Digital consumer harms - A taxonomy, root cause analysis and methodologies for measurement

Report - Prepared for the Department for Digital, Culture, Media and Sport (DCMS)

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Executive summary

Digital markets, technologies and social media have profoundly changed the consumer experience and have often led to a richer, more personalised one. Consumers[1] can now make their choices from a range of products (or services) that is wider than ever before; have access to large amounts of readily available information, communicate publicly on their experiences, and can receive recommendations for specific products, based on their preferences, to help their decisions. However, there is growing recognition that consumers in digital markets are subject to a range of new and amplified risks that can produce significant detriment. These include (amongst others) distorted decision-making, algorithmic discrimination, exploitation of behavioural biases, and exposure to fraud and scams.

There are still important evidence gaps regarding the scale and prevalence of these harms, due to the pace of technological and business model change and improvement, as well as the difficulties in accessing relevant commercial data. In light of this, the Department of Digital, Culture, Media & Sport (DCMS) commissioned London Economics and Plum Consulting to pursue independent research on potential harms that can arise as a result of digital technologies; the prevalence, severity and root causes of these harms; and potential methodologies for quantifying digital consumer harms.

London Economics and Plum Consulting produced this report by developing a taxonomy of harms and harmful practices, supported by an evidence review on the prevalence and severity of digital harms experienced by consumers. The taxonomy is underpinned by the analysis of the root causes that lead to such categories of harms and harmful practices. This report includes a proposed framework for quantifying such harms applied to two illustrative examples. This research is intended as a starting point for understanding the relative prevalence and scale of digital consumer harms and will feed into the evidence base for DCMS policy teams.

The taxonomy

The report presents a taxonomy of digital consumer harms, building on existing taxonomies by organisations' such as the CMA (2020), Ofcom (2019) and the ICO (2021). It is also informed by the literature review found in Chapter 3.

The taxonomy includes both harmful outcomes as well as practices that lead to harmful outcomes. The two are closely related and including the harmful practices in the taxonomy is necessary to characterise the specific nature of digital consumer harms.

The taxonomy is organised into five overarching categories of digital consumer harm/harmful practices:

- Barriers to effective, informed consumer decision-making
- Misleading or false content
- Barriers to switching and multi-homing
- Unfair consumer data practices

[1] For the purpose of this report, a consumer is defined as an individual entering into an exchange with a firm. This includes consumers of online services where non-monetary exchange takes place (e.g. exchange of data or attention for services)

- Exploitative behaviour

Root cause analysis

This report identifies an underlying set of drivers of consumer harm. Root causes are factors that characterise firm-consumer interactions in a digital environment which give rise to specific consumer harms. The digital nature of the markets under consideration creates a specific set of root causes of harm that are particularly impactful in a digital context.

The following root causes were identified:

- Market imperfections
- Cognitive biases
- Firms' adverse data practices
- Automated, personalised data-based decision-making
- Use of choice architecture
- Digital literacy and consumer awareness
- Services' lack of enforcement

Some of the identified root causes are instances of factors that are also common in non-digital environments, e.g., market imperfections. However, digital markets can be particularly conducive to processes that generate adverse consumer outcomes; for instance, digital markets have shown a tendency to "tip in the favour of one, or a few, firms".[2] Similarly, the use of choice architecture and the exploitation of cognitive biases feature in offline markets, but their scale and impact in digital markets poses a distinctive new challenge. In addition, a number of root causes are uniquely 'digital', for example automated personalised decision-making and adverse data practices.

Measurement and quantification of harms

While the existence of digital consumer harms is well documented both theoretically and empirically, robust evidence on the prevalence and severity of individual harms is sparse. For many harms in the taxonomy, there is a distinct lack of reliable observational studies and evidence calculating the level of harm in aggregate across the entire economy.

The key reason for this is that the information required to complete quantitative evaluation of harms is often commercially sensitive. Therefore, the evidence available typically comes from surveys and experiments, and in some cases is even limited to a simple review of market outcomes. As a result, it can be difficult to obtain a full, unbiased picture on the prevalence and severity of individual harms. This report proposes two methodologies for the measuring of digital consumer harms. The proposed methodologies provide a basic foundation for further evidence gathering.

The report proposes two approaches:

[2] HM Treasury (2019).

- **Top-down approach:** Uses total size of market to estimate harm. By estimating the total market size one can disaggregate this to arrive at an estimate of the total market affected by a harm (this is referred to as 'market at risk'). The market-at-risk can be further scaled down to arrive at an estimate of actual harm (this is referred to as realised harm).
- **Bottom-up approach:** This begins by calculating the harm experienced using a representative case (this can be an individual or group of individuals). An estimate of realised harm is then calculated using the population the case is representative of.

Chapter 5 discusses the methodologies in more detail and provides illustrative examples of these approaches. A top-down approach is used to calculate the market at risk as a result of online choice architecture and excessive advertising. A bottom-up approach is used to calculate the potential harm of excessive advertising. The worked-through examples are not intended to be robust estimates of the selected harm, they are instead used to show how the methodologies can be applied. The proposed approaches also allow for an identification of evidence gaps, which can be used to inform further research and data collection.

Key findings and recommendations

The report includes three key findings:

- Most digital consumer harms lack a strong evidence base, and some lack an obvious means of quantifying their prevalence and severity. While there is fairly good evidence of harmful outcomes from dark patterns and fake reviews in some digital markets, evidence of these harms is lacking in other sectors. Other digital consumer harms considered in this report have medium-low evidence bases and some of these - such as algorithmic and price discrimination - appear to be especially difficult to quantify.
- The report has identified seven root causes of digital consumer harms, some are a result of decisions made by digital firms (i.e. use of online choice architecture), others are a result of human biases and understanding of digital technologies (i.e. digital literacy and consumer awareness), whilst the final root cause - market imperfections - results from characteristics of digital markets. Multiple root causes interact to produce specific harms, and in some cases this interaction can amplify the harm consumers' experience. For example, the use of online choice architecture can negatively affect consumer decision making online, and this can be even more effective if it targets consumers that display behavioural biases which make them more susceptible to online choice architecture practices.
- There may be particular opportunities to address harmful uses of online choice architecture and automated decision-making through targeted action. While some root causes of digital consumer harms (e.g. market imperfections) are already being considered by a range of government policy work, others (e.g. digital literacy) are - and must be - addressed through a diverse programme of action, these root causes are less well understood and may be appropriate to address through more targeted means.

These findings give rise to two recommendations:

- **Recommendation 1:** The government supports further gathering of the evidence base in relation to digital consumer harms. The quantification methodologies set out in Chapter 5 can allow for the estimation of digital consumer harms. However, the methodology that can be applied and the extent of the quantification will be dependent on the data available. Thus, considering ways in which access to data for government, regulators and academia can be improved will allow for quantification approaches to improve.
- **Recommendation 2:** The government explores ways of tackling the root causes of digital consumer harms, and especially harmful uses of online choice architecture and automated decision making based on their prevalence and tractability.

1 Introduction

The digital economy is a source of innovation and economic growth, it has transformed the consumer experience and delivered substantial benefits. Online, consumers can compare and easily choose between a range of products and prices; product information is widely available, allowing people to make more informed choices; and products or services can be accessed or delivered in a very short time

Since 2010, the number of British individuals shopping online for food and other groceries has doubled to 30%, with the key driver of this trend being cited as convenience and choice[3]. A large proportion of retail trade in the UK now takes place online, with internet sales representing more than 30% of total retail sales in 2021.[4] The COVID-19 pandemic brought with it an acceleration of online activity, in many cases replacing long-established practices such as in-person meetings and medical appointments with video calling and virtual GP services. The digital economy is also significant for the recreational activities it facilitates, with 70% of adults using social networking services[5] and 62% of adults playing games on an electronic device in 2020.[6]

As the digital economy has a large and growing impact on people's lives - with 89% of adults using the internet daily or almost every day[7]- there is a growing recognition that, in digital markets, consumers can also face a range of new and amplified risks. These can range from excessive prices and discrimination, to emotional distress or anxiety.

In line with Government's ambition to make sure that digital markets work efficiently and fairly for consumers, the UK Government needs to strengthen its understanding of the risks' consumers face and their underlying drivers. This will complement recent initiatives to promote positive outcomes for consumers in digital markets including through work to establish the new pro-competition regime for digital markets[8] and the recent publication of the National Data Strategy.[9]

London Economics and Plum Consulting produced this report that will be used to build on the existing evidence base and help estimate the cost of some specific digital harms to consumers.

1.1 Digital markets benefit consumers, but also pose new risks

Digital markets deliver numerous benefits for consumers, providing a range of new products and services that are designed, marketed and personalised with the analysis of consumer data. However, digital markets have given rise to new risks for consumers. It is often the same features that bring benefits that can also cause harm, including higher prices and lower quality.

[3] Statista (2022a).

[4] ONS. Internet sales as a percentage of total retail sales (ratio) (%).

[5] Ibid.

[6] Ofcom (2021a).

[7] ONS. Internet Access: Internet access - households and individuals.

[8] DCMS, BEIS (2021).

[9] DCMS (2020).

These features are not necessarily inherently negative and in some instances can lead to both consumer benefits as well as harms. There is, however, a need for further consideration and analysis of the evidence base. While they often mirror well-understood features within markets in non-digital settings, in a digital setting some of these features have significant consequences for market dynamics. In some cases, they can give rise to concentrated markets and the emergence of large dominant digital firms that are present across multiple markets. Where this dominance is uncontested the efficiency of the market process can be affected and consumers harmed. In other cases, the features can lead to the emergence of harmful processes which make use of the seamless and expedient nature of digital markets, such processes can induce impulsive behaviour by consumers that can lead to harm.

These features are outlined below:

- The extensive use of data, algorithms and analytics means that the value of the service offered is increased for both businesses and consumers. However, **information asymmetry**[10] means that the balance of power associated with transactions can be further shifted from the consumer to the business. Access to increasing amounts of consumer data amplifies the information advantage of some firms.
- Some digital markets exhibit **network effects** (e.g., online platform services). This means that the value of the service to users increases as the total number of users of that service increases. This can be of benefit to the digital consumer as these networks can be used to amplify consumer demands. However, these effects reduce the incentive for business users and end users (collectively ‘consumers’) to switch to rival platforms, or ‘multi-home’ with several smaller platforms, making new entry challenging and hence reducing market contestability.[11]
- With high fixed set-up costs and low marginal operational costs, large firms benefit from significant **economies of scale.** These are often passed to consumers in the form of reduced prices. However, economies of scale can give market power to incumbent firms and can act as a barrier to entry/expansion for potential entrants.[12]
- Some firms operate **vertically integrated**[13] **ecosystems**[14] (e.g., e-commerce platforms integrating their complementary products and services around their core service). This can be of benefit to a consumer as it effectively provides a ‘one-stop-shop’. However, it can at times undermine competition if such firms leverage their market power in one part of the supply chain to harm competition at other stages of the supply chain.
- Businesses operating in the digital environment can more effectively design the **choice environment** facing consumers in a way that encourages specific decisions. The way in which choices are presented can shape consumers’ cognitive and emotional response, these features can be tailored to specific consumers more easily in digital markets than elsewhere to influence decision making.
- The large number of choices available across many digital markets means that consumers are often influenced by **ratings and recommendations** from people that are unknown to them. This can be a positive as it helps consumers make informed decisions. However, it

[10] Information asymmetry refers to situations where one party to a transaction has more or better information than the other. This can lead to inefficient transactions and in extreme cases to market breakdown.

[11] BEIS (2021a).

[12] Ibid.

[13] The presence of one firm at multiple stages of the supply chain in which it operates.

[14] A network of complementary products or services spanning different markets.

creates a challenge as some ratings and recommendations are not always legitimate and/or verified.

- Digital markets are increasingly fast-moving, and decisions at the click of a button have immediate impact. End users have also developed a reduced tolerance for delay leading to **default behaviour** (a propensity to accept whichever default option is presented to save time and effort) and are prone to **status quo bias** (a preference for remaining with the existing option even where this is not the rational choice). This reduces the likelihood of users switching to new/rival firms' services, even where they might offer better value.[15]

1.2 This report

This report uses the current evidence base to develop a taxonomy of digital consumer harms, highlights the root causes of these harms and posits methodologies for initial quantification of digital consumer harms.

- **Chapter 2** presents a taxonomy of digital harms, building on existing taxonomies.
- **Chapter 3** presents the findings from a literature review covering the harms included in the taxonomy and focusing on measurement and quantification of harms**.**
- **Chapter 4** undertakes an analysis of the root causes of the identified harms and the linkages between them, building on the evidence assessment.
- **Chapter 5** discusses methodologies for quantifying digital consumer harms and implements illustrative quantifications of two specific harms (deceptive online choice architecture and excessive advertising) to illustrate how the methodologies could work in practice.
- **Chapter 6** presents the key conclusions and takeaways from this research.

[15] BEIS (2021a).

2 Taxonomy of digital consumer harms

2.1 Developing the taxonomy

The taxonomy presented in this report was developed to help identify and categorise sources of digital consumer harms. The taxonomy is an initial attempt to establish a core set of categories for digital consumer harms based on a literature review. **We would expect this to evolve over time as well as be adapted according to the precise way in which it is used.**

The harms included in the taxonomy are heavily influenced by the digital consumer issues outlined in the Digital Markets Taskforce advice,[16] which discusses potential consumer harms arising from: barriers to effective and informed decision making; activity or content which could lead to economic detriment for consumers and businesses; barriers to switching and multi-homing; and coordination failures. Other existing taxonomies of online/digital harms (and related areas) were also used to develop the proposed taxonomy, these are summarised in Table 1.

Table 1 Existing taxonomies of online harms

Taxonomy	Description
Ofcom (2019)	Ofcom identifies a range of harms that can arise online, grouping them into seven categories. These include: competition policy; consumer protection; data protection; cybersecurity; media policy; content policy; and health policy.
PwC (for DCMS) (2020)	This study identifies a large number of potential online harms, grouping them into six "families": Digital content; Digital interactions; Media and other services; Data abuse; Consumers and workers; and Competition abuse.
ICO (2021a)[17]	The ICO identifies a range of harms that may result from the use (or misuse) of individuals' personal data.
CMA (2020b)[18]	The CMA identifies a number of direct and indirect consumer harms that may result from competition problems in digital advertising markets.
Online Advertising Programme consultation[19]	Two high level categories of harms are identified, harmful advertising content and harmful advertising targeting and placement.
CMA (2022a)[20]	The CMA introduces 21 Online Choice Architecture (OCA) practices that they propose are grouped into three main categories: Choice Structure; Choice Pressure; Choice Information.

16 DMA (2020a), Appendix G.

17 ICO (2021a), Annex B.

18 CMA (2020b). Market study final report.

19 DCMS (2022c).

20 CMA (2020a). Online Choice Architecture

2.2 A taxonomy of digital consumer harms

The taxonomy is organised into five overarching categories of digital consumer harms (Table 2). While the categories are presented as separate, in practice they are not mutually exclusive. For example, barriers to switching may enable firms to 'overcharge' consumers.

The harms included are the most common and general ones with enough available data to construct the evidence base. This taxonomy is not exhaustive; moreover, it could be expanded as time goes by due to the nature of digital markets and the pace of digital development.

Table 2 Categories of harms in scope of the study

Category	Description
Barriers to effective, informed consumer decision-making	The way in which digital services are designed, and choices and terms of service are presented, may negatively impact decision-making.
Misleading or false content	The information that consumers are presented with during the purchase journey may be incorrect, purposely misleading and/or hidden.
Barriers to switching and multi-homing[21]	Factors such as loss of data, content or reputation, lack of interoperability and sales strategies by digital firms may affect the ability of consumers to switch or use similar services simultaneously.
Unfair consumer data practices	Consumers' personal information may be exploited to their detriment. For instance, firms may use data to engage in unlawful discrimination, or use personal data in ways that generate feelings of anxiety and concern.
Exploitative behaviour	Consumers may be 'overcharged' for digital services. For zero-price digital services, consumers may be 'overcharged' in terms of the personal data they share, or their exposure to advertising.

The taxonomy focuses on harms associated with commercial transactions between consumers and firms. For this reason, it does not consider some harmful online content and conduct, specifically: illegal and age-inappropriate content; and conduct such as bullying, trolling and harassment.[22] In the case of multi-sided markets (where a platform acts as an intermediary between two groups of users, such as buyers and sellers), the focus is on the consumer side. The emphasis is on direct harms rather than indirect harms.

Within each category, the taxonomy describes the digital harms in one of two ways:

- **As a harmful outcome for consumers,** i.e., the direct harm experienced by consumers.
- **As a practice that can lead to harmful outcomes for consumers,** i.e., actions by firms/individuals that can result in direct harm to consumers.

[21] Multi-homing refers to the simultaneous use of similar services from different providers.

[22] For more information on content and conduct harms, see Ofcom (2019), p. 31.

The two are closely related, and including harmful practices in the taxonomy as intermediate outcomes is necessary to characterise the specific nature of digital consumer harms.

Table 3 Taxonomy of Digital Consumer Harms

Harms from barriers to effective, informed consumer decision-making

Harm	Description
Distorted consumer choices* (dark patterns)	The way in which choices are presented and framed by firms online can induce consumers into choices that are not in their own best interest. Such choices include purchasing unsuitable products and spending less time and effort searching for alternatives.
Misinformed consent*	The way in which terms and conditions associated with a transaction in a digital market are framed can result in consumers accepting terms and conditions without fully understanding important items such as privacy settings.
Excessive use/addiction*	Digital services might be designed to encourage excessive use/addiction to the ultimate detriment of users. This damage can be financial in nature (e.g., excessive spending on loot boxes) or in terms of health (e.g., deteriorating mental health).

Harms from misleading or false content

Harm	Description
Fake reviews**	During the purchase process, a consumer may be exposed to misleading information that may influence them to acquire products or services of lower quality, or purchase a product that is unsuitable for their needs.
Fraud/scams**	Consumers can be exposed to fraudulent business practices when purchasing a product or service online. Such practices can lead to financial harms (e.g., purchasing of defective, counterfeit, or low quality products or services). This also includes fake/fraudulent advertising that induces consumers to purchase products and services they would otherwise not.
Loss of trust in buying and selling online*	Reports of fraudulent activity online may deter some users from online purchases. This may impose costs on those users, but will also affect other users, who benefit from a larger pool of buyers and sellers.

Harms from barriers to switching and multi-homing

Harm	Description
Service tying/bundling**	Service tying and bundling refers to a strategy where a firm offers a combination of distinct services.[23] This can be beneficial; however, if the firm has market power over at least one of the services, it is possible that tying or bundling can harm consumers by restricting competition and innovation. It has been argued that, in certain circumstances, tying can raise prices and prevent consumers from choosing alternative services that offer higher quality.[24]
Factors that prevent switching**	Consumers may be deterred from switching to alternative services because of the hassle of signing up to a different service or the possibility of loss of data, published content or personal reputation (e.g., seller rating) on the platform they are leaving. Other factors that may deter switching include lack of technical interoperability and high switching costs. Consumers might become locked into using an inferior service when an alternative service might better fit their needs.
Lack of alternative services*	For some types of services, there may not exist viable alternatives, or consumers may not be aware of them. In such a case, the incumbent firm(s) will not have incentives to innovate or improve services for its users.

Harms from unfair consumer data practices

Harm	Description
Algorithmic discrimination**	The use of algorithms coupled with biases inscribed in the data can lead to consumers with protected characteristics paying higher prices for factors not associated with cost.
Algorithmic targeting**	The use of algorithms coupled with biases inscribed in the data can lead to targeting of certain groups with advertisements that are inappropriate.
Loss of control of personal data*	Consumers' personal data may be shared without permission. However, even legitimate and authorised use of personal data may cause consumers to fear they have lost control of their personal data, generating concerns and anxiety, potentially exposing consumers to health and wellbeing harms.

[23] Either by making the use/purchase of one service conditional on the use/purchase of another service (tying), or by making it so that consumers can only obtain the firm's services together (bundling).

[24] Etro , F. and Caffarra, C. (2017).

Harms from exploitative behaviour

Harm	Description
Excessive data collection*	In zero-price digital markets, personal data may contribute to the price paid for access to digital services. In such markets, firms may use market power, or exploit information asymmetries, to extract more data from their users than they would be able to in a competitive environment. As consumers value their personal data and privacy, this may lead to consumer harm.[25]
Excessive advertising*	In some digital markets, exposure to advertising may contribute to the price paid for access to digital services. In such markets, firms may use market power to expose consumers to excessive advertising or lower quality advertising than they would see in a competitive environment. This may harm consumers by degrading the quality of experience.
Excessive prices*	Firms may, for example, exploit market power to charge consumers higher monetary prices for goods and services than would be expected in a competitive environment. This may impose direct financial harms on affected consumers.

* Direct harm experienced by consumers

** Practice that can lead to direct harm for consumers

[25] Budzinski, O., Gruesevaja, M. and Noskova, V. (2020).

3 Literature Review

This chapter provides a short description of the taxonomy's categories. It also summarises findings of a rapid evidence review on consumer harms linked to the use of digital technologies, with a particular focus on publications addressing measurement and quantification issues.

3.1 Barriers to effective and informed consumer decision making

3.1.1 Overview

Digital markets have handed additional power to consumers by easing access to more information and choice. In this environment, where people are more likely to collect a wide array of information before making a decision (e.g., purchasing a product online), it has been critical for businesses to develop new capabilities to increase people's attention, monitor their behaviours and streamline the customer experience to maintain or raise their revenue.

Online Choice Architecture (OCA) is integral to consumer decision making online. Choice Architecture describes the contexts in which consumers make decisions and how choices are presented.[26] OCA is the design of online systems or interfaces (e.g., websites) presented to users (e.g., product placement) to influence their decisions. OCA is often used positively to help consumers, i.e., match people with suitable information or products, saving time and effort. However, it can also be used in ways that are not in their interests, i.e., practices that take advantage of consumers' behavioural biases, and act as a barrier to effective and informed decision-making. Some OCA practices are always used at the detriment of consumers, for example:

- **Drip pricing** where only part of an item's price is initially shown and the total amount to be paid is revealed at the end of the buying process.
- **Excessive complexity** where too much information is provided or is difficult to understand due to overly technical or obscure language (e.g., lengthy and overly technical terms of service that consumers may accept without understanding or reading them).
- Use of **decoys** where an option is added to the choice set to make the other option(s) look more attractive (e.g., businesses wanting to increase sales of higher-priced products may show extreme alternatives such as an obviously inferior option and/or even more expensive product).

Other types of OCA practices are inherently neutral and can lead to both beneficial and adverse outcomes, depending on the designer's intent. For instance, **defaults** (i.e., predefined settings applied so that a consumer must take active steps to change) can enhance the user experience and make transactions more efficient. However, it can also lead to automatic and unintended purchases (e.g., cancellation insurance automatically included when purchasing flight tickets).[27]

3.1.2 Barriers to effective and informed consumer decision making: Distorted consumer choices

Consumers exhibit a number of biases that can affect their decision-making and welfare. For example, consumers tend to stick with default settings (status quo bias); are influenced by the way

[26] CMA, (2022b).

[27] Ibid.

choices are presented (framing effects); and tend to focus on short term benefits and costs (myopia).[28]

Firms which analyse their consumers' behaviour can take advantage of these biases by developing default options that benefit them or framing choices to highlight certain information. This is a particular concern for digital platforms and digital service providers, which have more information than traditional firms on consumer behaviours and the ability to rapidly test and implement changes to user interfaces to maximise engagement, click-throughs and purchases.[29]

These capabilities have led to concern about "dark patterns"[30] for instance. These user experience (UX) design practices can have the effect of diminishing consumer's autonomy, obfuscating or selectively showing information, or pressuring customers into certain choices. The recently published CMA (2022) discussion paper on online choice architecture defines dark patterns as "a set of deliberately manipulative practices identified by user experience designers"[31] that form a subset of the broader concept of online choice architecture that is distinguished by the fact that these practices "are likely to be harmful or deceptive all the time".

Our review of the literature on distorted choices found the following:

Evidence of harm

- Research[32] cited by the Stigler Committee found that employing "mild dark patterns" increased the percentage of consumers who ultimately agreed to a "data protection plan" (a commercial service that included data protection and credit history monitoring) by 228%. Employing "aggressive dark patterns" increased the percentage of consumers who accepted the data protection plan by 371%.[33]
- Blake et al. (2020) examined the impact of hidden versus upfront fees on a ticketing website. They found that hiding buyer fees until later in the purchase process i.e., drip pricing increased total revenue by roughly 20%.[34] Drip pricing was the subject of study commissioned by the Office of Fair Trading (OFT).[35]
- In Australia, the Federal Court ruled that hotel comparison site Trivago had misled consumers through the use of strikethrough prices[36] and text in different colours, because Trivago often compared the rate for a standard room with the rate for a luxury room at the same hotel. This may have led to consumers being tricked into thinking they were paying discounted prices when in fact they were not.[37]

[28] CMA (2020b). Appendix L: summary of research on consumers' attitudes and behaviour.

[29] FTC (2021).

[30] Dark patterns are "user interface design choices that benefit an online service by coercing, steering, or deceiving users into making unintended and potentially harmful decisions." See CMA (2022b).

[31] Ibid.

[32] Luguri, J. and Strahilevitz, L. (2021).

[33] Stigler Center (2019).

[34] Blake, T., Moshary, S., Sweeney, K., Tadelis, S. (2021).

[35] OFT (2013).

[36] This refers to "comparisons with own previous pricing ('was/now' or 'strike through' pricing): The use of 'was/now' or 'strike through' price statements (such as 'was $150/now $100' or '$150 now $100') is likely to represent that consumers will save an amount (being the difference between the higher and lower price advertised) by purchasing the product during the sale period." ACCC (2021a).

[37] ACCC (2020).

Evidence of practices that can lead to harm

- In its work in the hotel online booking sector, the CMA outlined that it had concerns about scarcity claims and pressure selling. For example, when online booking platforms make claims as to how many people are looking at a room, how many rooms may be left or how long a price is available. The aim of these scarcity claims was to create a false impression of room availability so potential customers rush into making a booking decision.[38]
- Mathur et al. (2019) at Princeton University used a web crawling exercise of 11,000 online shopping websites to assess the global prevalence of dark patterns. The authors found 1,818 instances of dark patterns and identified that 183 websites engaged in dark patterns for deceptive purposes. They also developed a taxonomy for the influence of dark patterns and their potential harm on user decision-making.

3.1.3 Barriers to effective and informed consumer decision making: Excessive use/addiction

Recommender systems are popular tools on e-commerce websites. They help consumers find products that are appropriate to them. For example, size recommendation systems can help customers better identify their clothing size when shopping online.[39] This can be an advantage to the consumer and reduce return costs for businesses.

However, there is a risk that digital services may purposefully create services that are addictive or habit forming. The harm to consumers in this case would be consumption of an excessive amount of content, which can also result in consumers spending more, as well as leading to the deterioration of their mental health. Some examples include:

- Loot boxes in video games. There are a number of addictive mechanisms which can be included in game design, such as "loot boxes" where players can pay for randomly determined in-game rewards.[40]
- Recommendation systems may recommend false, provocative or dangerous content to consumers in order to maintain engagement. This might include, for instance, videos promoting 'miracle cures' for serious illnesses or conspiracy theories such as the Earth is flat.[41] Autoplay features may also help to encourage excessive use and addiction to digital services.[42]

Some OCA practices exploit consumers' fear of missing out or incentivise their habit forming and addictive behaviours by promoting false, provocative, or dangerous content. Recommendation algorithms, for instance, often work by amplifying content that generates interaction from users – even if their reactions are negative.[43] This may harm users by encouraging them to consume lower-quality content than intended and detracts from the positive intentions of recommended content which is aimed to provide a personalised experience. Additionally, even content which is not of a low quality can still be harmful, e.g., for the self-esteem of consumers.

[38] CMA (2019a).

[39] Abdulla, G. M. and Borar, S. (2017).

[40] Goodstein, S. A. (2021).

[41] Stigler Center (2019).

[42] FTC (2021).

[43] Menczer, F. (2021).

Our review of the literature on excessive use/addiction found the following:

Evidence of harm

- The European Parliament (2019) produced a review of the literature on internet and gaming addiction and indicated that there is strong evidence of adverse effects on mental wellbeing. They highlight cross-country studies suggesting that prevalence of problematic internet use may range from 14% to 55%[44] and that internet gaming disorder may affect 1.6%[45] of adolescents.
- Sohn et al. (2019) determined that 23.3% of children and young people had problematic smartphone usage, calculating that this was associated with significantly higher odds of depression, anxiety, stress and poor sleep quality.
- Braghieri et al. (2022) use data on Facebook's expansion throughout the US college system in the mid-2000s to explore the impact of Facebook on mental health. The authors found that there was an increase in poor mental health, and that this increase was approximately 22% of the impact a job loss would have on mental health. The authors also studied specific aspects of poor mental health, finding an increase in depression of 2 percentage points.
- Allcott et al. (2020) conducted an experiment assigning 2,743 Facebook users to either a group deactivating Facebook for four weeks or a control group. It was found that those who deactivated Facebook experienced an increase in wellbeing, and the authors highlight that this is approximately 25-40% of the increase associated with psychological interventions such as self-help therapy. In addition, 80% of the treatment group felt that deactivation had a positive influence on them.
- Bao et al. (2021) adopts an instrumental variables approach using data from a survey of the Chinese population to explore the link between social media use and life satisfaction. They obtain a highly significant and negative coefficient that indicates that an additional hour spent on social media per day is associated with a decrease in life satisfaction of 0.113 (on a 1 to 5 scale).
- Perlis (2021) explores the relationship between social media and self-reported symptoms of depression among US adults. The authors conducted a survey at two different points in time and ran a logistic regression with the outcome variable being an increase of 5 points or more in PHQ score. The use of Snapchat, Facebook and TikTok were associated with a statistically significant increase in depressive symptoms, with odds ratios of 1.53, 1.42 and 1.39 respectively.
- Lin et al. (2016) explored the link between social media use and depression among U.S. Young Adults. They calculated that those in the highest quartile of social media use were 66% more likely to have depression. Twenge et al. (2018) use data from a national survey of U.S. school children to also examine this relationship, obtaining a significant correlation of 0.05 between depressive symptoms and social media use.
- Lundahl (2020) indicates in her review of the literature in the area that estimates of compulsive users typically range from 4.5% to 9.7% of social media users, whilst acknowledging that there is no consensus on the definition of addiction in this context.
- Research for FFT Education Datalab found that 71% of daily social media users in England experience internet withdrawal symptoms.[46]

[44] Laconi et al. (2018).

[45] Muller et al. (2014).

[46] Jerrim, J. (2019).

3.1.4 Barriers to effective and informed consumer decision making: Misinformed consent

The UK GDPR sets a high standard for consent, which must be unambiguous and involve a clear affirmative action (an opt-in). It specifically bans pre-ticked opt-in boxes. It also requires distinct ('granular') consent options for distinct processing operations. Consent should be separate from other terms and conditions and should not generally be a precondition of signing up to a service. GDPR is well adhered to in the UK and these rules help to limit the barriers to effective and informed decision-making.[47]

However, the framing and content of services' terms and conditions can make them opaque to users in many real-world use cases. Such practices can potentially cause a range of non-financial harms, including inducing unwanted data disclosures and privacy invasion.[48] However, the effect in terms of harms can be difficult to pin down, as a) terms and conditions govern many different aspects of users' online experience; and b) a misinformed choice does not always result in harm that is easily recognisable to the consumer. For example, consumers agreeing to data processing activities that they do not fully understand does not mean that this processing is always directly harmful to them. Overall, the evidence surrounding misinformed consent is much more limited than the evidence surrounding other harms in the taxonomy.

3.2 Misleading or false content

3.2.1 Overview

In a digital environment, consumers have much greater access to content to help guide purchase decisions, such as expert reviews, blog posts and especially customer reviews. Where this content is reliable and accurate, online consumers should be able to make more well-informed purchase decisions than they might otherwise in an offline context.

Certain harms may arise when consumers use platforms and services to buy or sell online. This includes purchases from online shops. It also includes buying from, or selling to, other users when facilitated by an online platform. Fake reviews might influence the purchase process, misleading consumers into purchases that they would not otherwise have made (for instance, buying low quality products). In addition, fake reviews distort competition by interfering with the quality signals that drive consumer choice, thereby imposing costs on legitimate sellers and platforms which are ultimately reflected in higher prices for consumers. Consumers may also inadvertently purchase counterfeit goods and products or fall victim to fraudulent websites and services, such as fraudulent investment services. Such harms are likely to be primarily financial in nature. However, there may be other impacts, such as emotional distress or anxiety.

3.2.2 Harms from misleading or false content: Fake reviews

Erroneous information about a product or seller may steer a consumer into a purchase decision they later regret. One potential mechanism for this is via fake reviews for products. A fake review is a consumer review that does not reflect an actual consumer's genuine experience of a good or service.[49] The CMA noted that reviews appear to form an important part of consumers' decision-

[47] ICO (2021b).

[48] CMA (2022b).

[49] BEIS (2021b).

making processes, although the importance of reviews varies by product sector.[50] Digitisation of consumer reviews and the ease of posting these have created a growing 'industry' that thrives on creating and selling fake reviews, misleading consumers.[51] Consumers may be harmed by fake reviews directly through products and services not reflecting the expected content based on the fake review; and indirectly through higher prices reflecting the cost of identifying and removing fake reviews, investment in quality signalling for genuine reviews, or distorted competition due to negative impacts on businesses with legitimate positive reviews.

Our review of the literature on fake reviews found the following:

Evidence of harm

- A Which? behavioural study found that **fake reviews** make consumers more than twice as likely to choose poor-quality products.[52] This is corroborated by He et al. (2021), who find that fake reviews generate a short-term uplift in sales, followed by a large number of one-star reviews, suggesting fake reviews influence consumers to buy poor quality products. However, the degree of harm suffered may be mitigated by consumers' rights to return products.

Evidence of practices that can lead to harm

- According to a report from Fakespot, an AI company, in 2020 over 30% of online customer reviews on major e-commerce sites were deemed fraudulent.[53]
- A paper by Luca and Zervas (2015) found that around 16% of restaurant reviews were likely to be fraudulent.
- He et al. (2021) found that Amazon deletes 23% of product reviews as fake, even for products where sellers were not found to be actively recruiting fake reviews (a process where sellers solicit users to purchase their products and leave a five-star review in exchange for a refund). For products for which fake reviews were recruited, it was found that on average 43% of reviews were deleted as fake.

3.2.3 Harms from misleading or false content: Fraud/scams

Consumers may be impacted by fraud or scams when purchasing online. For instance, consumers might believe they are purchasing genuine goods when they are actually buying counterfeits. These harms may be particularly true for more vulnerable consumers, e.g., people with mental health problems are three times more likely to have fallen victim to an online scam.[54]

Our review of the literature on fraud/scams found the following:

[50] CMA (2015).

[51] Which? (2021a).

[52] Which? (2020a).

[53] Fakespot (2021).

[54] Money And Mental Health Policy Institute (2020).

Evidence of harm

- Ofcom surveyed UK consumers and found that 27% claimed they had been exposed to scams, fraud or phishing in the previous four weeks.[55] However, this figure includes incidence of scams between individuals, which is not in the scope of this study.
- Which? Analysed data from Action Fraud, finding that between April 2020 and March 2021 there were £2.3 billion in damages for consumers.[56]
- A study for the EUIPO, which focused primarily on intellectual property infringement, reported that 9% of Europeans claimed they were misled into buying counterfeit products.[57]
- A Trading Standards article on the sale of counterfeit goods online found that counterfeiting costs the UK economy £4bn per annum.[58] However, a challenge here is that many consumers knowingly purchase counterfeit goods, largely because they are cheaper.[59]
- In terms of advertising, an experiment by Which? highlights the opportunity to gain traction with fake ads and the lack of safeguards against fraudulent advertising.[60] Through advertising with market leading companies Google and Facebook, they were able to gain significant traction on the social media page for a fake brand they created.

3.2.4 Harms from misleading or false content: Loss of trust in buying and selling online

During the past few decades, online retail has become increasingly popular with rapid growth across international markets. Between 2010 to 2020 in the UK, for example, online retail has more than quadrupled as a share of total retail sales,[61]implying the generally positive experience consumers tend to have online.

Concerns about nefarious or fraudulent practices in e-commerce can impact the willingness of consumers to engage in online transactions. The OECD found that around 15% of internet users in the EU28 abstained from purchasing online on account of concerns regarding the delivery or the return of the product in 2017.[62]

While there is a considerable amount of literature on the role of trust in relation to transactions involving personal data (including reactions to data breaches and data practices such as sharing data with third parties), we have found no further evidence on the relationship between trust and misleading and false content. Overall, the evidence surrounding loss of trust is much more limited than the evidence surrounding other harms in the taxonomy.

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[55] Ofcom (2021b).

[56] Which? (2021b).

[57] EUIPO (2021).

[58] Trading Standards Scotland - Counterfeit Goods Online.

[59] IPO (2020).

[60] Which? (2020b)

[61] ONS. Internet sales as a percentage of total retail sales.

[62] OECD (2019).

3.3 Barriers to switching and multi-homing

3.3.1 Overview

Some digital firms, and especially the largest platforms, offer a range of distinct services which are packaged together. This can be of benefit to consumers, in terms of the reduced search costs and improvement to the quality of the services offered. Indeed, such practices are common in offline and online markets 'in almost any given industry and are usually considered beneficial by the companies employing them as well as their customers'.[63]

However, consumers may be harmed if they cannot easily switch providers or access similar services from different providers simultaneously. Barriers to switching and multi-homing pose a problem for consumers as there may exist an alternative service which better fits their needs. If consumers cannot easily switch away from a particular platform, that platform will lack incentives to improve its service, and may have the ability to overcharge its users.

3.3.2 Barriers to switching' or multihoming: Service tying/bundling

Firms in digital service markets may engage in tying and bundling practices. This can be beneficial as it can lead to better quality services and reduced search costs.[64] However, such practices can also allow firms to entrench their dominant market position and restrict innovation. As with many digital consumer harms, while bundling and tying are common and longstanding commercial practices in many markets, the harmful effects can be amplified by the characteristics of digital markets. Providers are able to bundle digital services in a way that feels natural to the users (e.g., by integrating different programs/apps with a common user interface).

Through tying and bundling, consumers are compelled or incentivised to purchase different products together. This happens frequently in digital markets, where "products often feature modularity or linkages with other products, whether in the form of hardware, software, or web-based services."[65] The nature of digital products could make technical tying and bundling relatively easy to implement, e.g. creating an ecosystem with a seamless interface between different products.[66] Firms may also engage in "self-preferencing" of their own products and services, which has been characterised as a tying strategy.[67] Tying or bundling can lead to long-term harm for consumers and competition in situations where a firm can leverage its market power in one market to foreclose competition in another.[68]

Our review of the literature on service tying/bundling found the following evidence of harm:

- In 1998, the US Department of Justice sued Microsoft Corp. for its practice of tying the operating system Windows with the Internet browser Internet Explorer.
- In 2017, the EU Commission fined Google €2.4bn for abusing its dominant position in the general search market by favouring its own comparison shopping service in its search

[63] Mandrescu. D. (2021).

[64] Ibid.

[65] OECD (2020).

[66] Ibid.

[67] Ibid.

[68] Ibid.

results. The Commission argued that Google's self-preferencing conduct foreclosed competing comparison shopping sites from the market, which reduced consumer choice.

- In 2018 the European Commission fined Google €4.3bn for requiring manufacturers to pre-install the Google Search app.[69] It has been argued that the practice can reduce consumer welfare and may also increase the price of mobile devices.[70]

3.3.3 Barriers to switching or multihoming: Factors that prevent switching

In some markets, for example where services are overly similar, or engaging with another service provider is perceived as a waste of time, consumers will not use multiple services simultaneously.[71] For effective competition to prevail, consumers need to be willing and able to switch to an alternative service provider if it has a superior offering.

It is generally recognised that there are many factors that can affect switching rates in some digital markets, in particular platform markets/ecosystems.[72] Key barriers to switching have been highlighted in major investigations including the Furman Review[73] and the CMA's (2022) interim report for the mobile ecosystems market study[74] which considers evidence for barriers to switching between devices using the iOS and Android operating systems. Some of the key barriers to switching in digital markets are outlined below:[75]

- Loss of personal data, where consumers moving to a new service are unable to take their history with them. This may mean loss of photos, messages and interactions, or the history of tracked activities.
- Loss of reputation, including ratings and endorsements such as buyer or seller feedback.
- Technical barriers, where competing services rely on different systems and standards that are not interoperable. This may also manifest itself in terms of the difficulties of transferring data, apps and subscriptions across devices.
- Inertia, where consumers display strong preferences for defaults, brands and services that they are familiar with.
- Users may find it difficult to adapt to different controls and functionality (learning costs), and this may be perceived as a hassle and thereby discourage switching.
- Loss of access to shared functionality, for example interacting with friends and family on iMessage.

3.3.4 Barriers to switching' or multihoming: Lack of alternative services

Even if consumers did want to switch, it is possible that in some circumstances the availability or awareness of viable alternative services may be limited. In part, this is because the 'winner-takes-all' nature of markets that exhibit strong economies of scale (including network effects) reduces the number of viable alternatives. It can also be a function of high search costs which can be further

[69] European Commission (2018).

[70] Etro, F. and Caffarra, C. (2017).

[71] HM Treasury (2019).

[72] Barriers include 'traditional' barriers such as loyalty rebates, but also barriers that are particularly effective in digital settings, such as limited interoperability between platforms and the need to learn new systems. See OECD (2020).

[73] HM Treasury (2019).

[74] CMA (2022c).

[75] Ibid.

exacerbated by self-preferencing. In addition, the digital economy continues to give rise to disruptive businesses, which are genuinely first-to-market in a given niche and bestow at least temporary monopolies on first movers.

Our review of the literature on lack of alternative services found the following:

Evidence of harm

- Citizens Advice used a combination of survey and analysis of market data to calculate that the "loyalty penalty" (the higher cost of services paid for existing customers compared to new customers) was £4.1 billion per year across 5 markets (mobile, broadband, home insurance, mortgages and savings accounts), which amounts to £877 for an average household.[76]

Evidence of practices that can lead to harm

- In relation to search engines, the CMA notes that "consumers may perceive little benefit to changing defaults, especially if the default search engine is the market leader (Google) and the alternatives are not well understood".[77]
- According to a Which? study, consumers tend to accept data collection based partly on a perceived lack of alternatives.[78]

3.4 Unfair consumer data practices

3.4.1 Overview

Transactions in digital markets yield a wealth of data on consumers and their preferences. CMA (2021) points out that the "availability of ever-greater volumes of data about consumers, coupled with the use of algorithmic systems, has resulted in the ability of firms to personalise their actions and interfaces to each consumer to an extent not previously possible." The CMA also notes that, firms can use "machine learning techniques to identify meaningful categories of consumers and apply different treatments to each category."

Often, personalisation generates benefits for consumers in the form of more appropriate, tailored products and services, reduced search costs and a better customer experience. However, consumer information can be exploited in ways that could cause harm. In particular, consumers may be subject to opaque algorithmic discrimination, where an algorithm has been trained on data which contains biases based on certain protected characteristics. Targeted advertising can be used inappropriately, e.g., in targeting vulnerable users and children. Consumers may also be receiving an unfair exchange for their personal information.

3.4.2 Unfair consumer data practices: Algorithmic discrimination or bias

The availability of massive data sets and emergence of new technologies (e.g., AI and Machine Learning Systems) is allowing organisations in the public and private sectors to derive new insights

[76] Citizens Advice (2018).

[77] CMA (2020b).

[78] Which? (2018).

and automate varied decision-making processes. Some algorithms run the risk of replicating or even amplifying human biases, especially people with protected characteristics.

Many applications of algorithmic decision-making use data on past behaviour to make predictions about future behaviour. This means that biases inscribed in the data can replicate existing biases and result in algorithmic discrimination (e.g., predicting career success based on a historical sample in which women were less likely to be represented in higher management positions). Firms may not intend to treat individuals with certain immutable characteristics differently. However, discrimination can result from the use of categories that are correlated with these characteristics as inputs for the algorithms. This can lead to less favourable market outcomes (e.g., higher prices) for individuals from certain groups.

Consumers online might be subjected to price discrimination, where personal data is used to infer a consumer's maximum willingness to pay and to adjust the prices they are shown accordingly. Of itself, this may not be inefficient: price discrimination could imply lower prices for some consumers, which may increase total welfare.[79] However, concerns have been raised that price discrimination, especially if coupled with behaviour that preys on consumer vulnerabilities, may be unfair to some groups of consumers.[80]

It is not surprising that there is limited empirical literature quantifying the harm to consumers arising from algorithmic bias. The lack of understanding around the extent and scale of algorithmic bias is identified as a major challenge by the CDEI.[81]

Our review of the literature on algorithmic discrimination found the following:

Evidence of harm

- Bartlett et al. (2019) found that algorithms were systematically charging otherwise-equivalent Latinx/African American borrowers higher rates for mortgages (the difference in interest rates was found to be between 2.0% and 5.3%).
- Bertrand and Weill (2021) explore the effect of possible algorithmic discrimination in the wider loans market (including business loans, car financing, credit card refinancing and home buying). The authors analysed loan acceptance, interest rates and loan maturity as outcome variables. It was found that a 1 percentage point increase in African American residents in an area was associated with a 0.07% increase in the interest rate, a 4.11% increase in the likelihood of a short loan maturity and a 0.9% increase in the likelihood of being rejected for a loan.
- A recent FCA market study on general insurance pricing practices highlighted the possible need for future work related to the relationship between algorithms and race.[82]
- It has been noted that in the past, black individuals in four US cities were half as likely to live in neighbourhoods with free same day shipping from Amazon Prime, due to the fact that Amazon focused their service on areas with a high concentration of Prime members.[83]

[79] Borgesius, F. and Poort, J. (2017).

[80] OECD (2018a).

[81] CDEI (2020).

[82] FCA (2021).

[83] Ingold, D. and Soper, S. (2016).

- Angwin et al. (2017) explore how algorithms may be leading to discrimination in the car insurance industry. To obtain a risk profile of each area, the authors divided the total liability payments made by insurance companies by the number of cars insured in that area. This was then compared for neighbourhoods with at least 66% minorities to other neighbourhoods for a specific profile of the consumer. It was found that premiums were up to 30% higher in the neighbourhoods with a high proportion of minorities.
- Kisat (2017) conducted a Randomised Control Trial in which loans were randomly assigned to either loan officers or an algorithm. Within these two groups, some loan applications included information on the demographics of the applicant, and some did not. It was found that when the demographic information was disclosed, the algorithm was 11% more likely to approve a loan for a man than a woman, 3% higher than when demographic information was not disclosed.
- A report from BEIS similarly concluded that, despite widespread perception that the practice is commonplace, there is limited empirical evidence of price personalisation on the internet.[84] Furthermore, an OECD report came to the same conclusion despite noting the existence of a Deloitte survey indicating that 40% of retailers using AI to personalise customer experience use AI to tailor pricing and promotions.[85]
- Azzolina et al. (2021) explored price personalisation by three major European airlines, and did not find robust evidence of price personalisation. For example, price differentials for Ryanair based on browser and OS were found to be less than 50 cents.
- Hüllman and Badmaeva (2019) assessed price discrimination by the eleven largest German e-commerce retailers and did not find widespread evidence of personalised pricing.
- Hannák et al. (2014) explored the possibility of price personalisation by 16 leading e-commerce websites according to features such as cookies and browser operating system and found evidence of price personalisation by 9 retailers. In some cases, the price variations were large, e.g., hundreds of dollars difference for a hotel room.
- Hupperich et al. (2018) investigated the extent of price personalisation in the hotel and rental car industry. Just 50,000 out of over 4 million data records showed evidence of price personalisation. Where discrepancies did exist, they were typically found to be just a few euros. The features most associated with price personalisation, although limited, were location, language settings, operating systems, and browser.
- Research indicates that many consumers regard price discrimination as "ethically wrong" or generally unfair.[86,87]
- Amazon had to scrap an automated recruitment tool after it exhibited bias against women as the algorithm taught itself that male candidates were preferable for the jobs advertised.[88]

3.4.3 Unfair consumer data practices: Algorithmic targeting

Targeted advertising is generally better for advertisers and consumers, based on increased relevance. The ability to use a range of increasingly granular data-points to personalise advertising

[84] BEIS (2021c).

[85] OECD (2018b).

[86] Borgesius, F. and Poort, J. (2017).

[87] BEIS (2021c).

[88] Reuters (2018).

content, is a key factor of the rapid growth of the online advertising industry during the past few decades.

Targeted advertising can also lead to consumer harms, however. The UK government's consultation on online advertising notes three types of harm from targeted ads: mis-targeting, discriminatory targeting and targeting of vulnerable people.[89] Mis-targeting refers to age-restricted adverts targeted at inappropriate audiences (e.g., children) or adverts placed next to harmful content. Discriminatory targeting involves adverts targeted on the basis of protected characteristics. Finally, targeting of vulnerable people involves, for example, targeting recovering gambling addicts with gambling adverts when they have taken steps to exclude themselves from receiving these types of ads.[90]

Our review of the literature on algorithmic targeting found the following:

Evidence of harm

- Targeted ads on Facebook for supermarket cashier positions were shown to an audience of 85% women.[91]
- Avery (2016) used data collected from a survey of university students to estimate that consumers are willing to pay $4.06 to avoid targeted ads.[92] It was also found that they were willing to pay $0.28 to decrease the frequency of ads when graphics are static, $2.71 to decrease the frequency of ads, $1.30 to avoid ads with animated graphics, and $3.73 to avoid animated graphics with the mean ad frequency level.

3.4.4 Unfair consumer data practices: Loss of control of personal data

The available evidence generally suggests that many consumers are concerned about data practices and the widespread collection of personal data.[93] However, assessing how consumers value their privacy is not straightforward. Such valuations are complicated by the mismatch between individuals' reported concerns about use of personal data and their observed behaviours (the so-called 'privacy paradox').[94]

Attempts to quantify how consumers value their privacy and their personal data often find inconsistent results, with valuations dependent on how the question is framed.

Our review of the literature on loss of control of personal data found the following:

Evidence of harm

- Winegar and Sunstein (2019) found that the median consumer is willing to pay $5 per month to maintain data privacy (along specified dimensions), but would demand $80 to allow access to personal data.

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[89] DCMS (2022c).

[90] Ibid.

[91] Bogen, M. (2019).

[92] Avery, K. (2016).

[93] See Kennedy et al. (2020).

[94] See Acquisti et al. (2016).

- Prince and Wallsten (2020) investigated how much compensation consumers would demand in order to share their data and explored how this differs by country. It was found that Germans value privacy more than people in the United States and Latin America.
- Which? (2021) surveyed a panel of UK consumers and found that those who were informed about how Google and Facebook use their personal data had a higher willingness to pay to restrict the use of their personal data and demanded more compensation for personal data use than uninformed consumers.[95]

3.5 Exploitative behaviour

3.5.1 Overview

Consumers are able to access a wide range of services and content online at no monetary cost. Many digital firms offer access to high quality services - such as tools for messaging, navigation, sharing content, learning, browsing, search and many more - in exchange for data or by selling online advertising inventory.

However, consumers may be harmed if they pay an excessive cost for a product or service. This may arise if a firm exploits its market power to charge a higher price (or non-monetary price) than would be expected in a competitive environment. Many digital services are zero-price services in which consumers are not charged a monetary price for the use of the service, with the services being funded through commissions paid by business users or through advertising. Consumers are effectively paying through their exposure to advertising and through the provision of their personal data (which can be used to generate consumer insights and/or to target digital advertising more effectively). The level of data collection or advertising may be excessive relative to the service that consumers are being provided with.

3.5.2 Harms from exploitative behaviour: Excessive data collection

A notable feature of many digital platforms is that they offer services to consumers at zero monetary price. Buiten (2020) notes that monopolists operating in zero-price markets may be able to collect excessive amounts of data by exploiting their dominant position. However, establishing the difference between a competitive non-monetary 'price' and an excessive one is challenging.[96] The OECD notes that for non-monetary units of exchange such as data or attention to advertisements, there is "no simple measure of value".[97] There are a number of difficulties with attempting to attach a monetary value to these elements, including heterogeneous consumer preferences, non-monetary factors,[98] and consumers' lack of experience with these 'currencies'.[99] Determining whether the non-monetary 'price' consumers pay is excessive also requires consideration of what would *not* be excessive. A key consideration here is whether consumers receive an appropriate service in exchange for their data.[100]

Our review of the literature on excessive data collection found the following:

[95] Which?, Accent and PJM economics (2021).

[96] Budzinski et al. (2020).

[97] OECD (2018c).

[98] Buiten, M. (2020).

[99] Budzinski et al. (2020).

[100] Buiten, M. (2020).

Evidence of harm

- The Bundeskartellamt found Facebook to have a dominant position in the social network market and found that Facebook's data collection practices constituted an exploitative abuse of dominance. However, the Bundeskartellamt notably did not attempt to prove that the data collection was 'excessive', instead arguing that Facebook's data collection practices were contrary to data protection law.[101]
- Curzon Price (2019) suggests that the level of data collection is excessive.[102] There is also theoretical work of Acemoglu et al. (2019) which suggests that because data sharing by users of online platforms also reveals information about other users, there is excessive data sharing.[103]
- Acemoglu (2020) highlights the potential scale of the effects of excessive data sharing, using the Cambridge Analytica scandal as an example. Information on over 50 million Facebook users was derived based on just 270,000 downloads of the Cambridge Analytica app.[104]

3.5.3 Harms from exploitative behaviour: Excessive advertising

Harm from excessive advertising could occur in instances where consumers find ads intrusive or annoying, as such those ads degrade the quality of experience when using digital services. A challenge here is that consumers' preferences are not uniform: some may find advertising (and ad targeting) useful.

There is very little quantification of the harm to consumers arising from excessive advertising. However, it can be noted that the scale of the problem is likely to have increased due to recent growth in the size of the digital advertising market in the UK. eMarketer estimated that in 2021 the total digital advertising spend reached £19 billion and noted that Google and Facebook account for shares of 40% and 29% respectively.[105]

3.5.4 Harms from exploitative behaviour: Excessive prices

Digital platforms have received considerable attention from competition authorities in recent years. Various reports and studies have noted the particular features of digital services markets which may give rise to competition concerns, namely economies of scope and scale, the importance of consumer data, strong direct and/or indirect network effects,[106] and barriers to switching.[107] In traditional markets, exploitative abuses may arise in the form of the charging of excessive prices to consumers. In digital markets, the focus has been on other forms of potential exploitative abuse, such as excessive data collection or advertisement exposure.[108]

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[101] Bundeskartellamt (2019).

[102] Curzon Price. (2019).

[103] Acemoglu et al. (2019).

[104] Acemoglu, D. (2020).

[105] Fisher, B. (2021).

[106] Direct network effects occur when the benefits to a user increase as the number of users increases. Indirect network effects occur when the benefit to users on one side of a platform market (e.g. buyers) increase with the number of users on the other side of the market (e.g. sellers). Both effects will tend to make larger platforms more valuable to users.

[107] HM Treasury (2019). Unlocking digital competition, Report of the Digital Competition Expert Panel.

[108] OECD (2020). Abuse of Dominance in Digital Markets.

Our review of the literature on excessive data collection found the following:

Evidence of harm

- The CMA highlights that expenditure on digital advertising, which is artificially high due to the market power of Google and Facebook, may be passed on to consumers in the form of higher prices.[109] They calculated that in 2019 the total spend on digital advertising amounted to approximately £500 per household. The ACCC have also raised concerns with the digital advertising market.[110]

3.6 Summary of literature review

Table 4 presents a summary of the results of the more detailed review for selected harms.[111] While some harms have relatively strong evidence, such as fake reviews and distorted consumer choices, the majority of harms have limited or very limited evidence. Further research across all of these harms would be useful, but 'Excessive use' and 'Algorithmic discrimination' may be especially valuable given their significant prevalence and severity but currently limited evidence bases.

Table 4 Summary of evidence for selected harms

Harm	Prevalence	Severity	Feasibility of quantifying	Major evidence types	Summary of evidence
Distorted consumer choices	**High**	**Medium**	**High**	**Experiments**	**Strong evidence of the use of dark patterns by online shopping websites**
Excessive use	High	High	Medium	Observational studies	Multiple studies identify a link between the use of services such as social media and mental health issues
Fake reviews	High	Medium	Medium	Observational studies, Case studies	Strong evidence of fake reviews on the internet, however less evidence related to the impact on consumers
Fraud/scams	High	High	High	Case studies	Bodies such as Which? and Trading Standards have quantified the consumer damage associated with fraud and counterfeit goods

109 CMA (2019). Digital Advertising Report.

110 ACCC (2021). Digital advertising services inquiry.

111 Bold text denotes that the harm is quantified below.

Harm	Prevalence	Severity	Feasibility of quantifying	Major evidence types	Summary of evidence
Barriers to switching	High	Medium	Medium	Case studies	There is some evidence to suggest that consumers may benefit from switching services more
Algorithmic discrimination	Medium	Medium	Low	Observational studies, Case studies	Strong evidence of discrimination in some markets (mostly insurance and lending in the United States)
Price discrimination	Low	Low	Low	Experiments, Case studies	Lack of evidence of widespread use, and where identified it is usually on a small scale
Excessive data collection	High	Medium	Low	Theory	Strong theoretical basis for excessive data collection, however the literature suggests it is very difficult to assign a monetary value to this harm
Excessive advertising	**High**	**Medium**	**Medium**	**Theory, Case studies**	**Virtually no evidence beyond the high level of profits of major players in the digital advertising space**

4 Root cause analysis

4.1 Overview of root causes

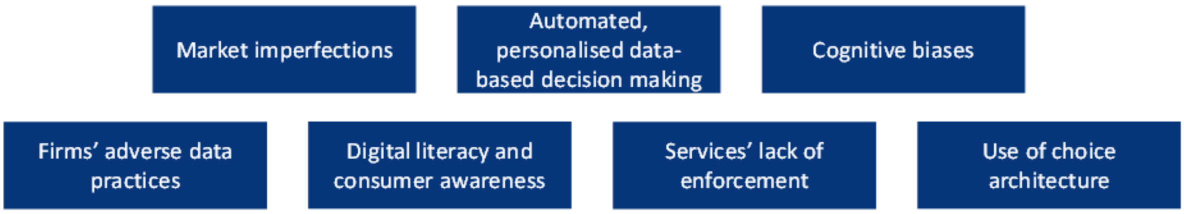
The categories of harms discussed in the previous chapter can be mapped to a set of root causes. Root causes are factors that characterise firm-consumer interactions in a digital environment which give rise to specific consumer harms. These root causes are useful to policy makers as they can ensure that any potential interventions target the cause not the symptom.

Root causes are not discrete; multiple root causes will interact to produce a specific harm, and so it is not always possible to identify the primary root cause associated with it. The causal chains that link root causes to observable harms typically combine multiple factors that establish a mechanism by which a harm is generated that can be complex and specific to a situation, market, firm, or individual.

Finally, some of the root causes of consumer harm are also root causes of consumer benefit. An example of this would be the creation of better options for digital consumers through automated personalised data-based decision making.

Based on the evidence review we identified **seven root causes** of the consumer harms (Figure 1). These root causes are presented in Figure 1 and discussed in greater detail below.

Figure 1 Root causes of digital consumer harms



4.2 Definitions of root causes

4.2.1 Market imperfections

Market imperfections are features which may impede the efficient functioning of markets. These imperfections are not uniquely digital and can exist in all markets. Examples of the most common market imperfections include:

- **Lack of market competition:** when competition is constrained in a market, the lack of competitive constraints facing firm/s operating in the market can lead to inefficient outcomes such as higher prices, lower quality, less innovation and less choice.
- **Asymmetric information**: when markets operate efficiently, buyers and sellers have equal information on goods or services. Where one party to a transaction holds more information than the other, this can distort market signals and lead to inefficient outcomes.
- **Barriers to market entry and expansion**: where potential competitors find it difficult to enter into a market and compete with the incumbent firm, or when existing competitors find it difficult to challenge the leading firm. Some include:

- □ **Network effects**: users get more value from the service the more other users there are on it. This includes:[112]
  - – Direct network effects: The value to platform users increases with the number of users on the same side of the (multi-sided) market (e.g., social media platforms).
  - – Indirect (or 'cross-side') network effects: The value to users on one side of the market increases as a new user on a different side joins the network (e.g., an increase in the number of sellers benefits buyers on a retail platform).
- □ **Economies of scale**: Per-unit cost falls as the number of units consumed grows. Digital services exhibit strong economies of scale, with large fixed costs and near-zero marginal costs. This can favour incumbent firms and make it difficult for potential competitors to enter the market.
- □ **Economies of scope**: In some cases, established players in digital services markets have branched out into adjacent markets (for instance, maps/location services and messaging services). This adds to the value of their data but may also raise barriers to switching for users.
- □ **The role of data**: Data is a crucial input to digital services, being used to optimise and develop new services, as well as to target advertising. The possession of large quantities of data may therefore confer a competitive advantage, which potential competitors may not be able to replicate.

■ **Lack of substitutes**: Digital markets, being an area of significant innovation, can lack sufficiently close substitutes, especially when services are first-to-market. This can limit how much choice consumers have.

4.2.2 Cognitive biases

Data collection allows businesses to deeply understand the market so they can serve consumers in more innovative, intuitive, and creative ways—resulting in consumers whose needs, wants, and desires are met. New technologies, such as AI, use this data to 'learn' about consumers' behaviour. Algorithms can therefore run the risk of replicating or even amplifying human biases.

Consumers show systematic (non-random) deviation from rational behaviour in decision-making and use persistent heuristics (i.e., shortcuts) to make decisions. There are a large number of heuristics that impact almost all the decisions we make in our everyday lives. These include:

- ■ **Anchoring**: People tend to overly rely on the first piece of information that they see.
- ■ **Decoy effect:** People tend to change their preference between two options when a similar but less attractive third option is introduced.
- ■ **Default bias**: People tend to maintain default choices rather than actively select a different option.
- ■ **Framing**: People tend to be influenced by the way by which options are presented to them (e.g., language, colour, size). The way in which price information is presented is known as price framing.[113]
- ■ **Information overload**: When presented with an excessive amount of information, people tend to base decisions on a subset of the relevant information.

112 BEIS (2021a).

113 DellaVigna (2009).

- **Priming**: People can be prompted (or 'led') to choices by cues given to them early in the decision-making process, without their conscious awareness.
- **Social proofing**: People tend to follow others and imitate group behaviours rather than making decisions independently.

The presence of these inherent biases means that human decision-making can be distorted by the way in which a choice is presented, and by the messages and signals people are exposed to during the decision-making process. There is reason to believe that the "personalisation at scale and intense systematisation"[114] enabled by the digital environment makes consumers in digital markets particularly prone to harms arising as a result of the exploitation of cognitive biases.

4.2.3 Firms' adverse data practices

The collection and use of consumer data can facilitate positive outcomes. It can help consumers locate and choose products that fit their specific needs. For example, targeted advertising allows brands to send different messaging to different consumers based on what the brand knows about the customer. The better a brand can demonstrate that it understands what its customers want and need, the more likely customers respond to advertising and engage with the brand.

However, adverse data practices can exploit consumers' choices and personalise the offer in detriment of consumer outcomes. To acquire user data, firms' practices may include measures that make it difficult for users to opt out or choose how their data is processed due to complicated interfaces or terms and conditions.

The creation of 'data lakes' (firms combining datasets from different parts of the business) and large-scale datasets is a key differentiator between digital markets and their offline counterparts. Data enables firms to gain a granular understanding of consumer behaviour, which can be used to extract consumer surplus and increase market dominance.[115]

Another adverse data practice is the creation of barriers to interoperability. This includes not allowing for standards or functionality to facilitate data sharing or data access.

4.2.4 Automated, personalised data-based decision making

Automated algorithms can be used to enhance the consumer experience. For example, price comparison sites can save time and money when navigating offers, take the hassle of switching suppliers, help consumers understand their consumption needs and potentially lead to changes in consumption behaviour. Price comparison sites can therefore help to shift traditional asymmetries in information and power between a consumer and a supplier.

However, the increasing sophistication of algorithms to analyse and predict consumer behaviour with only limited human oversight, as well as the availability of cheap data storage and computing power, has enabled firms to automate and personalise their interactions with consumers to an unprecedented extent.[116] This includes personalising the prices at which services are offered, which products get recommended to consumers, which ads get displayed, and many others.

[114] CMA (2022a), para. 1.19, p. 6.

[115] DellaVigna (2009). For example, incumbent firms can use the large datasets they collect from users in one market and use those datasets to enter other markets with a significant advantage.

[116] CMA (2021).

While this can generate benefits for consumers (such as better offers, reduced search costs) and for firms (such as efficiency gains from automation, better products and services), a number of factors can make automated, personalised data-based decision making a cause of consumer harm. This includes:

- Personalised pricing in a way that is opaque or unexpected to the consumer and enables the firm to extract consumer surplus very effectively;
- More general personalisation, where algorithmic systems can be used to optimise consumer interactions in the firm's favour (e.g., through choice architecture, see below); and
- Unfair ranking and other design choices to influence consumer preferences in the firm's favour.

A special case of harmful automated, data-based decision making is algorithmic discrimination, a form of personalisation regarding protected characteristics. Many applications of algorithmic decision-making use existing data on past behaviour to train the algorithm, which is then used to make predictions about future behaviour. This means that biases inscribed in the data (e.g., the systematic exclusion of certain groups of observations from the sample) can replicate existing biases (e.g., predicting career success based on a historical sample in which women were less likely to be represented in higher management positions).

4.2.5 Use of choice architecture

Choice architecture is a neutral term; a well-designed website, app or digital service built with consumers' interests in mind will help consumers choose between suitable products, make transactions faster, and recommend new relevant products or services.[117]

But, in a digital environment, firms can design all aspects of the interaction between them and their customers in minute detail and thereby influence consumer behaviour in ways that are unprecedented in offline settings.

Design choices can be used deliberately to guide customers towards decisions and actions that benefit the firm. Harmful use of choice architecture attempts to exploit consumers' cognitive biases to induce behaviour that reduces the benefit for consumers from the transaction; for example, if they are led to purchase products that are unsuitable for their needs or offer them poor value.[118] A recent CMA discussion paper on online choice architecture provides a taxonomy that distinguishes between choice architecture in relation to choice structure (the design and presentation of options), choice information (the content and framing of information provided), and choice pressure (the indirect influence of choices, e.g. through claims of scarcity or prompts and reminders).[119]

Besides the direct effect on consumer behaviour, online choice architecture can also be employed to strengthen market power and weaken competition in digital markets, which can also have an indirect effect on consumers.

[117] CMA (2022a).

[118] CMA (2022b).

[119] Ibid.

4.2.6 Digital literacy and consumer awareness

Digital literacy relates to consumers' skills and understanding of digital services and markets, including the technical skills and know-how needed to navigate the digital environment safely and to take action to protect themselves against adverse outcomes.[120] In the UK (as well as most other countries), good progress has been made in improving digital literacy with the number of internet non-users halving between 2011-2018.[121] Low levels of digital literacy and awareness may, for example, make consumers more susceptible to fake reviews, fraud or scams.

Consumers may also be unaware or not understand what personal information they are sharing with a digital service, or how that information will be used. People may also lack awareness of their legal rights as consumers, such as their data subject rights under the Data Protection Act, right to request refunds, or how to access the relevant regulators and ombudsman services.

4.2.7 Services' lack of enforcement

Digital firms have strong incentives to govern their services and conduct self-regulatory measures to ensure a good user experience. Nonetheless, firms do not always manage to effectively police their platforms, enforce their terms of service, and comply with their legal obligations. Lax enforcement on an e-commerce platform may, for instance, lead to a greater volume of fake reviews or counterfeit products on the platform. While firms often have considerable leeway when it comes to implementing and enforcing rules within the law,[122] a lax or unbalanced approach can have adverse effects on consumers.

In addition, bad actors online continue to adapt their behaviour in response to measures taken by firms to protect consumers. This can make it difficult for firms to maintain an adequate level of enforcement, e.g., against online scams.

4.3 Linking harms to root causes

Harms can be linked with their root causes via causal chains. This section describes the relationships between the different types of consumer harms and their root causes. Often several distinct causes are involved in the manifestation of particular harms.

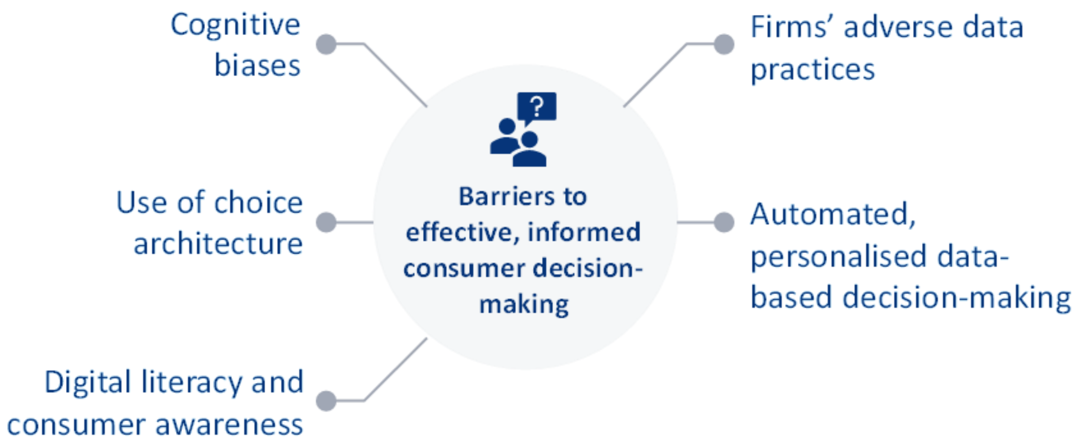
[120] DCMS (2021b).

[121] ONS (2019). Number (millions) and percentage of adult internet non-users, UK, 2011 to 2018

[122] E.g. While the GDPR sets clear rules for the provision of information to ensure informed consent, it stops short of prescribing the format in which information must be provided to fulfil the requirement for informed consent (e.g. European Data Protection Board (2020), para. 66, p. 16.

4.3.1 Barriers to effective, informed decision-making

Figure 2 Root causes of barriers to effective, informed decision-making



Barriers to effective, informed consumer decision-making are often caused by consumers' cognitive biases. Cognitive bias does not, by itself, lead to significant adverse outcomes for consumers. However, cognitive biases can, in some circumstances, make consumers vulnerable to manipulation, for example when firms apply harmful choice architecture. The deliberate exploitation of cognitive biases through the application of harmful choice architecture represents a distinct digital consumer harm. That said, certain uses of choice architecture are ubiquitous and generally well understood by consumers as a feature of a competitive market (for example the use of time limited offers, or price framing).

Digital literacy and consumer awareness are also root causes of barriers to informed decision-making. For example, a user might not be aware of tell-tale signs that a website is designed to encourage higher spending, or they might not understand the implications of the terms and conditions they are signing up to when using a digital service.

Firms' adverse data practices provide them with information that can inform the choice architecture they deploy. A lot of granular data on consumers together with powerful, automated analytical tools to classify and test consumer responses (e.g., to different rankings of search results) is likely to magnify the harm caused by cognitive biases and reduce consumers' ability to make decisions for their own benefit.

4.3.2 Misleading or false content

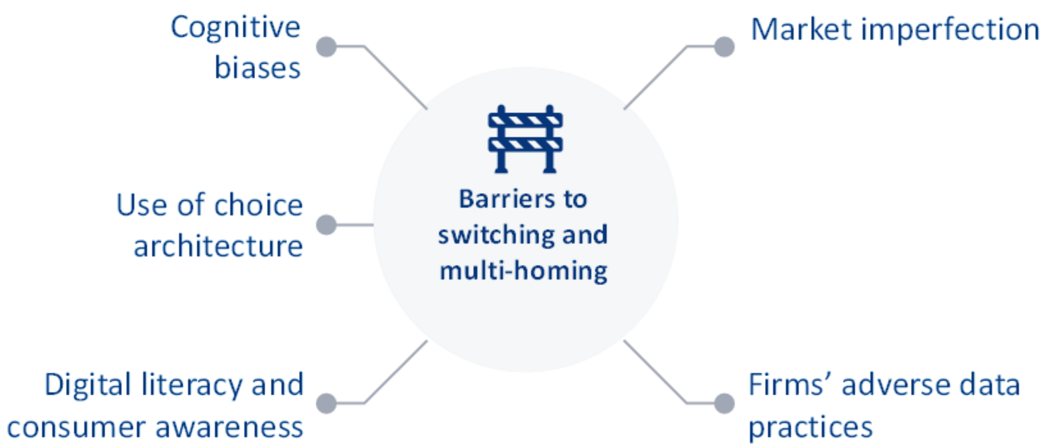
Figure 3 Root causes of misleading or false content

Digital literacy and consumer awareness may impact a digital customer's ability to identify misleading or false content. Consumer unawareness of the tell-tale signs of fraud/scams often leave them susceptible to harm online, in addition, consumers may lack the digital skills to safely navigate and interact online.

While digital platforms in principle have an interest in accurate information being available to consumers, a lack of enforcement is a key reason why misleading and false content continues to be a major source of consumer harm. The lack of enforcement is not necessarily malign, there can be technical reasons as the identification and monitoring of fake and misleading content is a significant challenge for firms.

4.3.3 Barriers to switching and multi-homing

Figure 4 Root causes of barriers to switching and multi-homing

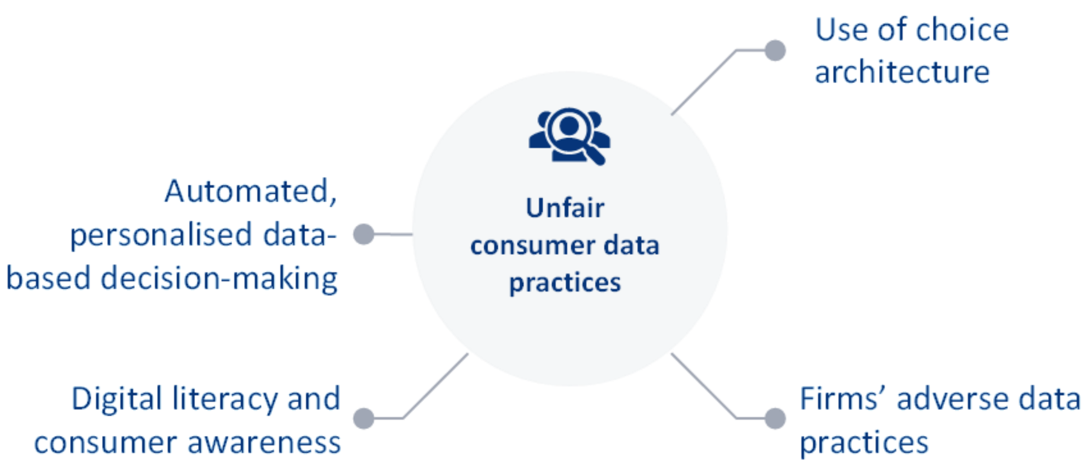


Many of the largest digital services firms operate as platforms at the centre of multi-sided markets and their wider ecosystems. The existence of market imperfections such as network effects in this setting, where the presence of more users enhances the value of the platform (e.g., social networks, eCommerce platforms), has the effect of locking in users to a particular platform and disincentivising switching and multi-homing. This may reduce consumer benefits as platforms are able to extract consumer surplus based on their market power, at least in the short term. In addition, in some digital markets where there are high barriers to entry, incumbents may simply be the only choice available for a while, giving them a temporary monopoly position and consumers nowhere to switch to.

Firms' adverse data practices may create technical barriers to interoperability, such as proprietary standards for data and difficult-to-use interfaces and processes to extract data, constituting an important additional cause. Firms may also use adverse online choice architecture to inhibit switching, for example by emphasising the network benefits of continued use of a platform, thereby exploiting cognitive biases such as default bias and social proofing. Finally, a lack of digital literacy and awareness of data protection rights (and data portability) can contribute to consumers' observed reluctance to change providers in digital services markets.

4.3.4 Unfair consumer data practices

Figure 5 Root causes of unfair consumer data practices



Unfair discrimination in digital markets, including discrimination based on protected characteristics, is enabled by the availability of granular consumer data, which may be collected, combined and interpreted in ways that are unknown and unexpected by users.

Choice architecture is often the vehicle which allows firms to implement unfair data practices (e.g., by encouraging consumers to opt in to intrusive data collection practices, and by restricting the choices that are available to an individual user).

Firms' data collection practices are a significant contributor too, as the large-scale collection of data (directly from consumers and from other sources) contributes to the problem and increases the amount of information that can be used to target users and personalise offers. This also interacts with a lack of consumer awareness and understanding of the terms and conditions under which they interact with firms online, what data they collect, and how this data is used. The CMA (2022a) notes that there are significant asymmetries between businesses and consumers that enable unfair practices. For example, "businesses can gather detailed information about how consumers respond to practices to set new standards for engagement (such as requiring that consumers hand over personal data in exchange for key services)".[123]

4.3.5 Exploitative behaviour

Figure 6 Root causes of exploitative behaviour

Market power as a consequence of market imperfections is typically at the root of excessive costs for consumers. Firms are said to have market power when they face a lack of competitive constraints, this enables them to raise prices above competitive levels. Network externalities, economies of scale and scope, barriers to entry and expansion are some reasons why firms have uncontested market power. There are other ways in which market power may distinctly manifest in digital markets, when the cost extracted from consumers is not necessarily a monetary loss but involves collecting excessive amounts of data from consumers or exposing them to excessive amounts of advertising.

Firms' adverse data practices can result in the creation of 'data lakes', the processing of and access to vast amounts of data can itself be an advantage to firms allowing them to extract consumer surplus and increase market power.

[123] CMA (2022a), para. 1.24, p. 7.

5 Measurement approaches

5.1 Measurement gaps

As highlighted in table 3, many of the harms that compose the taxonomy present a distinct lack of reliable observational studies and evidence that calculate the level of harm across the economy. It is typically not feasible to collect the relevant data for more than a small proportion of firms and markets. Such data is often commercially sensitive and therefore not widely available.

Measurement of harm is often restricted to specific retailers, platforms or markets. Given that the behaviour of market participants may differ greatly within and between markets, an assessment of the conduct of a specific market participant or within a specific market cannot be easily extrapolated to the wider economy to calculate the aggregate level of harm.

The evidence available typically comes from surveys and experiments, and in some cases is limited to a simple review of market outcomes. As a result, it can be difficult to obtain a full, unbiased picture on the prevalence and severity of individual harms. For example, when assessing the valuation of data privacy to consumers there is an inconsistency between their observed behaviour and reported attitudes around data privacy (the ‘privacy paradox’).

Furthermore, in the case of online platforms, even if a mechanism for harm is established it can be difficult to disentangle whether the harm arises from the platform itself or from the way the platform is used. This is perhaps best illustrated by the possible harm that social media use may have on mental health. Using data on individuals’ mental health status as well as their social media consumption, it is not always possible to distinguish between the effect of the social media platform itself with the effects of the way that user interacts with the platform (e.g., harm arising from viewing content that causes distress or bullying).

5.2 Quantifying digital consumer harms: methodological considerations

This section provides an overview of two methodologies that can be used to estimate digital consumer harms. These are top-down quantifications and bottom-up quantifications. The proposed methodologies provide a basic foundation for further evidence gathering. These methodologies can be built on and are by no means exhaustive.

The principle behind a top-down approach to quantification of harm is to first estimate the total size of a market e.g., annual online retail spending or number of active users on a platform. Once an estimate for total market size is calculated the next step would be disaggregating the total market size to estimate the proportion of the market that could be affected by the harm (this we refer to as market-at-risk[124]). Following this, one could then disaggregate the market-at-risk to arrive at an estimate for the actual market that is harmed (this we refer to as realised harm). An example of this could be the purchase of counterfeit goods in an online marketplace- by taking the prevalence of counterfeit goods on a platform (proportion of the market that could be affected by the harm) and then using the proportion of people that use that platform, you can estimate the average number of consumers affected by the harm (market-at-risk). Once the market at risk is estimated, specific

[124] The market at risk provides an estimate of harm if all purchases or all consumers would be subject to the harm.

transaction data for consumers who purchased counterfeit goods would then allow the market-at-risk to be scaled down to an estimate of realised harm.

The principle of a bottom-up approach is to calculate the harm experienced using a representative case i.e., an individual or a group of individuals. This estimate is then scaled up to the relevant population for an estimate of realised harm. An example of this would be calculating the level of harm suffered by an individual consumer as a consequence of algorithmic price discrimination- one could first calculate the harm experienced by one individual or group of individuals (representative case), following this, realised harm can be estimated by multiplying the representative case harm by the number of people in the population who are identified as likely to have also been targeted.

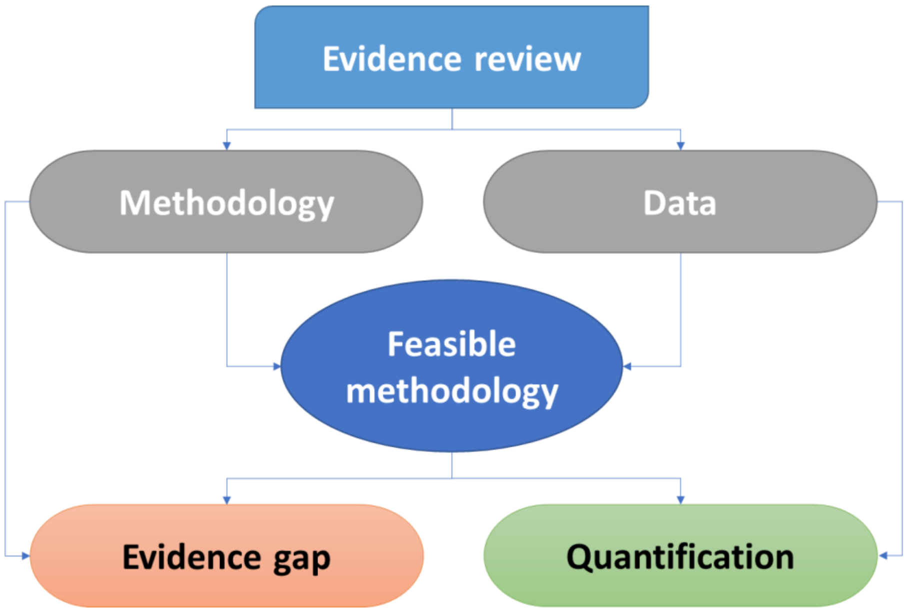
The choice of either a bottom-up and top-down approach is dependent on the available data for quantification. As such, it is important to conduct a scoping exercise. An initial evidence review provides insights into relevant theories, models, data sources, and whole quantification exercises that have been conducted in the past to quantify a given harm. The evidence review underpins a) the selection of a feasible methodology that can be implemented with the available data; and b) the value added of the new quantification exercise (no duplication of existing work).

The availability of relevant data is often the most important factor when choosing a quantification method. The assessment of the available data is therefore a crucial element of the evidence review. The assessment of data needs to look for at least the following:

- What topic does the data cover? Does it relate to specific harm?
- What form and structure does the data have? Is it a percentage? Is it a pound-sterling amount?
- Are there limitations to the data? Does the data only apply to certain populations? Can results be generalised? Does the data only relate to specific economic sectors (e.g., retail only)?
- Is the data reliable? Does it come from statistical agencies or from anonymous blog posts?
- What are the gaps in the data? Can these be filled by, for example, commissioning a survey?

On this basis, a feasible methodology (including whether to use a top-down or bottom-up approach) for quantification can be selected. Similar questions were used to identify the methodology for the illustrative examples below. By comparing what is possible with the available data with other theoretical approaches, the evidence gap that would need to be filled can also be identified.

Figure 7 From evidence review to quantification



5.3 Top-down quantification of harm

This section provides the overarching structure to the top-down approach, including the general type of data that would be required. In addition, it presents an illustrative example of quantification for the market-at-risk from deceptive online choice architecture. Lastly, it provides some conclusions on the appropriateness of this methodology.

5.3.1 Top-down quantification of harm: general methodology

As noted above, the principle behind a top-down approach to quantification of harm is to start at the total size of a market and disaggregate this figure to estimate realised harm. This is typically done in three steps.

Step 1: Calculate the total market size relevant for the quantified harm

To calculate realised harm with a top-down approach, we first need to understand in which market the harm occurs. For example, the illustrative example below looks at harms from practices that distort consumer decision making when purchasing goods and services online, hence, the affected market is online retail, and a relevant measure of harm is the consumer spending in that market.

Data to estimate the total market size is typically available from statistical agencies like the Office for National Statistics or the Northern Ireland Statistics and Research Agency. Certain market sizes may not be directly available from these agencies, but typically should be estimable from their data.

Step 2: Calculate the market-at-risk

Estimating the market-at-risk is useful to understand the proportion of the market that is likely to be affected by the harm. This recognises that a consumer harm may not affect the entirety of a given market. The part of the market which is affected is the market-at-risk.

Defining the affected market can be complex. For instance, the illustrative example below shows that not all online retailers try to employ practices that distort consumer decision making, so only a subset of consumer spending with online retailers is affected. The market-at-risk provides an upper-bound to the harm that could be occurring. This is estimated as follows:

$$Size\ of\ market\ at\ risk = Total\ market\ size * Maximum\ prevalence\ of\ harm$$

Data that can be used to estimate a market-at-risk can come from market studies and academic literature. Relevant evidence is often partial (e.g., limited to a narrow use case), in that it contains information on the prevalence of certain harms, but does not use this for market-level quantification. Although direct estimates are often not available, literature may be used as the basis for assumptions on the size of the market-at-risk.

Step 3: Calculate realised harm

The market-at-risk provides an estimate of harm if all purchases or all consumers would be subject to the harm. This may not be the case. For instance, the illustrative example explains that not all consumers will be affected by practices that distort decision making, some consumers may purchase goods and services with or without such practices being employed.

If the impact of the harm on consumers is estimable or known, then the market-at-risk and the change in consumer behaviour can be used to calculate realised harm. The exact methodology to calculate this will depend on the structure of the data. However, if the change in consumer behaviour can be expressed as a proportion (e.g., as increased likelihood of purchases), then realised consumer harm can be calculated as follows:

$$Realised\ harm = Market\ at\ risk * Impact\ on\ consumers$$

As for the market-at-risk, academic literature may be used for an assumption-driven estimate of realised harm. Other than that, consumer surveys or consumer experiments may provide a direct estimate to show the impact of the harm on behaviour.

The section below provides an illustrative example of the top-down approach applied to the use of OCA. Note that no data was identified that would have allowed for step 3 to be calculated. As such, the illustrative example only provides a market-at-risk estimate.

5.3.2 Top-down quantification of harm: Illustrative example - Market-at-risk due to deceptive OCA

This section provides an illustrative example of the top-down approach applied to the use of OCA. The illustrative example only provides a market-at-risk estimate and is intended to be for illustrative purposes.

OCA has additional features that distinguish it from choice architecture offline, most notably that the user experience can be negatively influenced at a very granular level, and that the impact of the choice architecture can be measured quickly and easily.[125] OCA may lead to consumer harm if online

[125] CMA (2022b).

user interfaces steer consumers towards decisions they would not have made otherwise or are not in their best interest.[126]

Methodology to estimate market-at-risk

Mathur et al. (2019) conducted a web-crawling exercise covering over 11,000 online shopping websites across the globe. For these websites, the authors examined the existence of text-based OCA[127] and classified whether the use of OCA was deceptive or not.

The findings of this paper can be used to proxy the prevalence of deceptive OCA across the web. This information can, in turn, be used to estimate a market-at-risk for deceptive OCA. We have done this in the three-step approach discussed above:

- **Step 1**: Establish the total market size for online shopping.
- **Step 2**: Calculate the prevalence of deceptive OCA using data obtained by Mathur et al. (2019).
- **Step 3**: Scale the size of the total market based on the prevalence of deceptive OCA.

Data to establish the total market size was obtained from the Office for National Statistics (ONS). The ONS provides information on online retail sales for Great Britain.[128] Data on the prevalence of deceptive OCA was obtained from Mathur et al. (2019). The web crawling exercise by Mathur et al. (2019) focused on 7 categories of OCA, covering 15 types of OCA. These are:

- **Sneaking**: Misrepresenting consumers' actions:
  - sneaking additional items into the consumers' basket;
  - partitioned pricing by adding hidden fees;
  - subscription traps by adding hidden subscriptions under the pretence of making a one-time purchase.
- **Urgency**: Artificially accelerating consumers' decision-making:
  - countdown timers;
  - "limited offer" messages.
- **Sensory manipulation:**[129] Using visual, language, etc., to steer consumers towards particular choices:
  - 'confirmshaming', or guilting consumers into accepting certain actions;
  - visual interference, or making certain options much more salient than others;
  - trick questions, e.g., by using negatives in tick-boxes ("click here if you do not wish to receive updates");
  - pressured selling.
- **Social proofing**: Influencing consumer behaviour by describing other consumers' behaviour:

[126] See chapter 3.1

[127] Note that the authors include both deceptive and non-deceptive OCA. Furthermore, the authors refer to the OCA under investigation as 'dark patterns'.

[128] Data collection for Northern Ireland is reserved to the Northern Ireland Statistics and Research Agency (NISRA). However, comparable data for Northern Ireland were not identified.

[129] Note that Mathur et al. (2019) refers to this as 'misdirection'.

  - activity messages such as “x number of people viewed this article in the last 24 hours”;
  - consumer testimonials with unclear origin.
- **Scarcity and popularity claims**: Signalling a product may become unavailable soon:
  - low-stock messages;
  - high-demand messages.
- **Obstruction**: Making it difficult to cancel services while it is easy to sign up for them.
- **Forced outcomes**: Forcing consumers to make a shopping account and share personal information before consumers can check out.

Quantification of market-at-risk

Establish the total market size for online shopping

The first step to take in the quantification is to calculate the total relevant market size. Mathur et al. (2019) focuses on online retail. Hence, this quantification will similarly focus on online retail.

Data was obtained from the ONS on internet retail sales in Great Britain. Comparable data for Northern Ireland was not identified. The ONS publishes the average weekly value for internet sales by month. This data was converted to an implied monthly value of internet retail and summed to an annual figure. Data was obtained for 2021, the most recently available year. The table below provides more detail.

Table 5 Calculation of total market size for internet retail

Month	Average weekly value for Internet retail sales (£ million)	Implied monthly sales value (£ million)[a]
January 2021	2,532.7	11,216.2
February 2021	2,454.7	9,818.8
March 2021	2,563.0	11,350.4
April 2021	2,369.7	10,155.9
May 2021	2,233.5	9,891.2
June 2021	2,195.7	9,410.1
July 2021	2,085.6	9,236.2
August 2021	2,011.2	8,906.7
September 2021	2,028.7	8,694.4
October 2021	2,207.6	9,776.5
November 2021	2,866.6	12,285.4
December 2021	2,823.5	12,504.1
Annual total		**123,246.1**

[a] This has been calculated by multiplying the average weekly value by the number of weeks in a given month. This has been calculated as the number of days divided by 7. For example, the number of weeks in January is calculated as 31/7. 28 days have been used for February, since 2021 was not a leap year.

Source: London Economics calculations based on ONS; Retail Sales Index - Internet Reference Tables (database: JE2J)

To aid the assessment of the calculated market-at-risk, we also calculated the size of population that may be subject to deceptive OCA in online retail. The ONS calculates that 87% of adults (16+) in

Great Britain have shopped online in the 12 months preceding data collection.[130] Based on ONS data, we calculate that there were 52,853,971 adults (16+) in Great Britain in 2020,[131] which implies an estimated population of 45,982,955 adults (16+) that have shopped online in the preceding 12 months.

We follow the ONS by excluding non-adults (15 years or younger) from our estimated population. It is likely that a substantial proportion of these non-adults do not have the agency to purchase products online. This means that the estimate may be conservative given that some non-adults close to the cut-off of 15 years may have the agency for online retail.

Calculate the prevalence of deceptive OCA

Mathur et al. (2019) conducted a web crawl of 11,266 websites. For each of these websites, they labelled whether any of the OCA highlighted above were present, and whether these could be classified as deceptive.

Recognising that not all retail websites are equal, one would ideally like to scale the existence of deceptive OCA by the size of the market served by each website. This information is not readily available. However, data can be obtained on page views per million users. This data can act as a substitute estimate of the size of a website at hand. Although page views are an imperfect substitute, or proxy, for the revenue generated by a website, the two should be related. Larger websites should both have more page views and higher revenues.

Based on this information, the table below provides the sum of page views per million across all crawled websites, and those websites exhibiting deceptive OCA. Using the proxy page view per million we estimate that 15.2% of all retail websites use one or more of the seven categories of OCA outlined earlier.

Table 6 Prevalence of deceptive OCA

	Total	As % of all websites	As % of websites with OCA
Total page views per million across all websites crawled	36,783.87	*N/A*	*N/A*
Total page views per million of websites with OCA	5,583.97	15.2%	*N/A*
Total page views per million of websites with deceptive OCA	256.24	0.7%	4.6%

Source: London Economics calculations based on Mathur et al. (2019)

Scale the size of the total market based on the prevalence of deceptive OCA

The market for internet retail in Great Britain at-risk from the deceptive OCA mentioned above, is then calculated as follows.

130 ONS; Internet Access – Households and Individuals. Data from 2020 (the most recently available year).

131 ONS: mid-year population projections. Most recently available data.

Table 7 Annual market-at-risk from deceptive OCA

Total value of the market [1]	£123,246.1 million
Percentage of websites with OCA [2]	15.2%
Of which, percentage of websites with deceptive OCA [3]	4.6%
Market-at-risk [1]*[2]*[3]	**£858.54 million**

Source: London Economics calculations

Calculating realised harm

To calculate realised harm, one would need to obtain data on the prevalence of OCA and data on consumers' response to it. Hypothetically, if 50% of consumers faced with an urgency prompt would not have bought a product without the prompt, then we could calculate realised harm by multiplying the relevant market-at-risk for the specific deceptive OCA practice by 50%.

Caveats

Mathur et al. (2019) data

The data used by Mathur et al. (2019) is limited. The web crawling exercise focused exclusively on online retail, and only on text-based OCA. As such, this quantification similarly must be restricted to the same parameters. This provides a lower bound for the actual market-at-risk from OCA as OCA may include non-text-based cues, such as the positioning of relevant information on different parts of a website.

Furthermore, Mathur et al. (2019) collected data on a global scale, rather than just for the United Kingdom. Although the web crawling exercise focused on English-language websites only, it is not guaranteed that the range of websites available to British users is identical to the ones available to a global population.

To check for this, we compared the 'global' prevalence of OCA with the prevalence on websites using a ".uk" domain. As calculated above, approximately 0.7% of all websites exhibit deceptive OCA. For ".uk" websites, this is approximately 1.0%. For the prevalence of OCA type, only five webpages with ".uk" domains were identified as having deceptive OCA. All five of these websites used urgency. Similarly, Table 6 shows that in the global data, urgency is by far the most common category.[132] Lastly, the table below shows the distribution of all observed OCA by type[133] for the global data and the ".uk" data only. As the table shows, the distribution of both are similar.

Table 8 Comparison between prevalence of OCA by type across the global and ".uk" data

OCA	Global data		".uk" domains	
	# observed pages	% of all OCA	# observed pages	% of all OCA
Social proof	325	17.9%	24	17.3%
Sensory manipulation	270	14.9%	18	12.9%
Urgency	481	26.5%	42	30.2%

[132] For both the ".uk" and the global data, all of the deceptive OCA classified under urgency are attributed to the use of deceptive countdown timers.

[133] This includes OCA which was not classified as deceptive.

OCA	Global data		".uk" domains	
	# observed pages	% of all OCA	# observed pages	% of all OCA
Forced outcomes	6	0.3%	0	0.0%
Obstruction	31	1.7%	2	1.4%
Sneaking	26	1.4%	3	2.2%
Scarcity and popularity claims	679	37.3%	50	36.0%
Total	*1,818*	*100%*	*139*	*100%*

Source: London Economics calculations based on Mathur et al. (2019)

As such, there are no strong indications that the range of OCA shown to UK consumers is substantially different from the global population. In the quantification, we have used the larger global data set. This represents a far-reaching, and therefore more stable, sample of OCA.

ONS data

Data on internet retail sales was obtained from the ONS only for Great Britain. The remit to collect data for Northern Ireland lies with NISRA. No comparable data has been identified. As such, the quantification is limited to cover only Great Britain and not the whole of the United Kingdom.

5.3.3 Top-down quantification of harm: Conclusion

In conclusion, a top-down approach is suitable if realised harm can be calculated proportionally to the size of a market. In other words, a top-down approach may work if the available data mostly consists of percentages (or if percentages can be estimated).

In a top-down approach, it is often easier to calculate a market-at-risk than to calculate realised harm. For the latter, the impact of the cause of harm on consumer behaviour also needs to be assessed. This requires a robust counterfactual, ideally using randomised methodologies (i.e., online experiments or field trials).

5.4 Bottom-up quantification of harm

This section provides an overarching structure for the bottom-up approach to estimating harm, including the general type of data that would be required. Then, it provides an illustrative example of the approach based on willingness to pay estimates. Lastly, it provides some conclusions on the appropriateness of this methodology.

5.4.1 Bottom-up quantification of harm: General methodology

As noted above, the principle of a bottom-up approach is to start at the individual level and then scale it up by population. This is typically done in two steps.

Step 1: Calculate the harm for a representative case

In the first step of a bottom-up quantification, we calculate the harm experienced by a single consumer first. It is important that this single individual is representative of the total population that is subject to the cause of the harm. For example, for digital harms, the representative case may only need to be representative of the adult population that has access to the internet, rather than the total population.

The representative case does not need to be an actual consumer. In fact, it is more likely that this is a statistical construct. Representative surveys are often used to obtain the data to estimate the representative case. From these surveys, the average response across all survey respondents would then be used to calculate the per-person harm.

The type of data for estimating the harm for a representative case typically comes from consumer surveys designed to specifically capture the individual harm. Occasionally, this type of information is available in academic or grey literature, in particular in literature on applied experimental economics or consumer policy. However, it is more likely that bespoke research, such as surveys or experiments, is needed.

Step 2: Calculate realised harm

Once the harm for the representative case is estimated, the realised harm can be estimated by multiplying this by the size of the relevant population. The calculation of harm then becomes:

$$Realised\ harm = Representative\ individual\ harm * Population\ size$$

This also illustrates why the individual case calculated in step 1 has to be representative. If the individual case is *not* representative, then the multiplication above is not valid. It would add bias to the calculation of the harm.

Data on the size of the relevant populations is typically available from statistical agencies, or can be estimated based on their data. For example, the ONS does not directly publish an estimate of the population with access to the internet, but it does publish the population size and the proportion of the population with access to the internet.

The section below provides a representative example of the bottom-up approach applied to excessive advertising.

5.4.2 Bottom-up quantification of harm: Illustrative example - estimate of representative case due to excessive advertising

Methodology for calculating representative case as a result of excessive advertising

One way of looking at potential harm from excessive advertising is to look at consumers' willingness to pay to either avoid ads or reduce the frequency with which ads occur. The assumption we apply is that willingness to pay can be used as a proxy to estimate the harm experienced as a result of firms exercising market power and degrading the quality of experience faced by users.

Avery (2016) uses a choice experiment to calculate willingness to pay to avoid or reduce the frequency of particular types of advertisement in smartphone applications. The table below summarises their findings.

Table 9 Willingness to pay to avoid or reduce ads

	Per individual, in $[a]	Per individual, in £[b]
WTP to avoid targeted ads	$4.06	£3.00
WTP to avoid animated ads appearing every 45 seconds	$3.73	£2.75
WTP to decrease frequency of static ads	$0.28	£0.21
WTP to decrease frequency of animated ads	$2.71	£2.00

[a] As originally published in Avery (2016). [b] Converted to Pound Sterling using the average exchange rate over 2016 (£1 = $1.355) as published by the Office for National Statistics.

Source: London Economics calculation based on Avery (2016), and ONS/NISRA data

As discussed in section 3.5.3, excessive advertising degrades the quality of experience for users. Using the Avery (2016) data we suggest that harms from excessive advertising can be defined as:

- **Seeing ads which are annoying**: where a user is willing to pay to avoid targeted ads, this may indicate that the user perceives such ads as annoying and quality reducing.
- **Seeing ads which are too frequent**: where the user is willing to pay to decrease the frequency of ads, this may indicate that the level of ads is too high and quality is declining.

The representative case harm based on the definitions can then be calculated as:

- Willingness to pay to avoid seeing ads which are annoying: WTP to avoid targeted ads. Total: [£3.00]
- **Willingness to pay to avoid seeing ads which are too frequent**: WTP to avoid animated ads appearing every 45 seconds + WTP to decrease frequency of static ads + WTP to decrease frequency of animated ads. **Total: [£4.96]**

The representative case harm is therefore £7.96. A caveat to this calculation is that the data in Avery (2016) is aimed at US consumers and smartphone applications only. For a UK-centred approach, a choice experiment on UK consumers not exclusively focusing on smartphones could be used to obtain individual willingness to pay information. This could, then, be similarly scaled using population statistics from the ONS and NISRA.

Calculating realised harm

To calculate realised harm, one would need to obtain representative population data for the population in the survey. If the Avery (2016) data was representative of say 100k individuals, we could multiply this by the representative harm calculated above to estimate realised harm.

5.4.3 Bottom-up quantification of harm: Conclusion

In conclusion, the foundation of a bottom-up approach is the knowledge about harms at a representative level. It is, therefore, suitable if data is available on the harm for a representative case. In terms of data structure, this will typically mean that your data includes information on pound-sterling values per individual. A bottom-up approach may also be appropriate if bespoke surveys can be commissioned that can provide a direct estimate of harm incurred by a representative individual.

5.5 Importance of data: revisiting harm from excessive advertising

In deciding which approach to take for quantification, the available data is typically a key deciding factor. The same harm can be quantified using different methodologies depending on what data is available.

To illustrate this point, we revisited the harm from excessive advertising. The section above estimated the harm using a bottom-up approach. Alternatively, we could have used a top-down approach using the click-through rate on advertisement as an indicator of advertisements being useful, we explore this below.

Quantification of market-at-risk

Establish the total market size for online advertising

CMA (2020)[134] estimated that Facebook generated between £50 and £60 per user in revenue in the UK in 2019. They argue that this possibly represents an unfair return on the data for their users, and that some may want to receive a greater share of the revenue generated.

We refined the calculations of the CMA (2020). Based on the – at time of writing – most recently published financial statements of Meta (Facebook's mother company),[135] we estimate that Facebook generated £49.09 per monthly active user in advertisement revenue in Europe across 2021.[136] With approximately 51.34 million monthly active users in the UK,[137] this implies UK-generated advertisement revenue of just over £2.5 billion for Facebook over 2021.

Calculating the prevalence of excessive advertising that may be quality reducing

We use click through rates as a proxy of quality of advertisement. Approximately 0.9% of ads shown to Facebook users are actually clicked.[138] If we assume that clicking on an ad shows revealed effectiveness of this ad[139], this implies that approximately 99.1% of ads on Facebook may represent potentially wasteful advertising spending. Based on this we then argue that this wasteful advertising spend may result in adverts on the platform that degrade the quality of service (since users do not engage with 99.1% of ads, we make a simplistic but strong assumption that 99.1% of ads on the platform are potentially quality reducing). The market at risk as a result of excessive advertising on Facebook is potentially £2.498 billion.

An important caveat to this is that we calculated advertisement revenue per monthly active Facebook user based on the financial statements of Meta. These financial statements only provide a breakdown by geographic region, not by country. It is possible that the average advertising revenue per user is higher in the UK compared to the rest of Europe. Indeed, eMarketer reported that spending on digital advertising in 2021 totalled to approximately £19.23 billion, with a market

134 CMA (2020b).

135 Meta Earnings Presentation Q4 2021.

136 The financial statements provide both advertisement revenue and number of monthly active users by geographic region (Europe being the relevant region for the UK). Meta files in US dollars. These have been converted to Pound Sterling using the relevant average exchange rates published by the Office of National Statistics.

137 Statista (2022b). Number of Facebook users in the United Kingdom from September 2018 to June 2022.

138 See e.g., Brafton (2022). Social Advertising Benchmarks for 2022.

139 Acknowledgement that click-through rate is a flawed proxy for effectiveness, given the impact of ads that are not clicked on, i.e. by increasing brand awareness.

share of 28.9% for Facebook.[140] This would imply UK-generated advertisement revenue for Facebook of around £5.6 billion. Notwithstanding this, the point that a proportion of advertisement spending can be considered 'wasted' based on click-through rates still stands.

Calculating realised harm

To calculate realised harm, data that offers insights on the proportion of the 99.1% of ads that are deemed to be quality reducing would need to be obtained. This would allow the £2.498 billion to be scaled down to an estimate of realised consumer harm.

5.6 Overarching conclusions

Methodologies to quantify digital consumer harms are needed as the evidence basis across harms is varied, and in places weak. This is as a result of a number of factors, namely; feasibility of data collection (the data set is too big); commercial sensitivities of data; studies too narrowly focused on specific retailers, platforms or markets; causal links for harms between the platform and a harm being difficult to establish; and, challenges of measurement e.g. surveys reflecting an inconsistency between observed behaviour and reported attitudes.

Because digital consumer harms take place within a transaction (firm-consumer) you can take a quantification approach that looks at both slides of this relationship; a firm first top-down approach, or a consumer first bottom-up approach.

The top-down approach starts at an estimate of the total relevant market size and adjusts this down to realised harm. The bottom-up approach first estimates the harm for a representative case and then scales the harm up to the entire relevant population.

The choice between these two methodologies is largely dependent on the availability of relevant data. A top-down approach is suitable if harm can be calculated as being proportional to something else. A bottom-up approach is suitable if harm can be easily expressed at an individual level (e.g., an average financial loss).

The top-down approach uses knowledge about consumers as the last step of the calculation. This has the benefit that, even if information at the consumer level is not available, the top-down approach can be useful for partial, illustrative quantifications of harms, and the calculation of a market-at-risk.

[140] Fisher, B. (2021).

6 Conclusion

Digital technologies are rapidly evolving, they present new opportunities to the consumer and new ways for the digital consumer to experience harm. This report uses the current evidence base to develop a taxonomy of digital consumer harms, highlights the root causes of these harms and posits a methodology to address gaps within the evidence base. The below sets out the key conclusions from each section of the report and posits recommendations based on our findings.

6.1 The taxonomy

The taxonomy is useful to help us classify and identify harms. It can furnish us with an understanding about how constituent online harms interrelate and produce a shared understanding of harms for further investigation. Taxonomies are not static, they are reflection of what they are categorising. As the digital market changes and adapts so must the taxonomy.

Recommendation 1: *That government supports further gathering of the evidence base in relation to digital consumer harms. The quantification methodologies set out in Chapter 5 can allow for the estimation of digital consumer harms. However, the methodology that can be applied and the extent of the quantification will be dependent on the data available. Thus, government, industry and academia should also consider ways to improve access to data which will allow for quantification approaches to improve.*

6.2 Root causes

This report identifies root causes that underpin the categories of harms. The analysis of the root causes concluded that most of them are cross-cutting and suggests that addressing them could be an effective way to find solutions for the issue and mitigate risk of taking a fragmented policy-making approach.

Recommendation 2: *The government explores ways of tackling the root causes of digital consumer harms, and especially harmful uses of online choice architecture and automated decision making based on their prevalence and tractability.*

6.3 Measurement and quantification of harms

Quantifying and measuring digital consumer harms is a challenge. Quantification is a challenge because of the volume of data needed and the commercial sensitivities of the data, additionally in some digital markets' consumers pay a zero monetary price, and so it can be a challenge to quantify harm in cases where a non-monetary exchange has taken place. Measurement is a challenge: because of the firm-consumer relationship, the driver of harms can be hard to establish. Similarly, surveys often show an inconsistency between observed behaviour and reported attitudes.

Recognising the challenges of the evidence base, this report posits a quantification approach to digital consumer harms and an illustrative quantification exercise for a few distinct harms. The top-down approach starts at an estimate of the total relevant market size and adjusts this down to realised harm. The bottom-up approach first estimates the harm for a representative case and then scales the harm up to the entire relevant population. This represents a starting point for more detailed research to quantify harm in specific markets, and a basis for understanding evidence needed to quantify specific online harms.

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