THE INFLUENCE OF AI ON CONSUMER BEHAVIOUR

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TABLE OF CONTENTS

1. Overview ... 3
2. Exploring consumer trends and developing a digital intensity index ... 4
2.1 Summary of the approach ... 4
2.2 Data summary ... 5
2.3 Questions analysed ... 7
2.4 Index construction ... 9
2.5 Econometric approach ... 10
3. Exploring the link between digital technology intensity and AI ... 17
3.1 Questionnaire design ... 17
3.2 Digital accelerators ... 18
3.3 Analysis of survey responses ... 19
3.4 Income bands ... 20
4. Estimating income and consumption levels of digital cohorts ... 21
4.1 Calculating net income ... 21
4.2 Calculating total consumption by age and income threshold ... 23
4.3 Data summary ... 25

1. OVERVIEW

Oxford Economics designed a research programme to explore how AI technologies can be expected to influence and shape the consumer landscape. Although the ultimate objective was to draw out forward looking perspectives through analysis of how digital technology has shaped consumer preferences and habits historically.

We analysed historical **consumer trends** data and used this to develop a **digital intensity index**. This analysis was conducted using YouGov data for UK consumers, which enabled an understanding of how technology has influenced consumer journeys and product selection. The development of a digital intensity index for UK consumers allowed the definition of digital accelerators and anchors and the identification of the demographic characteristics of each group. The highest index scores indicated consumers that used technology frequently and had relatively more positive attitudes to technology; these consumers were defined as digital accelerators. Digital anchors made limited use of technology and had relatively less positive attitudes about it, thereby achieving the lowest index scores. The remaining consumers achieved scores in the middle of the distribution and were defined as digital agnostics. This workstream is covered in chapter 2.

This was followed up by a new survey of UK, US, Australian and German consumers to explore their **attitudes towards using AI technologies** when learning about, purchasing, and using products or services. The survey allowed us to develop contemporaneous insights for a wider pool of countries and to test the hypothesis that attitudes to AI mirror patterns apparent in previous waves of digital technology. For example, we tested whether consumer cohorts that were more likely to be digital accelerators demonstrated positive attitudes towards using AI technologies. This workstream is covered in chapter 3.

In the final workstream, we bult **consumer spending forecasts** out to 2030 for digital accelerators, digital anchors, and digital agnostics. We modelled the purchasing and spending power of these groups accounting for their demographic characteristics and income potential over time. This workstream is covered in chapter 4.

2. EXPLORING CONSUMER TRENDS AND DEVELOPING A DIGITAL INTENSITY INDEX

Our analysis leveraged proprietary data to examine the evolution of consumer trends since 2019 and to create a digital technology index for different consumer profiles.

We worked with YouGov's Profiles database for the UK to develop two indices: the **digital trends** index and the **digital intensity** index. The digital trends index was designed to evaluate changes in digital behaviours over time, offering insights into evolving consumer trends. The digital intensity index, on the other hand, was designed to assess the differences across demographic and socioeconomic groups, identifying cohorts that are more digitally engaged, referred to as "digital accelerators" and those with lower levels of digital engagement, referred to as "digital anchors".

2.1 SUMMARY OF THE APPROACH

YouGov Profiles[1] is a consumer data platform that provides access to over 2 million data variables sourced from a global panel of more than 27 million members. This platform gathers and refreshes data on a weekly basis, covering key areas such as demographics, psychographics, attitudes, and behaviours, offering access to the latest consumer insights.

From this database, we identified a set of questions that distinguish a consumer's attitudes and adoption of digital technologies. These questions were grouped into three main pillars that were analysed separately: device and app usage, online shopping behaviour, and attitudes toward technology and the internet. Subsequently, the responses to the key questions were averaged to form a digital trends and digital intensity index.

To assess digital trends and digital intensity, two versions of the index were developed using the same set of key questions. The digital trends index tracks changes in digital behaviours over time. It is constructed using data published through an online tool of YouGov, which includes a historical time series reflecting the national average, as well as averages broken down by specific socioeconomic and demographic characteristics.

The digital intensity index evaluates differences in digital engagement across demographic and socioeconomic groups. It is constructed using respondent-level data obtained from the YouGov database, covering the period from Q4 2023 to Q3 2024. Econometric analysis was used to identify key differences in digital intensity index scores based on demographic characteristics, while controlling for other factors.

[1] YouGov, "YouGov Profiles", accessed December 2024

Respondents that achieved the top and bottom 25% of digital intensity scores were categorized as digital accelerators and digital anchors, respectively. Digital accelerators are those who are highly digitally engaged, while digital anchors are the least digitally engaged.

Furthermore, using the same modelling approach applied to digital accelerators and anchors, we assessed the attitudes of individuals who identified as early adopters of technology. Respondents who answered "yes" to questions like "I'm always keen to use new technology products as soon as they enter the market" were examined to understand the characteristics of these early adopters. We modelled the probability of being an early adopter and identified the key demographic factors that define these individuals.

2.2 DATA SUMMARY

Data was obtained from YouGov's Profiles database for the UK. This database summarises information collected from consumers in YouGov's nationally representative panel, which is available on a quarterly basis.

In addition, the database includes socioeconomic and demographic characteristics that allow for the analysis of the variation within each group. The socioeconomic and demographic characteristics analysed include age, income, education qualification, gender, location, and family. The final selection of characteristics was based on those that were found to indicate significantly different digital index scores or early adopters. The age groups 55-64 and 65+ were only available in the latest quarters, while 55+ was available for the whole period assessed.

Fig. 1. Demographic and socioeconomic characteristics

Category	Group
Age	18-24
	25-34
	35-44
	45-54
	55-64
	65+
Gender	Male
	Female
Income	under £14,999
	£15,000 to £29,999
	£30,000 to £44,999
	£45,000 to £69,999
	£70,000 to £99,999
	£100,000 and over
Parent[2]	Younger family (At least one child < 18 years)
	Older family (At least one child > 18 years)
	No children (Not a parent/guardian)
Education qualification	No formal qualifications
	Other (GCSE or equivalent)
	University
Location	Urban
	Town and fringe
	Rural
Employment status	Working full/part time
	Not working
	Retired

As the analysis assesses digital trends and digital intensity, two versions of the index have been developed requiring two distinct datasets:

- **Trends data:** The trends data is published via an online data tool and includes a historical time series of the national average and average by single socioeconomic and demographic characteristic. Only responses dating from 2019 Q1 to 2024 Q3 have been included in our analysis due to missing data for several questions prior to 2019. In addition, results from "Daily activities done on your mobile/cell phone" (Fig. 2) and "Purchase journey" (Fig. 3) have been estimated for the missing quarters using historical trends to fill in the gaps in the data.

[2] The labelling for the parent categorisation has been changed in the following tables to simplify the text. The label as published in the YouGov database can be found in brackets.

This dataset underpins the digital trends analysis, which explores changes in digital trends over time.

- **Individual data:** To analyse digital intensity, respondent-level data was obtained from the YouGov database, covering Q4 2023 to Q3 2024. Each row initially represented an individual, including responses to relevant survey questions alongside demographic and socioeconomic characteristics—age, income, gender, education, employment status, parental status, and location. Due to missing data in some cases, responses were grouped by shared characteristics, creating a new dataset where each row represents the average survey responses of similar individuals.

From YouGov's Profiles database, a set of variables was identified that distinguish a consumer's attitudes and adoption to develop a digital intensity index. A detailed list of the questions used in the index is included in the next section.

2.3 QUESTIONS ANALYSED

2.3.1 Questions used to construct the digital trends and digital intensity index

To construct the digital trends and digital intensity indices, made up of three sub-indices, key questions from the YouGov Profiles database were identified for each sub-index. The three sub-indices are device and app usage, online shopping behaviour, and attitudes towards technology and the internet.

The device and app usage sub-index included questions on the usage of digital devices and apps by consumers in their daily lives including advanced technologies like smart home devices and adoption of new technologies. The online shopping behaviour sub-index focused on consumer habits related to e-commerce and purchasing decisions online. The attitudes towards technology and internet sub-index included questions on consumer's beliefs and attitudes toward digital technologies, online retail and the internet in general, which provide deeper understanding of their engagements with digital ecosystems.

A list of the key questions is provided in Fig. 2, Fig. 3 and Fig. 4, overleaf.

Fig. 2. Questions included in the device & app usage category

Category	Question	Answer
Daily activities done on your mobile/cell phone	Which, if any, of the following activities do you regularly use your mobile/cell phone for? By regularly we mean at least once a day. Please select all that apply.	Activities included are: Finance and banking; Health tracking; Online shopping; Paying bills.
Smart home appliances ownership	Thinking about smart home appliances, which, if any, of the following do you own/have in your home? Please select all that apply.	Smart appliances included are: Smart home security cameras, sensors, or alarms; Smart voice-controlled speaker; Smart light system; Smart home thermostat; Smart meter; Smart microwave oven; Smart fridge/freezer; Smart hob; Smart vacuum cleaner; Smart scale or other smart health tracking device; Smart kettle; Smart washing machine/ tumble dryer; Smart dishwasher; Other.
App used for online banking on smartphone	Do you use an app to perform online banking on your smartphone? And if so, who has provided this app? By online banking, we mean accessing your bank account with your smartphone, checking your balance or transferring money from your account (ACH/wire transfer)?	"Yes, I use an app provided by my bank to perform online banking"
		"Yes, I use an app to perform online banking, but not provided by my (main) bank"
		"No, I don't use any app for online banking"
		"Not applicable - I don't use my smartphone for online banking"
		"Not applicable - I don't have a smartphone"

Fig. 3. Questions included in the online shopping behaviour category

Category	Question	Answer
Online shopping by category[3]	Please indicate whether you tend to make most of your purchases online (i.e. via the internet) or offline (i.e. in store, over the phone etc). If you rarely or never buy this type of product, please choose "Not applicable". The products included are: clothes and shoes; electronic devices; financial products; holiday and travel; music, videos and books.	"All online"
		"Mostly online"
		"Evenly split"
		"Mostly offline"
		"All offline"
Purchase Journey	Which of these actions, if any, did you do at any point in your decision process of where or what to buy? Please select all that apply.	"Browse online to see what is available"
		"Order something online and collect it from store or other physical location, i.e. 'click and collect'"
		"Use an app to purchase in-store; Use an app to purchase online"
		"Browse in stores to see what was available"

[3] Not applicable - I do not purchase these types of products and don't know were excluded, so the results only show those who purchased the product.

Fig. 4. Questions included in the attitudes category.[4]

Category	Question
Statements agreed with about technology and devices	"I think in the future, artificial intelligence will help humans in most of their daily tasks."
	"Technology changes my life for the better."
Statements agreed with about internet activities and behaviours	"I find the pace of new technology a bit overwhelming."
Statements agreed with about retail	"Online shopping makes my life easier."
Statements agreed with about advertising	"I'm more likely to engage with adverts that are tailored to me."

2.3.2 Questions used in the early adopters' analysis.

From the YouGov database, we have also assessed those who indicated that they were early adopters of technology by answering the yes to the following questions:

- I'm actively on the lookout to buy new technology devices and services.
- I'm always keen to use new technology products as soon as they enter the market.

2.4 INDEX CONSTRUCTION

To build the indices, the responses to the key questions outlined above were averaged. When a question had multiple sub-responses, these sub-responses were first averaged before averaging across questions. For example, the average proportion for each of the four activities listed in the question about daily activities on a mobile phone was first calculated. This average was then combined with the averages from the other two questions in the device & app usage sub-index, which include smart home appliances ownership and apps used for online banking on smartphones. The averages were then re-scaled to form the index.

As the analysis assesses the digital trend and intensity, two versions of the index have been developed:

- **Digital trends:** For digital trends analysis, national and demographic responses are indexed to a baseline of Q1 2019, set at 100.
- **Digital intensity:** Individual survey responses from the past year are then combined into an index that ranges from 0 to 100.

Each sub-index was given equal weighting to calculate the aggregate index score. The digital trends index evaluates the change in the index over time, while the digital intensity index assesses the differences between demographic and socioeconomic characteristics and identifies digital accelerators and anchors.

[4] Those agreeing responded that they "definitely agree" or "tend to agree" with the statement. Other responses available included: "neither agree nor disagree"; "tend to disagree"; "definitely disagree".

2.5 ECONOMETRIC APPROACH

We used econometric modelling to identify demographic and socioeconomic characteristics which were independently associated with statistically significant differences in average scores of different cohorts of respondents. Notably, this approach enabled us to assess the impact of various demographic and socioeconomic characteristics simultaneously, isolating each factor's unique impact while controlling for others' influence.

For this assessment, we used two types of models:

2.5.1 OLS regression

Ordinary Least Squares (OLS) models, widely used in economics, are used to estimate the relationship between one or more independent variables and a dependent variable. In our analysis, the dependent variables are the digital intensity index and the sub-indices while the independent variables are the demographic and socioeconomic characteristics detailed in Fig. 1.

The primary objective of OLS is to find the linear relationship that best fits the data by minimizing the sum of squared differences (the residuals) between the observed values and the values predicted by the model.

We used OLS models to analyse average differences between index scores. These models were designed to compare each demographic and socioeconomic characteristics cohort against a reference group, allowing us to measure how the index score varies relative to this reference group while controlling for the influence of other characteristic cohorts within the model.

Fig. 5 and Fig. 6 display the results for the digital intensity index and sub-indices, respectively for different demographic characteristics. These show the difference in digital index scores compared to the reference group, which is reported for each demographic category in parenthesis in the first column. A higher score indicates that the characteristic has a higher digital index score compared to the reference group. Where all the scores are negative, the reference group has the highest digital index score out of these cohorts. The differences between these scores can be compared across demographic and socioeconomic characteristics for the aggregate index (Fig. 5) as well as across sub-indices (Fig. 6). Asterisks (*) indicate statistically significant differences compared to the reference category.

Fig. 5. Econometric results from the digital index score models

	Group	Digital Index
Age Base (25-34)	18-24	-0.2
	35-44	-4.6***
	45-54	-9.0***
	55-64	-16.2***
	65+	-27.9***
Gender Base (Male)	Female	-3.0***
Income Base (£30,000 to £44,999)	under £14,999	-9.3***
	£15,000 to £29,999	-4.9***
	£45,000 to £69,999	4.9***
	£70,000 to £99,999	9.2***
	£100,000 and over	13.9***
Parent Base (Younger family)	Older family	-2.4**
	No children	-6.6***
Education qualification Base (University)	No formal qualifications	-11.4***
	Other (GCSE or equivalent)	-4.7***
Location Base (Urban)	Town and fringe	-0.6
	Rural	-0.2

*significance level: *** p<0.01, ** p<0.05, * p<0.1*

Source: YouGov data analysed by Oxford Economics

Fig. 6. Econometric results from the sub-index score models

	Group	Device & App	Online shop	Attitudes
Age Base (25-34)	18-24	-1.7	-4.9***	6.2***
	35-44	-2.0	-1.3	-6.8***
	45-54	-4.9***	-2.8**	-12.3***
	55-64	-12.8***	-4.6***	-18.6***
	65+	-24.6***	-11.4***	-26.0***
Gender Base (Male)	Female	0.3	3.1***	-10.1***
Income Base (£30,000 to £44,999)	under £14,999	-7.5***	-8.7***	-4.6***
	£15,000 to £29,999	-3.4***	-4.8***	-2.8***
	£45,000 to £69,999	4.4***	3.6***	3.0***
	£70,000 to £99,999	6.3***	7.1***	7.1***
	£100,000 and over	10.3***	8.4***	12.2***
Parent Base (Younger family)	Older family	-3.3***	0.9	-2.8**
	No children	-9.8***	0.7	-5.5***
Education qualification Base (University)	No formal qualifications	-4.9**	-8.5***	-11.9***
	Other (GCSE or equivalent)	-1.7**	-3.9***	-4.8***
Location Base (Urban)	Town and fringe	-0.8	1.3	-1.8*
	Rural	-1.5	1.4*	-0.3

*significance level: *** p<0.01, ** p<0.05, * p<0.1*

Source: YouGov data analysed by Oxford Economics

2.5.2 Probability models

The logit model, also known as the logistic regression model, is a statistical method used to predict a binary outcome, like yes or no, (which is the form of the responses to the key questions that make up the digital intensity index) based on one or more independent variables. The independent variables are the demographic and socioeconomic characteristics detailed in Fig.1.

Logit models were used to analyse how these various characteristics influenced the probability that a respondent was categorised as a digital accelerators, early adopters, and digital anchors. Outputs from the model were expressed in terms of odds ratios, and similar to the OLS regression model, the influence of each characteristic was defined by comparison to a reference group. The results from the probit models are described in Fig. 7 to Fig. 8.

Fig. 7. Econometrics results (odds ratios) for digital accelerators and anchors.

		Odds ratio	
	Group	Digital accelerators	Digital anchors
Age Base (25-34)	18-24	0.3***	2.8***
	35-44	0.2***	20.3***
	45-54	0.1***	33***
	55-64	0.0***	303.2***
	65+	0.0***	6473.2***
Gender Base (Male)	Female	0.6***	3.8***
Income Base (£30,000 to £44,999)	under £14,999	0.0***	8.8***
	£15,000 to £29,999	0.3***	3.9***
	£45,000 to £69,999	17***	0.1***
	£70,000 to £99,999	55***	0.1***
	£100,000 and over	365.1***	0.0***
Parent Base (Younger family)	Older family	0.1***	2.1***
	No children	0.1***	7.1***
Education qualification Base (University)	No formal qualifications	0.7***	40.7***
	Other (GCSE or equivalent)	0.4***	6.5***
Location Base (Urban)	Town and fringe	0.6***	1.2***
	Rural	0.8***	1.7***

*significance level: *** p<0.01, ** p<0.05, * p<0.1*

Source: YouGov data analysed by Oxford Economics

Fig. 8. Econometrics results (odds ratios) for early adopters.

	Group	Odds ratio Early adopters
Age **Base (25-34)**	18-24	1.4***
	35-44	0.6***
	45-54	0.4***
	55-64	0.3***
	65+	0.1***
Gender **Base (Male)**	Female	0.3***
Income **Base (£30,000 to £44,999)**	under £14,999	1.4***
	£15,000 to £29,999	1.1**
	£45,000 to £69,999	1.0
	£70,000 to £99,999	1.0
	£100,000 and over	1.5***
Parent **Base (Younger family)**	Older family	0.7***
	No children	0.5***
Education qualification **Base (University)**	No formal qualifications	0.7***
	Other (GCSE or equivalent)	0.7***
Location **Base (Urban)**	Town and fringe	0.8***
	Rural	0.8***
Employment status **Base (Working full/part time)**	Not working	0.7***
	Retired	0.5***

*significance level: *** p<0.01, ** p<0.05, * p<0.1*

Source: YouGov data analysed by Oxford Economics

These were translated into probabilities[5] for each socioeconomic characteristic to facilitate interpretation. The probabilities of being a digital accelerator, digital anchor, or early adopter, by demographic characteristics can be found below.

[5] We used the *margins* command in STATA to calculate the marginal effects (predicted probabilities) for each socioeconomic characteristic.

Fig. 9. Econometrics results (probabilities) for digital accelerators and anchors.

	Group	Probability of being a digital accelerator	Probability of being a digital anchor
Age	18-24	30%	1%
	25-34	42%	0%
	35-44	28%	5%
	45-54	21%	7%
	55-64	9%	23%
	65+	3%	57%
Gender	Male	27%	21%
	Female	24%	28%
Income	under £14,999	1%	37%
	£15,000 to £29,999	4%	31%
	£30,000 to £44,999	8%	22%
	£45,000 to £69,999	32%	10%
	£70,000 to £99,999	44%	8%
	£100,000 and over	62%	2%
Parent	Younger family	35%	19%
	Older family	21%	23%
	No children	19%	30%
Education qualification	No formal qualifications	25%	39%
	Other (GCSE or equivalent)	21%	27%
	University	28%	16%
Location	Urban	25%	24%
	Town and fringe	22%	25%
	Rural	24%	27%

*significance level: *** p<0.01, ** p<0.05, * p<0.1*

Source: YouGov data analysed by Oxford Economics

Fig. 10. Econometrics results (probabilities) for early adopters.

	Group	Probability of being an early adopter
Age	18-24	27%
	25-34	21%
	35-44	15%
	45-54	10%
	55-64	7%
	65+	4%
Gender	Male	19%
	Female	7%
Income	under £14,999	15%
	£15,000 to £29,999	13%
	£30,000 to £44,999	12%
	£45,000 to £69,999	12%
	£70,000 to £99,999	12%
	£100,000 and over	17%
Parent	Younger family	17%
	Older family	14%
	No children	10%
Education qualification	No formal qualifications	11%
	Other (GCSE or equivalent)	11%
	University	15%
Location	Urban	13%
	Town and fringe	11%
	Rural	11%
Employment status	Working full/part time	14%
	Not working	10%
	Retired	9%

*significance level: *** p<0.01, ** p<0.05, * p<0.1*

Source: YouGov data analysed by Oxford Economics

3. EXPLORING THE LINK BETWEEN DIGITAL TECHNOLOGY INTENSITY AND AI

In this workstream, Oxford Economics and Cognizant designed a survey that was fielded to a representative sample of adults in the UK, US, Australia, and Germany. The primary purpose of the survey was to collect data to test the hypothesis that characteristics which we had found to characterise a digital accelerator (workstream two) were similarly predictive of an individual's attitudes towards artificial intelligence (AI). We also used the survey to gather data to assess the current state of preferences for AI-functions across the customer journey.

3.1 QUESTIONNAIRE DESIGN

The survey, conducted online by YouGov on behalf of Oxford Economics, included a total of 8,451 respondents: 2,110 in the UK, 2,312 in the US, 2,023 in Australia, and 2,006 in Germany. The survey was structured around three stages of the consumer journey: learn, purchase, and use. For each stage of the journey, consumers were asked if they would be open to using or being influenced by different AI-enabled technology features, such as chatbots or digital voice assistants, and explored the motivations behind their responses. In addition, the survey included a section exploring respondents' willingness to use these same features in their consumer journey across different sectors including financial products and services; healthcare; energy and utility; communications; entertainment; retail; travel and hospitality; and, government.

Fig. 11. Demographic and socioeconomic characteristics

Category	Group	UK sample size distribution	US sample size distribution	Australia sample size distribution	Germany sample size distribution
Age	**18-24**	234	268	219	184
	25-34	337	460	369	302
	35-44	365	348	415	293
	45-54	338	292	239	400
	55+	835	944	782	828
Gender	**Male**	1,023	1,125	987	976
	Female	1,087	1,187	1,036	1,030
Income Band[6]	**1**	144	285	102	91
	2	160	208	45	195
	3	209	211	85	239
	4	164	200	171	228
	5	192	187	202	232
	6	166	170	110	174
	7	128	125	96	149
	8	102	128	115	85
	9	89	150	170	66
	10	70	111	143	52
	11	78	104	100	117
	12	54	66	174	40
	13	56	25	93	N/A
	14	42	24	66	N/A
	15	N/A	4	33	N/A
	16	N/A	12	34	N/A
	Don't know	86	55	61	N/A
	No personal income	N/A	N/A	N/A	44
	Prefer not to answer	372	245	223	294

To ensure representativeness, the final data was statistically weighted to reflect the national profile of all adults aged 18+ in each country.

3.2 DIGITAL ACCELERATORS

As noted, our analysis of the consumer profiles data (workstream two) indicated that in the UK, characteristics which independently predicted the likelihood that an individual was classified as a digital accelerator according to our index were age (44 and under) and earnings (£45,000 and over). Although we could straightforwardly match this age category in our survey data for other markets (Australia, Germany, and the US), earnings categories did not map one-to-one.

[6] Country-specific income bands shown in Fig. 12

We, therefore, needed to form assumptions for what an equivalent earnings threshold should be in these other markets. In the UK, those with a personal income of £45,000 made up approximately 18% of our sample. In other markets, we defined those with a similar relative income as follows:

- In the US, high earners have a gross income of over $80,000 (25% of survey sample).
- In Australia, high earners are defined as those who earn more that AUD 84,000 (23% of survey sample).
- In Germany over €42,000 (22% of the survey sample).

3.3 ANALYSIS OF SURVEY RESPONSES

Using the survey responses, for each age and income cohort, as well as for the overall sample average, we calculated the weighted proportion of respondents who responded affirmatively to each question, indicating positive attitudes towards AI.

To test whether digital accelerators' characteristics were also predictive of respondents' AI enthusiasm we conducted a series of comparisons across the two key demographic characteristics identified in the previous chapter, age and income. Comparisons were made between respondents aged 18-44 and high earners against the overall average and each other. A higher proportion indicates a greater willingness to apply AI-led functions in consumer products and services.

Statistical significance tests were conducted to determine whether observed differences in responses were meaningful.

3.4 INCOME BANDS

Fig. 12. Income bands for questionnaire (as in Fig. 11)

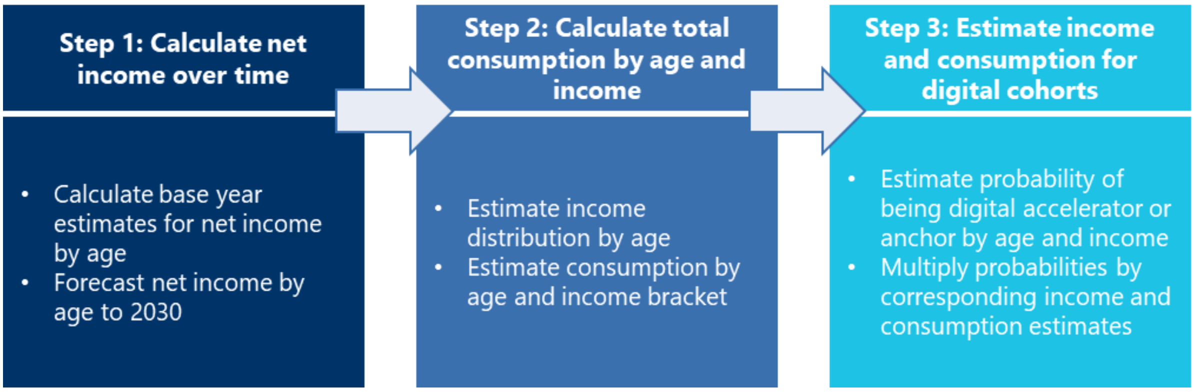
Income Band Label	UK income bands	US income bands	Australia income bands	Germany income bands
1	under £5,000 per year	Less than $10,000	$750 or below	Under 500€
2	£5,000 to £9,999 per year	$10,000 - $19,999	$751-$1000	500€ to 1,000€
3	£10,000 to £14,999 per year	$20,000 - $29,999	$1001-$1500	1,000€ to 1,500€
4	£15,000 to £19,999 per year	$30,000 - $39,999	$1501-$2000	1,500€ to 2,000€
5	£20,000 to £24,999 per year	$40,000 - $49,999	$2001-$2500	2,000€ to 2,500€
6	£25,000 to £29,999 per year	$50,000 - $59,999	$2501-$3000	2,500€ to 3,000€
7	£30,000 to £34,999 per year	$60,000 - $69,999	$3001-$3500	3,000€ to 3,500€
8	£35,000 to £39,999 per year	$70,000 - $79,999	$3501-$4000	3,500€ to 4,000€
9	£40,000 to £44,999 per year	$80,000 - $99,999	$4001-$5000	4,000€ to 4,500€
10	£45,000 to £49,999 per year	$100,000 - $119,999	$5001-$6000	4,500€ to 5,000€
11	£50,000 to £59,999 per year	$120,000 - $149,999	$6001-$7000	5,000€ to 10,000€
12	£60,000 to £69,999 per year	$150,000 - $199,999	$7001-$10000	10,000€ and more
13	£70,000 to £99,999 per year	$200,000 - $249,999	$10001-$15000	N/A
14	£100,000 and over	$250,000 - $349,999	$15001-$30000	N/A
15	N/A	$350,000 - $499,999	$30001-$80000	N/A
16	N/A	$500,000 or more	$80001 and above	N/A

4. ESTIMATING INCOME AND CONSUMPTION LEVELS OF DIGITAL COHORTS

This workstream builds on the previous work aimed at understanding digital accelerators and their purchasing behaviour. As described, in workstream two we found that certain age and income cohorts in the UK were more likely to be digital accelerators. Moreover, we also observed this trend in the survey data in terms of socioeconomic and demographic characteristics that predicted the likelihood of respondents indicating that they were more inclined to use AI in their purchasing decisions. As such, we consider that there was a sound foundation to apply these findings to identify digital accelerators and anchors in other markets where we gathered survey data (Germany, Australia, the US).

In workstream four, we developed forecasts that predicted the spending and purchasing power of digital accelerators, digital anchors and all other consumers in each of these four markets. This involved a multi-stage modelling approach illustrated in Fig. 15.

Fig. 13. Summary methodology for workstream four



4.1 CALCULATING NET INCOME

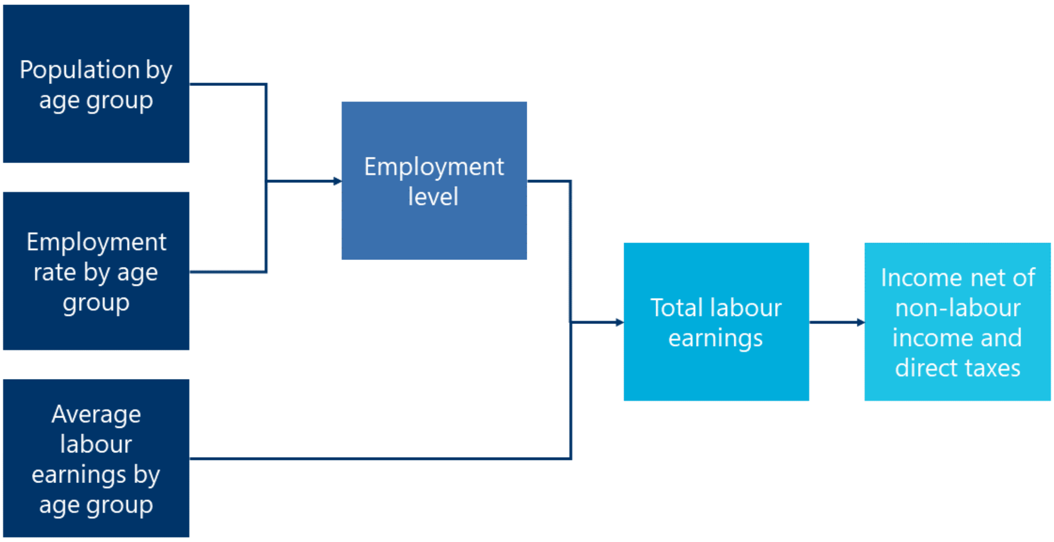
4.1.1 Calculating base year estimates for net income

Fig. 14 illustrates the multi-stage approach we undertook to calculate net income by single year age cohorts in 2023.[7] We first combined population by age with employment rates by age to estimate the number of people employed for each year of age. We then combined these employment levels with average labour earnings to estimate total labour earnings by age. Finally, we adjusted labour earnings to account for non-labour income and direct taxes to derive estimates of net income by age.

[7] For countries that we were unable to find data relating to 2023, we sourced the latest available data and forecasted the relevant variables to 2023 using the same forecast approach as outlined in section 4.1.2.

The remainder of the section will outline the details of each stage involved in the calculation.

Fig. 14. Steps taken for the calculation of net income for the base year



The most recent population estimates for single-year age cohorts in the UK, US, Australia, and Germany were obtained from their respective national statistics databanks. Employment rates were sourced similarly, but available by age group (e.g. 25-35 year olds) rather than single-year age cohorts. We used linear interpolation between age group employment rates to impute the employment for each single-year age cohort.[8] This approach allowed for a more nuanced view, avoiding the use of age group averages—which mask variation across specific ages. We combined population by age with our imputed employment rates by age to estimate employment levels by age in each key market for the base year.

Data on average labour earnings were also available by age group rather than single-year cohorts. We used linear interpolation to impute earnings for each single-year age cohort. We multiplied employment levels by average labour earnings to estimate total labour earnings for each single-year age cohort.

Labour earnings were adjusted to include non-labour income, resulting in gross income. To do this, we estimated the ratio of gross income to labour income for the whole economy using national gross income estimates from Oxford Economics. This ratio was applied consistently to labour earnings of each single-year age cohort to estimate gross income for each single-year cohort.

We calculated direct taxes (i.e. income tax plus employee social security contributions) as a share of gross income using Oxford Economics databank and used this ratio to convert our gross income

[8] Linear interpolation is a method used to estimate values within a range of known data points, assuming a constant rate of change between them.

estimates into net income estimates. These ratios were calculated for the whole economy and applied uniformly to each single-year age cohort.

4.1.2 Forecasting net income in 2030

Each of the key variables discussed in 3.2.1 were forecasted to 2030 to produce estimates of net income by single-year age cohort in 2030. Firstly, we sourced population forecasts by age group (e.g. 25- to 29-year-olds) from Oxford Economics' databank.[9] We multiplied population by single-year age in 2023 by the population growth rate (from 2023 to 2030) for their respective age groups to estimate population by single-year age in 2030.

Oxford Economics produces national forecasts for the employment rate and average labour earnings. For these variables, we conducted analysis of historical growth rates to identify age groups where the employment rate or average earnings have grown faster/slower than the national average. To begin, we assumed that historic differences compared to national growth rates were maintained over the forecast horizon to produce age-group specific projections for employment rates and average earnings. These results were then constrained to ensure that national growth rates aligned with those in Oxford Economics' databank.

4.2 CALCULATING TOTAL CONSUMPTION BY AGE AND INCOME THRESHOLD

The steps outlined above provide us with estimates of average net income by age. However, our analysis focuses on predicting the spending and purchasing power of digital accelerators, who are defined by both their age and income. To achieve this, we developed estimates of the income distribution, to determine the proportion of each single-year age cohort that fall into the different digital user categories.

4.2.1 Estimating the income distribution by age

We sourced data regarding the national income distribution for each of the four key markets. These data show the income earnt at each decile, which we compared to the median. We assume that these ratios reflect the income distribution within each single-year age cohort. For example, if the income of the 8th decile is 50% larger than the median income then we assume that for each individual age the 8th decile of earnings in that age is 50% larger than the median income for that age.[10] From this, we were able to impute the income distribution (by decile) for each individual year of age.

The income thresholds presented in 0 reflect those used to define digital user cohorts. For each single-year age cohort, we calculated at which point in their income distribution those thresholds are located. For example, an annual income of £30,000 may be near the top of the income distribution for 17-year-olds but will likely be lower down the income distribution for 50-year-olds. We then estimate the share of income within each single-year age cohort that is earnt by individuals in each of the thresholds detailed in 0.

[9] Forecasts by single-year age cohorts were not available.

[10] We multiplied our estimates of average earnings by age by the national ratio of median to mean earnings to derive an estimate of median earnings by age.

Fig. 15. Income bands by country

Band	UK income bands	US income bands	Australia income bands	Germany income bands
01	under £14,999	Less than $19,999	$2500 or below	Under 1,500€
02	£15,000 to £29,999 per year	$20,000 - $49,999	$2501-$5000	1,500€ to 2,500€
03	£30,000 to £49,999 per year	$50,000 - $69,999	$5001-$7000	2,500€ to 4,000€
04	£50,000 to £69,999 per year	$70,000 - $119,999	$7001-$15000	4,000€ to 5,000€
05	£70,000 to £99,999 per year	$120,000 - $149,999	$15001-$30000	5,000€ to 10,000€
06	£100,000 and over	$150,000 or more	$30001 and above	10,000€ and more

4.2.2 Estimating consumption by age and income bracket

We sourced data on household consumption split by income decile for each of the key markets. We calculated consumption-to-income ratios for each income decile.[11] Households with lower incomes typically spend a higher proportion of their income on consumption given much of what they purchase may be necessities. As incomes increase, household typically save a proportion of their income and therefore spend a smaller share of their income on consumption.

For each income threshold detailed in 0, we applied the relevant consumption-to-income ratios to estimate consumption by single-year age cohort and income bracket.

4.2.3 Estimating income and consumption for each digital cohort

The process of applying the estimated income and consumption levels to digital accelerators and digital anchors involved two main steps:

- **Estimate the probability of being a digital accelerator or digital anchor:** The first step involved estimating the probability of an individual being classified as a digital accelerator or digital anchor within each age and income cohort. This methodology closely follows the approach outlined in Section 2.5 of this document. However, instead of using historical survey data from YouGov's Profiles database, the digital intensity index was based on data collected from the consumer survey conducted as described in chapter 3. Additional details on the methodology are available in Section 2.5.

- **Multiply probabilities by the corresponding income and consumption estimates:** In the second step, the probabilities of being a digital accelerator or digital anchor were combined with the income and consumption estimates derived from Sections 4.2.1 and 4.2.2. This enabled the estimation of income and consumption levels for each digital cohort based on the calculated probabilities for each demographic group.

[11] For Australia and Germany, data were split by income quintile.

4.3 DATA SUMMARY

Our dataset was sourced primarily from the national statistical authorities for the UK, US, Australia, and Germany, as well as from the Oxford Economics databanks. See Fig. 16 for a full list of the data sources used for this workstream.

Fig. 16. Sources used to collect data for model development

Definition	Country	Source
Population by age group	UK	ONS
	US	US Census Bureau
	Germany	Eurostat
	Australia	ABS
Employment by age group	UK	ONS
	US	BLS
Expenditure by disposable income decile	UK	ONS
Median personal income by age group	US	US Census Bureau
Mean annual expenditure by decile of income before taxes	US	BLS
Employment rate by age group	Germany	Eurostat
Mean labour earnings by age group	Germany	Destatis
Average household spending by net household income	Germany	Destatis
Employment to population ratio by age group	Australia	ABS
Average weekly total cash earnings by age group	Australia	ABS
Aggregate household consumption by income quintile	Australia	ABS
Population by age group	All markets	Oxford Economics
Employment, total		
Earnings, quarterly total, gross, LCU		
Government revenue, employee social security contributions, LCU		
Income, personal disposable, nominal, LCU		
Tax revenue, income, LCU		

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