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alma economics

Price Personalisation: Evidence from the UK online market

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Executive summary

Background

The growth of the digital economy, along with advances in data collection and the use of algorithms, has greatly expanded the capacity for companies to practice price personalisation. Price personalisation is a pricing strategy in which the same seller charges different consumers different prices for the same good or service, with these differences driven by consumer characteristics and behaviours that signal their willingness to pay (Department for Business, Energy & Industrial Strategy; OECD).

Price personalisation is effectively a form of price discrimination that takes into account consumers' individual characteristics and behaviours. Price discrimination can take several forms, notably first-degree discrimination, which involves substantial variation in prices across individuals, and third-degree discrimination, which applies different prices to distinct consumer groups[1].

In the past, sellers had limited ability to identify consumers' willingness to pay and to set personalised prices. Today, this is increasingly possible, as companies can collect extensive data on consumer demographics, location, online browsing and purchase history, and social media activity, and can systematically test prices—for example, through A/B testing[2]—to uncover differences in consumers' willingness to pay.

Despite this, and despite some media coverage and anecdotal evidence, convincing evidence of widespread price personalisation practices remains limited[3]. In particular, only a small number of studies have examined the prevalence of price personalisation practices, and those that have often found little or no evidence[4]. There are, however, some notable exceptions.

The US Federal Trade Commission conducted a study in 2025 on surveillance pricing, with interim results suggesting that companies track consumer characteristics and behaviours—such as location, demographics, and even mouse movements—to inform pricing strategies.

An international study of an online dating app conducted in 2021 across six countries (New Zealand, the US, the Netherlands, South Korea, India, and Brazil) found that older consumers were charged significantly more: participants aged 30–49 paid, on

[1] Second-degree price discrimination, or menu pricing, occurs when all consumers are offered the same set of options and choose between them based on their preferences, such as selecting basic or premium services.

[2] In an online pricing context, A/B testing typically works as follows: (i) Consumers are randomly split into different groups; (ii) Each group is shown a different version of a webpage, offer, or price (for example, Price A versus Price B); (iii) The seller then observes how each group behaves—such as whether they make a purchase, how quickly they buy, or how much they spend. By comparing outcomes across the groups, firms can infer how sensitive different consumers are to price changes and identify differences in willingness to pay. This information can then be used to refine pricing strategies, including personalised pricing.

[3] Also, see the recent news report on Instacart allowing artificial intelligence–driven pricing tests, as well as previous allegations that Uber charges higher prices for users with low phone battery levels.

[4] For example, see a study of the online airline market and another on the German online retail sector.

average, 65% more than those aged 18–29 for a monthly subscription. An investigation by Which? in the UK found similar practices: individuals aged 30–49 were likely to pay 48% more (an average difference of £24) for a 12-month *Plus* subscription, while those over 50 paid 47% more (£23.59).

Finally, a large-scale international study conducted in 2012 (covering the US, Germany, Spain, South Korea, and Brazil), which analysed 200 sellers and 600 products, found some evidence of price personalisation based on the origin of the URL. For certain product categories, users visiting a seller's website via a discount aggregator were offered prices up to 23% lower than those visiting the same site directly[5].

Although price personalisation is often perceived as a negative practice, it does not necessarily harm consumers and can, in some cases, be beneficial. When personalised pricing is applied, some consumers may benefit from discounts, lower prices, or increased access to products[6]. Others may pay more, yet the overall impact could still be positive if the benefits to those paying less outweigh the losses to those paying more. Nevertheless, concerns may arise even in such cases if fears about online price personalisation discourage consumers from making online purchases, or if the consumers who ultimately pay higher prices are particularly vulnerable (Office of Fair Trading).

Research objectives

The aim of this study is to provide systematic and up-to-date evidence on the prevalence of price personalisation practices in the UK online business-to-consumer sectors. We explore the prevalence of price personalisation across a broad range of sectors, as well as in selected sectors in more depth.

A secondary objective is to explore whether price personalisation, where it occurs, is associated with specific consumer characteristics and vulnerabilities, i.e. whether certain groups of consumers are more likely to be exposed to personalised pricing. In particular, we focus on vulnerabilities or traits related to (i) financial difficulties, (ii) mental health challenges, and (iii) neurodivergence[7]. This focus is informed by prior research on harmful online choice architecture, which suggests that consumers with vulnerabilities are disproportionately affected by such practices[8]. We also examine how prices shown to consumers vary according to demographics, device types, browsers, and behaviours.

Establishing a formal or statistical relationship between price differences and consumer characteristics typically requires a large consumer sample, particularly when pricing

[5] The study also identified evidence of location-based price differences, mainly for digital products such as e-books and video games, which may reflect variations in digital rights costs and competitive conditions, and not necessarily PP.

[6] It can enable products to be offered—or offered on specific terms—that might not be feasible without such price differentiation.

[7] While these characteristics do not inherently constitute vulnerabilities, they may in some contexts be associated with increased susceptibility in market interactions.

[8] For example, see a report recently commissioned by Citizens Advice.

strategies are driven by complex algorithms that require extensive data to be reverse engineered. Given the relatively limited sample in this study, the objective is not to establish a formal link, but rather to identify preliminary evidence that can inform and guide more systematic investigation in future research.

Methodology

Data collection involved gathering prices for the same products across different consumer profiles. We used two complementary methods: (i) a survey-based approach (Phase 1), in which a large sample of participants recorded prices shown via direct links, and (ii) a synthetic profile approach (Phases 2 and 3), in which researchers used controlled profiles to record prices in settings where prices are only revealed after user interaction (e.g., apps and multi-step journeys).

Data analysis involved assessing the degree of price variation and exploring whether observed differences were associated with consumer characteristics. We used (i) quantitative analysis to measure the extent of variation, (ii) descriptive analysis to examine patterns by profile characteristics, and (iii) case studies combining descriptive and statistical analysis for selected products or sellers where we identified substantial and/or repeated price variation[9].

An important aspect of the research design was to control for the impact of dynamic pricing as far as possible. Dynamic pricing is a pricing strategy in which prices are adjusted in real time based on market demand and supply.

For the survey-based approach, data collection took place within a single day, minimising exposure to dynamic pricing or other factors that may cause prices to vary across days. In addition, the time at which each respondent completed the survey was recorded, including both start and finish times, allowing us to examine whether any observed price variation was a function of time, and therefore potentially attributable to dynamic pricing.

For the synthetic profile approach, data were collected across four days. Price variation was measured only within a given day. Any price differences observed across days were not treated as evidence of price personalisation. In addition, the research team was able to identify price changes across profiles in real time and communicate these to others involved in data collection. This allowed us to assess whether a price change represented a time-related shift potentially attributable to dynamic pricing, or variation across profiles independent of timing. In cases where there was clear evidence that a price change was driven by timing, it was not recorded as an instance of price variation. Finally, for platforms where dynamic pricing is more prevalent, such as taxi services, the data collection window was determined to be two hours.

Our approach was implemented in three phases.

- **Phase 1** involved collecting data across a wide range of products and sectors

through a consumer survey.

- **Phase 2** used a synthetic profile approach to collect data for a targeted set of sectors where data collection via a consumer survey is more challenging.
- **Phase 3** focused on the transport sector using synthetic profiles, motivated by the findings from Phase 2.

These three phases are further discussed in the next section.

Phase 1

In Phase 1, a large number of survey participants (1,688 in total and around 120 per product) were asked to visit 100 webpages corresponding to 100 different products and record the prices displayed[9]. In addition to price information, we collected data on participants' demographics, location, and the device and browser used, as well as responses to questions designed to infer financial vulnerability, mental health status, and neurodivergence. The survey was conducted on the same day by all participants to minimise the potential impact of dynamic pricing or other time-sensitive factors on the prices observed.

Phase 2

In Phase 2, we created 20 artificial profiles with varying characteristics (age, gender, device and browser type used to access online products). We also simulated the three vulnerabilities that are the focus of our research by constructing digital footprints[10] consistent with each vulnerability. In total, the 20 profiles were used to visit 35 products across 34 sellers[11]. Each product was visited four times (four waves) over the course of a month, generating four sets of prices for each product and synthetic profile[12].

Phase 3

In Phase 3, we conducted a deep dive into the transport sector, motivated by the high price variation identified in Phase 2, which we sought to explore further. Specifically, using the 20 synthetic profiles constructed in Phase 2, we collected data across three transport platforms and three alternative routes over a two-week period, with observations gathered on three to five occasions (days).

Phases 1, 2 and 3

[9] This was facilitated by providing direct links within the survey and asking participants to click on each link, observe the price, and then return to the survey platform to record it. Each participant was asked to visit seven links—not all participants had to visit 100 links. The links were randomised across participants. Because of this randomisation, the number of visits per link, and therefore the number of prices collected, varied across links. On average, each link was visited by 119 participants, with the minimum number of visits being 88 and the maximum 152.

[10] This involved searching for specific keywords (e.g. debt help), visiting particular websites (e.g. depression support groups), and sending emails and posting on social media using keywords linked to the three potential vulnerabilities.

[11] For one of the products, a dating platform, we used a different approach—see the methodology section for further details.

[12] The profiles were operated by Alma researchers across multiple devices, including laptops and smartphones, with a VPN configured to London. This approach allowed us to control for location while preventing platforms from assuming that all devices originated from the same place (our London office).

In total, across all phases, we collected and analysed prices for 144 products from 87 online sellers[13] across multiple consumer profiles, as well as over time. To our knowledge, this is the most comprehensive study of price personalisation in the UK and internationally.

Key findings

While the majority of products within scope did not exhibit price variation—different survey participants or synthetic profiles recorded the same price for the same product—there is strong evidence that price variation is more prevalent in certain sectors. Specifically, **we observed low levels of price variation in the retail sector, compared with substantial variation in sectors such as transport, packaged holidays, hospitality, and ticket sales. A third of the platforms in these sectors demonstrated high price variability.** The majority of the variation identified is unlikely to be driven by dynamic pricing, as our methodology largely controls for it. This evidence of price variation is interpreted as a strong indication of price personalisation.

In terms of the type of price personalisation, **we found a strong indication of first-degree price personalisation in one case—a taxi service platform.** In particular, for the four routes we examined for this seller (in Phases 2 and 3), we found that nearly every consumer was charged a different price. These differences averaged between 11% and 25%, meaning that, on average, each consumer faced a price that differed from those offered to others by 11% to 25%. While some of this variation could, in principle, be attributed to dynamic pricing—which may be more intensive in this sector—the frequency and magnitude of the differences are difficult to explain solely through such mechanisms. In addition, the correlation between prices and consumer characteristics identified for this seller is also consistent with first-degree price personalisation.

The remaining instances of price variation **align more closely with third-degree price personalisation**, as price variation is more discrete and/or associated with a limited set of consumer characteristics.

In the cases where we found price variation, we explored the degree to which this can be explained by consumer—survey participant or synthetic profile—characteristics. **In the majority of the cases, we were unable to provide a clear link between price variation and the consumer characteristics that were under examination in our study.** However, there were a few notable exceptions.

For the taxi service platform examined in Phases 2 and 3, we found strong associations between prices and gender, age, and device type. However, these relationships appear to depend on the route, as the direction of the effects of gender, age, and device on prices varies across routes. Overall, this suggests that price personalisation is more

[13] For some sellers, we collected prices for more than one product, and there was some overlap between the sellers included in our survey-based and synthetic profile approaches.

complex than the simple application of a premium or discount to specific consumers, with prices also influenced by additional factors such as the route.

For the second taxi service platform (examined in Phase 3 only), we also found an association between prices and device type, with prices being 9% higher for smartphone users compared to laptop users.

We found a strong correlation between prices and device type in three more cases (in the survey-based approach / Phase 1).

- In two of these (a train ticket booking platform and a hotel booking platform[14]), smartphone users observed lower prices (by 19% and 10%, respectively) compared with desktop or laptop users.
- In one case (a bus ticket booking platform), smartphone users observed higher prices than desktop or laptop users (by 6%).

In total, we found five products that showed a correlation between price and device type—two taxi service platforms in Phases 2 and 3 and three in Phase 1. Device type may serve as a proxy for unobserved consumer characteristics (e.g. age and income) that influence willingness to pay, which may help explain why prices vary by device.

In one case (a hotel booking platform), price variation was strongly associated with **login status**: consumers who were logged in to their account on the seller's website at the time they viewed the price observed prices that were 10% lower than those who were not logged in.

Similarly, there is **some indication that gender may be associated with price variation**, as part of the observed variability appears to be correlated with gender. However, further evidence—such as larger samples, more platforms, and an assessment of whether consistent premiums exist across genders—is required before any firm conclusions can be drawn.

We found some evidence that is consistent with a pricing strategy that combines dynamic pricing and price personalisation, with the degree of price personalisation appearing to vary depending on market conditions.

We found no evidence of price personalisation linked to consumer vulnerabilities within the scope of this study (financial difficulties, mental health challenges, and neurodivergence status). However, there is some indication that the neurodivergent group in our sample experienced greater price variation—often in the form of premiums—than other groups. This result should be treated with caution, given the small sample size, and further evidence would be needed to support any robust conclusions.

[14] This is the same seller where we observed that prices vary depending on login status, although this refers to a different product (for some sellers we explored more than one product).

The remaining instances of price variation could not be linked to any consumer traits or behaviours captured in the study, suggesting that they may be associated with characteristics or data points beyond the scope of this research.

An important limitation of this study is that we were only able to examine a limited set of consumer characteristics, while several other characteristics and behaviours—such as purchasing history and complex real-world online behaviours and journeys—may have been omitted or not adequately captured. Our synthetic profiles created digital footprints for vulnerabilities that may not approximate the real behaviours of vulnerable consumers online. **The relatively small sample size should also be considered when interpreting the results**, particularly given the challenges of identifying strong association between prices and consumer characteristics, which typically require larger samples.

All in all, a key finding of this study is that certain sectors are more likely to offer different prices to different consumers; that is, personalised pricing appears to be more prevalent in specific sectors. Further research would provide valuable additional insights. This could include studies that more closely reflect real consumer behaviour and journeys, as well as research incorporating purchasing histories or larger sample sizes to enable more robust quantitative analysis.

Introduction

1.1 Definition

Price personalisation (PP) is a pricing strategy in which the same seller charges different consumers different prices for the same good or service (hereafter referred to as products), with these differences driven by consumer characteristics and behaviours that signal their willingness to pay (Department for Business, Energy & Industrial Strategy; OECD). This definition rests on three key conditions:

1. The cost of supplying the product is the same for all consumers.
2. Consumers differ in their willingness to pay for the same product.
3. Sellers are able to infer these differences in willingness to pay from consumers' characteristics and behaviours.

PP is sometimes used interchangeably with price discrimination. Price discrimination is a well-established business practice and occurs, for example, when students receive discounts for products. In practice, however, PP refers specifically to a form of price discrimination that takes into account consumers' individual characteristics and behaviours. Furthermore, in PP, consumers usually do not realise they are being charged differently, unlike with student discounts. This lack of transparency is another common feature of PP.

PP is often conflated with perfect, or first-degree, price discrimination, in which each consumer is charged an individualised price, as well as with dynamic pricing, which instead refers to prices that vary over time in response to changes in demand or supply.

In this research, we consider first- and third-degree (or group) PP. First-degree PP is largely theoretical, as firms are unlikely to know each consumer's exact willingness to pay and offer a fully personalised price. In practice, first-degree discrimination occurs when many consumers face different prices based on a variety of individual characteristics. The distinction between first-degree and third-degree PP is that, in the former, we observe substantial price variation across consumers driven by multiple characteristics, whereas in the latter, prices vary less across individuals and are influenced by a limited set of consumer characteristics.

Finally, there is a related concept beyond the scope of this research: search discrimination. This occurs when consumers with different willingness to pay are directed towards different sets of products within the same category—for example, products shown to affluent consumers may be more expensive or premium compared with those shown to budget-conscious consumers.

1.2 Evidence base

While the growth of the digital economy, together with advances in data collection and algorithmic tools, has significantly increased firms' ability to personalise prices, empirical evidence of widespread PP remains limited, though there are notable exceptions.

- A US Federal Trade Commission (2025) study indicates that firms may use PP based on location, demographics, and even behavioural signals such as mouse movements to shape pricing strategies.
- An international study of an online dating app (2021) and a UK investigation by Which? found strong age-based price differences.
- A large-scale international study conducted in 2012 found some evidence of price variation based on the point of access, with users arriving via discount aggregators being offered prices considerably lower than those visiting a website directly.

1.3 Objectives

The aim of this study is to explore the degree to which PP is taking place in the UK online market. The focus is on business-to-consumer products and covers a wide range of sectors and sellers.

To meet the project objectives, we examine the degree to which:

1. Prices vary across consumers; and
2. Prices are associated with consumer characteristics.

Evidence of "considerable" price variation is interpreted as a strong indication of price personalisation. This is because we account for the possibility of dynamic pricing, making it difficult to attribute considerable price variation to factors other than personalised pricing.

Linking observed price differences to specific consumer characteristics would provide additional evidence of PP. However, this is difficult to achieve, as identifying a formal or statistical relationship between price differences and consumer characteristics typically requires a large consumer sample, especially when pricing strategies are driven by complex algorithms that rely on extensive data and are difficult to reverse-engineer.

The remainder of this report is structured as follows:

- Section 2 summarises our methodology.
- Section 3 presents the results of the research.
- Section 4 summarises the main findings and provides concluding remarks.

Annexes provide additional technical details and insights.

Methodology

2.1 Introduction

Our approach involves two key tasks.

1. Collecting price data to assess the extent to which different consumers experience different prices for the same product. We use two alternative methods to collect price data: a survey-based approach and a synthetic profile approach.
2. Analysing the price data to assess the degree of price variation and to explore its relationship with consumer characteristics. To do this, we employ (i) quantitative analysis to measure price variation, (ii) descriptive analysis to examine links with consumer characteristics, and (iii) case studies which involve a combination of descriptive and statistical analysis focused on specific products or sellers.

Our approach is implemented in three phases.

- **Phase 1** involves collecting data across a wide range of products and sectors through a consumer survey.
- **Phase 2** uses a synthetic profile approach to collect data for a targeted set of sectors where data collection via a consumer survey is more challenging.
- **Phase 3** focuses on the transport sector using synthetic profiles, motivated by the findings from Phase 2.

These three phases are further discussed in the following section. We first present a summary, followed by a fuller exposition in this section and the Appendix.

2.2 Summary

This section summarises the methodology used to collect price data implemented across the three Phases. For clarity, a product refers to either a good or a service, and a seller is a business that sells products to consumers online through webpages and/or smartphone applications.

- **Phase 1: survey-based approach.** Under this approach, we conducted a survey in which 1,688 individuals were asked to visit 100 webpages corresponding to a set of 100 products from 66 sellers and record the prices displayed. In addition to recording prices, participants provided a wide range of information, including their demographics, online behaviour, and financial, mental health, and neurodivergence status.
- **Phase 2: synthetic profiles approach.** Under the synthetic profile approach, we created 20 artificial profiles, which Alma researchers then used to record prices for 35 products from 34 sellers. The sample of sellers included a subset of those examined in the survey-based approach—where evidence of price variation had

already been identified—and sellers that were difficult to study using the survey approach due to the complexity or number of options required to access price information on sellers' websites or smartphone applications.

- Phase 3: Transport sector deep dive. In Phase 3, we conducted a deep dive into the transport sector using the 20 synthetic profiles constructed in Phase 2. We collected data across three transport platforms and three alternative routes over a two-week period, with data gathered on three to five occasions (days).

The advantage of the survey-based approach used in Phase 1 is that it enabled us to efficiently collect prices across a large number of sellers and a wide range of potential consumers. In contrast, the synthetic profile approach used in Phases 2 and 3 made it possible to access sellers and products where prices are only revealed after user interaction (e.g., flight tickets and food delivery services), which could not be captured through the survey method. Additionally, this approach allowed us to explore the impact of particular online behaviours (such as late-night shopping), consumer demographics and vulnerabilities. The synthetic stage helped us further examine potential evidence of PP identified in the survey-based analysis.

Table 1 summarises our sample across the three Phases. Overall, we collected prices for 144 products from 87 sellers. For some sellers, we collected prices for more than one product, and there was some overlap between the sellers included in the three Phases.

Table 1. Sample composition across Phases

Phase	Approach	Products	Sellers	Participants/profiles
Phase 1	Survey-based	100	66	119*
Phase 2	Synthetic profile	35	34	20
Phase 3	Synthetic profile	9	3	20
Total		144	87	-

Note: * The number of participants visiting each of the 100 products varied. On average, 119 participants visited each product, resulting in an average of 119 price recordings per product. In total, 1,688 participants completed the survey.

For Phases 1 and 2, we selected the sellers from which pricing data were collected based on the sectors identified by the Department for Business, Innovation, Science and Trade, in line with the department's priorities and policy remit, as well as prior evidence of PP. Phase 3 was motivated by the findings from Phase 2 and focused exclusively on the transport sector.

The sectors covered in Phases 1 and 2 include:

- e-Commerce.
- Entertainment.
- Retail.
- Software as a Service (SaaS).
- Travel.

Commerce covers major marketplaces; Entertainment includes TV and video on demand services, and event tickets, such as concerts and theatre performances; Retail encompasses several key sub-sectors, including consumer electronics, clothing & footwear, games & toys, groceries, and food delivery; SaaS includes software; Travel covers air travel, accommodation & hotels, ground transportation, and packaged holidays. We also included one dating platform (as part of Phase 2), motivated by evidence from previous research.

The selection of sellers was primarily based on web traffic. We used *SimilarWeb* data to identify the sites with the highest traffic within each sub-sector—our selection reflects the largest sellers in the targeted sectors. Additional platforms were included to ensure representation of small- and medium-sized sellers. For each selected seller, one or two products were chosen. Products were selected at random from different site placements (e.g., homepage versus deeper listings) to capture both popular and less visible items.

In Phase 1, the sample comprised a relatively larger share of retail products. In Phase 2, it shifted towards transport (e.g. taxis, air travel, and rail), alongside holidays, hospitality, and ticket sales. The number of products by sub-sector across the three Phases is provided in Annex A.

2.3 Phase 1: Survey-based approach

2.3.1. Survey administration and content

The survey was programmed and hosted on SurveyMonkey. Most questions were closed-ended, and the survey was designed to be completed within approximately ten minutes to minimise respondent burden and maintain data quality. The survey consisted of the following main sections[15].

- **Background and online shopping behaviour**. The background and online shopping behaviour section included questions on the frequency of online purchases, late-night shopping habits, the tendency to buy spontaneously, and the likelihood of sticking with familiar products versus trying new alternatives.
- **Price recording exercise.** The main part of the survey asked respondents to visit

[15] There was also introductory text and comprehension section, explaining the purpose of the survey and participation requirements. To support data quality, respondents were at this stage required to confirm they were not using an incognito browser during participation.

seven different web links corresponding to seven different products, return to the survey, and record the prices for those products. For each product, respondents were also asked to indicate whether they were logged into a personal account on the seller's website. If they were unable to see a price a product, they were instructed to enter "123456." Following this experience, respondents were asked once to share which browser and type of device they were using to complete the survey.

- **Price personalisation perception** questions were included to gauge respondents' awareness of the practice and their attitudes toward it—see Annex B1 for more details.
- **Demographic and vulnerability screening** comprised the final survey section, where respondents answered questions used to classify them into vulnerability group, alongside collecting standard demographic information.

To control for temporal pricing fluctuations and further reduce confounding factors influencing price variation, all platforms were visited within a single day (in November 2025).

2.3.2 Sample

A total of 1,688 respondents were recruited[16] through the online recruitment platform Prolific, representing a broad cross-section of the population (See Annex B2 for more information). The target sample for the survey was divided into four groups to help determine whether there is an association between price variations and certain consumer vulnerabilities: consumers experiencing financial difficulties, consumers reporting a mental health condition, and consumers reporting a form of neurodivergence. Consumer vulnerability was measured using survey questions. Financial vulnerability followed the approach used by the FCA's Financial Lives, while mental health and neurodivergence relied on direct self-reports[17]. More details on the measurement of vulnerability are provided in Annex B3. A fourth group, a control group, was also included to serve as a baseline to compare the effects (if any) associated with the other three groups.

The categorisation of respondents into the four groups was determined through screening questions incorporated within the survey instrument[18]. These questions identified whether participants met the criteria for any of the three vulnerability traits. As these traits are not mutually exclusive, respondents could belong to more than one of the vulnerable groups. However, the control group consisted of respondents who did

[16] Participants were paid £0.70 to take part.

[17] Mental health challenges and neurodivergence were self-reported by participants, while financial vulnerability was inferred from their responses to questions on financial challenges and resilience.

[18] Initially, we planned to use pre-existing participant information from Prolific to categorise respondents. When joining the platform, participants provide extensive demographic and personal details, including whether they have a mental health condition or identify as neurodivergent. However, we found that this information could be outdated, potentially because participants' mental health status or awareness of a condition may change over time. Consequently, we revised our sampling approach to the method described above.

not meet the criteria for any of the three vulnerability traits and therefore served as the comparison group. To ensure adequate representation across the categories, the sampling design aimed for at least 25% of the total sample to fall into each of the four groups[19].

The composition of the sample across the four main respondent groups is shown in Table 2. The percentages across groups sum to more than 100% because the three vulnerability groups are not mutually exclusive; a survey respondent may therefore fall into more than one vulnerability category[20]. The sample also included participants with variation across age, gender, and income levels (see Annex B1).

Table 2. Final survey sample composition achieved by group

Respondent group	Number of responses	Percentage of sample
Financial vulnerability	621	37%
Mental health	809	48%
Neurodivergence	524	31%
Control	544	32%
Total	1,688	100%

Source: Alma Economics survey and analysis.

2.3.3 Randomisation

Each respondent was randomly assigned a subset of seven products from a total pool of 100 products. That is, each participant recorded prices for up to seven products. The assignment of products to participants followed the principles of randomisation, ensuring that each product had an equal probability of being assigned to any given respondent[21].

The data collection process functioned as planned. Most respondents were able to access the web links and record product prices, with only a few minor exceptions. Likewise, the randomisation of products to participants operated as intended. See Annex B4 for more details.

This randomisation strategy was intended to strike a balance between the number of products and the number of participants in the sample. Collecting data from many products and sellers was necessary to reliably assess the prevalence of PP, while also ensuring the inclusion of a large and diverse pool of participants with varied

[19] We were able to partially manage the sampling using Prolific's pre-screening criteria. While these criteria were not fully accurate, they still helped us balance the sample. Additionally, we increased the sample size to further control the composition of the sample.

[20] Among respondents, 45% had one vulnerability, 38% had two, and 16% had all vulnerabilities.

[21] Under this approach, the number of visits per web link / product approximates a normal distribution, resulting in an expected average of approximately 118 visits per link across the sample, typically ranging between 100 and 140. This provided a sufficiently large number of price recordings for each of the 100 products.

characteristics, behaviours, and traits. The approach, therefore, balanced these two aspects of the sample design[22].

2.4 Phase 2: Synthetic profiles approach

We constructed 20 synthetic profiles with varying demographics, traits, and behaviours, which were used to visit 35 products over a four-week period during January-February 2026—four waves of fieldwork. For 34 of the 35 products, prices were collected on four separate occasions during this period, resulting in a maximum of 20×34×4 = 2,720 price observations[23]. The final product examined was related to an online dating platform, for which a different approach was used. For further details, see Box 1 in the Findings section.

The approach involved the following steps.

1. **Determine the sellers to include.** The selection was partly guided by the survey results, focusing on sellers that showed evidence of price variation. We also included sellers where prices are harder to observe through the survey approach, as users must complete several steps or make decisions before the price becomes visible.
2. **Define the synthetic profiles.** We created profiles varying in age, gender, browser type, and device type (laptop versus smartphone). The latter was motivated by survey findings of price differences between laptops and smartphones.
3. **Define the digital footprint.** We simulated vulnerabilities by engaging in online activities designed to reflect specific traits, such as visiting social media groups focused on mental health or financial assistance or searching for terms like “debt advice” or “depression”.
4. **Define the online behaviours.** We designed online behaviours to assess their potential influence on PP. These included 'late-night shopping' (visiting sellers’ websites or apps after 11:00 pm), simulating impulsive behaviour by spontaneously adding items to the online basket, and seeking discounts by sorting products by price or visiting sales sections. We also varied log-in status, with some profiles browsing while logged into personal accounts on sellers’ websites or apps and others browsing anonymously, based on survey findings indicating that log-in status may affect pricing. These behaviours were randomly assigned across the synthetic profiles to ensure they did not confound the effects of consumer demographics or vulnerabilities.
5. **Implement the approach.** This involved manually creating the digital footprint

[22] The sampling strategy also aimed to reduce the risk of triggering dynamic pricing by capping the number of visits per link at approximately 150. This risk was potentially higher for smaller websites or in cases where supply is more limited, such as hotel rooms.

[23] Some websites were not accessible to certain profiles due to the sites blocking them or requesting additional security details, which could not be bypassed at the time. In total, we collected 2,638 prices, which is 82 fewer than the maximum possible of 2,720.

and online behaviours, visiting the selected sellers, and recording prices.

2.4.1 Synthetic profiles

The synthetic profiles were evenly divided between male and female users and spanned an age range from 18 to 70 years, with a balanced representation of younger, middle-aged, and older profiles.

The 20 synthetic profiles were assigned either to one of three vulnerability groups—financial difficulty, mental health challenges, and neurodivergent—or to a control group, with each group containing five profiles.

While financial difficulty, mental health challenges, and neurodivergence do not inherently constitute vulnerabilities, they may in some contexts be associated with increased susceptibility in market interactions. The selection of these was guided by previous research on harmful online choice architecture, indicating that consumers with certain vulnerabilities are disproportionately impacted by such practices[24]. The characteristics and vulnerabilities of the 20 profiles are shown in Table 3.

[24] For example, see a report recently commissioned by Citizens Advice.

Table 3. Synthetic profiles

Profile	Age	Gender	Vulnerability	Browser	Device
1	33	Male	Control	Chrome	Smartphone
2	19	Female	Control	Firefox	Smartphone
3	27	Female	Control	Edge	Laptop
4	42	Male	Control	Brave	Smartphone
5	60	Male	Control	Brave	Laptop
6	29	Male	Financial	Chrome	Laptop
7	50	Male	Financial	Edge	Smartphone
8	19	Female	Financial	Firefox	Smartphone
9	38	Female	Financial	Brave	Laptop
10	63	Female	Financial	Edge	Laptop
11	22	Male	Mental Health	Edge	Smartphone
12	44	Male	Mental Health	Chrome	Laptop
13	70	Male	Mental Health	Brave	Smartphone
14	31	Female	Mental Health	Firefox	Laptop
15	45	Female	Mental Health	Chrome	Smartphone
16	18	Male	Neurodivergence	Firefox	Laptop
17	61	Male	Neurodivergence	Edge	Laptop
18	25	Female	Neurodivergence	Brave	Smartphone
19	45	Female	Neurodivergence	Edge	Smartphone
20	69	Female	Neurodivergence	Chrome	Laptop

The devices used were also evenly split between smartphones and laptops and equally distributed across browser types. Four browsers were used: Chrome, Firefox, Edge, and Brave. Laptops accessed websites via browsers, while smartphones used either mobile applications or websites[25]. Finally, personal accounts were created on all sellers' websites or apps. Most synthetic profiles accessed prices while logged into their seller accounts (15 out of the 20 profiles), while the remaining profiles were not logged in, to assess whether being logged in to a personal account makes a difference.

[25] Most smartphone users accessed products via smartphone apps where available (as some sellers did not have applications), while some smartphone profiles used websites in order to introduce greater profile variability.

Each synthetic profile had an email account (Gmail, Outlook, or Mail), as well as Facebook and Instagram accounts, which were used to create accounts on seller websites and/or apps and facilitate the creation of the digital footprint[26]. These accounts were set up approximately two months before the fieldwork began, and the synthetic users were signed in to them throughout the study.

We used a VPN to vary the IP address for each profile[27]. The VPN did not hide browsing history but provided different IP addresses. The purpose of using the VPN was to mimic real-life behaviour, where users access websites/apps from different locations. The VPN location was always set to London[28].

2.4.2 Traits and digital footprint

Vulnerabilities were simulated by generating digital footprints. All profiles, except for the control profiles, engaged in online activities designed to reflect specific vulnerabilities (e.g., seeking debt advice or information on depression) or other social media behaviours, such as joining particular interest groups and posting content. We considered the ethical implications of our social media activity to minimise any potential impact. For example, commenting on social media posts was strictly prohibited across all platforms, whereas liking posts was restricted to content published by pre-specified groups or institutions, not individuals. The rules of conduct of our social media activity are detailed in Annex C.

Four types of online activity were used to simulate profiles with potential vulnerabilities, as summarised in Figure 1.

[26] Setting up email accounts always required gender and age, and in some cases a phone number. For seller account creation, the required inputs varied, but typically only a name and email address were needed.

[27] The VPN was refreshed each time we changed synthetic profiles and across the four waves of fieldwork. That is, a different IP address was used per profile and wave.

[28] Except for the dating platform, for which we selected alternative locations: London, Manchester, Glasgow, and the Isle of Man.

Figure 1. Digital footprint generation

Google searches	Search **six** relevant keywords on Google and follow a link related to the search. The keywords are specific to the vulnerability (for example, debt help or depression).
Social media and forums	1. Visit a vulnerability-related Facebook group and like three posts 2. Visit a vulnerability-related Instagram group and like three posts 3. Visit three vulnerability-related threads on Reddit 4. Visit a vulnerability-related support group website
email	email a "friend" *(emailed a temporary account created for this research)*
Post on Facebook	Make a post on Facebook wall *(see the social media Rules of Conduct in the Annex for ethical considerations)*

Source: Alma Economics. Table outlining digital footprint across platforms, including Google searches, social media engagement, email communication, and posting on Facebook.

This digital footprint was created before visiting the products and recording prices and was repeated across all four waves.

The control group comprised profiles from diverse demographic backgrounds and engaged in limited online activity beyond visiting the products to collect price data. Specifically, prior to visiting the products, control group profiles accessed their social media accounts (Facebook and Instagram) and visited popular websites (bbc.co.uk, google.com, and youtube.com). This differed from the digital footprint described above, which was created to simulate a vulnerability-specific footprint.

2.4.3 Behaviours

We also examined the extent to which prices vary based on specific types of user behaviours. Four types of behaviours were explored.

1. Late-night shopping: Visiting sellers and recording products after 11 pm.

2. Sales offers and discounts: Where possible, we sorted products by price or visited sections of the sellers' websites or apps featuring sales, low-price items, or special offers before viewing the products. In practice, profiles assigned this behaviour first visited the sites to explore offers, sales, or low-price items, then returned later to record the price of the product.
3. Adding/removing items from the basket: Spontaneously adding and removing a product from the basket before viewing the price. Similar to the behaviour described above, profiles assigned this behaviour first visited the sites, spontaneously added and removed items from the basket, and then returned later to record the price of the product.
4. Browsing products using multiple tabs: Creating a digital footprint by opening multiple tabs within the same browser window. Each product was visited in a new tab within the same window, rather than in a new window, which served as the baseline.

These behaviours were randomly assigned across synthetic profiles, including vulnerabilities and waves.

These behaviours are primarily informed by previous research indicating that they are associated with increased vulnerability to potentially harmful practices. Higher levels of impulsivity, for example, are common symptoms of several mental health conditions and can impair individuals' ability to regulate their spending behaviour. Impulsive tendencies may be further intensified during late-night shopping, particularly when individuals are unable to sleep or wish to conceal their purchasing behaviour from others. In addition, sleep deprivation has been shown to undermine self-control and decision-making, further increasing susceptibility to harmful Online Choice Architecture practices.

2.4.4 Practical aspects

- All digital activity and price recording were conducted by Alma researchers.
- Before visiting the products and recording prices, we created the digital footprint for each profile. This procedure was repeated in each week (wave) over the four-week period. Specifically, prior to visiting the products in each wave, we first visited webpages and social media groups associated with vulnerabilities.
- We used four smartphones and four laptops to conduct the fieldwork. Each device was assigned to a specific vulnerability: one laptop and one smartphone for financial vulnerability, one laptop and one smartphone for mental health vulnerability, one laptop and one smartphone for neurodivergence, and one laptop and one smartphone for the control group. As a result, each device was used for two or three synthetic profiles[29].

[29] We distributed profiles across devices so that age and gender were approximately evenly balanced. In other words, each device included profiles spanning a variety of ages and genders.

- Visits to the products were randomised across profiles and waves.
- Fieldwork was conducted between 9:30 am and 6:00 pm, except for late-night shopping fieldwork.
- For the taxi service platform, to mitigate the impact of dynamic pricing, prices were collected by all synthetic profiles within the same two-hour window.

2.5 Phase 3: Transport sector deep dive

Motivated by the strong indication of price personalisation in the taxi service platform examined in Phase 2, we conducted a deep dive into the transport sector.

Data were collected on three transport sellers: two taxi service platforms and one train operating company[30]. One of the taxi platforms was also analysed in Phase 2, where we identified strong evidence of price variation. The other two sellers were not covered in either Phase 1 or Phase 2.

The approach used to collect price data was similar to that employed in Phase 2. Specifically, we used the 20 synthetic profiles constructed in Phase 2 to visit the three sellers' websites and apps and collect prices[31]. For each wave, all prices were collected within a two-hour period. This follows the same approach used for the taxi service platform in Phase 2. However, there were some differences.

- The digital footprint was constructed only once during the first wave of data collection. In Phase 2, the digital footprint was created at the start of each wave prior to data collection.
- No online behaviours, such as late-night shopping or adding and removing items from the shopping cart, were examined.
- Data was collected over a period of two weeks, compared with four weeks in Phase 2.
- For each seller, price data were collected for three routes. In total, this resulted in price data for nine "products" per wave.
- Three waves of data were collected for two of the sellers, resulting in 180 data points per seller (3 waves × 3 routes × 20 profiles). For the third seller, data were collected across five waves due to technical challenges in accessing profiles. Some profiles were temporarily or permanently suspended, so

[30] Phase 3 took place in March 2026, while Phase 2 took place in January–February 2026.

[31] The same devices used in Phase 2 were also employed. For the taxi service platform analysed in Phase 1, five new seller accounts were created to replace those that had been permanently blocked by the end of Phase 2. The new accounts matched the Phase 2 profiles in terms of name, gender, age, and other characteristics, differing only in email addresses and phone numbers.

additional profiles were created, and extra waves were required to compensate for missing data from certain profiles. For that seller, 217 data points were collected, with the number of price observations varying by profile, route and wave.

For the two taxi service platforms, data were collected for the three routes set out in Table 4—the first two routes are on-demand whereas the third one is pre-booked. In the case of the train operator, the routes are not disclosed in order to avoid identifying the operator.

Table 4. Phase 3 taxi service provider routes

Route	From	To	Time
1	Stratford Station	The British Museum	Pick-up now
2	SE8 3FT	NW6 1JT	Pick-up now
3	SE8 3FT	NW6 1JT	Pick-up tomorrow @7.30

Findings

This section sets out the findings, structured into three main parts corresponding to the three phases.

- Section 3.1 presents the results from Phase 1 (survey-based approach).
- Section 3.2 covers Phase 2 (synthetic profile approach) and presents various analyses, including three case studies.
- Section 3.3 outlines the findings from Phase 3 (transport deep dive).

3.1 Phase 1: Survey-based approach findings

Price differences may reflect recording errors by participants, due to typos or mis-recordings in cases where a website displays multiple prices—for example, original and discounted prices[32]. To address this, all price data were manually verified rather than relying solely on automated processes, ensuring that these potential issues were carefully identified and ruled out.

A five-step process was applied to the data for each product. This began with (1) counting the unique prices in the raw data, (2) adjusting for obvious typos or mis-recordings, and (3) checking against visible pricing options on the website (such as standard versus sale prices shown to all users). The final two steps focused on (4) ensuring that any remaining price differences were consistent across multiple respondents, rather than one-off entries that might reflect recording errors, and (5) exploring the degree to which the differences could not be explained by consumer characteristics or other factors such as login status, time of submission, or device type.

Steps 1 to 4 are discussed in Annex B5 with Step 5 presented in the following text.

Out of the 100 products examined, we found evidence of price variation in eight. We conducted statistical analysis, primarily using summary statistics, to assess whether this variation could be explained by consumer characteristics, vulnerabilities, or other factors. We found that observable factors accounted for variation in four products, whereas the remaining four either showed no association with such factors or had too few instances of price differences to allow clear patterns to be identified. These are discussed further in the following section.

Price variation explained by observed consumer characteristics

Explained price variation based on logged-in status

For one product from an online hotel booking platform, two distinct prices were recorded: £93.47 and £103.86. Out of 115 total observations, 6 respondents saw the lower price, while 109 saw the higher price. A detailed check showed that 83% (5 of 6)

[32] Participants were asked to record the discounted price.

of those seeing £93.47 reported that they were logged in (1 did not provide device information), whereas only 8% (9 of 109) of those seeing £103.86 were logged in, with 92% (100 of 109) either not logged in or not reporting the device they used. This pattern strongly suggests that login status largely accounts for the observed price variation, with logged-in users tending to see lower prices. The difference represents an approximate 11% price disparity based on login status.

Table 5. Login status-based price variation – online hotel booking platform

Price observed	Respondents (n)	Logged in (n, %)	Not logged in/Unknown (n, %)
93.47	6	5 (83%)	1 (17%)
103.86	109	9 (8%)	100 (92%)
Total	115	14 (12%)	101 (88%)

Source: Alma Economics survey and analysis

Explained price variation based on device

In another product from an online train and coach ticket platform, two distinct prices were recorded: £13.50 and £11.00. Among 93 total observations, 84 respondents saw the higher price, while 9 saw the lower. A detailed check revealed that 83% (70 out of 84) of those seeing £13.50 accessed the site via laptop or desktop, whereas 100% (9 out of 9) seeing £11.00 used a smartphone[33]. This pattern strongly suggests that device type can explain the variation in prices observed, with mobile users tending to see lower prices. The difference amounts to approximately 19% price difference based on the device.

Table 6. Device-based price variation – online train and coach ticket platform

Price observed	Respondents (n)	Laptop/Desktop (n, %)	Smartphone (n, %)
£13.5	84	70 (83%)	14 (17%)
£11	9	0 (0%)	9 (100%)
Total	93	70 (75%)	23 (25%)

Source: Alma Economics survey and analysis.

In another product from the same online hotel booking platform discussed above, two distinct price points were noted: £379.65 and £341.69. Across a total of 114 recorded observations, 74 respondents encountered the higher price, while 40 saw the lower one. Closer inspection showed a clear device-related pattern: 92% (68 out of 74) of those who viewed the £379.65 price accessed the site using a laptop or desktop

[33] This is a self-reported metric—we asked participants to state their device type, and it may include misstatements.

computer, whereas 98% (39 out of 40) of those who saw the lower £341.69 price used a smartphone. Smartphone users experienced a price that was 10% lower than that offered to laptop or desktop users[34].

Table 7. Device-based price variation – online hotel booking platform

Price observed	Respondents (n)	Laptop/Desktop (n, %)	Smartphone (n, %)
£379.65	74	68 (92%)	6 (8%)
£341.69	40	1 (2%)	39 (98%)
Total	114	69 (61%)	45 (39%)

Explained price variation based on time of day and device

For the final product from an online coach ticket platform, three different prices were consistently observed: £10.36, £10.38, and £11. Among the 131 observations, 38 respondents were shown the highest price, 45 the middle price, and 48 the lowest price.

Further analysis indicates that these differences may be linked to the time at which the survey was completed. Respondents completing the survey after 1 pm reported a price of £10.36, while those completing it before 1 pm reported prices of either £10.38 or £11.00.

Device type also appears to play a role. As illustrated in Table 8 all respondents who accessed the site before 1 pm using a laptop were shown a price of £10.38, whereas all respondents who saw the £11.00 price accessed the site via a smartphone—a price difference of c. 6%. This finding contrasts with the two cases discussed above, whereby smartphone users were offered lower prices.

[34] Further research could investigate whether vulnerabilities are associated with factors such as device type or browser type, which was beyond the scope of this study.

Table 8. Device and time-based price variation - online coach ticket platform

Price observed	Respondents (n)	Began survey before ~ 1 pm	Began survey after ~ 1 pm	Laptop /Desktop (n, %)	Smartphone (n, %)
£10.36	48	0 (0%)	48 (100%)	46 (96%)	2 (4%)
£10.38	45	45 (100%)	0 (0%)	45 (100%)	0 (0%)
£11.00	38	30 (79%)	8 (21%)	0 (100%)	38 (100%)
Total	131				

Source: Alma Economics survey and analysis.

Unexplained price variation

The four products that exhibited price variation not linked to consumer characteristics that we explored are shown in Table 9. Except for the first product, either only a small number of participants saw a price different from the majority—for example, just five out of 118 for the second product—or the price difference was minimal, as in the case of product 4.

Table 9. Products with unexplained price variation

Seller - Sector	Unique Prices	Price List (with respondent counts)
Seller 1 - Marketplace	2	£6.22 (76), £5.50 (11)
Seller 2 - Marketplace	2	£199.19 (113), £119.19 (5)
Seller 3 - Homeware retailer	2	£764.00 (116), £645.00 (3)
Seller 4 - Event ticketing platform	3	£25.20 (90), £25.00 (3), £25.95 (3)

Source: Alma Economics survey and analysis.

While these instances raise the possibility of personalised pricing, due to purchasing history, for example, or other factors not observed in this study, alternative explanations—such as A/B testing, dynamic pricing mechanisms, or other unobserved variables—cannot be ruled out.

Overall, the survey findings suggest that price variation is limited among the products and sellers examined. We find some evidence consistent with third-degree PP based on device type and log-in status, but this does not appear to be widespread across the products or sellers examined.

3.2 Phase 2: Synthetic profiles approach findings

This section presents the results of the synthetic profile approach. As outlined in the methodology, we constructed 20 synthetic profiles with varying demographics and vulnerabilities, which were used to visit specific sellers and collect prices for a set of 35

products. We conducted four waves of data collection, recording prices for the same products at four points over a four-week period.

In particular, this section includes:

- A summary of price variation, assessing the extent of variation across profiles.
- Descriptive analysis investigating how price variation may relate to synthetic profiles, vulnerabilities, behaviours, and demographics.
- Three case studies that explore in detail selected sellers exhibiting notable (significant or atypical) price variation.
- Additional insights.

3.2.1 Price variation

Of the 35 products within scope, 18 exhibited no price variation, whereas the remaining 17, approximately 50% of them, showed at least some degree of variation. One of these cases involved the dating application—see Box 1.

To analyse the data and assess the intensity of price variation, we defined a reference price as the median price and constructed three metrics. The reference price was wave-specific, as prices may vary over time or across waves due to dynamic pricing or other factors leading sellers to reset prices. In other words, the median price is calculated separately for each wave.

1. **Unique price count:** The average number of distinct prices observed per product across the four waves. If, in one wave, we observe five unique prices and, in the remaining three waves, six unique prices, the unique price count is 5.75.
2. **Price variation incidence:** The proportion of profiles offered a price different from the reference price. A value of 50%, for example, indicates that half of the profiles were exposed to a price that deviated from the reference, while the remaining half were offered the reference price.
3. **Deviation from the reference price:** The average percentage difference from the reference price. A value of 20% means that, on average, the prices that differed from the reference price deviated from it by 20% in absolute terms.
4. **Price variation:** A binary indicator distinguishing between high (H) and low (L) price variation[35]. Price variation is classified as high when the incidence is equal to or exceeds 10%, meaning that more than 10% of profiles observe a different price. Price variation is classified as low when the incidence is below 10%. The 10% cut-off is to some extent arbitrary, but it provides a simple and transparent rule for separating cases with more limited variation from those where variation is more widespread.

[35] For avoidance of doubt, price variation is not linked to potential consumer harm, which is outside the scope of this research.

These metrics for all 16[36] products that exhibited variation are provided in Table 10[37] and are summarised in Table 10.

[36] The seventeenth product is the dating platform discussed in Box 1.

[37] The table is sorted based on the unique price count column.

Table 10. Phase 2 price variation summary

Product	Sector	Unique price count	Price variation incidence	Deviation from reference price	Price variation
Product 1	Taxi service platform	11.8	94%	25%	H
Product 2.1	Secondary ticket marketplace	7.25	63%	4%	H
Product 2.2	Secondary ticket marketplace	5.75	54%	3%	H
Product 3	Travel/holiday agency	5.5	47%	5%	H
Product 4	Accommodation marketplace	3	25%	2%	H
Product 5	Clothing e-commerce retailer	2.75	14%	47%	H
Product 6	Airline	2.5	29%	6%	H
Product 7	Airline	2.25	17%	2%	H
Product 8	Cloud storage and file-sharing software	2.25	28%	6%	H
Product 9	Travel/holiday agency	2.25	14%	13%	H
Product 10	Package holiday provider	2	14%	2%	H
Product 11	Marketplace	1.75	4%	15%	L
Product 12	Ticketing platform	1.5	4%	5%	L
Product 13	Video game platform	1.5	3%	22%	L
Product 14	Accommodation marketplace	1.25	3%	0%	L
Product 15	Coach ticket platform	1.25	3%	9%	L

Source: Alma Economics fieldwork and analysis.

- For Product 1, a taxi service provider, there were, on average, 11.8 unique prices per wave—we observed roughly 12 different prices on average. The incidence of price variation was 96%, meaning that 96% of profiles were offered a price differing from the reference price. The deviation from the reference price was 25%, indicating that when the price differed from the reference, it did so by an average of 25%—see case study 1 for more details.
- Products 2.1 and 2.2 are from the same ticket-selling platform. In both cases, we observed a high number of unique prices—7.25 and 5.75, respectively. The price variation incidence was 63% and 54%, meaning that more than half of the 20 profiles saw a price different from the reference price. The average deviation from the reference price was around 3–4%. See case study 2 for more details.
- Product 4, related to holiday services, exhibits similar variation to Product 3, with an average of 5.50 unique prices per wave, around 50% of the 20 profiles seeing a different price, and an average price deviation of 5% from the reference price.
- Products 5 to 10 show lower variation in unique prices, ranging from 2 to 3 per wave, with an average price variation incidence between 14% and 29%—that is, between three and six of the twenty profiles saw a different price. For most of these products, the average deviation from the reference price ranges from 2% to 6%, with one exception—Product 6 from an online clothing retailer—which shows an average price deviation of 47%. See case study 3 for more details.
- Products 11 to 15 show significantly less price variability across our fieldwork, with more than 95% of profiles seeing the same price.

These five products (products 11–15) are categorised as having low price variability, because the vast majority of profiles saw the same price (price variation incidence of less than 5% meaning that more than 95% of the profiles saw the same price), whereas the remaining 11 discussed above (product 1–11) are classified as having high price variability (price variation incidence of more than 10% meaning that more than 10% of the profiles saw a different price). Therefore, we find that on around one in three of the products within scope, there was a high degree of price variation across profiles.

Box 1: Dating app experiment

The dating app experiment primarily aimed to assess whether prices vary across individuals based on age, building on previous evidence documenting significant price differences. We also examined whether age and location, approximated using a VPN, affect pricing. For this purpose, we used the four locations available through the VPN service used: London, Manchester, Glasgow, and the Isle of Man.

We relied on 16 of the twenty profiles used in the main experiment (eight male and eight female profiles), with ages ranging from 18 to 70. For each profile, a temporary account was created solely to check and record the subscription price. The platform was accessed only once, after which the account was immediately deleted. This different approach was motivated by previous evidence and by technical challenges associated with accessing the platform from the devices used in the main experiment.

We found minimal price variation, with a different price observed for only one of the 16 profiles examined (i.e., less than 5% of the profiles), which is significantly lower than that reported in previous research (see the Executive Summary).

The reference price for the Plus monthly subscription was £9.99. One profile—a 61-year-old male (the third oldest profile) using a London location—was shown a price of £6.99.

3.2.2 Descriptive analysis

This section offers further insights based on additional, largely exploratory analysis, including examination of:

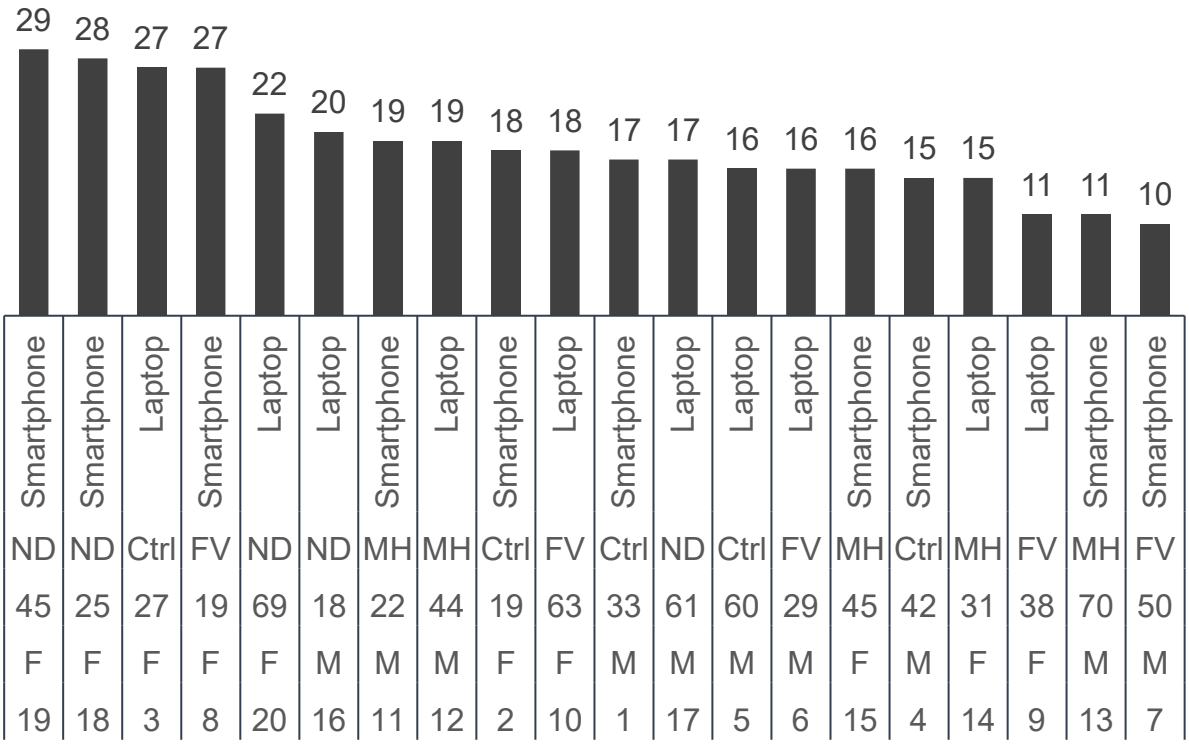
- Price variation across the 20 synthetic profiles.
- Price discounts and premiums among sellers.
- Price discounts and premiums by seller and vulnerability.
- Price discounts and premiums by seller and behaviour.

In cases where significant price variation is observed, we also conduct more sophisticated quantitative analysis (regression analysis) to examine the statistical relationship between prices and profile characteristics. These results are presented in the case studies at the end of this section.

Price variation across the 20 synthetic profiles

Figure 2 presents the number of instances (products × waves) in which each profile was shown a price that differed from the reference price. The number displayed at the bottom corresponds to the profile ID. M and F denote Male and Female, respectively; Ctrl indicates the control group; FV the financially vulnerable group; MH the mental health group; and ND the neurodivergent group.

Figure 2. Price variation by profiles



Source: Alma Economics fieldwork and analysis.

Price variation is not uniform across profiles. For most profiles (11 out of 20), prices differed from the reference price on 15 to 19 occasions. Six profiles (3, 8, 16, 18, 19, and 20) experienced more than 20 instances in which prices diverged from the reference price. Of these six profiles, five are female and four belong to the neurodivergent group. Out of the 10 profiles experiencing the most variation, seven were female. In contrast, three profiles (7, 9, and 13) exhibited fewer price variations, with 10 or 11 instances when the price differed from the reference price.

Price discounts and premiums among sellers

Table 11 presents the number of instances where prices are below the reference price (discounts) and the number of instances where prices are above the reference price (premiums).

Table 11. Direction of price variation by product

Product number	Sector	Discounts	Premiums
Product 1	Taxi service platform	33	32
Product 2.1	Secondary ticket marketplace	25	25
Product 2.2	Secondary ticket marketplace	24	18
Product 3	Travel/holiday agency	22	14
Product 4	Accommodation marketplace	6	11
Product 5	Clothing e-commerce retailer	11	0
Product 6	Airline	12	11
Product 7	Airline	10	3
Product 8	Cloud storage and file-sharing software	0	22
Product 9	Travel/holiday agency	2	9
Product 10	Package holiday provider	10	1
Product 11	Marketplace	0	3
Product 12	Ticketing platform	0	3
Product 13	Video game platform	2	0
Product 14	Accommodation marketplace	0	2
Product 15	Coach ticket platform	0	2

Source: Alma economics fieldwork and analysis.

We have grouped the products into three categories.

- Category 1: Of the sixteen products that exhibit price variation, six show a relatively balanced distribution between prices below and above the reference price. These include products 1, 2.1, 2.2, 3, 4, and 6.
- Category 2: Of the sixteen products that show price variation, four predominantly or exclusively offer prices below the reference price (discounts). These are products 5 (Clothing e-commerce retailer), 7 (Airline), 10 (Package holiday provider), and 13 (Video game platform).
- Category 3: Of the sixteen products that show price variation, six predominantly or exclusively list prices above the reference price (premiums). These include products 8 (Cloud storage and file-sharing software), 9 (Travel/holiday agency), 11 (Marketplace), 12 (Ticketing platform), 14 (Accommodation marketplace), and

15 (Coach ticket platform).

Several interesting cases appear within Categories 2 and 3. Product 5 records 11 instances of price variation, all of which are discounts. Product 8 likewise records 22 instances, all of which are premiums. Product 10 features 10 discounts and only 1 premium, whereas product 9 features 10 premiums and 2 discounts. This implies that sellers exhibiting price variation appear to follow their own pricing strategies.

Price discounts and premiums by seller and vulnerability

Table 12 shows the difference between the number of observed price discounts and price premiums by product and vulnerability. For example, a value of -3 indicates that a particular group for a specific product experienced three more discounts than premiums, while a value of 3 indicates three more premiums than discounts. The purpose is to examine whether certain profile groups consistently experience discounts or premiums compared to others.

Table 12. Direction of price variation by product and vulnerability

Product	Sector	Control	Financial	Mental Health	Neurodivergence
Product 1	Taxi service platform	-3	-4	-3	9
Product 2.1	Secondary ticket marketplace	1	2	-1	-2
Product 2.2	Secondary ticket marketplace	-5	0	0	-1
Product 3	Travel/holiday agency	-4	-3	1	-2
Product 4	Accommodation marketplace	3	0	1	1
Product 5	Clothing e-commerce retailer	-1	-1	-3	-6
Product 6	Airline	-1	1	3	-4
Product 7	Airline	-3	-3	0	-1
Product 8	Cloud storage and file-sharing software	5	5	4	8
Product 9	Travel/holiday agency	0	1	0	6
Product 10	Package holiday provider	-2	-2	-1	-4

Product 11	Marketplace	0	0	3	0
Product 12	Ticketing platform	1	1	0	1
Product 13	Video game platform	0	0	0	-2
Product 14	Accommodation marketplace	1	0	0	1
Product 15	Coach ticket platform	2	0	0	0

Source: Alma economics fieldwork and analysis.

There are four noteworthy cases.

- Product 1 (Taxi service platform): Discounts are mainly observed for the control, financial vulnerability, and mental health groups, whereas neurodivergent profiles predominantly face price premiums. Specifically, there are nine more instances of premiums than discounts for neurodivergent profiles, while the other groups mostly receive discounts.
- Product 9 (Travel/holiday agency): All groups except neurodivergent profiles show a roughly equal number of discounts and premiums. Neurodivergent profiles, however, experience more premiums than discounts, with six additional premium cases compared to discounts.
- Product 8 (Cloud storage and file-sharing software): Similarly, there is an indication that neurodivergent profiles experience more premiums than other profiles.
- Product 2.2 (Secondary ticket marketplace): Across vulnerability traits, discounts and premiums are generally balanced. The exception is the control group, which experiences primarily discounts, with five more discount cases than premiums. Product 5 (Clothing e-commerce retailer): Discounts occur most frequently for profiles associated with mental health conditions and neurodivergence.

Although these findings should be interpreted cautiously, given the small sample size, there is some indication that the neurodivergent group in our sample experienced more price variation, often in the form of premiums, than the other three groups. This does not imply targeted pricing strategies toward neurodivergent individuals but rather highlights a pattern that could be explored further with a larger sample.

Price discounts and premiums by seller and behaviour

Finally, Table 13 presents a similar analysis by product and behaviour. In principle, sorting by price could indicate that consumers are more price-sensitive and therefore more likely to be offered discounts; however, we do not find evidence supporting this. Likewise, profiles simulating impulsive behaviour (add/remove) and late-night shopping

could be less price-sensitive and might therefore experience premiums more often, but our results do not support this hypothesis.

Table 13. Direction of price variation by product and behaviour

Product	Sector	Sort on price	Add/remove	Multiple tabs	Late night shopping
Product 1	Taxi service platform	-2	2	-3	NA
Product 2.1	Secondary ticket marketplace	3	1	-1	2
Product 2.2	Secondary ticket marketplace	2	1	-3	-3
Product 3	Travel/holiday agency	2	2	0	2
Product 4	Accommodation marketplace	-2	-1	0	4
Product 5	Clothing e-commerce retailer	-1	-1	0	-1
Product 6	Airline	1	1	0	-2
Product 7	Airline	1	0	-2	-2
Product 8	Cloud storage and file-sharing software	1	1	0	0
Product 9	Travel/holiday agency	0	1	-1	0
Product 10	Package holiday provider	-1	-3	0	-3
Product 11	Marketplace	0	0	1	0
Product 12	Ticketing platform	0	0	1	2
Product 13	Video game platform	0	0	0	-1
Product 14	Accommodation marketplace	0	0	0	1
Product 15	Coach ticket platform	0	0	0	0

Source: Alma Economics fieldwork and analysis.

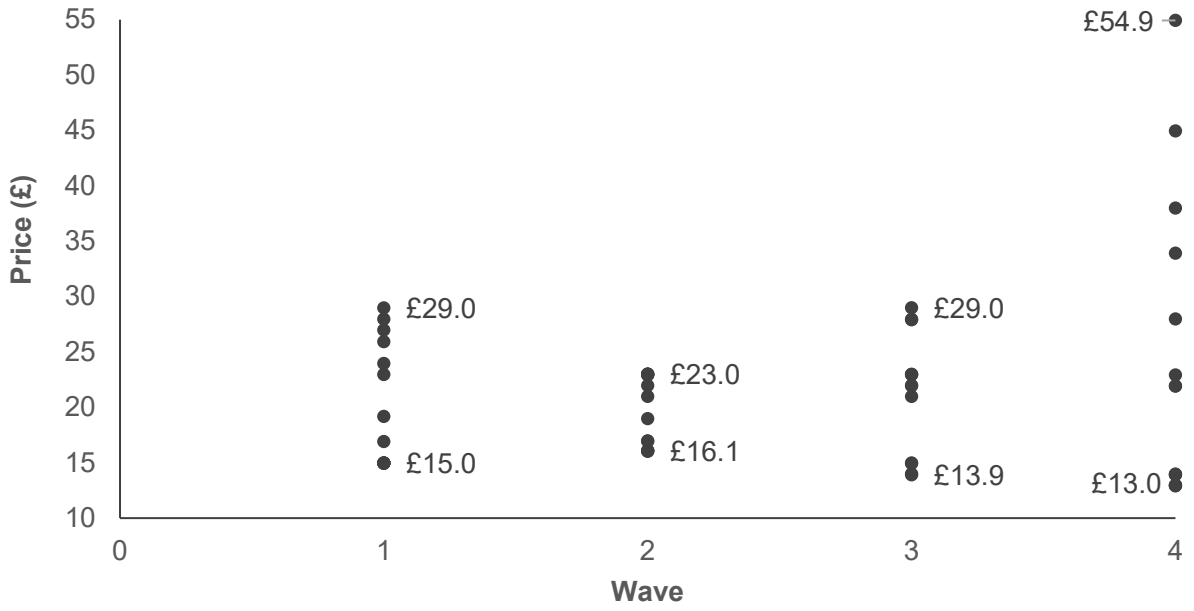
Overall, we do not observe a systematic relationship between specific behaviours and particular price patterns. These findings should nevertheless be interpreted with caution

due to the small sample sizes and the inherent limitations of simulating such behaviours using synthetic profiles.

3.2.3 Case study 1: Product 1 - Taxi service platform

This section offers additional analysis and findings concerning Product 1 related to a taxi service platform for which we observed the highest variation. Figure 3 shows the price variation across waves. Across all profiles and waves, we focused on the same route (from a specific origin to a specific destination), looking for the cheapest fare option[38]. There is considerable variation in all waves, particularly in wave 4, where prices range from £13 to £55. Waves 1 and 2 show price ranges from £14 or £15 to £29. Wave 2 exhibits less variability, but it remains substantial, with prices ranging from £16.1 to £23. This variation may reflect both price personalisation and dynamic pricing, or a combination of the two—personalised pricing itself can vary over time depending on market conditions.

Figure 3. Product 1: Price variation by wave

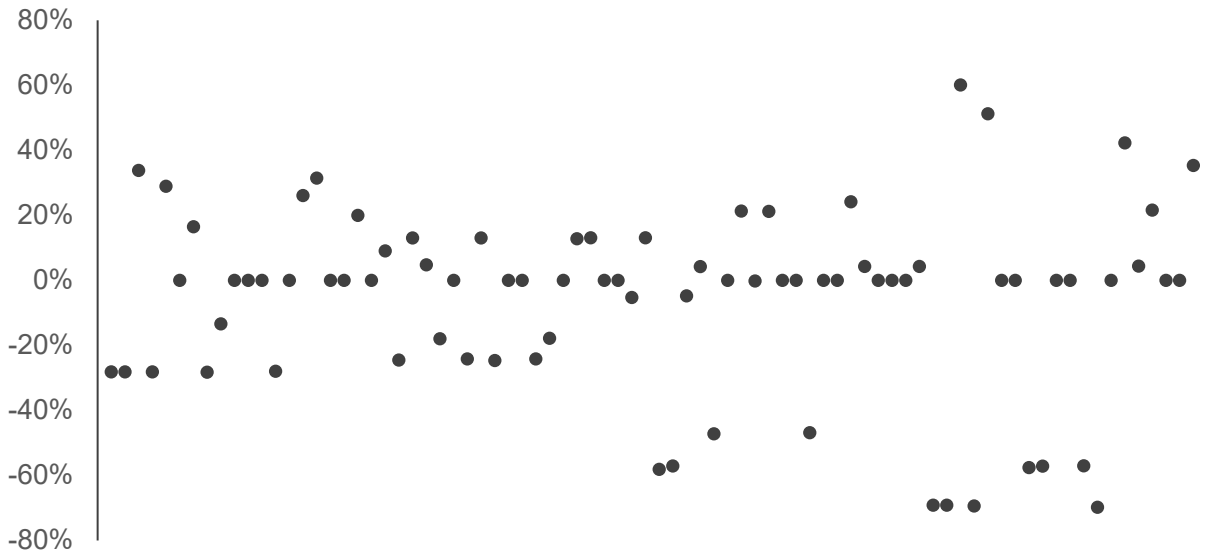


Source: Alma Economics fieldwork and analysis.

Figure 4 shows the percentage difference of all prices collected from the reference price and conveys a similar story to the previous data. That is, a large proportion of profiles experienced a different price, and the prices varied considerably across profiles.

[38] The same option was consistently examined, so the observed price variation is not driven by differences in taxi options.

Figure 4. Product 1: Deviation from reference price



Source: Alma Economics fieldwork and analysis.

We investigated the extent to which the observed price variation could be explained by synthetic profile characteristics, including gender, age, device, and browser. To do so, we exploit the significant variation observed for this product and estimate regression models capturing the multivariate relationship between prices and these characteristics. The results, presented in Table 14, are quite striking.

Table 14. Product 1: Regression analysis

	ALL	Desktop	Smartphone
Gender (Female == 1)	0.25***	0.44***	0.27***
Age (log)	0.18**	-0.02	0.31***
(Browser)x(Desktop)			
Chrome	-0.04		
Firefox	0.34***	0.35**	
Edge	0.30**	0.14	
Brave	-0.20	-0.35*	
Sample size	69	30	39
R-squared	29%	53%	31%

Note: Regression models estimated using Ordinary Least Squares; the dependent variable is the log of price; The models include an intercept and time dummies to account for potential differences in mean prices across waves; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; source: Alma Economics analysis.

We report three models: one using all data, and two separate models splitting the data by desktop and smartphone devices. In all models, we include time variables to control

for differences in prices across waves, thereby explicitly accounting for dynamic pricing across waves.

Across all models, being a female is associated with approximately 25% higher prices, with the effect more pronounced on laptops[39]. Specifically, on laptops, prices for female profiles are 44% higher than for male profiles, whereas on smartphones, the difference is 27%.

Age is also positively associated with price, particularly on smartphones; this relationship does not appear to hold for laptops, where the coefficient of age is small and not statistically significant. For smartphones, the estimated coefficient indicates that a 10% increase in age is associated with a 3.1% increase in price, which is economically significant[40]. For example, the predicted price difference between a 25-year-old and a 50-year-old smartphone user is approximately 21%[41].

Additionally, laptops tend to show higher prices than smartphones when the platform is accessed via Firefox or Edge; however, the browser-specific results should be interpreted with caution due to the low number of observations per browser.

These findings reinforce the view that the observed price variation for this product cannot be explained by dynamic pricing, as dynamic pricing alone cannot account for correlations between prices and consumer characteristics.

Interestingly, when the accounts were set up, we did not provide gender or age information—only an email address. However, creating the email accounts themselves required both gender and date of birth. Gender may also be inferred from the name. Indeed, the platform appears to have identified gender, as it is displayed under the personal information section of the account details[42]. As we did not provide this information directly, this suggests that the platform inferred it from the name or other available data. Regarding age, this would only be possible to identify from the information provided during the email account creation.

We estimated several additional models, altering aspects such as the sample (e.g., different waves, excluding large price changes), variable transformations, and employing clustered standard errors to test the robustness of our results. Despite the relatively small sample size, the findings remain largely consistent. Although the coefficient estimates show some variation across these sensitivity checks, they continue to be both economically and statistically significant. In summary, a considerable part of the

[39] The dependent variable is in logarithms, so the coefficient estimates represent either semi-elasticities or elasticities. For binary variables such as gender, device, and browser (coded 0/1), the coefficients represent semi-elasticities. For example, a coefficient of 0.3 indicates that changing the variable from 0 to 1 (e.g., being female) is associated with a 30% increase in price. The age variable is also in logarithms, so its coefficient represents an elasticity. In this case, a coefficient of 0.3 means that a 1% increase in age is associated with an average 0.3% increase in price.

[40] Economically significant refers to an effect that is material or large enough to have important practical or real-world implications.

[41] (ln(50)-ln(25))*0.31 = 21%

[42] This was not consistent across all profiles examined. In some cases, the platform identified the profile's gender, while in others it did not.

observed price variation on product 1 is associated with factors such as gender, age, and device, providing a strong indication of personalised pricing.

Furthermore, we estimated models including vulnerability variables to capture any differentiated pricing between the control and vulnerability groups. While we found economically significant differences between the control group and vulnerable groups, these differences were not statistically significant.

This finding does not preclude the possibility that vulnerable consumers may, in practice, face higher prices. In certain contexts, specific groups could plausibly be perceived as more vulnerable. For example, women requesting a taxi at night or travelling with children may have fewer alternatives and a greater urgency to secure transport. Similarly, older customers may be more likely to experience mobility constraints, thereby limiting their available options.

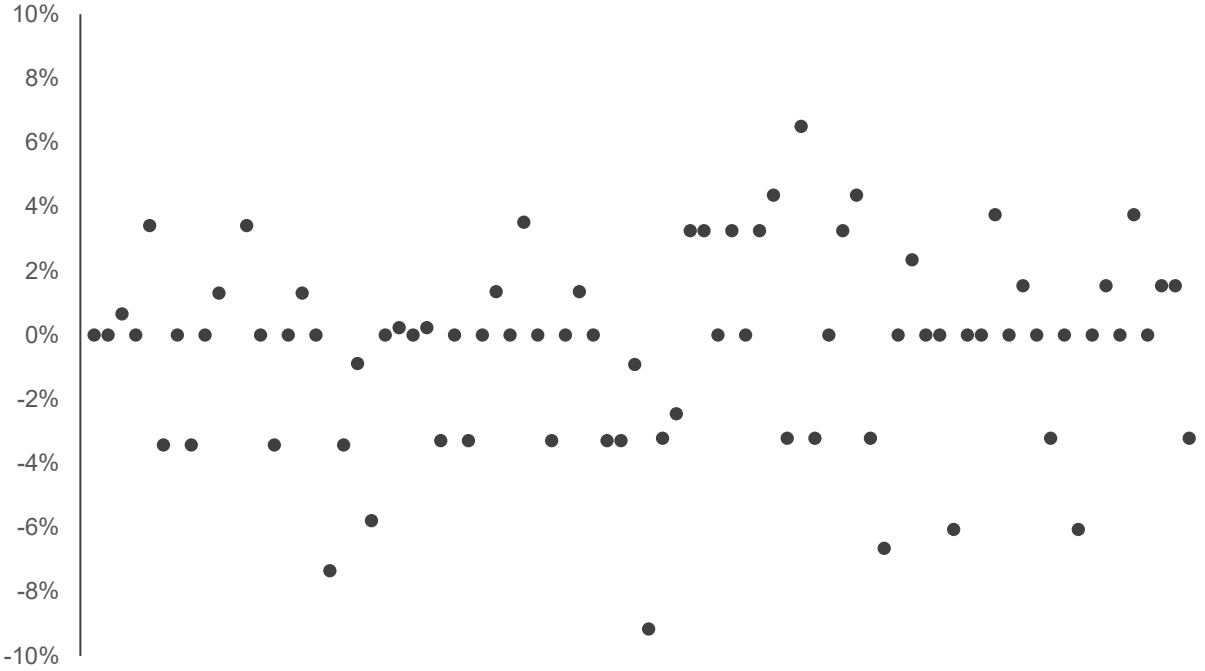
3.2.4 Case study 2: Products 2.1 and 2.2 - Ticket resale platform

This section provides additional insights for Products 2.1 and 2.2, for which we found significant price variation. Both products refer to the same seller, a ticket resale platform. The two tickets we explored were: A Night at the Opera by Candlelight (feat. Nessun Dorma)—two general admission tickets—and the Olivia Dean concert—one floor section ticket. In both cases, prices were analysed for the same date and event location.

Figures 4 and 5 show the price variation—the percentage difference of each recorded price from the reference price. For Olivia Dean (Product 2.2), a price differential of around 66% was observed but excluded from the plot to allow for better visualisation of the remaining results[43]. With the exception of this observation, the percentage difference from the reference price is always below 10% and typically below 7%. While the price deviations are not large, they appear to be consistent, indicating that consumers are more likely to encounter a price that differs from the reference price.

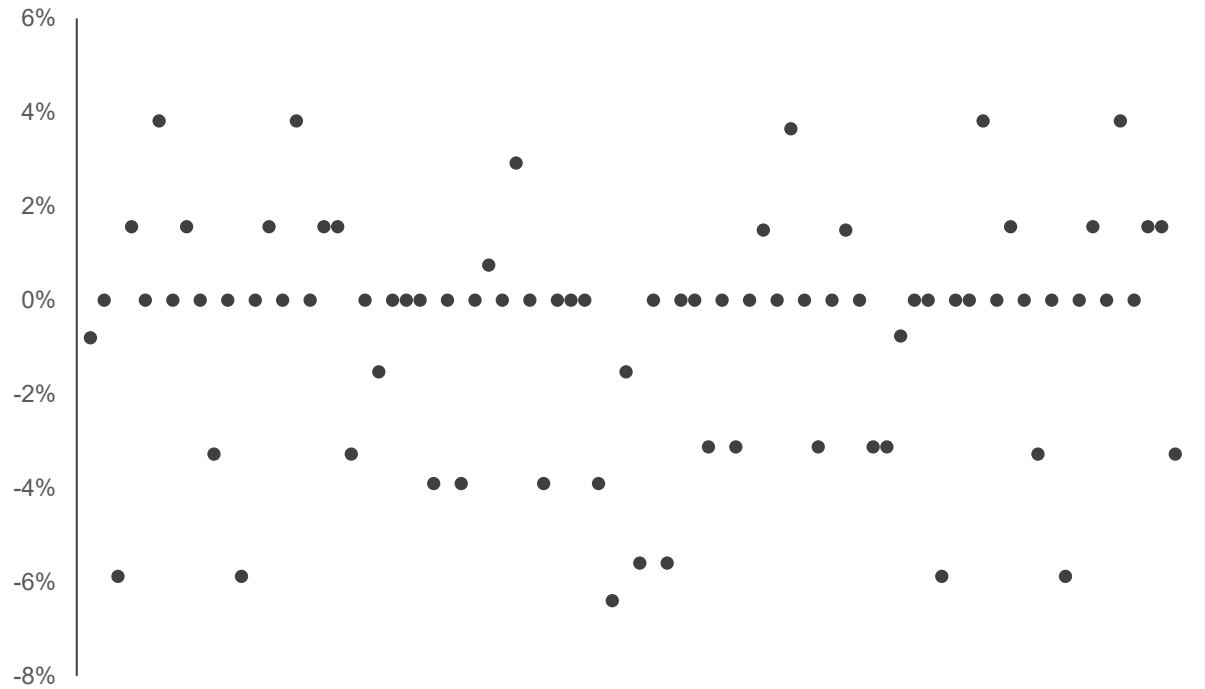
[43] This price was 66% lower than the reference price and was observed for synthetic profile 11, representing a 22-year-old male with mental health challenges using a smartphone.

Figure 5. A Night at the Opera (Product 2.1): Deviation from reference price



Source: Alma Economics fieldwork and analysis.

Figure 6. Olivia Dean (Product 2.2): Deviation from reference price



Source: Alma Economics fieldwork and analysis.

Similar to the first case study, we exploit the significant variation observed for this seller and estimate regression models to examine the extent to which prices are correlated with specific profile characteristics and vulnerabilities (see Table 15 for a sample of

these models)[44]. In both cases, we found correlations that are close to zero and not statistically significant, indicating no relationship between prices and these factors. The only exception is for Olivia Dean prices, where we observed a negative correlation between prices and gender, with male profiles seeing prices that were, on average, 1.3% lower. These findings suggest that price variation is not strongly linked to observed characteristics, apart from a small association with gender in one of the two products.

Table 15. A Night at the Opera and Olivia Dean: Regression analysis

	A Night at the Opera (Product 2.1)	Olivia Dean (Product 2.2)
Gender (Female ==1)	0.01	-.013**
Age (log)	0.02	0.00
Device (Smartphone==1)	-0.02	0.00
Sample size	80	78
R-squared[45]	46%	47%

Note: Regression models estimated using Ordinary Least Squares; the dependent variable is the log of price; The models include an intercept and time dummies to account for potential differences in mean prices across waves; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; source: Alma Economics analysis.

3.2.5 Case study 3: Product 6 - Clothing retail platform

Product 6 is offered by a clothing retail platform, and the only product where all prices that differed from the reference price were associated with a discount—these were visible discounts offered on the platform. Another notable insight is that these discounts were substantial, with the average discount observed being 47%[46].

[44] We also estimated a pooled model, combining all data across both products to increase the sample size and the statistical power of the analysis. Even in this case, we found no effects that were statistically and/or economically significant.

[45] The relatively high R-squared reported are primarily driven by the time effects.

[46] The magnitude of discounts was similar across waves.

Figure 7. Product 6: Deviation from reference price



Source: Alma Economics fieldwork and analysis.

There were eleven instances of observed price discounts affecting six profiles. Two of these profiles received discounts consistently (in three or all four waves), while the remaining four received a discount only once.

We also examined whether these discounts were correlated with any observed consumer characteristics. There were some associations with device type and gender: smartphones and female profiles were somewhat more likely to receive a discount. The strongest correlation was with logged-in status—every profile that received a discount was logged in. We cannot rule out the possibility of personalised discounts; however, a larger sample would be needed to test this.

3.3 Phase 3: Transport sector deep dive findings

Table 16 summarises price variation across the nine cases—three sellers and three routes per seller—within Phase 3. As discussed in the methodology section, Phase 3 focuses on the transport sector, motivated by findings from Phase 2, and examines two taxi service platforms and one train operator[47].

[47] The approach used in Phase 2 differed slightly from that used in Phase 3, as discussed in the methodology section.

Table 16. Phase 3 price variation summary

Seller	Route	Unique price count	Price variation incidence	Deviation from reference price	Price variation[48]
Taxi service provider 1	3 (pre-booked)	13.6	97%	14%	H
Taxi service provider 1	1	13.2	98%	16%	H
Taxi service provider 1	2	11.3	89%	11%	H
Taxi service provider 2	3 (pre-booked)	3.7	45%	27%	H
Taxi service provider 2	1	2.3	13%	18%	H
Taxi service provider 2	2	1.7	10%	23%	H
Train operator	3	1.7	7%	3%	L
Train operator	2	1.3	2%	39%	L
Train operator	1	1.0	0%	-	None

Source: Alma Economics fieldwork and analysis.

- Almost all cases, eight out of nine, exhibited some degree of price variation.
- In six of these eight cases, there was high variation intensity, defined as a price variation incidence of 10% or greater (meaning that at least 10% of profiles observed a price different from the reference price).
- For the first taxi service platform, a similar pattern was observed across all three routes. That is, almost every profile observed a different price, with differences ranging between 11% and 16%. This variation is consistent with that observed for the same platform in Phase 2.
- For the second taxi service platform, the pre-booked route (Route 3) exhibited substantial price variation, with a price variation incidence of 45%, meaning that almost half of the profiles (approximately 10 out of 20) observed a different price.

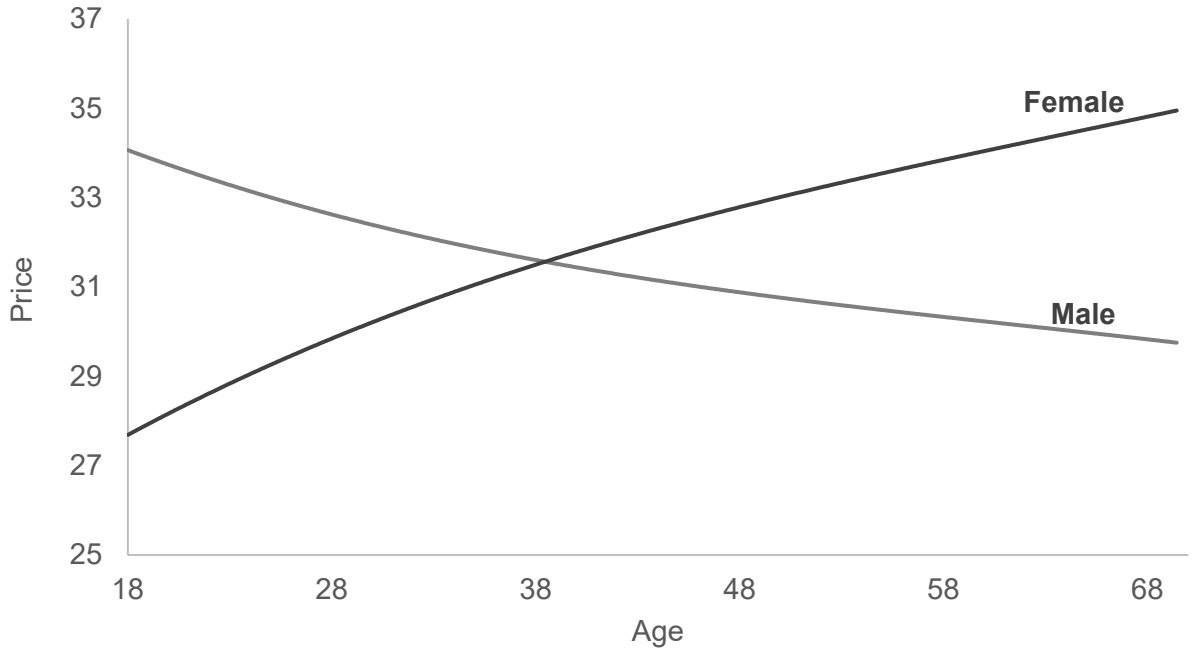
[48] A binary indicator distinguishing between high (H) and low (L) price variation. Price variation is classified as high when the incidence is equal to or exceeds 10%, meaning that more than 10% of profiles observe a different price. Price variation is classified as low when the incidence is below 10%.

- In both taxi platforms, price variation for the pre-booked route (Route 3) was higher than for the on-demand routes (Routes 1 or 2).
- For Routes 1 and 2 on the second taxi service platform, price variation was observed only in the third wave; in the first two waves, no variation was detected. Interestingly, for Route 1, 7 out of 20 profiles observed a price different from the reference price, while for Route 2 this was the case for 6 profiles. All six profiles that observed a different price for Route 2 also observed a different price for Route 1.
- For the train operator-Route 3, two prices were observed: £30 and £31, with 24 out of 60 cases observing the higher price. For the second route, only one profile observed a different price: £32.40 instead of £48. This was Profile 7 (age 50; male; financial; smartphone user).

We also explored the correlation between prices and profile characteristics.

- We found a material correlation in the case of the first taxi platform between price variation and age, gender, and device type. Specifically, higher age was associated with higher prices for female profiles, whereas higher age was associated with lower prices for male profiles—see Figure 8. We also found that smartphone profiles were associated with higher prices for male profiles (c. 12%) and lower prices for female profiles (c. 14%). This represents a materially different relationship from that identified in Phase 2 for the same taxi service provider (albeit for a different route).

Figure 8. Taxi service provider 1: Relationship between price, age and gender



Note: These are predicted prices from a regression model in which log(price) is regressed on age, gender, and device type, including interaction terms between the explanatory variables.

- For the second taxi service provider, Route 3—where considerable price variation was observed—we found that prices are correlated with device type, with smartphone profiles experiencing approximately 10% higher prices than desktop profiles.
- For the remaining products, the lower level of price variation makes it difficult to identify clear patterns in relation to profile characteristics.

Key Findings and Conclusion

This section summarises the key findings, outlines the study's limitations, and presents the conclusions.

4.1 Key findings

Phase 1: Survey-based approach

- Out of the 100 products we investigated using the survey-based approach, we found evidence of price variation in eight cases.
- In four of these cases, the observed price differences could be explained by device type and log-in status. Specifically, in one case, variation was associated with log-in status: users who reported being logged in at the time of the visit observed prices that were, on average, 9% lower. In two cases, variation was explained by device type, with smartphone users observing lower prices (19% and 10%, respectively) compared with desktop or laptop users. In one additional case, price variation was associated with device type, with smartphone users observing prices 6% higher than those on desktop or laptop devices.
- Device type may reflect consumer characteristics or traits, including age and income, which could lead to differences in willingness to pay. Future research could explore the link between device type and pricing practices, as well as the association between device type and consumer traits, to shed further light on these relationships.
- In the remaining four cases, we were unable to identify any association between price variation and observed participant characteristics. This could be explained, at least in part, by the small number of participants observing different prices.
- Overall, the survey approach provides evidence of a low prevalence of price variation: for the vast majority of products explored, most participants observed the same price.

Phase 2: Synthetic profiles approach

- Out of the 35 products we investigated using the synthetic profile approach, we found evidence of price variation in 16, while the remaining 18 showed no variation. In other words, for these 16 products, different profiles observed different prices, whereas for the remaining 18, all profiles experienced the same price.
- One product—a route related to a taxi service platform—displayed notable differences, with almost all profiles experiencing a different price with an average price roughly 25% above or below the reference (median) price.
- A ticket resale seller also demonstrated substantial variation. For the two products

we explored for that seller, over 50% of profiles encountered a different price from the reference price, with an average price difference of 3–4%.

- Eight additional products showed material price variation[49], while the remaining five had only minimal differences. Overall, roughly one in three products explored using the synthetic profile approach exhibited a high degree of price variation.
- Of the platforms that exhibit price variation, six show a relatively balanced distribution of prices below and above the reference price (median price). Four predominantly or exclusively offer prices below the reference price (discounts), whereas six predominantly or exclusively list prices above the reference price (premiums).

For products showing a high degree of price variation, we examined whether these differences could be attributed to specific profile characteristics. In most cases, however, we were unable to link the observed variation to profile characteristics in this study, which is not unexpected given the small sample size and the inherent limitations of reverse-engineering pricing strategies.

However, there are a few exceptions.

- One notable exception is the taxi service platform, where we find strong evidence that price variation is linked to consumer characteristics. Specifically, we found that female profiles, on average, experienced 25% higher prices than male profiles for the specific route explored. Age was also correlated with price, with the estimated difference between a 25-year-old and a 50-year-old smartphone user/profile around 21%. Device type also mattered, with profiles using smartphones generally facing lower prices than profiles using laptops. Overall, the magnitude of price variation observed for this platform and the association with profile characteristics are consistent with first-degree PP.
- We also found some evidence of greater variability among female and neurodivergent profiles. We identified six out of the twenty synthetic profiles as experiencing high price variability. Of these, five were female (out of ten female profiles), and four were neurodivergent (out of five neurodivergent profiles), suggesting a higher incidence of substantial price variability within these groups.

Finally, we found some evidence consistent with a pricing strategy that combines dynamic pricing and PP, with the extent of personalisation appearing to vary with market conditions. In particular, both the level of price variation and the profiles experiencing it often differed across waves, suggesting that PP may be complex and dependent on additional factors, including market conditions.

Phase 3: Transport deep dive

- Almost all cases within the scope of Phase 3—eight out of nine—exhibited some

[49] Several alternative prices offered and/or a non-negligible (10%+) profiles experienced prices different from the reference price.

degree of price variation, with six of these eight cases showing high variation. This was particularly evident for the two taxi service platforms, and to a lesser extent for the train operator.

- For the first taxi service platform (the same platform examined in Phase 2), almost every profile observed a different price, with differences ranging between 11% and 16%, consistent with the findings from Phase 2.
- For the second taxi service platform, price variation was high but to a lesser extent.
- We found a high correlation in the case of the first taxi platform between price variation and age, gender, and device type. However, the pattern of correlation differs materially from that identified in Phase 2 for the same taxi service provider (albeit for a different route). This suggests that personalisation may be route dependent.
- For the second taxi service provider, and for one route—where considerable price variation was observed—we found that prices are correlated with device type, with smartphone profiles experiencing approximately 10% higher prices than desktop profiles.

4.2 Limitations

The findings of this study should be interpreted in light of its limitations. Across both approaches, the analysis was restricted to a relatively small selection of products, typically tracking only a single product per seller over a short period. This limitation was particularly pronounced in the synthetic profile approach and may help explain the lack of correlation between price differences and profile characteristics. In other words, the relatively small sample size should be taken into account when interpreting the results, particularly given the challenges of identifying strong correlations between prices and consumer characteristics, which typically require larger samples.

Some of the price variation attributed to personalisation may, in part, reflect the influence of dynamic pricing. While several mitigation measures were taken to reduce the impact of dynamic pricing and other time-dependent factors, it is possible that some of the variation identified still remains attributable to these influences.

For the synthetic profile approach, we used specific profile characteristics and behaviours to trigger potential PP, while many other characteristics or behaviours might be missing, for example:

- Purchasing history: Synthetic profiles did not have a purchasing history, which may influence price variation and personalisation in the real world.
- Vulnerabilities: Vulnerabilities were simulated based on digital footprints, primarily through website visits and social media group activity, and it is likely that these did not accurately reflect the individuals' characteristics.

- Behaviours: Similarly, behaviours were simulated using a finite, predefined set, which may not fully capture real consumer actions and behaviours. In addition, behaviours were simulated over a relatively short time window, whereas price personalisation may be triggered when such behaviours occur over a longer time frame.
- Online journeys: The consumer journey can influence prices—both within a seller's website and through external sources such as aggregator sites and search engines—whereas our approach, which relied on limited and specific journeys, may not have fully captured these dynamics.
- Unobserved factors: There may be other consumer characteristics or behaviours that are used by sellers to personalise prices which may be missing from our research design, therefore under-estimating PP.

The survey-based approach may face a similar limitation, though to a lesser extent. The main limitation relates to online journeys. Our survey approach used direct links that participants clicked to access sellers' websites. As a result, it may not have fully captured the diversity of real consumer journeys, both within a seller's website and via external channels such as aggregator sites, personalised ads, and search engines.

For both the synthetic profiles and survey approaches, these limitations suggest that the variety of personal characteristics, journeys, and behaviours is under-represented relative to actual consumer behaviour, which in turn implies that price personalisation may be under-detected in our analysis.

4.3 Practical challenges and future research

The synthetic profile approach used in Phases 2 and 3 was particularly challenging to implement. We had to create accounts on social media platforms, email providers, and seller websites. This was often difficult to manage from a single device, so multiple devices were used, and the process required phone numbers and one-time passwords (OTPs). Importantly, some social media providers blocked accounts, meaning we had to recreate them before data collection began. In addition, some sellers temporarily or permanently blocked accounts.

To the best of our knowledge, this is the first time a synthetic profile approach has been implemented at this scale, and we therefore operated in relatively untested territory. Future research using synthetic profiles would benefit from using a single device per profile, together with a dedicated phone number for OTP verification, and from creating accounts (social media and seller accounts) gradually, using multiple devices.

4.4 Conclusion

This conclusion reflects the contributions of two legal scholars, Miroslava Marinova and Germán Johannsen, whose views are presented as part of the report's analysis. Taken

together, their observations suggest that there could be limited application of current law to the complex practices involved in algorithmic personalised pricing.

A central theme emerging from both contributions is the need to develop a clearer theory of harm in digital markets. While the evidence suggests that price differences are not widespread across all sectors, they appear frequently in certain sectors where firms have strong data capabilities. In this context, the research exposes the limits of traditional categories such as first- and third-degree price discrimination: what was once a clear distinction between group-based segmentation and theoretical individual pricing has become blurred. The categories of customer segmentation that underpin these practices are often not transparent to consumers, marking a significant departure from widely accepted and more visible group pricing strategies such as student discounts. Marinova argues that, in the digital economy, the key concern is no longer simply the price outcome but "whether consumers are able, in practice, to understand and respond to them... consumers may be unable to assess the basis on which prices are set or to compare outcomes across users. Observable price differences may indicate that pricing varies across users, but do not, on their own, reveal whether the underlying mechanism is transparent and contestable or opaque and resistant to effective consumer response."[50] Where pricing depends on inferred behaviour or hidden data, consumers may no longer be able to compare offers or exercise effective choice.

This is particularly relevant given the increasingly blurred distinction between personalised and dynamic pricing. While dynamic pricing traditionally refers to price changes based on market conditions such as supply, demand or timing, in digital environments the two approaches often overlap, making it unclear to consumers whether a price reflects general market fluctuations or individual targeting. Personalised pricing itself may also fluctuate in response to market conditions, meaning that prices can vary both across consumers and over time. Although consumers tend to view dynamic pricing more favourably when it is clearly linked to market conditions, evidence consistently finds that consumers react more negatively when similar price variation appears personalised.[51] Together, these observations point towards the need for a clearer theory

[50] Miroslava Marinova, *Comments on the Draft Report: Price Personalisation: Evidence from the UK Online Market* (2026).

[51] See Annex B1 for our survey results, where 71% of participants felt negatively about price personalisation. See also

Gerrit Hufnagel, Manfred Schwaiger and Louisa Weritz, '*Seeking the Perfect Price: Consumer Responses to Personalized Price Discrimination in E-Commerce'* (April 2022) 143 Journal of Business Research 346.

Xi Chen, David Simchi-Levi and Yining Wang*, 'Privacy-Preserving Dynamic Personalized Pricing with Demand Learning'* (October 2021) Institute for Operations Research and the Management Sciences.

Gabriele Pizzi, Virginia Vannucci, Yupal Shukla and Gaetano Aiello*, 'Privacy Concerns and Justice Perceptions with the Disclosure of Biometric Versus Behavioral Data for Personalized Pricing: Tell Me Who You Are, I'll Tell You How Much You Pay'* (2022) 148 Journal of Business Research 420.

Ana Isabel Canhoto, Brendan James Keegan and Maria Ryzhikh, *'Snakes and Ladders: Unpacking the Personalisation-Privacy Paradox in the Context of AI-Enabled Personalisation in the Physical Retail Environment'* (14 January 2023; published in Information Systems Frontiers 2024) 26.

of harm that focuses on situations in which consumers cannot effectively understand, compare, or respond to prices.

Johannsen highlights the need to move beyond treating different digital practices in isolation. He argues that the key issue is not simply whether consumers are charged different prices, but how prices are set and how personalisation practices influence the consumer decision-making process.[52] In practice, personalised pricing, dynamic pricing, behavioural targeting, and the design of online interfaces frequently operate together rather than as separate processes. Consumers may find it difficult to distinguish whether a particular price reflects market conditions, behavioural profiling, personalised targeting, or some combination of these factors. Johannsen therefore recommends **a policy approach that treats algorithmic pricing holistically, recognising that these practices form part of a broader commercial strategy rather than discrete regulatory categories**. These observations are consistent with wider discussions on digital fairness, which focus on how consumers interact with increasingly complex digital environments.[53] In this context, potential disadvantage may arise not only for particular groups, but can arise situationally from switching costs, limited transparency, and the structure of digital markets

A further concern raised by Johannsen is the potential for personalised pricing to contribute to discriminatory outcomes. The report's preliminary findings on the use of demographic data suggest that personalised pricing may, in certain contexts, function as a mechanism for systematic discrimination along protected characteristics. In light of these concerns, Johannsen advocates consideration of **sector-specific ex ante regulation where personalised pricing is persistent**, widespread, and linked to protected characteristics, alongside stronger enforcement where systematic discrimination is identified. He also suggests that evidence of such practices could warrant a formal market study or investigation by the competition authority.

Both scholars also highlight **possible implications for competition policy.** Current legal frameworks address some aspects of algorithmic pricing but do not clearly recognise personalised pricing as a distinct regulatory category. As Marinova demonstrates, data protection law, including the UK GDPR, regulates the use of personal data through principles such as fairness and transparency but does not directly address pricing outcomes. At the platform level, frameworks such as the Digital Markets Act and the UK's Digital Markets, Competition and Consumers Act introduce additional obligations for firms with significant market power, although neither directly regulates personalised pricing as a standalone practice. Consumer law similarly does not prohibit dynamic or variable pricing but instead focuses on fairness, transparency, and the provision of material information. By contrast, Article 6 of the EU Consumer Rights Directive requires traders to inform consumers when prices are personalised using

[52] Germán Johannsen, *Comments on the Draft Report: Price Personalisation: Evidence from the UK Online Market (2026).*

[53] Natali Helberger and others, *Digital Fairness for Consumers* (BEUC 2021); BEUC, *Each Consumer a Separate Market*? (2023).

automated decision-making, while the Unfair Commercial Practices Directive focuses on whether commercial practices distort consumer behaviour.[54] These provisions do not apply directly in the UK following Brexit, although UK consumer law contains analogous requirements relating to fairness, transparency, and the provision of material information.

Marinova further suggests that personalised pricing could, in certain circumstances, be considered an exploitative abuse of dominance under Chapter II of the Competition Act 1998, drawing on excessive pricing case law such as United Brands. However, both scholars recognise significant limitations. Competition law requires proof of dominance, and there is currently no clear or established theory of harm for algorithmic personalised pricing. Moreover, concerns may arise even where no firm holds a dominant position. The growing use of algorithmic pricing tools, particularly where supplied by third-party providers or adopted across multiple firms, raises broader questions about competition. For example, algorithms may facilitate tacit coordination or increase alignment in pricing outcomes, potentially softening competition or sustaining higher prices even in circumstances where traditional forms of collusion would be difficult to establish. These issues suggest that further consideration should be given to the role that competition law may play in addressing algorithmic pricing practices, particularly in relation to dominant firms and the wider competitive effects of pricing technologies.

Both scholars identify **a need to strengthen transparency measures.** Johannsen recommends extending reference-pricing rules to personalised and dynamic prices, for example by requiring firms to display the lowest price offered in the previous 30 days alongside the current price.[55] This would provide consumers with a meaningful benchmark against which to assess prices and could reduce the scope for dynamic pricing to obscure personalised pricing[i]. Such a requirement would go beyond existing transparency obligations, which generally require businesses to provide clear information about their pricing practices but do not require disclosure of historic pricing benchmarks. Marinova similarly argues that the development of an evidence-based theory of harm, potentially through future competition law enforcement, will be an important step in determining whether more targeted forms of regulation are required.[50] Emerging international developments, such as the New York Algorithmic Pricing Disclosure Act (2025), also indicate growing regulatory interest in these issues, although further evidence will be required to assess the effectiveness of these approaches in practice[56].

The OECD has highlighted the importance of understanding the practical deployment and governance of algorithmic systems when assessing their effects on competition and consumer welfare, and on engagement with businesses and other stakeholders to build

[54] Directive 2011/83/EU of the European Parliament and of the Council on Consumer Rights [2011] OJ L304/64, art 6; Directive 2005/29/EC of the European Parliament and of the Council concerning Unfair Business-to-Consumer Commercial Practices [2005] OJ L149/22.

[55] Germán Oscar Johannsen, *Pricing Innovation and Personalisation: Consumer Policy Recommendations in Times of Algorithms* (16 June 2026) SSRN <https://ssrn.com/abstract=> accessed 23 June 2026.

56 New York Algorithmic Pricing Disclosure Act (2025); see also emerging US state-level restrictions and investigations into ‘surveillance pricing’.

a more detailed understanding of digital market practices[57]. Existing evidence has largely been derived from observed market outcomes, consumer research, and legal analysis. While these approaches provide important insights, they offer only a partial view of the commercial and technical processes that shape pricing decisions. **Discussions with firms could therefore help clarify how pricing models are developed, what data and signals are relied upon and the extent of human oversight.** Platform engagement could help address remaining evidence gaps and improve the evidence base for future policy and regulatory decisions.

Overall, the central question raised is not only whether consumers are informed, but whether they are able, in practice, to understand, compare, and respond to prices. As pricing practices continue to evolve, this may require ongoing consideration of how existing legal frameworks apply, and whether further developments may be needed to support effective consumer engagement in digital markets.

[57] OECD, *Algorithmic Competition: Background Note* (OECD Competition Committee, 2023)

Annex A: Distribution of sellers by sub-sectors

A1. Phase 1: Survey-based approach

Table 17. Number of products by sector (Survey)

Sub-sector	Count of products
Accommodation and hotels	3
Beauty and cosmetics	12
Books	3
Clothing and footwear	9
Consumer electronics	10
Coupons and rebates	1
Event ticket	4
Food/drink delivery order	1
Games and toys	1
Groceries	10
Ground transportation	1
Health and beauty goods	1
Household goods	26
Marketplace	7
Package Holidays	2
Pets	2
Pharmacy	2
Sports and outdoors	3
Transportation and excursions	2
Total	**100**

A2. Phase 2: Synthetic profile approach

Table 18. Number of products by sector (Synthetic profile approach)

Sub-sector	Count of products
Accommodation and hotels	3
Air travel	3
Books	1
Clothing & Footwear	1
Consumer electronics	2
Dating	1
Event ticket	3
Food/drink delivery order	2
Games & toys	3
Ground transportation	3
Household goods	1
Marketplace	3
Package Holidays	2
Software	3
Transportation and excursions	2
TV	2
Total	**35**

Annex B: Survey

B1. Survey: Additional findings

This annex presents survey findings related to respondents' awareness, perceptions, and attitudes toward price personalisation as captured by the survey.

Table 19 shows responses to the question: "Before today, were you familiar with the idea of price personalisation?" The majority of respondents (58%) indicated they were not familiar with the concept, while 39% reported prior awareness and 4% were unsure.

Table 19. Familiarity with price personalisation (n=1,688)

Response	Count	Percentage
Yes	656	39%
No	972	58%
I don’t know	60	4%

Table 20 presents data for the question: "Do you think the prices you see for the same product may differ from those shown to others, depending on who you are, where you are, or how you shop?" Nearly half of respondents (49%) believed that prices may vary based on personal or contextual factors, 19% disagreed, and 32% were unsure.

Table 20. Belief that prices may differ based on personal/contextual factors (n=1,688)

Response	Count	Percentage
Yes	828	49%
No	325	19%
I don’t know	535	32%

Table 21summarises responses to the question: "How do you feel about the idea of price personalisation in general?" Respondents expressed mixed attitudes, with the largest group reporting a very negative view (39%), followed by 32% somewhat negative, 16% neutral, 13% positive (very or somewhat), and 2% uncertain.

Table 21. Attitudes toward price personalisation in general (n=1,688)

Response	Count	Percentage
Very negative	650	39%
Somewhat negative	533	32%
Neutral	265	16%
Somewhat positive	178	11%
Very positive	29	2%
I don't know	33	2%

B2. Survey: Sample and demographics

Table 22-24 outline the number and percentage of respondents across three demographic variables: gender, age, and income, showing good representation across key demographic variables.

Table 22. Survey composition: Gender

Gender	Number of respondents	Percentage of respondents
Female	1,044	62%
Male	637	38%

Source: Alma Economics survey and analysis.

Table 23. Survey composition: Age

Age	Number of respondents	Percentage of respondents
18-24	94	6%
25-34	430	25%
35-44	471	28%
45-54	366	22%
55-64	227	13%
65-74	85	5%
75-84	15	0.01

Source: Alma Economics survey and analysis.

Table 24. Survey composition: Income

Income	Number of respondents	Percentage of respondents
Up to £9,999	64	4%
£10,000-£29,999	423	25%
£30,000-£49,999	466	28%
£50,00-£69,999	290	17%
£70,000-£89,999	196	12%
£90,000-£109,999	93	6%
£110,000-£129,999	36	2%
£130,000 and above	40	2%

Source: Alma Economics survey and analysis.

B3. Survey definitions of vulnerability

The survey sample was divided into four groups depending on their survey responses: financially vulnerable consumers, those reporting a mental health condition, those reporting a form of neurodivergence, and a control group without any of these vulnerability traits.

Participants who self-reported a **mental health condition** (anxiety and/or depression) or a form of **neurodivergence** (ADHD, autism, dyslexia, or other specified conditions) were categorised accordingly. These were derived from Prolific's pre-screening questions, and participants' responses were based on either suspected or formally diagnosed conditions. They were:

1. Do you experience anxiety and/or depression?
    a. Yes, anxiety
    b. Yes, depression
    c. Yes, both
    d. No
2. Are you diagnosed with or suspect that you have any of the following conditions? Please select all that apply.
    a. Attention Deficit Hyperactivity (ADHD)
    b. Autism Spectrum Disorder (this includes Asperger's, Autism Disorder, High Functioning Autism or Pervasive Developmental Disorder)
    c. Dyslexia
    d. Other, please specify

e. No

Financial vulnerability was assessed in line with the Financial Conduct Authority's approach (p.69), which defines vulnerability in terms of three characteristics: over-indebtedness, low savings, and low financial capability. The following questions were included in the survey to assess respondents' financial resilience and capability:

1. Keeping up with domestic bills and credit commitments
   "To what extent do you feel that keeping up with your domestic bills and credit commitments is a burden?"
   - Adults indicating that it is "a heavy burden" or "somewhat of a burden" were considered more likely to have low financial resilience.
2. Resilience to income loss
   "If you lost your main source of household income, how long could your household continue to cover living expenses without borrowing or asking for help?"
   - Those reporting they could manage for *less than three months* were identified as having low financial resilience.
3. Confidence managing money
   "How confident do you feel managing your money?" (0 = not at all confident, 10 = completely confident)
   - Adults giving themselves a score of 0–3 were classified as having *low financial capability*.

Respondents meeting one or more of these criteria were categorised as financially vulnerable, consistent with the FCA's definition.

Participants who **did not** meet any of the above criteria, including those without a reported mental health condition, a form of neurodivergence, or indicators of financial vulnerability, were included in the **control group.**

B4. Survey: Data quality

Randomisation

The approach for allocating a random sample of seven product/service links (out of a possible 100) of products and services to respondents observed as expected under a normal distribution. As shown in Table 25, the observed mean (119) and standard deviation (10.6) of visits per product/service link closely match the expected values calculated from the assumed normal distribution (*mean*=118, *standard deviation* =10.5)[58]. The observed range, that is, the minimum and maximum number of visits per product/service link, aligned well with the theoretical 99% confidence interval. As such, the randomisation worked as intended.

Table 25. Expected and observed distribution of survey respondent visits per product/service link

Statistic	Expected value	Observed value
Mean	118	119
Standard Deviation	10.5	10.6
Minimum	91 (99% lower bound)	88
Maximum	145 (99% upper bound)	152

Source: Alma Economics survey and analysis.

Broken links or inaccessible prices

To help monitor and ensure data quality in the price recording exercise, respondents were instructed to enter “123456” whenever a product/service link did not display a price or could not be accessed. Overall, broken links or inaccessible prices were limited. Across all product/service links, the number of “123456” entries ranged from 0 to 8, with an average of just 1.56 entries per link, indicating that only around one to two respondents per link could not access the link or view the price. As shown in Table 26 31% of links had no “123456” entries, and a further 33% had only one such entry, while progressively smaller proportions had two or more “123456” entries, reflecting a generally low occurrence of broken links or inaccessible prices. In short, all product/service links functioned as intended, and respondents were generally able to observe and record prices.

[58] Mean: $\mu = N\frac{k}{L} = 1688\frac{7}{100} = 118$; Standard deviation: $\sigma = \sqrt{\sigma^2} = \sqrt{N\frac{k}{L}(1-\frac{k}{L})} = \sqrt{1688\frac{7}{100}(1-\frac{7}{100})} = 10.5$

Table 26. Distribution of "123456" entries per product/service link

Instances of "123456" entries per link	Percentage of links
0	31%
1	33%
2	13%
3	9%
4	7%
5	3%
6	2%
7	1%
8	1%

Source: Alma Economics survey and analysis.

B5. Survey findings: Step 1 to 4

As discussed in the Findings section in the main body of the report, a five-step process was applied to the data for each product. This began with (1) counting the unique prices in the raw data, (2) adjusting for obvious typos or mis-recordings, and (3) checking against visible pricing options on the website (such as standard versus sale prices shown to all users). The final two steps focused on (4) ensuring that any remaining price differences were consistent across multiple respondents, rather than one-off entries that might reflect recording errors, and (5) verifying that the differences could not be explained by contextual factors such as login status, time of submission, or device type.

Steps 1 to 4 are discussed in the following section in detail, while Step 5 is discussed in the main body of the report.

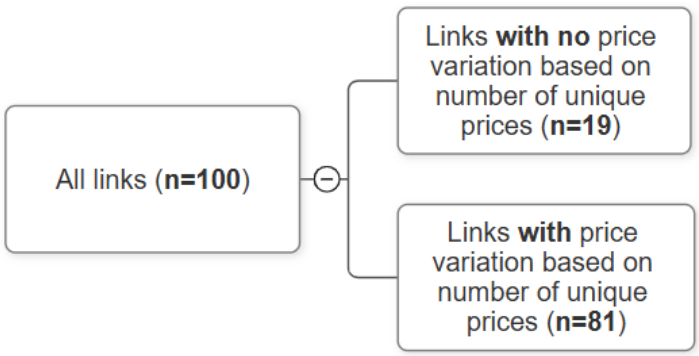
Step 1: Count unique prices

What was examined: Every price submitted by respondents for each of the 100 products was summarised and reviewed. This captured the full range of what different people saw when visiting the same product, before any adjustments.
How it was treated: We first counted the number of distinct (unique) prices recorded for each product. Any product with two or more unique prices was flagged as showing possible price variation, while products with just one price across all respondents were marked as not showing variation. This step acted as a first pass to find products where prices varied, without making any assumptions about the reasons behind those variations.

Example: Prices submitted: £9.99 (60 respondents), £99.9 (3 respondents), £11.50 (25 respondents), and £12.00 (1 respondent). Step 1 identified four unique prices, and the product would be flagged as having price variation.

Results: Of the 100 products, 81 had more than one unique price. The remaining 19 products had a single price reported by all respondents (see Figure 9).

Figure 9. Products/links following initial screening for price variation



Step 2: Adjustment for typos and misrecordings

What was examined: Prices that stood out as inconsistent with the majority pattern for a product, such as missing decimal points, mix-up of digits, and clearly implausible amounts far outside the expected range for the product.

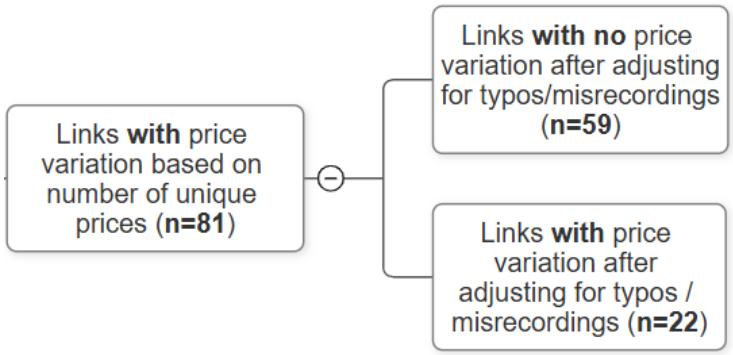
How it was treated: Prices that seemed to be the results of typos and misrecordings were either corrected to match the likely intended value or removed entirely. The count of unique prices was then recalculated for each product.

Example: Prices submitted: £9.99 (60 respondents), £99.9 (3 respondents), £11.50 (25 respondents), and £12.00 (1 respondent).

Price adjustment: £9.99 (63 respondents), £11.50 (25 respondents), £12.00 (1 respondent). £99.90 was considered a misrecording of £9.99 because: (i) 99.9 is an unrealistic price for this product; (ii) it is possible that it is the result of a misplaced decimal. The count of £9.99 and £99.90 for these two prices was merged. Step 2 identified three unique prices after adjusting for typos and misrecordings, and the link would continue to be flagged as having price variation.

Results: Of the 81 products initially flagged as exhibiting price variation in Step 1, 59 were found to have inconsistencies due to typos or misrecordings, leaving a single consistent price. This reduced the number of products with genuine price variation to 22 (see Figure 10).

Figure 10. Products / links flagged for price variation after adjustments for typos



Step 3: Adjustment for visible price options on the website

What was examined: For the remaining products, we checked whether the recorded price differences corresponded to multiple pricing options openly displayed on the product page, such as a standard price alongside a sale price, a member discount, or a bundle option visible to all visitors[59].

How it was treated: If prices clearly reflected transparent, non-personalised options (i.e., not hidden or tailored to individual users), they were excluded from the count of unique prices, as they did not indicate personalised pricing.

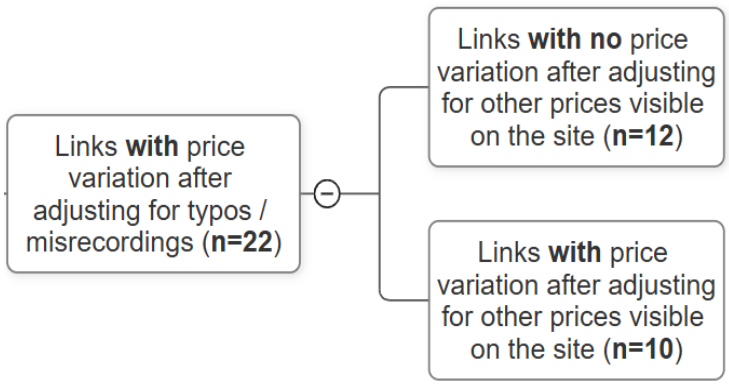
Example: Prices retained: £9.99 (63 respondents), £11.50 (25 respondents), and £12.00 (1 respondent). After closer inspection, it was determined that the original price of the product was £11.50 and the current sale price is £9.99. We interpret the £11.50 as a misreporting, where participants reported the original price instead of the sale

[59] Participants were instructed to record the current price displayed on the product page exactly as it appeared, including any discounted prices.

price. As such, the two counts for these two were merged and considered as one unique price.

Results: Of the 22 products flagged as showing variation in Step 2, 12 could be explained by visible website pricing options, reducing the number of products with unexplained variation to 10 (see Figure 11).

Figure 11. Products / links flagged for price variation after adjusting for visible website pricing options



Step 4: Check for repeated prices

What was examined: Whether each price was reported by at least two respondents, suggesting a pattern rather than random one-off entries.

How it was treated: Single prices (submitted by only one person) were excluded as probable isolated recording errors. A product stayed flagged only if at least one unique price had been submitted by two or more people, indicating more systematic variation.

Example: Prices retained: £9.99 (92 respondents) and £12.00 (1 response). As £12.00 was only reported by one person, this was removed. Step 4 identified one unique price after adjusting for repeated prices, and therefore, it was concluded that there was no price variation.

Results: Of the ten products, eight had at least one distinct price reported by two or more respondents. The remaining two showed no variation after excluding single reports (see Figure 12).

Figure 12. Products / links flagged for price variation following a check for repeated prices

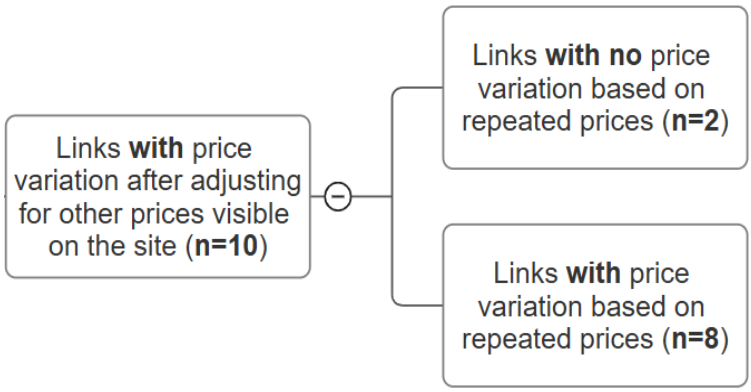
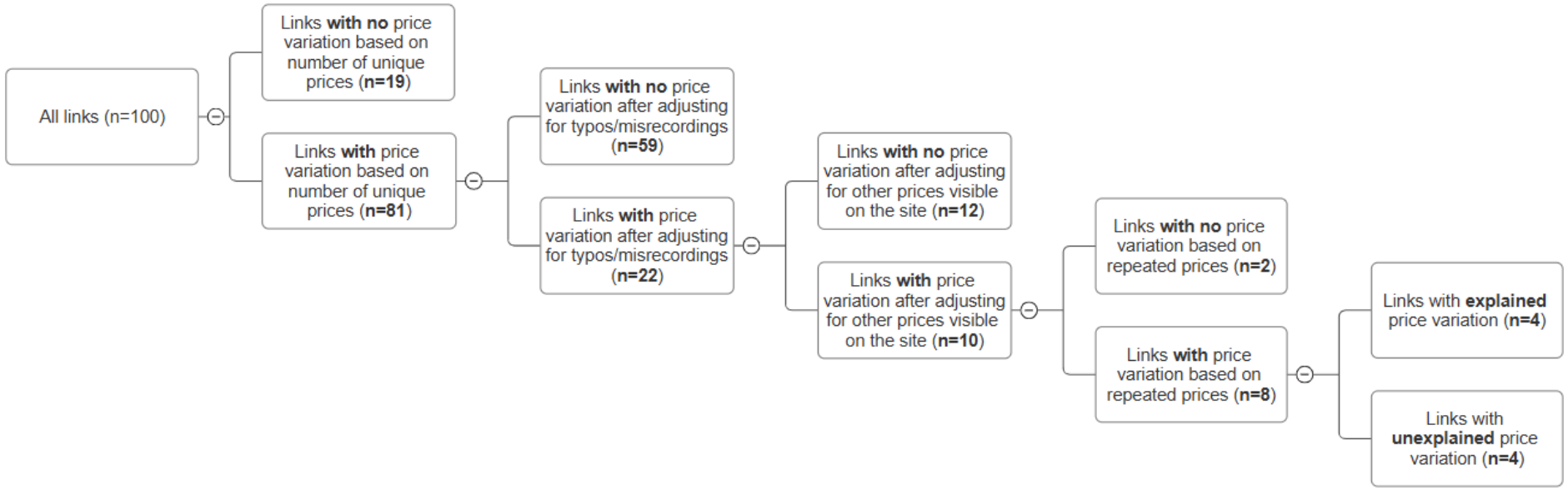


Figure 13. Overview of products / links flagged for price variation across all five analysis steps



Annex C: Synthetic profiles - social media rules of conduct

As part of the fieldwork and development of the digital footprint, all team members used social media in a responsible and professional manner. Any posts, shares, or likes directly supported the aims of the research and adhered to the following rules:

- Commenting on social media posts was strictly prohibited across all platforms, including Facebook, Instagram, and Reddit.
- Liking or interacting with posts made by individuals on any social media or other online platforms was not permitted under any circumstances.
- Liking was permitted only for posts published by pre-specified groups or institutions.

We also implemented strict privacy settings on our social media accounts, ensuring that the profiles and posts are hidden and that the accounts cannot be contacted by other users.

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