---|---|---|
| Deliveroo | ✓ | ✓ | ✓ | ✓ | ✓ | – | 7 |
| Duke Energy | ✓ | ✓ | ✓ | ✓ | ✓ | – | 7 |
| Equifax | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| PornHub | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| Target (Circle and app) | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| WhatsApp | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| Sky News website/app | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| Android Phone | ✓ | ✓ | – | ✓ | ✓ | ✓ | 6 |
| Amazon Kindle | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| Reddit | ✓ | ✓ | ✓ | ✓ | – | ✓ | 6 |
| Plaid | – | ✓ | ✓ | ✓ | ✓ | ✓ | 6 |
| Cox Internet | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| GEICO | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| Zoom Workplace | ✓ | ✓ | – | ✓ | ✓ | ✓ | 6 |
| iPad (Apple) | ✓ | ✓ | ✓ | ✓ | ✓ | – | 6 |
| Fox News | ✓ | ✓ | ✓ | ✓ | ✓ | – | 5 |
| Windows Laptop | ✓ | – | ✓ | ✓ | ✓ | ✓ | 5 |

| Organisation | May use for marketing / ads | May combines sources | Permits inferring traits | May disclose to commercial partners | Policy permits open-ended retention | May use data to train AI | Data categories listed as potentially collected (of 16) |
|---|---|---|---|---|---|---|---|
| ITVX | ✓ | ✓ | ✓ | ✓ | ✓ | – | 5 |
| Starbucks | ✓ | ✓ | ✓ | ✓ | ✓ | – | 5 |
| Xbox / Microsoft account | ✓ | ✓ | ✓ | ✓ | ✓ | – | 5 |
| AEP Ohio smart meter | ✓ | ✓ | ✓ | ✓ | ✓ | – | 5 |
| Microsoft 365 | ✓ | ✓ | ✓ | ✓ | ✓ | – | 5 |
| HID Global (access badges) | ✓ | ✓ | ✓ | ✓ | ✓ | – | 5 |
| My McDonald's app | ✓ | ✓ | ✓ | ✓ | ✓ | – | 4 |
| Google Search | ✓ | ✓ | ✓ | ✓ | ✓ | – | 4 |
| Google Assistant / Gemini | ✓ | ✓ | ✓ | ✓ | – | ✓ | 4 |
| BBC Bitesize | ✓ | ✓ | ✓ | ✓ | ✓ | – | 4 |
| Apple Laptop | ✓ | ✓ | ✓ | ✓ | ✓ | – | 4 |
| Amazon Alexa | ✓ | ✓ | ✓ | – | ✓ | ✓ | 3 |
| Google Maps | ✓ | ✓ | ✓ | ✓ | – | ✓ | 3 |
| Boots Advantage Card | ✓ | ✓ | ✓ | ✓ | ✓ | – | 3 |
| Specsavers optician | ✓ | ✓ | ✓ | ✓ | ✓ | – | 3 |

| Organisation | May use for marketing / ads | May combines sources | Permits inferring traits | May disclose to commercial partners | Policy permits open-ended retention | May use data to train AI | Data categories listed as potentially collected (of 16) |
|---|---|---|---|---|---|---|---|
| Apple Mail (iCloud Mail) | ✓ | ✓ | ✓ | ✓ | ✓ | – | 3 |
| Ford F-150 (FordPass) | ✓ | ✓ | ✓ | ✓ | ✓ | – | 2 |
| Amazon Prime Video | ✓ | ✓ | ✓ | ✓ | ✓ | – | 2 |

# APPENDIX E

# Appendix E: Technological Methodology

### 1. Aim and Scope

The study asks: what do published policies, technical materials and other evidence indicate could be captured, generated or inferred about a model person or model household during one ordinary day, both through the products and services they choose to use and through the wider systems operating around them, including systems they never actively signed up to? Rather than look at one app or one company, it looks at the products and services used by the model person or model household and the wider systems operating around them during the modelled 24-hour period. It maps what published policies, technical materials and other evidence indicate may be collected, generated or inferred about the model person or model household and how that information may subsequently be processed. For the purposes of the analysis, information is classified as collected data, generated data or inferred data in accordance with Section 2.

Three model household types were chosen and each was defined twice, once for each country. That gives six modelstudy groups: a working-age adult living alone, a couple with two children, and a retired woman living alone, in the UK and the US. Each is an evidence-based model household built from common demographic features, routines and product and service use, meaning an evidence-led and recognisably ordinary model household, with a named example model person or model persons so the day can be written realistically.

Four kinds of data relationship are counted. Primary use, where a model household uses a product or service for the immediate purpose for which it appears in the modelled day. Data flows, where an organisation receives or records the information about the model person or model household because of something that happened in the day, without the household using it. Standing records, where an organisation or institution holds an ongoing record about a model person or model household independently of activity in the modelled day. And ambient capture, where cameras, number-plate readers or similar surrounding systems may record a model person, model household, vehicle or other associated identifier without a primary use by the model household.The study does not observe the behaviour of real people. It records documented capabilities, permissions and supported modelling assumptions concerning what may be collected, generated, inferred or otherwise processed.. It records what organisations' published policies and supporting materials indicate they may collect, generate, infer or do with information about a model person or model household. The organisations counted in the headline figures are those that appear in the modelled days and their data flows. Standing records sit in a separate layer and are not in that count.

The methodology identifies and classifies documented capabilities, permissions, practices and supported modelling assumptions for research purposes. A classification or count does not, by itself, establish that the relevant processing occurred in any particular interaction or for every user, nor does it constitute a determination of lawfulness, necessity, proportionality or legal compliance. Where the study relies on an assumption about a product feature, setting or modelled behaviour, the resulting finding should be read subject to that assumption.

## 2. The model households

Each model household is represented by one study record. It holds the country, a one-line description of who lives there, the named model person or model persons and a short model profile, the fixed parameters described in section 2.1 and a set of prevalence figures. Every parameter carries its value and a sentence naming the evidence behind it.

### 2.1 The fixed parameters

Parameters are generally selected from common or prevalent characteristics for the relevant model household type in each country. The UK and US members of each pair are built by the same rule, so any difference between them comes from the country and not from the model person or model household. Two parameters, the working pattern and the number of children, do not always take the most common value, and each says why.

#### Working-age solo households

Sam and Bob are men because more men than women live alone in young and middle adulthood.[44] They are 34 because 34 is the median age of men under 45 who live alone.[45] Sam is an administrator and Bob an office worker. Both split the week between the office and home. Working on site every day is still the most common pattern for office jobs, but hybrid is the most common way office staff work from home in Great Britain, and it has grown every year since 2022 while full-time home working has fallen.[46]

#### Families

Both model couples are married because married couples are the largest family group in

[44] Esteve et al., 2020, Living alone over the life course, Population and Development Review 46(1), https://doi.org/10.1111/padr.12311; Eurostat, EU Labour Force Survey, Household composition statistics, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Household_composition_statistics. Men chosen ahead of women because men are the larger group living alone in young and middle adulthood: about 1.4 men to every woman among 25 to 29 year olds living alone in Europe and North America, and 20.2 per cent of EU men aged 25 to 54 single without children against 12.2 per cent of women.

[45] ONS, 2025, Families and households in the UK: 2024, https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/families/bulletins/familiesandhouseholds/2024; US Census Bureau, 2024, Current Population Survey, America's Families and Living Arrangements tables, https://www.census.gov/topics/families.html; Esteve et al., 2020, as note 47. 34 chosen because it is the median age of people living alone under 45. Under 45 is used because it is the band in which men outnumber women among people living alone; above it women take over, and the older household covers that. 4.1 million of the 8.4 million people living alone in the UK are under 65; 7.5 million Americans aged 25 to 44 live alone. The same age is used in both countries so the pair differ only by country.

[46] ONS, 2024, Who are the hybrid workers?, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/whoarethehybridworkers/2024-11-11; ONS, 2025, Who has access to hybrid work in Great Britain?, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/whohasaccesstohybridworkingreatbritain/2025-06-11; US Bureau of Labor Statistics, 2025, Occupational Requirements Survey: office and administrative support occupations, https://www.bls.gov/ors/factsheet/office-and-administrative-support-occupations.htm; US Bureau of Labor Statistics, 2023, About 1 in 3 workers in management, professional and related occupations teleworked, November 2023, https://www.bls.gov/opub/ted/2023/about-1-in-3-workers-in-management-professional-and-related-occupations-teleworked-november-2023.htm. On site is the largest group: 78.5 per cent of US office and administrative support jobs allow no telework, and 72 per cent of workers in Great Britain are not hybrid. Hybrid chosen ahead of fully remote because it is the larger home-working group in Great Britain, 28 per cent against 13 to 14 per cent, and administrative and secretarial occupations are among the four occupational groups with the highest hybrid rates. Hybrid chosen ahead of fully on site because it is the arrangement that has grown since 2022 while home-only working has fallen; in the US, 21.6 per cent of sales and office workers teleworked in November 2023, 12.0 per cent for all their hours and 9.6 per cent for some. This is the first of the two departures from the most common value.

both countries.[47] The parents are 40 and 43 in the UK and 37 and 39 in the US because those are the average ages of first-time parents, plus3 11-years.[48]

Each model family has two children because two-child families are the largest group at the US parents' age and the second largest in the UK, and because children of 11 and 8 put a child with Each model family has two children because two-child families are the largest group at the US parents' age and the second largest in the UK, and because children of 11 and 8 put a child with a smartphone and a child without one in the same household.[49] David works fully from home because 35 to 44 year olds have the highest rate of home working in the US.[50]

### Older households

Margaret and Carol are women because more women than men live alone in later life.[51] They are 75 because 75 is the median age of older people who live alone.[52] Both are retired because very few people are still working at 75.[53]

### Home and location

Sam rents privately because more people under 35 rent privately than own or rent from a council. He lives in Manchester because young private renters are concentrated in large cities.[54] Bob rents because most Americans under 35 rent.[55] He lives in Columbus because it is a mid-size city with an above-average share of people living alone.[56]

The model UK family owns with a mortgage because more people aged 35 to 49 own with a

[47] ONS, 2025, Families and households in the UK: 2024, as note 48; US Census Bureau, 2024, America's Families and Living Arrangements: 2022, P20-587, https://www2.census.gov/library/publications/2024/demo/p20-587.pdf. Married chosen ahead of cohabiting or lone parent because it is the largest group: 65.1 per cent of UK families are married or civil-partnered couples; 65 per cent of US family groups with children are maintained by married parents.

[48] ONS, 2024, Births by parents' characteristics, England and Wales, https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/livebirths/datasets/birthsbyparentscharacteristics; Mathews and Hamilton, 2016, Mean age of mothers is on the rise, NCHS Data Brief 232, https://www.cdc.gov/nchs/products/databriefs/db232.htm; US Census Bureau, Table MS-2, Estimated median age at first marriage. Ages derived by adding eleven years, the age of the elder child, to the average age of first-time parents in each country.

[49] ONS, 2023, Families and households in the UK: 2023, https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/families/bulletins/familiesandhouseholds/2023; US Census Bureau, 2023, Current Population Survey ASEC, Table F1, https://www2.census.gov/programs-surveys/demo/tables/families/2023/cps-2023/tabf1-all.xls; Eurostat, 2025, Nearly 25% of EU households had at least 1 child in 2024, https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20250707-1; Ofcom, 2026, Children's Media Lives. Two children chosen ahead of one, the largest group in the UK (45 per cent one, 41 per cent two) and in the US overall (43 per cent one, 36 per cent two), because both child data pathways must be present in the day: an 11-year-old with a first smartphone, ownership rising from 56 per cent at 10 to 83 per cent at 11, and an 8-year-old without one. At the US parents' own age, 35 to 39, two children is the largest group at 40 per cent against 32 per cent with one. The EU benchmark is 37.6 per cent with two. This is the second departure from the most common value.

[50] US Bureau of Labor Statistics, Current Population Survey telework data, https://www.bls.gov/cps/telework/highlights.htm. Fully remote chosen for one US parent because 35 to 44 year olds have the highest US teleworking rate, about 27 per cent

[51] ONS, 2025, Families and households in the UK: 2024, as note 48; Centre for Ageing Better, 2025, The State of Ageing 2025: our ageing population, https://ageing-better.org.uk/our-ageing-population-state-ageing-2025; Pew Research Center, 2025, Smaller shares of older Americans live alone today than in 1990, https://www.pewresearch.org/short-reads/2025/12/04/a-smaller-share-of-older-us-adults-live-alone-today-than-in-1990/. Women chosen ahead of men because they are the larger group living alone in later life: 40.9 per cent of UK women aged 65 and over in households live alone against 27.0 per cent of men; 1.7 million women aged 75 and over in England live alone against 0.8 million men; 31 per cent of US women aged 65 and over live alone against 19 per cent of men.

[52] ONS, 2025, as note 48; US Census Bureau, 2024, Living Arrangements Varied Across Age Groups, https://www.census.gov/library/stories/2024/05/living-arrangements.html. 75 chosen because living alone rises steeply with age and 75 is the median age of older people living alone: 51.1 per cent of UK people living alone are 65 or over, and the 75-and-over band holds about 59 per cent of them; 43 per cent of US women aged 75 and over live alone against 27 per cent at 65 to 74. The same age is used in both countries.

[53] Ministry of Housing, Communities and Local Government, 2025, English Housing Survey 2024 to 2025: headline findings on demographics and household resilience, https://www.gov.uk/government/collections/english-housing-survey-2024-to-2025-headline-findings-on-demographics-and-household-resilience; Social Security Administration, 2025, Fact Sheet on Social Security, https://www.ssa.gov/OACT/FACTS/; US Bureau of Labor Statistics, 2023, Labor force participation of people aged 75 and older, https://www.bls.gov/opub/mlr/2023/highcharts/data/dubina-chart7.stm. Retired chosen ahead of working because very few people work at 75: 62 per cent of outright-owner households in England have a retired reference person; 93 per cent of Americans aged 75 and over receive Social Security and 8.5 per cent are in the labour force. Margaret's income is the State Pension and a small occupational pension; Carol's is Social Security and savings.

[54] ONS, 2023, Housing, England and Wales: Census 2021, https://www.ons.gov.uk/peoplepopulationandcommunity/housing/bulletins/housingenglandandwales/census2021; Ministry of Housing, Communities and Local Government, 2023, English Housing Survey 2021 to 2022: private rented sector, https://www.gov.uk/government/collections/english-housing-survey. Private renting chosen ahead of owning or social renting because it is the largest group for his age: 46.4 per cent of household reference persons aged 16 to 34 in England rent privately, the highest share of any age group, and one-person households are the most common private-renter household at 34 per cent. Manchester chosen because private renting by the young concentrates in large cities.

[55] U.S. Census Bureau, Housing Vacancy Survey, First Quarter 2026. The homeownership rate for householders under 35 was 36.8%, meaning roughly 63.2% were not homeowners. The Census Bureau reports this as the lowest homeownership rate of any age group. https://www.census.gov/housing/hvs/files/currenthvspress.pdf?utm_source=chatgpt.com

[56] US Census Bureau, 2026, Quarterly Residential Vacancies and Homeownership, first quarter 2026, https://www.census.gov/housing/hvs/current/index.html; US Census Bureau, 2025, American Community Survey 2024 one-year estimates, table B11001, https://api.censusreporter.org/1.0/data/show/latest?table_ids=B11001&geo_ids=05000US39049,01000US. Renting chosen ahead of owning because only 36.8 per cent of householders under 35 own, so most rent. Columbus chosen as a mid-size city with an above-average share of people living alone: 33.1 per cent of households in Franklin County are one person against 28.9 per cent nationally.

mortgage than rent or own outright. They live in outer Leeds because family homes are mostly houses outside the expensive city centres.[57] The US model family owns with a mortgage because most Americans aged 35 to 44 own their home and most owners have a mortgage. They live in the Charlotte suburbs for the same reason.[58]

Margaret owns her home outright because most people over 65 own outright. She lives in a small Yorkshire town because outright owners are concentrated outside the largest cities.[59] Carol owns her home outright because most Americans over 65 own their home and most of those owners have paid off the mortgage. She lives in Tucson because Arizona attracts more older movers than any other state relative to its size, and Tucson has a higher share of over-65s than Arizona or the US.[60]

**Cars**

Sam has a car because most households in England and Wales, including in Manchester, have one.[61] Bob has a car because almost every US household has one.[62]

The model UK family has one car because one car is the largest group among English households.[63] The model US family has two cars because two cars is the largest group among US households.[64]

Margaret has a car because most women over 70 hold a driving licence.[65] Carol has a car because few Americans over 65 are non-drivers.[66]

**Internet**

All six model households are online because almost every household in both countries is.

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[57] ONS, 2023, Housing, England and Wales: Census 2021, as note 57; Ministry of Housing, Communities and Local Government, 2025, English Housing Survey 2024 to 2025, as note 56. Owning with a mortgage chosen ahead of renting or owning outright because it is the largest group: 47.8 per cent of household reference persons aged 35 to 49 own with a mortgage, the highest share of any age group, and 58.8 per cent of couples with dependent children do. Outer Leeds chosen because owner-occupied family homes are mostly houses outside the high-price city centres.

[58] US Census Bureau, 2026, Quarterly Residential Vacancies and Homeownership, as note 58; Federal Reserve Board, 2025, Economic Well-Being of U.S. Households in 2024, Survey of Household Economics and Decisionmaking, https://www.federalreserve.gov/publications/report-economic-well-being-us-households.htm. Owning with a mortgage chosen ahead of renting or owning outright because it is the largest group: home ownership at 35 to 44 is 61 to 62 per cent and about two thirds of owners hold a mortgage. The Charlotte suburbs chosen for the same reason as Leeds.

[59] Ministry of Housing, Communities and Local Government, 2025, English Housing Survey 2024 to 2025, as note 56; ONS, 2023, Housing, England and Wales: Census 2021, as note 57. Owning outright chosen ahead of owning with a mortgage or renting because it is the largest group: 79 per cent of household reference persons aged 65 and over are owner-occupiers and 74 per cent own outright. A small town chosen ahead of a large city because outright ownership sits away from the largest cities: 22 to 23 per cent of London households own outright against 38 per cent in the rest of England.

[60] US Census Bureau, 2026, Quarterly Residential Vacancies and Homeownership, as note 58; US Census Bureau, 2022, Domestic Migration of Older Americans: 2015-2019, P23-218, https://www.census.gov/library/publications/2022/demo/p23-218.html; US Census Bureau, 2025, American Community Survey 2024 one-year estimates, table B01001, https://api.censusreporter.org/1.0/data/show/latest?table_ids=B01001&geo_ids=05000US04019,04000US04,01000US; Morrison Institute for Public Policy, 2025, Pima County profile 2025, https://morrisoninstitute.asu.edu/sites/g/files/litvpz841/files/2025-07/pima_2025_county_profile.pdf. Owning outright chosen because it is the largest group: home ownership among householders aged 65 and over is 78.4 per cent, the highest of any age group, and 64 per cent of those owners own free and clear. Arizona chosen because it has the highest net migration rate of people aged 65 and over of any state, 18.2 per 1,000, gaining 21,440 a year in 2015 to 2019, second only to Florida in numbers. Tucson chosen ahead of Phoenix because older outright ownership sits away from the largest metro, and Pima County, which is the Tucson metro, has a higher share of people aged 65 and over, 22.4 per cent, than Arizona at 19.7 per cent or the US at 18.0 per cent, with 65 per cent of households owning their home.

[61] ONS, 2023, Car or van availability, Census 2021, table TS045, https://www.ons.gov.uk/datasets/TS045/editions/2021/versions/1; Greater Manchester Combined Authority, 2023, Car availability: Census 2021 briefing, https://greatermanchester-ca.gov.uk/media/9704/car-availability-gmca-census-2021-briefing-final.pdf. A car chosen ahead of no car because the majority of households have one: 77 per cent in England and Wales and 61 per cent in Manchester.

[62] Pew Research Center, 2024, 1 in 10 Americans rarely or never drive a car, American Community Survey 2023, https://www.pewresearch.org/short-reads/2024/11/14/1-in-10-americans-rarely-or-never-drive-a-car/. A car chosen ahead of no car because 92 per cent of US households have at least one vehicle.

[63] Department for Transport, 2022, National Travel Survey 2021: household car availability, https://www.gov.uk/government/statistics/national-travel-survey-2021/national-travel-survey-2021-household-car-availability-and-trends-in-car-trips. One car chosen ahead of two because it is the largest group: 45 per cent of English households have one car, 33 per cent two or more and 22 per cent none.

[64] Pew Research Center, 2024, as note 64. Two cars chosen ahead of one because it is the largest group: 36 per cent of US households have two vehicles, a third have one, 22 per cent three or more and 8 per cent none.

[65] Department for Transport, National Travel Survey, driving licence holding, as note 65. A car chosen ahead of no car because about two thirds of women over 70 hold a full driving licence.

[66] Pew Research Center, 2024, as note 64. A car chosen ahead of no car because only 11 per cent of US adults aged 65 and over are non-drivers and 92 per cent of households have a vehicle.

Sam and Bob are smartphone-first because smartphones carry most adults' online time.[67] The model families have home broadband because almost every mortgaged household does.[68] Margaret and Carol use a smartphone and a tablet and fewer services because most people over 75 are online but use a narrower range.[69]

**Banking**

Sam and the model UK family hold two current accounts, with Lloyds and Monzo, because nearly half of 25 to 34 year olds hold a second account and Monzo is the largest app-based bank.[70]

Margaret holds one account, with Lloyds, because second accounts are concentrated among younger adults. The three model US households hold one account, with Chase, because there is no US evidence that most people hold two.[71]

Table 1 condenses the main parameters. The last column is the phone platform and wearable each person is modelled as owning. It is a profile setting, and it decides which platform defaults, such as browser, maps and mail, that the model person is modelled as using when products and services are selected for the day in section 4. The matched product lists, the pool from which each day is chosen, run to between 62 and 126 entities per household and are described in section 3.3. The organisations that actually appear in a day number between 44 and 88 and are counted in section 6.

### Table 1. The six model households: main fixed parameters

| Model household | Model person(s) | Ages | Work | Home | Device ecosystem |
|---|---|---|---|---|---|
| UK-S | Sam, Manchester | 34 | Full-time administrator, office-based, | Private renter, one-bed flat, one car | iPhone and Apple Watch |
| US-S | Bob, Columbus, Ohio | 34 | Full-time office worker, hybrid | Renter, one car | iPhone and Apple Watch |
| UK-F | Priya and Tom, Leeds; girl 11, boy 8 | 40 and 43 | Tom full-time, Priya part-time | Mortgaged semi in outer Leeds, one car | Priya Android and Fitbit; Tom iPhone and Apple Watch |

[67] Ofcom, 2025, Online Nation 2025, https://www.ofcom.org.uk/media-use-and-attitudes/online-habits/from-apps-to-ai-search-how-the-uk-goes-online-in-2025; Pew Research Center, 2025, Mobile Fact Sheet, https://www.pewresearch.org/internet/fact-sheet/mobile/. Only 5 per cent of UK adults lack home internet and smartphones account for about three quarters of adults' online time; 97 per cent of US adults under 50 own a smartphone and 95 per cent use the internet.
[68] Ministry of Housing, Communities and Local Government, 2024, English Housing Survey 2023 to 2024, https://www.gov.uk/government/collections/english-housing-survey; Pew Research Center, 2025, as note 69. 99 per cent of mortgagor households in England have home internet; 80 per cent of US adults subscribe to home broadband.
[69] Ofcom, 2025, Online Nation 2025, as note 69; Ofcom, 2025, Adults' Media Use and Attitudes report 2025, https://www.ofcom.org.uk/siteassets/resources/documents/research-and-data/media-literacy-research/adults/adults-media-use-and-attitudes-2025/adults-media-use-and-attitudes-report-2025.pdf; Pew Research Center, 2025, as note 69. Online chosen ahead of offline because four in five UK adults aged 75 and over have home internet, and 78 per cent of US adults aged 65 and over own a smartphone and 70 per cent have home broadband. Fewer services because narrow internet use is more common among older users.
[70] Vocalink, 2019, 2019 marks the tipping point for digital challenger banks, https://www.vocalink.com/newsroom/2019/2019-marks-the-tipping-point-for-digital-challenger-banks/; Monzo, 2025, Annual Report 2025, https://monzo.com/annual-report/2025. Two accounts chosen ahead of one because 48 per cent of 25 to 34 year olds hold a secondary current account, and a third of Monzo's customers use it as their main bank. Monzo chosen as the second account because it is the largest app-based bank; Lloyds as the first because it is the largest high-street current-account provider, from the product corpus in section 3.1.
[71] As note 72. One account chosen for Margaret because the secondary-account evidence is specific to 25 to 34 year olds. One account chosen for the US households because no US evidence puts a second current account in the majority. Chase chosen because it is the largest US retail bank, from the product corpus in section 3.1.

| Model household | Model person(s) | Ages | Work | Home | Device ecosystem |
|---|---|---|---|---|---|
| US-F | Maria and David, Charlotte, North Carolina; girl 11, boy 8 | 37 and 39 | Both full-time, David fully remote | Mortgaged suburban house, two cars | Maria iPhone and Apple Watch; David Android and Fitbit |
| UK-O | Margaret, small-town Yorkshire | 75 | Retired, State Pension and small occupational pension | Owns outright, one car | Android phone and iPad |
| US-O | Carol, Tucson, Arizona | 75 | Retired, Social Security and savings | Owns mortgage-free, one car | iPhone and iPad |

### 2.2 Health and Care

Health and care status is a fixed parameter for every model household, informed by evidence on common health and care circumstances for people of the relevant age.

Margaret and Carol, for example, each have two managed long-term conditions because most people over 75 have a long-term illness and more than half of those over 65 have two or more.[72] Each has an adult daughter living elsewhere who has become involved after a fall or a health event, because most older people who receive help get it from family rather than paid carers, and that family member is most often a daughter.[73] That parameter is what brings a medical-alert pendant, location sharing with the daughter and patient portals into the older households' days.

## 3. Building the product service and system research set

### 3.1 Categories and construction of the research set

The research set starts from 39 product, service and system categories. Thirty-three are ordinary consumer categories: messaging, social media, streaming, banking, health, smart home, wearables and so on. Six categories involve organisations or systems that may receive, record or hold information about a model person or model household even though the model household does not directly use or choose them: credit-reference agencies, utilities and

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[72] NHS England (2025), Health Survey for England: limiting and non-limiting longstanding illness by age, 2012 and 2022, supplementary information, 6 June 2025, https://digital.nhs.uk/supplementary-information/2025/hse-longstanding-illness-including-limiting-and-non-limiting-in-2012-and-2022; Kingston et al., 2018, Projections of multi-morbidity in the older population in England to 2035, Age and Ageing 47(3), 374-380; Watson, K. B., Wiltz, J. L., Nhim, K., Kaufmann, R. B., Thomas, C. W. and Greenlund, K. J. (2025), Trends in multiple chronic conditions among US adults, by life stage, Behavioral Risk Factor Surveillance System, 2013-2023, Preventing Chronic Disease, 22, 240539, https://www.cdc.gov/pcd/issues/2025/24_0539.htm. Two conditions chosen because it is the largest group: 66 per cent of adults aged 75 and over in England have a longstanding illness, 54 per cent of people aged 65 and over have two or more conditions, and 79 per cent of US adults aged 65 and over have two or more chronic conditions.

[73] Maplethorpe, Darton and Wittenberg, 2015, Social care: need for and receipt of help, Health Survey for England 2014, chapter 5; Carers UK, 2024, Facts about carers, https://www.carersuk.org/media/ocxheq2c/facts-about-carers-dec-2024-final.pdf; Reckrey et al., 2025, Use of paid family care in the community, Journal of the American Medical Directors Association 26(9); Schulz and Eden (eds), 2016, Families Caring for an Aging America, National Academies Press; National Alliance for Caregiving and AARP, 2020, Caregiving in the U.S. 2020, https://www.caregiving.org/wp-content/uploads/2021/01/full-report-caregiving-in-the-united-states-01-21.pdf; ONS, 2023, Unpaid care, England and Wales: Census 2021; Pew Research Center, 2022, Financial Issues Top the List of Reasons U.S. Adults Live in Multigenerational Homes, https://www.pewresearch.org/social-trends/2022/03/24/financial-issues-top-the-list-of-reasons-u-s-adults-live-in-multigenerational-homes/. Family help chosen ahead of paid care because it is the larger group: among people aged 65 and over in England receiving help with daily activities, 82 per cent of men and 75 per cent of women had no formal support; 33 per cent of unpaid carers care for a parent living elsewhere and 8 per cent for a parent in their own home; in the US only 30 per cent of older adults needing help with self-care or mobility had any paid care, at least 17.7 million Americans are family caregivers of someone aged 65 or over, and half of caregivers of adults care for a parent or parent-in-law. A daughter chosen ahead of a son or spouse because she is the most-named helper: 38 per cent of women aged 65 and over receiving help with everyday tasks named a daughter, and for personal care a daughter and a spouse were named equally at 45 per cent each; women are 59 per cent of unpaid carers in England and Wales and 61 per cent of US family caregivers; a third of US adults in multigenerational households give caregiving as a major reason.

insurers, premises and vehicle surveillance, workplace identity systems, government records and loyalty schemes.

Products are found by a builder inside the study platform, one category at a time. The builder asks the model for the most-used products in each category under a union rule: a product qualifies if it ranks highly in the published usage charts, or if it is the most used within a particular group such as children or older people. The second leg exists because the top charts alone under-represent children and older people, whose most-used services rarely reach the overall top ten.[74] The six indirect or institution-mediated categories are ranked by how much of the population they cover rather than by app usage. Each request carries the six model household descriptions and the names already in the list, so the same product is not proposed twice.

Every candidate comes back with its category, its country, a one-sentence basis for inclusion naming the source and rank, and at least one citation with a link and a verbatim quote. A researcher reviews the candidates, removes any that should not go forward, and imports the rest for screening. The basis and sources are stored with the record and shown on the product's page.

### 3.2 Screening

Each candidate is then screened against the 11 criteria in Table 2, four of them mandatory. The model gathers evidence for each criterion by web search and scores it 0, 1 or 2: no credible evidence, partial evidence, clear evidence. A candidate passes with at least 1 on every mandatory criterion and at least 15 of the 22 available points, because 15 of 22 is the platform's Each candidate is then screened against the 11 criteria in Table 2, four of them mandatory. The model gathers evidence for each criterion by web search and scores it 0, 1 or 2: no credible evidence, partial evidence, clear evidence. A candidate passes with at least 1 on every mandatory criterion and at least 15 of the 22 available points, because 15 of 22 is the platform's standard pass mark of ten out of fourteen, 71 per cent, applied to eleven criteria.[75] A passing candidate enters the the product, service and system research set automatically.

## Table 2. Screening criteria

| Number | Criterion | Mandatory |
|---|---|---|
| 1 | Creates a documented data relationship with an identifiable organisation responsible for the relevant data practice | Yes |
| 2 | Forms part of an ordinary activity or surrounding system in the modelled day | Yes |
| 3 | Mediates or records at least one episode or ambient condition of the day | No |

[74] Ofcom, 2025, Online Nation 2025, as note 69; Ofcom, 2025, Adults' Media Use and Attitudes report 2025, as note 71; Ofcom, 2025, Children and Parents: Media Use and Attitudes, https://www.ofcom.org.uk/media-use-and-attitudes/media-habits-children/children-and-parents-media-use-and-attitudes-report-2025; Pew Research Center, 2025, Mobile Fact Sheet, as note 69; Age UK and Centre for Ageing Better, as note 54. The overall usage charts are Sensor Tower State of Mobile, Business of Apps, the Apple App Store and Google Play top charts and Similarweb; device categories use StatCounter, Kantar, Canalys, Counterpoint and Statista.
[75] The platform's screening standard is ten points of fourteen across seven criteria; applied to eleven criteria the same 71 per cent gives 15.7, rounded down to 15.

| Number | Criterion | Mandatory |
|---|---|---|
| 4 | Has a functional equivalent in the paired country | No |
| 5 | Governed by public documents that can be captured and archived | Yes |
| 6 | Supported by evidence as ordinary or prevalent for the relevant model household. | Yes |
| 7 | Fits the model household's life stage and household form | No |
| 8 | Adds a type of data collection, generation, inference or other data relationship not already represented in the research set | No |
| 9 | Carries a child-specific data pathway (family groups) | No |
| 10 | Involves sensitive or high-stakes data | No |
| 11 | May collect, generate, infer or record information about additional household members or bystanders | No |

Ambient-capture systems and standing-record organisations are admitted by a manual override, because a number-plate camera operator or a licensing authority is not a consumer product and fails the screen on its face, yet holds information about the model person or model household. The override records who admitted the product and why, and the product is marked as manually admitted rather than as having passed.

The builder proposed 556 candidates across 39 categories. A further 13 were added by hand when the review of the days found products missing: the connected cars, health apps, telecare services, school monitoring and the national ANPR service. Of the 569, 167 passed the screen, 38 were admitted by override, 11 of the hand-added products were not selected through the The builder proposed 556 candidates across 39 categories. A further 13 were added by hand when the review of the days found products missing: the connected cars, health apps, telecare services, school monitoring and the national ANPR service. Of the 569, 167 passed the screen, 38 were admitted by override, 11 of the hand-added products were not selected through the candidate-screening process and are identified separately from candidates that passed the screening test, 5 failed, 3 were left unfinished and 345 were not needed for any household’s day and were left unscreened. The 11 hand-added products were included where review of the modelled day identified a relevant product, service or system missing from the candidate set; their inclusion was recorded with the reason and supporting evidence and they are not represented as having passed the screening test. The resulting research set holds 217 entities.[76]

[76] Counts as at 16 September 2026 from the study database: 569 screening records, of which 479 carry the builder’s own provenance, 77 were builder candidates whose category was restored by hand, 11 were added in the completeness review and 2 carry no provenance.

### 3.3 The research-set matching matrix

Each of the 217 research-set items is assessed against each of the six households. The model is given the entity, the household's description, ages and profile, and the rest of the corpus, and asked one factual question: is this product, service or system relevant to this model household, either because the model household uses it or because it may collect, generate, infer, receive or hold information about the model person or model household? Where two products compete in the same category, the model picks the one the household's type is most likely to use, from the market split, and allows the rival only if a different member of the household would use it. That single-winner rule is switched off for the six indirect or institution-mediated categories because all three credit reference agencies hold a file on the same person at once. [77]

Each pair returns a matched flag, the relationship to the model household (mapped where applicable to primary use, data flow, standing record, ambient capture or none), a likelihood, a prevalence percentage where one exists, who in the household is involved, a reason and citations. The matched counts are 109 entities for UK-S, 104 for US-S, 126 for UK-F, 124 for US-F, 64 for UK-O and 62 for US-O. A matched entity becomes a candidate for that household's day.

## 4. Constructing the modelled days

### 4.1 Episodes and products

Each model household's modelled day is a 24-hour weekday divided into 13 episodes. The final episode is sleep. Sam and Bob wake at 06:45 because half of adults are up by 07:00 on a weekday and those travelling to work rise earlier.[78]The families wake at 06:30 because the school day starts between 08:45 and 09:00 in England and at about 08:15 in the US, and washing, dressing, breakfast and the school run take place before it.[79] Margaret and Carol wake at 07:00 because half of adults are up by then.[80]

The model working-age households sleep from 23:15, the model families from 23:00 and the model older households from 22:00, because about seven in ten, six in ten and between a quarter and a half of adults respectively are asleep by those times.[81] Between 9 and 15 products, services and system are in use in each model household overnight: the phone and watch recording sleep and heart rate, the health app the watch feeds, the smart speaker, the

[78] ONS, 2023, Time use in the UK: March 2023, Figure 3, percentage of adults doing specified activities at specified times on a weekday, https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/timeuseintheuk/march2023 (data file https://www.ons.gov.uk/visualisations/dvc2631/fig3/datadownload.xlsx); US Bureau of Labor Statistics, 2025, American Time Use Survey 2024, Table A-3A, percent of the population engaging in selected activities by time of day, https://www.bls.gov/tus/tables/a3-2024.htm. On a UK weekday 71 per cent of adults are still asleep at 06:30, 53 per cent at 07:00 and 41 per cent at 07:30; in the US 67 per cent are asleep at 06:00, 43 per cent at 07:00 and 25 per cent at 08:00. 06:45 chosen ahead of 07:00 because those up first are the ones travelling to work: the share of UK adults travelling rises from 2.6 per cent at 06:30 to 10 per cent at 08:00, and the share in paid work jumps from 16 per cent at 08:00 to 34 per cent at 09:00.
[79] Department for Education guidance on the school day, under which most primary schools in England start between 08:45 and 09:00; National Center for Education Statistics, 2022, National Teacher and Principal Survey 2020-21: average K-12 school start time by school type, https://nces.ed.gov/surveys/ntps/estable/table/ntps/ntps2021_fl05_s12n, average start 08:16 for elementary and 08:11 for middle schools; ONS, 2023, as note 79, UK adults average 53 minutes washing and dressing and 46 minutes preparing food and drink a day. 06:30 chosen ahead of 06:45 because the school run adds a fixed departure the solo households do not have.
[80] ONS, 2023, and US Bureau of Labor Statistics, 2025, as note 79. 07:00 chosen because it is the median waking time: 47 per cent of UK adults and 57 per cent of US adults are up by 07:00 on a weekday.
[81] ONS, 2023, and US Bureau of Labor Statistics, 2025, as note 79. On a UK weekday 44 per cent of adults are asleep at 22:30, 65 per cent at 23:00 and 78 per cent at 23:30; in the US 47 per cent are asleep at 22:00, 72 per cent at 23:00 and 86 per cent at midnight. 23:15 chosen for the working-age households because about seven in ten adults are asleep by then; 23:00 for the families because six in ten are; 22:00 for the older households because between a quarter and a half of adults are already asleep and the older households keep the earlier end of the range.

video doorbell, the smart meter and its communications network, the broadband connection, the overnight cloud backup and, in themodel older households, the personal alarm pendant.

Each model episode has a start and end time, a title, a description of what happens and the kinds of services involved, a justification and sources drawn from a registry of 110 references.[82] Each modelled day includes at least one money or administrative moment, such as a credit-score check, an insurance renewal, a contract switch, a mortgage payment or a buy-now-pay-later checkout, because those are the moments that trigger reporting to lenders, insurers and credit reference agencies in the background.[83] Where such an activity is plausible within the model but does not occur every day, it is treated as a periodic overlay and excluded from the conservative daily headline floor.

For each episode, the model identifies which organisations or systems may collect, generate or infer information about the model person or model household, receive that information through a data flow, create an ambient capture or hold an associated standing record without being directly used by the model household.

For each model episode the model then identifies which matched products and services are used by the model household in that episode.. It receives the model household description, the model episode and the candidates tagged by category, and returns the products used with a reason and citations, plus the alternatives it rejected and which product beat them. Each model person's phone platform is decided first, from market data, and applied to every default such as browser, weather, maps and mail. Every product doing a different job in the episode is picked; several apps at once is normal and is not a tie-break. A single-winner rule applies only between candidates doing the same job for the same model person, decided on platform and market-share evidence, and never to the six indirect or institution-mediated categories. An empty list is a valid answer.

Every episode of every model household is then reviewed by hand. A product is removed only on one of four grounds: it belongs to the wrong country, its own reasoning argues it is not used, it duplicates another entry for the same product from the same company, or it contradicts the fixed profile, for example the wrong phone platform. Same-category news, social and website products are kept together even where the model's reasoning claims a single winner, because people read several in one sitting.[84] Removed products go into a hidden list with the reason and the product kept instead. Nothing is deleted.

### 4.2 Data flows and standing records

For each episode, the model identifies which organisations or systems may collect, generate

[82] The registry holds 110 references and is stored in the study database; every episode's justification cites into it.
[83] Consumer Financial Protection Bureau, 2012, Key Dimensions and Processes in the U.S. Credit Reporting System, Key Learnings, https://files.consumerfinance.gov/f/201212_cfpb_credit-reporting-white-paper.pdf: the nationwide credit reporting agencies "receive information from approximately 10,000 furnishers of data. On a monthly basis, these furnishers provide information on over 1.3 billion consumer credit accounts or other 'trade lines'"; a consumer's file must list every entity that accessed it, and inquiries arise from applications for credit and from reviews by lenders and insurers. Consumer Financial Protection Bureau, 2025, What is a credit inquiry?, https://www.consumerfinance.gov/ask-cfpb/what-is-a-credit-inquiry-en-1317/: "An inquiry is a request to look at your credit report for the purpose of determining your eligibility for credit, employment, housing, insurance, or other purpose." Financial Conduct Authority, 2023, Credit Information Market Study: final report, MS19/1.3, paragraph 4.2, https://www.fca.org.uk/publication/market-studies/ms-19-1-3.pdf: the Principles of Reciprocity are "the framework by which lenders and other data contributors share credit information with CRAs", and the report's remedies make sharing by regulated lenders mandatory. A credit-score check, an insurance quote, a new contract, a mortgage payment and a buy-now-pay-later checkout are each either a monthly furnishing event or an inquiry under these rules.
[84] Ofcom, 2025, Online Nation 2025, as note 69: UK adults use several news and social services in one session; the study's own review of every day found the model's single-winner reasoning removed real simultaneous use.

or infer information about the model person or model household, receive that information through a data flow, create an ambient capture or hold an associated standing record without being directly used by the model household. The candidates are the household's matched entities in the the six indirect or institution-mediated categories. The model is also told which products are in use, so it can name the route.

The analysis distinguishes ambient capture from mediated data flows. Ambient capture covers cameras, number-plate readers and similar systems encountered in the modelled day; mediated data flows occur through a named organisation or service associated with a primary use..[85] Each flow records the route, the concrete mechanism, whether the organisation holds a file or merely receives data, a reason and citations. A flow can only be asserted where the episode triggers it.

Standing records are identified once for each model household. The model is asked which candidate bodies hold an ongoing record about a model person independently of activity in the modelled day, reasoning from the profile: no car means no vehicle-keeper record, no job means no live payroll record. Each entry names the authority, its legal or contractual basis, how the record is kept current or matched against other data, a reason and citations. The six households have 42 standing records between them.

### 5. Gathering and analysing the documents

For every research-set item the model is first asked to find, but not analyse, the organisation's official privacy documents: privacy policy, terms, cookie policy, data-processing agreement, transparency report and security pages. It is told to prefer the organisation's own website. The links are stored against the entity.

Each finding carries a title, an explanation, the source document and a verbatim quote. Where a document cannot be read, the model records it. Press coverage and regulator action are recorded as background only.

Of the 217 research-set items, 185 have documents and a completed analysis. The gathered documents number 2,340 across the 217 entities, of which 1,821 belong to the 143 organisations that appear in the six days.

### 6. Producing the figures

Each household's headline figures come from its day and the analyses of the products in it. The count of distinct organisations is 68 for UK-S, 62 for US-S, 88 for UK-F, 81 for US-F, 49 for UK-O and 44 for US-O. Every figure carries an evidence list

[85] Home Office, 2026, National ANPR standards for policing and law enforcement, version 3.5, for ambient capture; the mediated route is named in each flow's record. The 75 flows across the six households divide into 23 ambient and 52 mediated.

naming each organisation counted, with a quote and a source link. A few figures, such as camera captures and heart-rate readings, are modelled by hand and labelled as such.

The six modelled  are then pooled into a single set of 143 organisations, 1,280 primary uses and 75 data flows,. Standing records are not in that count.

For the pooled figures, each organisation's privacy documents are searched for wording that shows a given practice, such as using data for marketing, combining it across sources or keeping it indefinitely. The search patterns are frozen so that every regeneration is comparable. A phrase counts only if it is not negated: a phrase is treated as negated if a word such as "not", "never" or "no" appears in the 90 characters before it, so "we do not sell your data" does not count as selling data.

Three further checks stop the search counting things it should not. A sentence in which the analyst wrote that no statement could be found is not counted as evidence of the practice. A clause that describes a protection rather than a use, such as an anti-profiling commitment or a privacy feature switched on by default, is not counted as data use. Sharing with a processor acting only on the organisation's instructions, the transfer of assets in a merger or bankruptcy, data the organisation received rather than sent, and sponsored arrangements are counted in the overall sharing total but kept out of the commercial tier.

Table 4 gives the pooled results. A sale-class finding is one where the organisation's own documents describe selling personal data, or passing it to advertisers or other third parties in return for money or other value, which several United States state privacy laws treat as a sale even where the word sale is not used.[86]

### Table 4. Practices permitted by documents across 143 organisations

| Practice permitted by privacy documents | Organisations | Per cent |
|---|---|---|
| Any documented onward sharing | 143 | 100 |
| Uses data for marketing | 118 | 83 |
| Combines data across sources | 114 | 80 |
| Inference or profiling | 109 | 76 |
| Commercial-partner sharing | 102 | 71 |
| Indefinite retention | 95 | 66 |
| Handles special-category data | 55 | 38 |

[86] California Consumer Privacy Act, Civil Code 1798.140(ad), and the Colorado, Connecticut and Virginia consumer privacy acts, each of which defines sale to include disclosure for monetary or other valuable consideration.

| Practice permitted by privacy documents | Organisations | Per cent |
|---|---|---|
| Data-sharing defaults switched on | 52 | 36 |
| Sale-class findings | 48 | 34 |
| AI or machine-learning training on data associated with the model person or model household (floor) | 35 | 24 |
| Keeps data after deletion | 22 | 15 |
| Shares with data brokers | 20 | 14 |

Each modelled occasion on which a model household uses a product or service for the immediate purpose for which it appears in the modelled day counts as one primary use. Across the six days there are 1,280 primary uses. For each primary use, the study counts how many of five practices the organisation's documents describe beyond the study-defined primary use/function to provide the service: using the data for marketing, combining it with data from other sources, drawing inferences about the person, sharing it with commercial partners, and keeping it indefinitely. The Across the 1,280 primary uses, these five documented practices produce 4,283 additional documented uses, an average of 3.4 per primary use. In 214 primary uses, the organisation's documents describe all five practices. Seventeen organisations have documents describing all five practices;

## 7. Archive and Reading Time

Every document in every relevant organisation's list is archived, so that each quote in the study can be checked against a dated local copy rather than a live page that may since have changed.[87]

Pages that come back blocked, missing or with fewer than 150 words are rendered again in a full browser, so that script-built pages are captured as a reader sees them. PDFs are converted to text. For Apple's multilingual licence PDFs the English count stops at the first heading in another language, giving 21,203 words for iOS 26 and 20,871 for watchOS 26.

The reading-time exercise asks the time required to read the documents included under the study's reading-time rules for each model household. he roster includes the organisations associated with the model household's modelled day, relevant data flows and standing records. The same rules apply to every model household. Only consumer-facing documents are kept: the terms or licence, privacy policy, cookie policy and product-specific notices. Business, developer and partner terms, data-processing agreements, transparency reports,

[87] The archive is dated 1 to 2 September 2026 and holds the raw or rendered page, the PDF where there is one, the extracted text, and a record of title, type, address, final address, status, fetch time, a SHA-256 hash, how it was rendered and the word, English-word and character counts.

white papers, security pages, index pages, support articles and the news or regulator pages stored as finding sources are dropped. UK model households read the UK, EEA or global version and US households the US or global version. A document shared by several products is counted once. Documents outside the word window are set aside: below 150 words a page is a shell rather than a document, and above 40,000 words it is a bundle of several documents.[88] Each document is sorted into three tiers: “services the model person or model household is modelled as using, work tools the employer signed up to, and records held about the model person or model household without direct sign-up. Words are divided by a reading speed of 238 words per minute because that is the measured average for adults reading non-fiction silently, with 250 words per minute shown alongside because that is the rate the established study of privacy-policy reading used.[89]

### Table 5. Reading time at 238 words per minute

| Model Household | Documents | Words | Hours |
|---|---|---|---|
| UK-S | 224 | 1,055,153 | 73.9 |
| US-S | 188 | 848,062 | 59.4 |
| UK-F | 257 | 1,184,835 | 83 |
| US-F | 233 | 1,118,224 | 78.3 |
| UK-O | 156 | 645,118 | 45.2 |
| US-O | 137 | 530,031 | 37.1 |

Two pages are excluded as bundles above the word window: the Plaid legal hub, which puts every Plaid document on one page at 141,904 words, and IRS Internal Revenue Manual section 10.5.1 at 70,172 words. The hours are floors: a secondary page that comes back below the 150-word minimum, such as a cookie notice, is left out of the count.

## 8. Design choices

Model households as the principal unit of analysis. The point is accumulation. Documented collection, generation, inference and other data relationships accumulate across members of a model household and across the products, services and systems associated with the

[88] The lower bound is the same threshold that marks a failed fetch; the upper bound is longer than any single consumer contract in the archive and removes legal hubs and internal manuals that put many documents on one page.
[89] Brysbaert, 2019, How many words do we read per minute? A review and meta-analysis of reading rate, Journal of Memory and Language 109; McDonald and Cranor, 2008, The cost of reading privacy policies, I/S: A Journal of Law and Policy for the Information Society 4(3), 543-568. 238 words per minute chosen because it is the meta-analysis figure for adults silently reading non-fiction; 250 shown alongside because it is the rate McDonald and Cranor used.

modelled day. Model profiles grounded in evidence. Both families deliberately have one iPhone parent and one Android parent so both ecosystems show up.

A product, service and system research set built by rule. The union rule, the published charts and the screening criteria make the list a reproducible sample, and the builder records the basis and sources for every candidate so the inclusion of any product can be audited. A hand-picked list could not be defended against a stated inclusion basis. The four mandatory criteria draw the boundary: there must be a documented data relationship with an identifiable organisation or system, it must be part of home life, its documents must be obtainable and archivable, and the activity must be ordinary for the model household. Without public documents, the relevant documented data practice cannot be coded; without evidence that the activity is ordinary or prevalent, it is not included as part of the modelled ordinary day.

**Indirect and institution-mediated organisations and systems treated differently**. The same list of six categories drives both the data-flow candidate pool and the tie-break exemption, so one definition governs both.

**The ordinary-day test**. Every product or service included as a primary use in a modelled day has to be the most likely choice for that household, backed by ownership or usage data. Sam drives a Ford Fiesta with FordPass, not a Tesla.

**Published documents as primary evidence**. Organisation-level findings are based principally on organisations' own published privacy policies, terms and supporting documents, with technical, regulatory, academic and other evidence used in the roles described in the study's evidence hierarchyA reason and a source for everything. Every product, flow, record and evidence row carries a written rationale and a URL so anyone can check it.

**Standing records kept separate**. The pooled universe matches the per-household counts, which cover products and flows only because they are ongoing records held independently of activity in the modelled day. Additional documented uses summed over primary uses.. The 4,283 additional uses permitted by organisations' documents are calculated across the 1,280 primary uses are a straight sum over uses because the study measures what a model household is exposed to across its day.

Each primary use is a separate modelled occasion to which the organisation's documented practices are applied for this calculation, so an additional documented use is counted for each applicable documented practice associated with each primary use every time the product is used. Counting each organisation once would measure the corpus, not the day.

[88] The lower bound is the same threshold that marks a failed fetch; the upper bound is longer than any single consumer contract in the archive and removes legal hubs and internal manuals that put many documents on one page.
[89] Brysbaert, 2019, How many words do we read per minute? A review and meta-analysis of reading rate, Journal of Memory and Language 109; McDonald and Cranor, 2008, The cost of reading privacy policies, I/S: A Journal of Law and Policy for the Information Society 4(3), 543-568. 238 words per minute chosen because it is the meta-analysis figure for adults silently reading non-fiction; 250 shown alongside because it is the rate McDonald and Cranor used.

All sharing counted, in tiers. Sharing with a processor still matters to the household, so every sharing clause counts, and tiering lets commercial-partner sharing  be read separately.

Classifier guards. The hedge guard exists because analyst notes saying no statement was found otherwise register as positives. The protective-context guards exist because privacy features described as on by default otherwise register as data use.[90]

English only. E.g. Apple's licence agreements carry every language in one file. Counting all of them would multiply the reading time several times over.[91]

## 9. Quality controls

Citation checks. Every model-produced citation is checked on the server. The URL is requested to confirm it resolves, then the page body is fetched and searched for the quote after stripping HTML and normalising whitespace, case and typographic punctuation. Each citation carries a status of ok, url_failed, quote_not_found, unverified or error. A timeout or a site that blocks bots gives unverified rather than a false fail.

Challenges. A researcher can challenge any model result with an argument and links. The model reconsiders from first principles, reads the links and weighs them as evidence rather than instructions.

Reproducing the published rows. The pooled counts must reproduce the per-household figures exactly, for example 42 of 68 retention findings for UK-US, before the classification pattern is frozen.

Reading the weakest case. Any figure at or near 100 per cent is checked by reading its weakest case. Every AI-training positive is read individually, which is why that figure is reported as a floor. Every keyword count is checked for polarity, because a raw count of "train" matches without reading the negations overstates the result by a wide margin.

Every evidence row has a URL. Where an organisation has no direct URL for a finding, the row falls back to its main privacy document, and any organisation with no documents at all is flagged. After each regeneration the data is checked against the new figures.

Hand review of every modelled day. Every episode of every household is reviewed for missing touchpoints, and the product, service and system research set is supplemented where the review finds a gap.

Archive quality. A fetch below the word threshold or with a status of 400, 403, 404 or 0 counts as failed and is rendered again in Chrome. A PDF whose text file holds raw bytes produces a nonsense count and is downloaded again and converted.

[90] The hedge guard was added after reading every AI-training match: four analyses, Kindle, Chase, Life360 and the school CCTV provider, had been counted as positives on sentences recording that no statement was found, and removing them took the figure from 39 to 35. The protective-context guards were added after reading the inference and defaults matches, where anti-profiling commitments and privacy features switched on by default had registered as data use.
[91] Apple, 2025, Software licence agreements for iOS 26 and watchOS 26, https://www.apple.com/legal/sla/. Each licence PDF carries every language in one file; the English text runs to 21,203 words for iOS 26 and 20,871 for watchOS 26, and counting all languages would multiply the reading time several times over.

### Table 6. Pass and fail criteria

**Citation checks**. Every model-produced citation is checked on the server. The URL is requested to confirm it resolves, then the page body is fetched and searched for the quote after stripping HTML and normalising whitespace, case and typographic punctuation. Each citation carries a status of ok, url_failed, quote_not_found, unverified or error. A timeout or a site that blocks bots gives unverified rather than a false fail.

**Challenges**. A researcher can challenge any model result with an argument and links. The model reconsiders from first principles, reads the links and weighs them as evidence rather than instructions.

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**Every evidence row has a URL**. Where an organisation has no direct URL for a finding, the row falls back to its main privacy document, and any organisation with no documents at all is flagged. After each regeneration the data is checked against the new figures.

**Hand review of every modelled day**. Every episode of every household is reviewed for missing touchpoints, and the product, service and system research set is supplemented where the review finds a gap.

**Archive quality**. A fetch below the word threshold or with a status of 400, 403, 404 or 0 counts as failed and is rendered again in Chrome. A PDF whose text file holds raw bytes produces a nonsense count and is downloaded again and converted.

| Check | Pass | Fail | On failure |
|---|---|---|---|
| Screening | Score of 1 or more on every mandatory criterion and at least 15 of 22 points | Otherwise | Excluded, or admitted by override with a reason |
| Citation | URL resolves and quote found | url_failed or quote_not_found | Status shown on the citation |
| Retention count | Matches the published figure | Differs | Rework until it matches |
| Keyword positive | Confirmed by reading | Negated or hedged | Removed, guard added |

| Check | Pass | Fail | On failure |
|---|---|---|---|
| Evidence row | Has a URL | No URL | Fall back to main document, flag if none |
| Archive fetch | Status 200 and above word threshold | Otherwise | Render in Chrome, patch by hand |
| PDF archive | Text extracted | Raw bytes | Download again, convert |

## 10. Repeating the study

All project data sits in a single database. Every step that uses a language model runs on the same model, Claude Opus 4.8, at medium reasoning effort with live web search switched on. Every prompt requires British English and an answer in a fixed data format.

### Table 7. Fixed settings

| Setting | Value |
|---|---|
| Language model, all steps | Claude Opus 4.8 |
| Reasoning effort | Medium |
| Web search | On, approximate location, high search context |
| Response language | British English, JSON only |
| Products per category in discovery | Up to 15 |
| Screening pass | Each criterion scored 0, 1 or 2; pass at 15 of 22 points with every mandatory criterion at 1 or more |
| Classifier negation window | 90 characters |
| Minimum words for a valid fetch | 150 |
| Maximum words for a countable document | 40,000 |
| Reading speed | 238 words per minute, 250 alongside |
| Archive fetch workers | 8 |
| Parallel Chrome renders | 4 |
| Citation check timeout and body limit | 8 seconds, 2 MB |
| Archive date | 1 to 2 September 2026 |

**Order**. Define the model households. Discover and screen candidate products, services and systems. Match the research set to the model households. Construct the modelled days and identify primary uses. Identify data flows, ambient capture and standing records. Gather and analyse documents. Produce the model-household measures and pooled analysis. Archive the documents and calculate reading time.

**Prompts.** Each model step uses a fixed system prompt whose rules are described in sections 3 to 7. One project-level override was in force: the evidence-gathering prompt used in screening carried a scope note stating that entertainment, streaming, gaming, social media and adult-content services used privately at home count as ordinary model household consumption, and that credit reference and credit-scoring agencies are in scope as holders of the household's data. No other prompt was altered.

**Software**. Python 3.11.4; Google Chrome 153.0.8010.37 for page rendering; pdftotext 25.02.0 for PDF text; PostgreSQL 14.17; Claude Opus 4.8 called through the Anthropic Python SDK 0.116.0.

**What will not repeat exactly**. The model steps use live web search and a reasoning model with no fixed seed. A rerun reproduces the rules and settings but not the exact outputs. The archive fixes the document text as at 1 to 2 September 2026, so reading time and classification can be rerun on identical inputs.

## 11. Limitations

**The product, service and system research set is model-found and model-screened**. The criteria are fixed and the pass rule is mechanical, but the evidence gathered and the scores given depend on a language model with live search. A rerun could produce a different list.

**The builder proposes more candidates than any model household uses or encounters in its modelled day**. Candidates not needed for a day were not screened, so the 217 research-set items are the products, services and systems required by the modelled days, not every product that would have passed.

**The modelled days are evidence-led scenarios, not observations or diaries of real people**. The 13 episodes per model household rest on time-use survey averages and cited justifications, not on diaries from real households.

**Product selection** is a likelihood judgement. Each product or service is selected as a likely choice for the relevant model household, not an observed choice of any real household. The rejected alternatives are recorded, but a different judgement would change the universe.

**Citations** are only as good as their status. A citation marked unverified has neither passed nor failed.

The keyword classifier has a bounded negation window and hand-added guards. Guards exist only for the errors found by reading, so unread errors of the same kind may remain. The AI-training figure of 35 is a floor, and dashes in the grids are floors.

**The additional-documented-use calculation** is a modelled calculation. Summing additional documented uses across primary uses does not adjust for overlap between repeated primary uses involving the same organisation does not allow for overlap between uses of the same organisation.

The UK family model household is slightly larger than the most common UK family. Two children were chosen over the modal one child to cover both child data pathways, so the UK family figures sit a little above what a one-child household would show. The US family is at the most common size for parents of its age.

**Reading time measures** reading, not understanding. The hours are floors, and the two excluded bundles remove real binding text from the totals.

**The archive is dated**. Documents change. A rerun against live pages later will give different word counts and may give different classifications.

**The pooled figures mix two countries**. UK and US differences are not visible in them and must be read from the per-household figures.

References to information that 'may', 'could' or 'can' be collected, generated, inferred or processed describe documented capabilities, permissions or supported modelling assumptions. They do not establish that every such action occurred in a modelled interaction, occurs for every real user or occurs every day. The findings depend on product choice, configuration, settings and opt-outs. Where an optional feature is assumed to be enabled in a modelled scenario, that assumption does not establish that it is enabled for every real user or by default. Numerical results are documented minimums, modelled estimates or reasonable ranges. Background activity for which no reliable daily count could be established is excluded, and countable observations measure frequency rather than severity.

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