THE UNIVERSITY OF MELBOURNE

Drawing Back The Curtain: Consumer Choice Online in a Data Tracking World

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EXECUTIVE SUMMARY

This report finds that consumers in Australia may face a very different set of outcomes for shopping online than they have traditionally experienced in bricks-and-mortar shops. Products they see on a screen at the same site may vary between consumers. Yet all customers walking into a supermarket see the same products, in the same shelf positions and prominence, advertised on shelf at the same prices. A profound but often invisible change is happening to consumer choice due to our shift to online shopping.

Consumers have been shifting to shopping online out of convenience, but many also do so out of necessity. This particularly applies to older people, those with disabilities and people with increased health risks.

The changes imposed upon them, sometimes invisibly, by switching to the online shopping environment, may not be avoidable. They may not be able to simply go to a traditional brick-and-mortar supermarket, as an example. Thus, it is important – and pressing – to understand what consumers gain and lose in the increasing shift to online shopping. This report explores that through a set of experiments and observational analysis.

'Product offering and steerage' in online shopping means a consumer may never see a product offered to other consumers visiting the same site if they do not scroll through all products offered in a search. Online shopping can thus lead to a narrowing of consumer choice.

Different consumers may see a different order of products presented. Since many people don't go past the first page of a list of products for online shopping, the impact of product being placed in a search result may effectively be the same as denial of product offering to some consumers.

The consumer may never know why their search result returned a different basket of top listed products. This is because the way such offering decisions are made is often invisible to the average consumer, running silently in the background. The criteria used are not transparent to most online shoppers, nor is the impact.

Finally, this report explores the nature of how consumers can be selectively and narrowly targeted through the use of a large online social media platform. This was done via 'shadowing', that is, taking research observations of the live purchase of online advertising to assess how consumers might be selectively targeted through ad buys.

Transparency is one way to prevent the potential for discrimination using these advertising tools. Consumer awareness on these topics has improved more recently, as more consumers have begun to understand how much of their data is being gathered without their permission or knowledge.[1] But this awareness and knowledge is not consistent and, while proving harm is happening from the existence of this micro-targeting capability is more difficult, this does not mean the harm is not happening.

This research raises core questions about transparency, accountability, consumer choice, and privacy. One of the more serious concerns raised by our research observations is whether vulnerable consumers may be narrowly targeted based on their own personal viewing and purchasing habits. In other words, their consumer information could be used against them, to their disadvantage or in order to manipulate them more effectively. Without understanding this is happening – or why – consumers cannot easily defend themselves.

INTRODUCTION

Innovation is important to a healthy economy and providing ever better services for consumers. Technology companies have been at the forefront of innovation for at least two decades, and this has undoubtedly provided valuable services to consumers. However, innovation can also bring change with less understood effects that may be less desirable. Due to the opaqueness at the back end of how online sites selling products to consumers actually work, these less-desirable impacts may not always be visible.[2]

This research explores if and how consumer profiling and target advertising may occur on online sites and how it may impact the consumer. This research is done through several methods. The first is a series of objective experiments testing online sites that consumers might visit to make purchases. This is done in order to observe what offerings, price variation and product steerage might be visible to the consumer browsing the site. We did not have access to retailers' back-end systems. The second is an observational analysis comparing what a consumer sees when shopping online versus in a bricks-and-mortar store. This is relevant for understanding the importance of how product offerings are ordered and presented to consumers. The third is shadowing of two organisations' purchase of advertising from a large social media platform company. In this case, we sought to observe how an organisation might target narrow groups of consumers. We also sought to observe whether groups not presented as an option on the social media company's list of categories might be targeted anyway – for example by using a combination of other micro-targeting to form a reasonable proxy for selecting that group.

Why does this matter? Because the technology may increase the possible level of micro-manipulations of a target group. If this is a vulnerable group, the risk of harm is significantly higher.[3] The micro targeting of such groups may amplify the power of persuasion. A narrower group can be sent a more specific message that can manipulate the specific buying choices of those consumers. Persuasion can slide into manipulation. Thus, our technical report is relevant for understanding broader potential social impact. This is particularly relevant given the recent shift by many consumers to online shopping.[4]

Such micro-targeting is in contrast to traditional broad-based advertising– think of the classic mail-out catalogue of 'back to school' children's clothes in your mailbox. This latter category of 'traditional' advertising to consumers might be via a paper-based catalogue sent to homes on a curated mailing list – for example homes with children. Such a catalogue broadcasts a price and product to all who read the brochure. It does not customise price and product steerage in a fine grain manner only to a specific customer based on real time knowledge of their purchase or web surfing habits.

Similarly, when consumers walk into a bricks-and-mortar supermarket, each one sees the same product lined up on the selves. One brand of laundry detergent may get premium shelf placement over another, but all shoppers can see all the brands on display, and the same product placement. A common price, clear to all, is also visible. Discounts may also be offered at checkout, such as coupons or loyalty programs, but they discount from a universally visible base price. Further, many of these discounts are visible and accessible to all, such as pamphlets available at the supermarket entry area that contain coupons or discounts that any customer can pick up and use. Consumers who look for them will often find them.

Is a consumer's background well enough known by the online retailer to steer him or her, for example, to a more expensive type of product because of some aspect of an online profile? This would depend on what tracking techniques, such as loyalty cards, a retailer may be able to rely on. A consumer may believe a search for meat on an online site will give them the same product, price and position presentation as the person sitting next to them.

We are unable to see methods online retailers may use to steer or deny a customer as we do not have access to backend systems. However, we can see if there is consumer impact.[5] Product-demotion or non-offering is akin to a sales assistant in a bricks-and-mortar store drawing a curtain in front of some products on the shelf when certain consumers browse the aisles. This raises questions about whether there may be invisible harm through lost opportunities for some consumers.

Consumers may be narrowly targeted for persuasion based on their own personal viewing and purchasing habits.[6] Such conduct undermines the potential for consumer agency and distorts the market by narrowing the possibility of consumers selecting the products that best suit their individual needs. It may give the façade of choice, without the real marketplace of choice.

This report follows on our earlier report, 'State of the Art in Data Tracking Technology'.[7] A third report in the series will be forthcoming.

HOW INTERNET COMPANIES TRACK YOU BEYOND THEIR PLATFORMS

It has become clear that technology giants such as Google and Facebook have been collecting large amounts of data on their users. When accessible, your web searches, location and photos are now these companies most valuable assets, helping to develop data driven innovation but also making predictions and targeting you with tailored advertisements. What is done with your data is not always clear and there are still aspects of this data collection that seem mysterious.[8]

It is important to distinguish between platform-based advertising, often associated with companies like Facebook and Google, and organisation specific analytics, observed when visiting a particular company's website. In the case of the former, the platform is collecting large amounts of data about individuals and then providing targeted advertising based on either direct matching of that data, or inference-based targeting, in which a series of attributes are determined for each individual. This is distinct from the type of predictive analytics that is possible on a company website as an example. Once a person visits the site, if their profile can be retrieved, predictive analytics of that customer, and customers similar to them, can be performed to generate highly targeted and business specific outcomes, for example, personal pricing, offers and listings.

There is some crossover between the two; the actions taken on a specific website may in turn feed into the platform advertisers through third-party tracking, and exchanges of information, some of which may be offline information about the customer. Such data will be used by the platforms to build a fuller and more accurate picture of an individual. For example, Google claims to '...capture approximately 70% of credit and debit card transactions in the United States'.[9]

A further example of such collection is targeted advertisements on third-party websites. Do you remember that shirt advertisement following you around the internet after you almost bought it? All it took was one visit and it seems to be the only thing you can see. This happens through the use of third-party cookies and tracking.

WHAT ARE COOKIES?

With its first appearance in 1995, a cookie is a small plain text file sent by a website (e.g. Amazon) to a browser (e.g. Chrome). The file is then stored on the user's computer and is sent back to the website's server whenever they return. It was created to facilitate the user's interaction with the website, allowing to be easily identified and not needing to re-select your preferred language for example. But this 'memory' offered by cookies can also be used to track the user's navigation of a website down to the time spent on each webpage. This provides valuable information for marketing purposes, enabling demographic[10] and behavioural targeting.[11]

HOW DO COMPANIES COLLECT DATA FROM THIRD-PARTY WEBSITES?

In order to track customers on third-party websites, companies such as Google and Facebook make use of third-party cookies. These are cookies that are set by websites not directly visited by the user. They represent the majority of cookies added by websites.

Facebook uses different ways to collect these cookies, but it always comes from an agreement with the first-party website. First-party websites have a lot to gain from sharing information about its users with Facebook. It enables them to trivially implement advertising, consumer analytics and social network integration.[12] Indeed, social plug-ins such as the Facebook 'like' and 'share' buttons are present on 32% of the top 10.000 sites.[13]

Part 1- Image 1 Plug-ins

This popular addition increases the host website's opportunity for exposure. What some may not realise is that incorporating these plug-ins on a website allows companies like Facebook and associated subsidiaries to collect cookies of the user's behaviour. This is done despite no user interaction with the plug-in itself. Recently, blocking third party cookies has become easier and so new solutions have been put in place to continue gathering information about users. One such solution is called a web beacon; Facebook calls it the 'Facebook Pixel'. It is an often-transparent image which is placed on a website to collect data and track conversion from ads. Being no larger than a 1x1 pixel, users do not notice it and it is harder to turn off via third party cookies. Increasingly third-party advertisers are using even more sophisticated techniques. It has been reported previously that this may include browser fingerprinting[14] to track users even when they are blocking cookies. Such techniques may use the accessible browser attributes, for example, plug-ins installed, screen size, fonts, etc. to uniquely fingerprint the browser.

This third-party data collection may come as a surprise, and that is the problem. Users do not expect to be tracked via plugins when they are not using them. It is important to note that information is gathered on both Facebook account holders and users who do not possess an account at all. For consumers who do possess a Facebook account, their browsing behaviour can be linked to their identities when they visit other websites that have implemented the social plug-ins. This makes Facebook's tracking particularly invasive.[15] The lifespan of these cookies is also alarming, some having a default maximum age of more than 30 years.[16] Facebook is not the only company who gathers data in this way, Google Buzz plugins and Twitter's Tweet button are used to track users in the same way.[17]

Furthermore, even those without a Facebook account will have shadow profiles — these are profiles that consist of data not explicitly handed to Facebook by the user. For example, it could be information provided by other users or information not immediately linkable to a known Facebook account. These shadow profiles can be used by advertisers, such as by providing a list of known email addresses, to access profile data for people who may not even have a Facebook account.[18]

WHAT IS BEING COLLECTED?

The collection of third-party cookies is extensive throughout the Internet, but what exactly is being collected by companies such as Facebook and Google? The information stored by the website is encoded in the cookies, it associates bits of data to specific users. For example, cookies will store information to identify you such as a user ID, your operating system and the browser you use.

Most tracking cookies will store unique identifiers, such identifiers come with the advertising platform and optionally the website as well. This enables tracking of a user across websites and even across different devices. It is this tracking across devices that can be particularly invasive, since it links two distinct profiles, for example, the profile from a person's phone and the profile from their laptop. If that user logs into the same website, or platform, like Facebook or Google, it will permit the profiles from the two devices to be linked from that point onwards.

Whilst it is possible to store further information within the cookie itself, and this is how cookies were intended to be used, it is not as common today. The preferred approach is to store an identifier only, which can be used to retrieve a detailed profile about the user. The type of information that will be collected and linked to this identifier includes products you click on, add to your cart or buy, and even the dwell time on particular pages. Since such information is often not stored on the client device when it is encoded, it is extremely difficult to determine the nature and scale of the data being collected.[19]

WHY IT IS COLLECTED?

The majority of digital advertising spending goes to the technology giants Facebook and Google. The tracking technology used enhances their marketing services through advertising networks such as Google AdSense and Facebook Audience Network. Their presence on a large number of websites allows them to implement advertisement retargeting very effectively.

Ad retargeting, also known as remarketing, is the process of showing products a customer has already viewed and interacted with in the past. 'Experts have found that only 2 per cent of potential customers 'convert' (i.e., buy a product) during the first visit to the company's website. Remarketing is designed to bring the 98 percent of users that don't buy a product back to the website for a second look.[20]

This marketing strategy is thus an effective way of using cookies to bring customers back for a second look. It is for this reason companies collect consumer data and make profit off it, often without consumers even noticing.

Beyond this, the profiles that companies are able to build about users can be used for alternative means. As noted above, the combining of additional datasets and offline data, including location information and credit card data, facilitates evaluation of effectiveness of campaigns. For example, with Google's offline data it may be possible to link an online advert with an offline purchase. The scope of such behaviour can go beyond simple marketing, to include subtle manipulation and behavioural change. The targeting opportunity this offers is worrying and has placed many of the main actors involved into the spotlight.

A/B TESTING

A/B testing is a user experience technique that provides two variants of the same item, for example, two variants of a webpage or an advertisement. It performs randomised trials, showing the variants to different groups and then tracking their behaviour to determine impact.

For example, using A/B testing, organisations can understand if a certain product layout performs better and if a difference between two different layouts is statistically significant. This method is widely used in development of the online shopping experience as a data driven approach to decision making. As it is hard to predict consumer behaviour and preferences, it is sometimes simpler to use A/B testing to support decisions rather than rely on intuition about what consumers may like.

An example would be the use of a header including the word 'free' vs the word 'promotion', or different choices of colour. The multiple versions of the website are randomly served to customers and the click rate or time spent on the website is evaluated. This measures the effectiveness of a design to optimise consumer satisfaction. Note that A/B testing is the simplest user experience technique. Multivariate testing, which compares more than two layouts or modifications, is more widespread and complex.

In the case of marketing, it could be in the form of differently worded adverts. By analysing the response rate, for example, click-throughs – whereby a user clicks on the advert, the advertiser can determine which advert draws attention and generates a reaction. There are clear benefits to this in user experience, for example, producing better and more usable websites. However, when used for marketing, it allows the refinement of manipulation, through testing of hundreds or even thousands of different adverts to determine what messages a particular group are most susceptible to. An example of which was the Trump election campaign in 2016, which is believed to have evaluated between 50,000 and 60,000 advert variants each day.[21]

CONSUMER VS TECHNOLOGY

A small number of very large companies now hold much of the control over consumer information. These companies may include large subsidiaries like Instagram and WhatsApp, both of which Facebook owns.

Companies share and combine user information, going beyond online activities. For instance, in the past, Facebook has associated information from third-party data brokers such as products bought in walk-in stores. This has now stopped but it still shows possible techniques used to increase profiling.[22]

The extent to which digital platforms, such as Facebook, collect and use consumer data would likely come as a surprise to many consumers. Personalising e-commerce sites has advantages. However, it 'may also be used to the user's disadvantage by manipulating the products shown (price steerage) or by customising the prices of products (price discrimination).[23] The consumer is at a disadvantage here, since 'we lack the tools and techniques necessary to be able to detect such behaviour'.[24]

There is a lack of transparency about the methods used by some digital platforms.

The transparency of these methods needs further work.

PART 1: EXPERIMENT 1 – PERSONA TESTING VIA DESKTOP ENVIRONMENTS

As individuals browsing the web, we may not notice that prices and offerings may differ. Indeed, two customers searching for the same product may be shown offerings in a different order, inducing steerage.

In some cases, products may be available to one individual but not another. This could include discounts that are more or less advantageous. This phenomenon is not new, with Amazon selling DVDs for different prices 20 years ago and only stopping this once it was discovered. Earlier research has measured the personalisation of web searches[25] and also price variation to different consumers online overseas.[26] More recently these practices have occurred in the US with Auto Insurance, as a recent investigative journalism essay noted in *The Mark-Up*:

> Allstate's Maryland filing reveals how an opaque algorithm it has been proposing around the country would have functioned in practice. It also offers a glimpse into a potential future where companies of all sorts, not just auto insurers, charge people different prices based on their behaviour—or expected willingness to pay, as projected by algorithms that draw on the seemingly limitless troves of data collected and sold about people every day.[27]

Although the insurance company's proposed use of algorithms for repricing did not go ahead, the proposal shows what is possible.

The experiment described in this report has been undertaken to help us to understand the current state in the Australian online shopping landscape.

INITIAL SET UP

For the experiment, 50 personas were created, with 40 personified via sets of 3 social media and Internet accounts. These include sets of 10 personas for each of the following cohorts: 22-year-old male, 22-year-old female, 66-year-old male and 66-year-old female, as well as a control sample of 10 personas with no social media and Internet accounts.

As required, each set was composed of a verified Google, Facebook and Twitter account with specific demographic information embedded. The accounts were created on specific Victorian IP addresses and all information has been recorded in a spreadsheet as such:

ID	First Name	Surname	D.O.B.	Postcode	VPN	Phone	Email
M1	Matthew	xxxxxx	Xx/xx/1997	36xx	#349144.XX.XX.28	xxxxxxxx	Matthew.xxxxxx@xxxxxx.xxx

Table 1

When undertaking the experimentation, uncontaminated images of Virtual Machines were used through for each persona. These images are running Windows 10 as their operating system and Chrome browser (without being signed-in). Using the revert to snapshot functionality of the Virtual Machines allowed every session to clear from browser cookies and browsing history, as well as anything associated with the operating system — which essentially resulted in starting each persona with a clean machine.

The screenshots were taken with the full-page screen capture offered by Chrome, capturing all information on the targeted pages.

PROCESS

For each persona, a set of screenshots were taken on the targeted websites. The protocol followed was the same each time:

1. Launch the Virtual Machine reverting to a 'clean-skin' image each time
2. Connect to persona's IP address through the corresponding VPN server and IP address
3. Connect to social media and Internet accounts (Facebook, Twitter, Google)
4. Browse persona-specific websites to build browsing history
5. Visit target websites, search for chosen products, screenshot results

In addition to this, for control purposes, a set of searches were performed without any accounts or browsing history. Screenshots were also collected for this category named 'No accounts'.

The specific browsing websites used for each group is detailed in the table below:

Persona	Browsing History
Females aged 22	https://www.complex.com/au https://darlingmagazine.org/ https://www.vogue.com.au https://www.dailymail.co.uk/ https://www.buzzfeed.com/
Females aged 66	http://www.luxurytravel.com.au/ https://www.news.com.au/ https://www.bhg.com.au/ https://www.lifestyle.com.au/ https://www.heraldsun.com.au/
Males aged 22	https://www.buzzfeed.com https://www.reddit.com https://hypebeast.com https://www.complex.com/au https://au.ign.com
Males aged 66	https://www.whichcar.com.au/ https://www.news.com.au/ https://www.apia.com.au/ https://www.heraldsun.com.au https://www.theage.com.au

Table 2

The products that were searched for on each target website are detailed in the table below:

Website	Shopping Item Category
Bunnings	Paint
Booking	Round 1: Melbourne CBD accommodation available between 13-14 June 2020 Round 2: Melbourne CBD, accommodation available between 8-9 November 2020
Coles	Round 1: Meat Round 2: Meat and Chocolate
JB Hi-Fi	Coffee machines
Target	Toys

Table 3

Browsing was done on the persona-specific websites before visiting the targeted websites. It also involved browsing within the websites by accessing links provided.

This was done to reinforce the demographic traits of our personas and give them a real Internet presence.

All information was then organised within a folder taking note of date and time of each screenshot.

Please refer to Appendix A for details of the research methodology.

Participants were browsing. They did not log in as users of the sites. Instead, this research was designed to mimic the browsing of aisles in a bricks and mortar store. No purchases were made from any retailers as part of this research.

We ran Round One of this experiment over a four-day period in February 2020, with the 10 personas per age/gender cohort visiting five online shopping sites. We ran a second round of testing in July 2020, with the same methodology as round one, over one day (see Appendix). We also ran informal probe tests of the sites before and after the Round One test. In Round Two, we ran formal tests using three personas per cohort of age/gender. The smaller number of personas was due to the fact that some persona accounts cease to function over time as well as due to time and resource constraints.

The goals of this second round of formal experiments were to test reproducibility and to further examine research areas where informal probe tests had shown variations that were of interest. We also ran informal probe tests of the sites before and after the Round One test.

Informal probes were visits to the online shopping sites using different browsers, with different settings (e.g. a standard browser on existing deployed devices as control groups, 'private browsing', 'incognito' or via Tor Browser, and/or varied browser histories). The probes included searches of the online shopping sites for a variety of products. The informal probes were done at different times of the day, and on weekends, over a period of several months, to see if patterns or anomalies of interest emerged. The probes allowed the research team to see how advertisements and products were placed over time amid the product ranges returned in search results. The informal probes were exploratory in nature, not formal experiments. Rather, they helped to inform the experiments' designs and focal points in both Rounds One and Two.

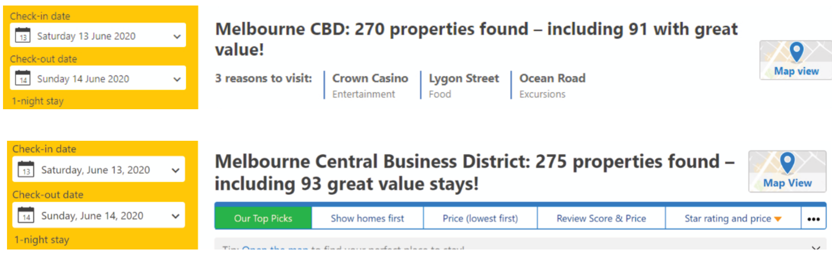
We used the personas cohorts to retest the following online sites in Round Two: Coles, Bunnings, Target and Booking.com. JB HiFi was not retested as we found the total value of the basket of top five returned items from a search did not vary in Round One and because informal probe testing did not pick up any variations of relevance.

FINDINGS OF EXPERIMENT ONE: PERSONA TESTING VIA A DESKTOP ENVIRONMENT

Overall, when testing different personas on online sites, we found the order of products presented can change from one visit to another and this may be affected by time. The frequency of the change would depend on the website, but this change in layout has been observed.

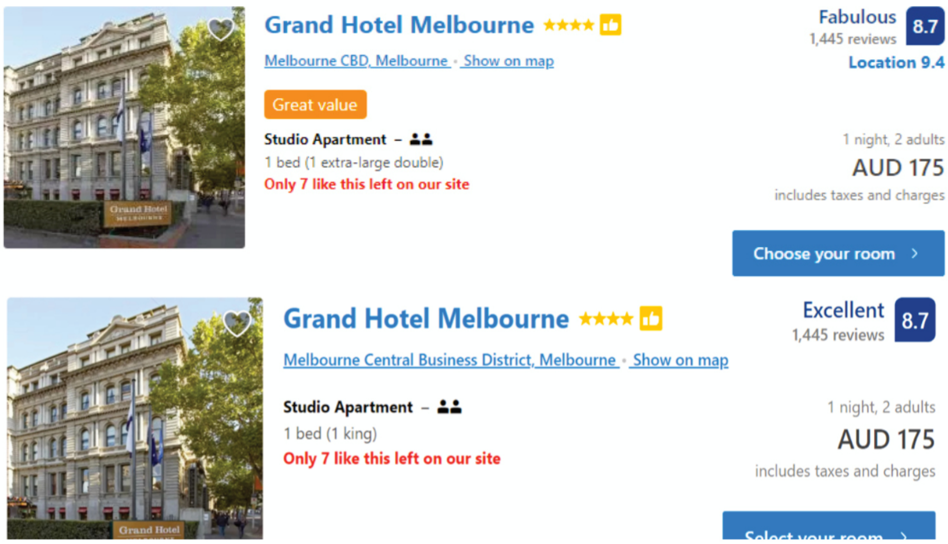
For example, we found a significant number of variations while visiting Booking.com. The following examples were from the Round One testing unless otherwise identified as Round Two.

In this example, there are 91 'great value' (search by persona F22-9) stays in one search and 93 in the other (search by persona F22-4):



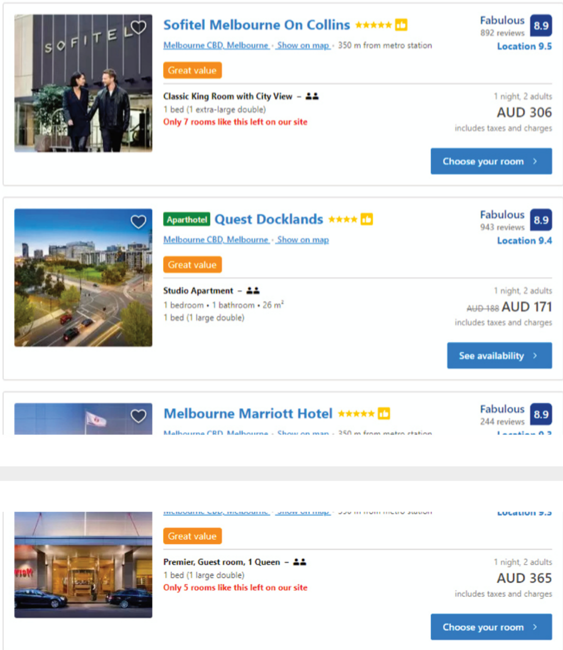
Part 1- Image 2 Screenshot of comparison of Booking.com

For one participant (ID: F22-10) the Grand Hotel is considered 'Great value' but not for another (ID: M22-3), despite the price offered to the consumers being identical:

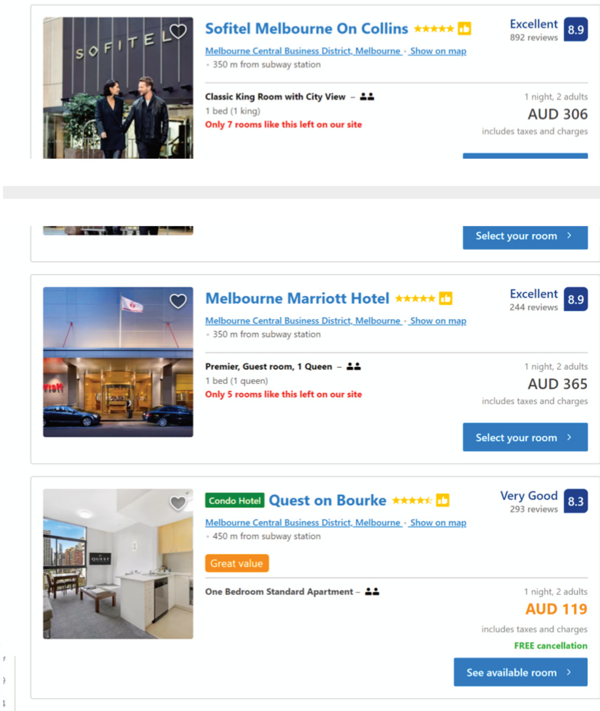


Part 1 Image 3 – Screenshot of comparison of the same hotel on Booking.com
(top: F22-10, bottom: M22-3)

In the following Booking.com test, we captured the top 25 listings returned on the search. Participant F66-2 was offered Quest Docklands at a price of $171. However Participant M66-1 was not offered Quest Docklands at all in the top 25 listings.



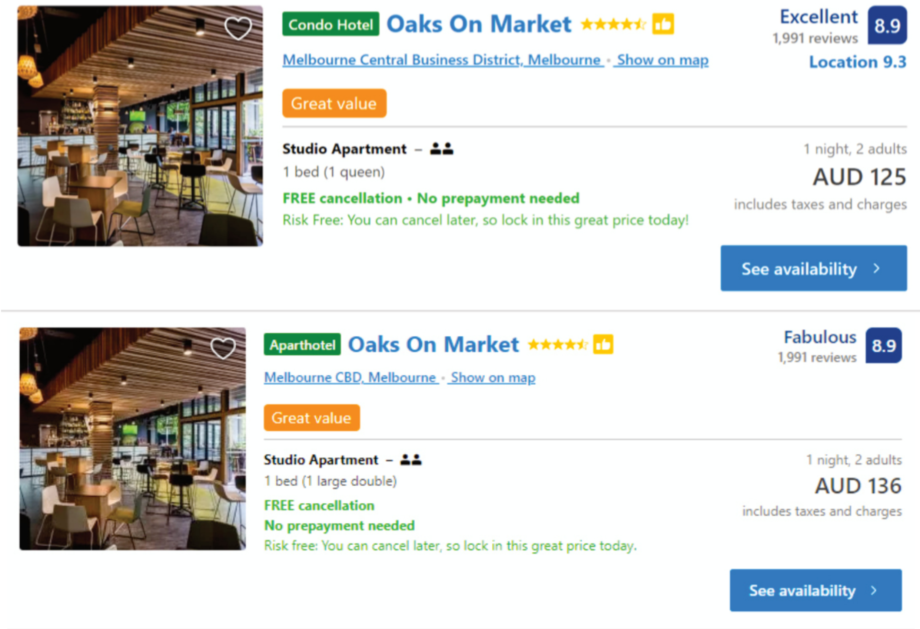
Part 1- Image 4 Screenshot of hotels on Booking.com for participant ID F66-2



Part 1- Image 5 Screenshot of hotels on Booking.com for participant ID M66-1

The readings in Part 1-Image 4 and Part 1-Image 5 above were taken within less than 10 minutes of each other.

In Part 1 – Image 6 below, there is a difference in price for what appears to be the same offering. An Oaks on Market Studio Apartment is $136 for participant ID F66-8 while it is only $125 for participant ID M66-5. This may be due to dynamic pricing or other factors. The image shots were taken on the same day within 20 minutes of each other.



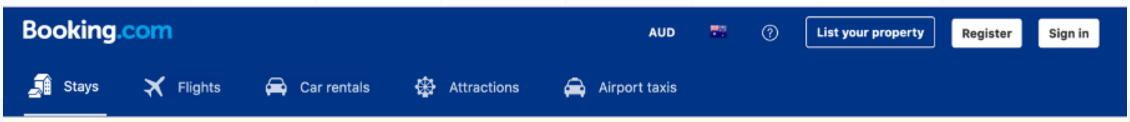
Part 1- Image 6 Screenshot of Booking.com highlighting different presentations of the same hotel for different participants (Round One testing)

Note that different names are also used, 'Aparthotel' vs 'Condo hotel'. On top of this, something observed multiple times is the interchanging use of beds; 'extra-large double' vs 'Queen'.

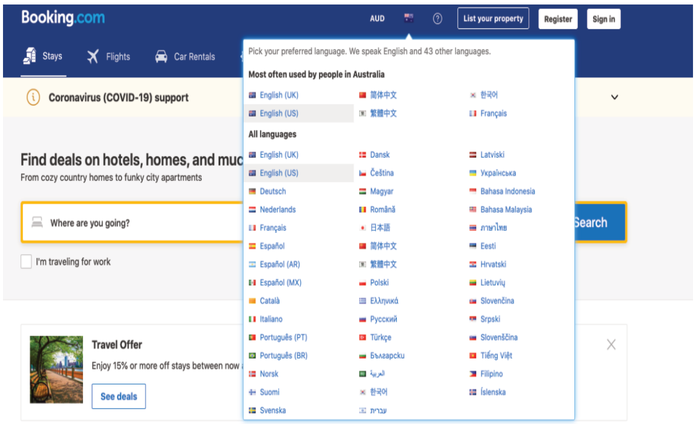
As a result of Round One testing, we hypothesise language settings impacts on the product descriptions offered. Our hypothesis is that something as small as the variation in the categorisation of 'British-English' or 'US-English' changes the product description that the consumer sees, such as the description of the type of room or the bed.

This is relevant because consumers may never toggle these language settings themselves. Indeed, they may not be aware of what their search preference settings are in this regard, nor that changing settings could impact on product descriptions. They may not even know that such a setting exists.

Some settings for visiting this site may inadvertently contradict other visible queues to the consumer. For example, the language selection tool is right next to the currency choice:



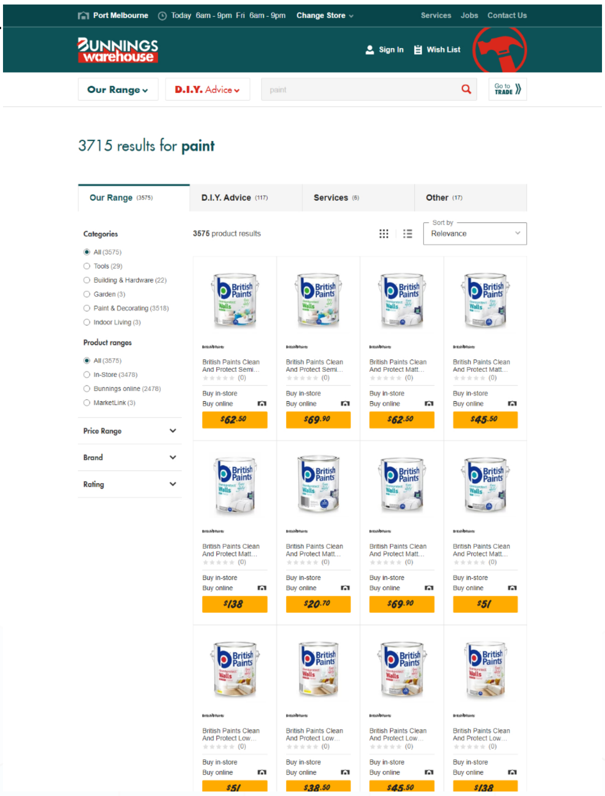
In this instance, a consumer might reasonably assume that the image of the Australian flag was indicating a search in Australian dollars. This is not the case: the flag indicates which language the search results should be returned in.



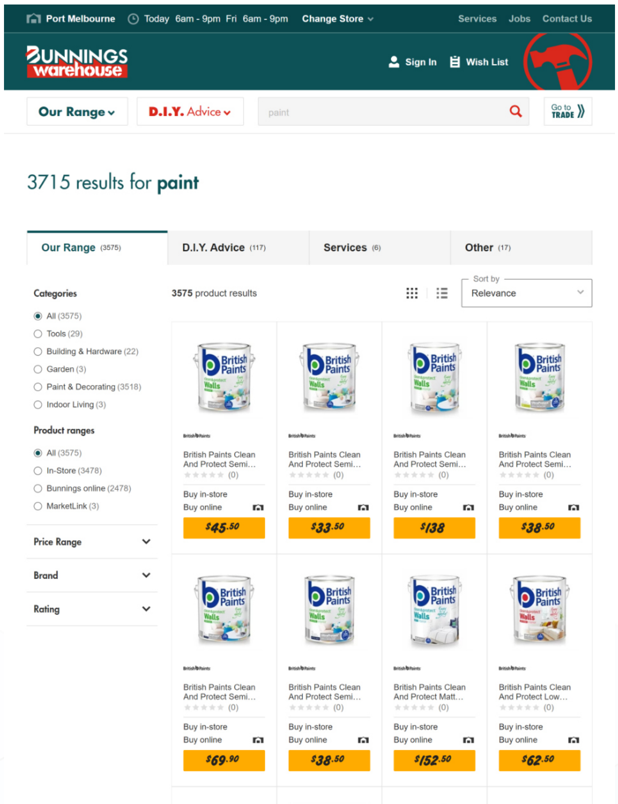
However, both English language options result in an Australian flag being displayed (despite neither being labelled as 'Australian' English):

Thus, a consumer might for example not change – or even look at – the language setting the online site had 'assigned' to them. Without knowledge that being labelled as using a 'different language' might alter product descriptions offered up, a consumer might have no motivation to change or investigate this setting.

The Bunnings screenshots are also an example of the different page layouts shown to customers. For example, page layouts for products varied on Bunnings.com with a variation in the products displayed in the first row. All of these Bunnings images are from Round One testing unless otherwise specified as Round Two.



Part 1 – Image 7 Screenshot of Bunnings product placement to one participant (F66-8)



Part 1 – Image 8 Screenshot of Bunnings product placement to participant (M66-5)

We observed that the Bunnings online sales site had changed orders of offerings for different customers doing searches. These two screenshots above were taken within a short time window on the same day.

In the case of Bunnings, to the eyes of the consumer, it appears that the ordering of the products is changing in search results returned. Different searches of the online store returned British Paint tins of varying sizes and types (e.g. 'Clean and Protect Semi-Gloss White Interior Paint' in a 2L pot in one case and a 4L pot in another, or 'matt' style paint in another result). In the comparison displayed above, one participant (F66-8) received British Paint products, priced at $62.50 and $69.90 as the first two offerings. However, for M66-5, the first two items shown were different products, priced at $45.50 and $33.50. One of the challenges is determining why differences are seen. A likely reason for the change in product presentation here is A/B testing. This is explored further in the next section.

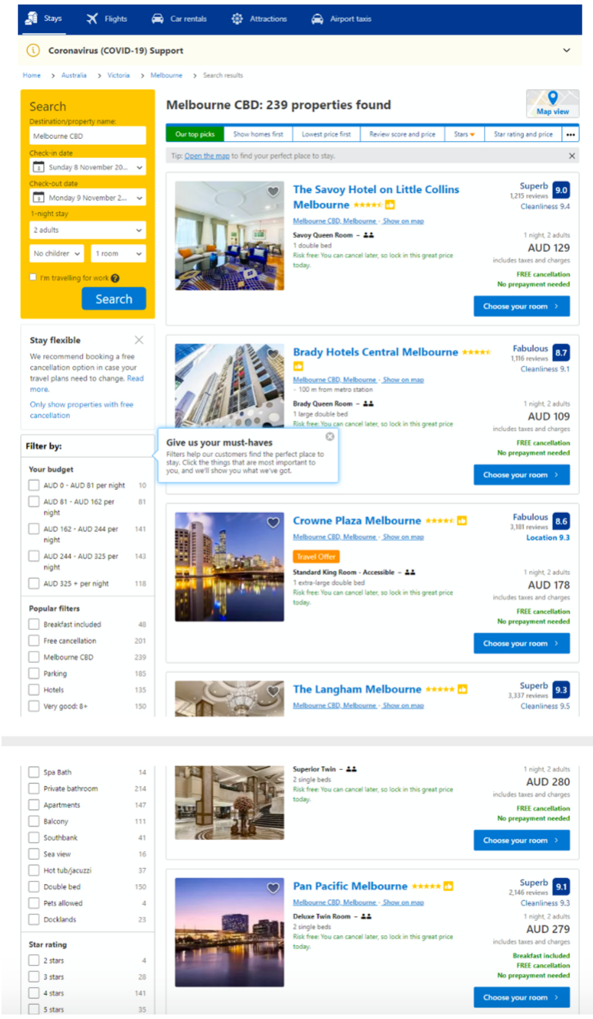
When comparing results between Round One and Round Two testing, both Bunnings and Booking.com showed variations in product order in both rounds. Target showed variation in product ordering in Round One but not Round Two.

In Round 2 testing, we confirmed variations in product ordering in the top five search returns at Coles, for the search term 'chocolate' but not for meat. There was no variation for meat in Round One. We did not test chocolate in Round One.

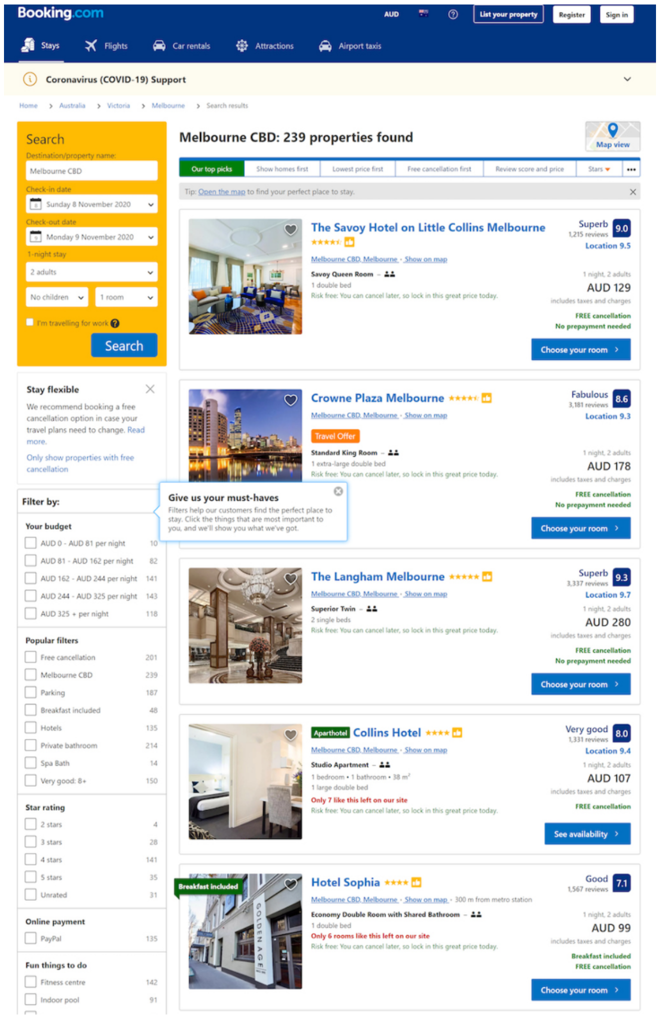
Examples of some of these Round Two variations are presented in the following section.

Images 9 and 10 below compare what hotel accommodation was offered to two different personas in Round Two testing on Booking.com.

Images 9 and 10 below compare what hotel accommodation was offered to two different personas in Round Two testing on Booking.com.



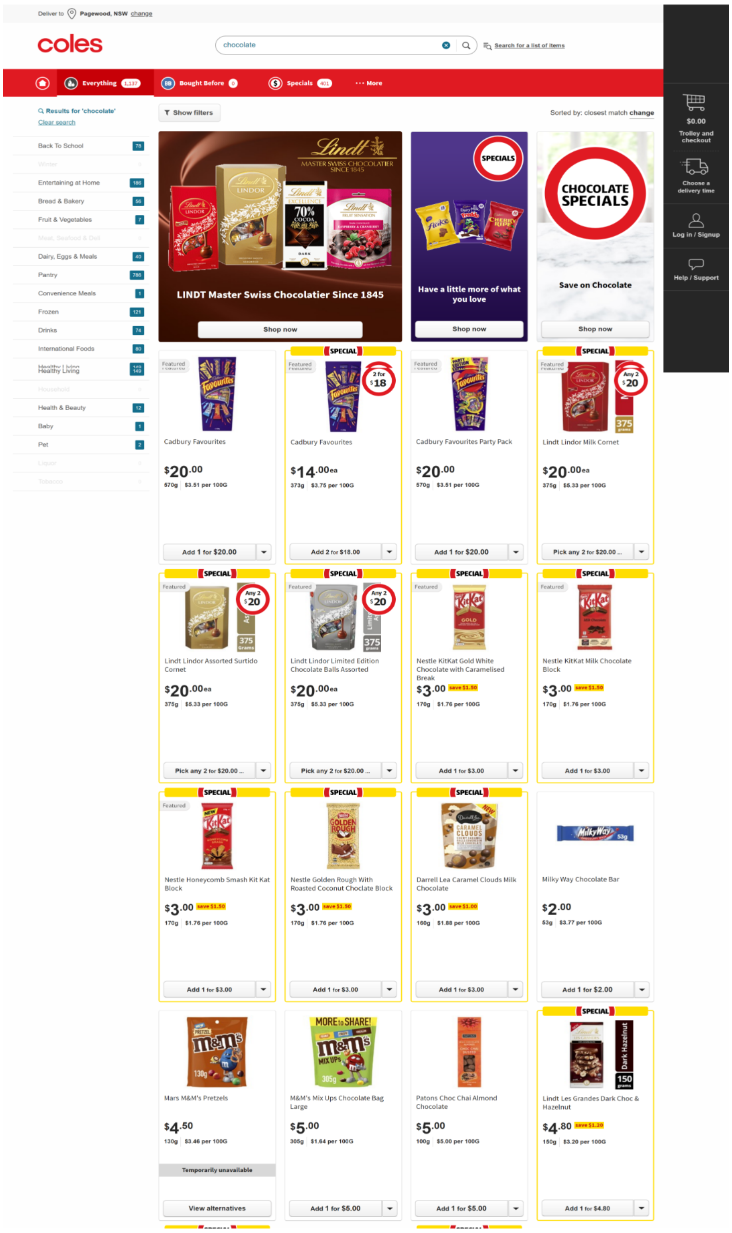
Part 1 – Image 9 Screenshot of Booking product placement to one participant (Round 2 – F14)



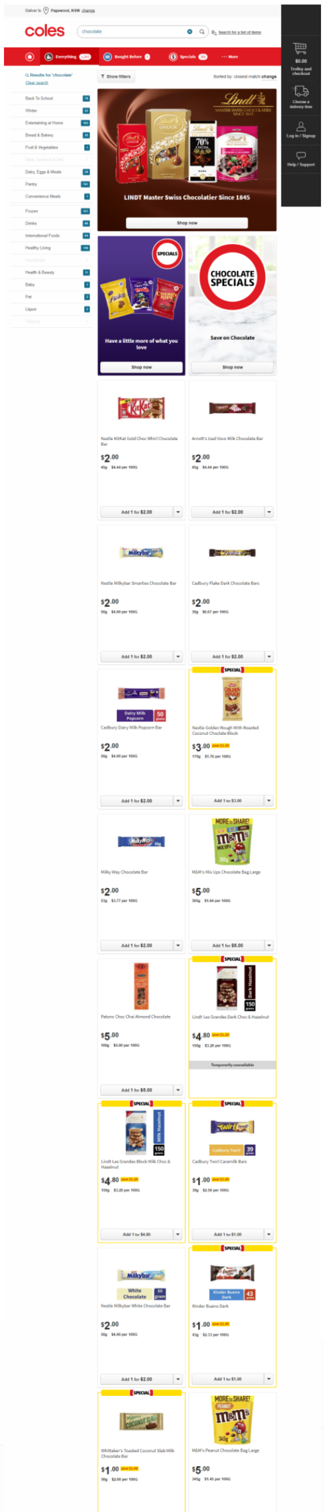
Part 1 – Image 10 Screenshot of Booking product placement for another participant (Round 2 - M19)

Visiting the Booking.com site, both participants received the same first product offering at the same price. However, the second offering differed. Persona F14 (22-year old female), was offered a less expensive hotel as a second choice (Brady Hotel at $109). Persona M19 (66-year old male, Image 10) was offered the Crowne Plaza at $178 as the second-choice option. Both personas received some listings that were unique to each of them in their top-five baskets, while some shared listings were in different positions. Images 9 and 10 were taken within half an hour of each other on the same day.

The following section discusses the experiments visiting the Coles online site. The images 11 and 12 below are what was returned for participant searches of Coles for chocolate.



Part 1 – Image 11 Screenshot of Coles product placement for one participant (Round 2 – F8)



Part 1 – Image 12 Screenshot of Coles product placement for another participant (Round 2 – M14)

Images 11 and 12 were taken within half an hour of each other on the same day. Persona F8 (22-year old female, Image 11) had a top-five basket total cost of $94, while Persona M14 (22-year old male, Image 12) had a basket total cost of $10. It should be noted that image 11 contained several "featured" products, while image 12 did not. Both tests were set to the same postcode.

In Round Two, the location was set to Pagewood NSW instead of the original Victoria postcode used in Round One tests because the researchers observed in informal probes after the Round One tests that the online shopping site seemed to send some device browsers to that NSW suburb automatically. We were unable to determine why the site did this. However, since we sought to ensure that all the personas in a given round were set to the same suburb postcode for the formal testing, the research team set this suburb in Round Two to the NSW postcode that appeared to be a default setting, as seen in our informal probes. In this way, we reduced the likelihood of the online retailer site automatically rolling over some personas to a different postcode setting than we had set them to in the experiment set up. This did not disturb the testing regime, as the important action was to ensure that the consistency of suburb occurred within each round, not necessarily between rounds. The layouts of the grid differ between the two screenshots due to different browser window resolutions.

ANALYSIS

Overall, we observed differences in presentation and total price for a basket of top-listed goods as described below. We analysed patterns of pricing for the first five slots returned on search results in the online retail sites, as described below.

In order to analyse the layouts, the prices of the first five products for each website were added together into a basket and an average was made for each cohort (target sample size of 10 personas per cohort). For instance, for each persona in the Female 22 cohort, we recorded the first five products that were presented, totalled the price of these five products for each persona, and averaged all the persona totals in the Female 22 cohort. We then repeated the process for each persona in each cohort. This resulted in reviewing more than 1,000 products across the five cohorts and all the online retail sites. The averages of these totals are presented in the table below.

We sought to observe any trends in pricing linked to the personas which would be considered as steerage.

Round One testing of a basket of top 5 search result returns,
Average total basket price per persona type

	F22	F66	M22	M66	No Account
Bunnings	$346.60	$357.20	$338.65	$370.83	$344.83
Coles	$56.07	$56.07	$56.07	$56.07	$56.07
JB Hi-Fi	$2,420	$2,420	$2,420	$2,420	$2,420
Target	$1,525	$1,525	$1,525	$1,674.20	$2,052.20

Table 4

Table 4 includes the average total price for a basket of top five goods returned on a particular search for Bunnings, Coles, JB HiFi and Target for each persona cohort. It is averaged across all the personas in that category (e.g. all the 22-year old females, etc) for that online retailer. For Round 1 testing, differences were present in the averages for Bunnings' and Target's baskets of top five search-returned goods. Bookings.com data was not included as it is a dynamic pricing aggregator site, thus a different sort of online shopping venue.

At Target, all males and females aged 22, and all females aged 66 had baskets totalling $1,525 each. Males aged 66 had seven $1,525 baskets, two $2,001 baskets and one $2,065 basket. In the 'No Account' category of personas, which had no browsing history, there were two $2,001 baskets, and eight $2,065 baskets.

At Bunnings, there were three different top-five basket prices of $325.40, $378.40 and $244.10, and all but the last of these were spread across the known personas. 'No Account' category is the only one with a $244.10 result, for one persona.

At JB Hi-Fi, all personas had baskets totalling $2,420. At Coles, all personas had baskets totalling $56.07.

Table 4a, below, presents the same data as Table 4, but for the Round Two (July) testing

Round Two testing of basket of top 5 search result returns,
Average total basket price per persona type

	F22	F66	M22	M66	No Account
Bunnings	$378.40	$339.73	$359.07	$339.73	$359.07
Coles Meat	$56.07	$56.07	$56.07	$56.07	$56.07
Coles Chocolate	$66	$66	$66	$94	$40.50
Target	$261.20	$261.20	$261.20	$261.20	$261.20

Table 4a

Each column reflects the average total price for the basket of the top five search-returned items. We did not observe different prices on identical goods in the experiment. The variation in average cohort totals reflects variation in the ordering of products presented.

The variation in the 'basket of 5' top items returned on a search for chocolates at Coles in Round 2 was explained by different compositions of the basket. As an example, the average total basket price was $66 for the F22 personas, $94 for the M66 personas and $40.50 for the No Account personas.

In the M66 category, persona M18's basket contained $14 Cadbury Favourites (373g), $20 Cadbury Favourites Party Pack (570g), $20 Cadbury Favourites (570g), $20 Lindt Lindor Assorted Surtido Cornet (375g) and $20 Lindt Lindor Milk Cornet (375g).

By contrast in the F22 category, persona F14 had these items in her basket: $2 Nestle KitKat Gold Choc Whirl Chocolate Bar (45g), $2 Arnott's Iced Vovo Milk Chocolate Bar (45g), $2 Nestle Milkybar Smarties Chocolate Bar (50g), $2 Cadbury Flake Dark Chocolate Bars (30g) and $2 Cadbury Dairy Milk Popcorn Bar (50g). Another variation was seen in the no-browsing history 'No Account' history. Here Persona NA3 had these items in their basket: $3 Nestle Golden Rough With Roasted Coconut Chocolate Block (170g), $3 Darrell Lea Caramel Clouds Milk Chocolate (160g), $2 Milky Way Chocolate Bar (53g), $4.50 Mars M&M's Pretzels (130g) and $5 M&Ms Mix Ups Chocolate Bag Large (305g). The prices for the same individual good did not vary, but the different baskets' contents caused considerable variation in average total basket price. We were not able to conclude based on formal tests the cause of this changing of the contents of the baskets, only to observe that it did occur.

n the following table, the 'No Account' category is the omitted category; it is the reference point and all the other categories are compared against it. A regression analysis suggests time is correlated.

	Bunnings basket price	Bunnings basket price	Target basket price	Target basket price
F22	1.8 (19.1)	25.4 (19.6)	-527.2*** (49.0)	-29.9** (12.1)
F66	12.4 (21.7)	12.4 (19.7)	-527.2*** (49.0)	-29.9** (12.1)
M22	-6.2 (19.8)	23.4 (21.2)	-527.2*** (50.4)	-29.9** (12.2)
M66	26.0 (20.2)	26.0 (18.4)	-378.0*** (49.0)	-29.9*** (9.7)
After cutoff		39.4** (14.9)		497.3*** (10.1)
Constant	344.8*** (16.2)	305.4*** (20.9)	2,052.2*** (34.7)	1,554.9*** (11.2)

Table 5. Regression Analysis

Table 5 is a regression showing the correlations between basket prices and persona categories. For example, the top left number reports that Bunnings offered top 5 baskets to F22 personas that cost $1.8 more on average than clean personas. The second number in that same cell (19.1) is the standard error of the estimate. This measures how reliable the measure of 1.8 is; larger is less precise. The first column mirrors the top row of Table 4. But notice that none of the estimates are statistically significant. If we had a bigger sample size, would we find something different? We think not, because Bunnings search results changed over time. If we control for whether the experiment occurred before or after the cut off time of 2:10pm 19/2/2020, we see in the second column the estimates move closer to each other. Target has a similar situation in columns 3 and 4. Without any controls, it looks like F22 personas are offered baskets that cost $527 less than clean personas, and this difference is statistically significant at the 0.1% level. But when we control for whether the experiment occurred before or after 2pm 20/2/2020, this difference almost vanishes. We suspect we did not completely control for changes over time, and that if we did, the differences would disappear entirely.

Some causes of this variation might potentially include A/B testing, variations in time of testing, changes to the retailer's systems and other unspecified causes. There may be more than one cause. Based on the best information we have, A/B testing is the most likely explanation for the variation at Bunnings. It may also be the case with Target's results.

Variation at Booking.com is more complex. For example, we hypothesise variations in qualitative descriptions could be attributed to whether a persona is perceived to use language settings as 'en-au', 'en-gb' or 'en-us'. This is useful to observe as consumers often only think of their setting as being 'English' without more nuance. Some consumers may not know or seek to change this setting in different apps they run. Thus, they may have a qualitatively different experience online shopping due to something as small as what version of English their device or app is set to – and they may not realise this is happening or why.

In Round Two testing, we found variations in products listed in the top five search returns at Booking.com and at Coles, for the search term 'chocolate'. The variation led to a price variation in the total basket of goods. There was no variation in Target in this round. Bunnings had variation in total basket prices in Round Two, and we hypothesise that this is likely to be A/B testing.

In the data we collected for both rounds of this persona experiment, at the times and dates we collected it, we did not find clear-cut cases of consumer's search results or prices being caused by their private information, such as browsing history. We were not able to draw definitive conclusions as to the basis of the different page layouts observed being caused directly by one of our persona groups.

In Round two testing, however, we found a surprising correlation for the search results for Coles 'chocolate' basket average prices. Larger device screens were associated with more expensive products being displayed prominently. We did not observe that consumers were offered different prices for the same good. However, we did observe that the baskets of top five search results had more expensive selections of products when viewed using a big screen. The table below shows this analysis.

Regression Analysis

	Coles 'chocolate' basket price
F22	25.5 (24.6)
F66	4.8 (25.3)
M22	25.5 (24.6)
M66	12.1 (27.5)
Big Screen	62.1*** (18.4)
Constant	19.8 (18.4)

Table 6

Table 6 is a regression analysis showing estimated correlations between basket prices of persona categories and screen sizes (whether the window is wider than 1200 pixels). Standard errors are in brackets. Only the one of the correlations in Table 6 are statistically significant at the 5% level ('Big Screen'). Specifically, that top five baskets on big screens cost about $62.1 more than on small screens. This inconsistency is worth further investigation.

We only used three computers for this round of the experiment. It is possible that the computer with the big screen had some other characteristic which led to more expensive search results. It is unclear how widespread this is -- we did not see any analogous variation in search results when searching for meat. We do not know the cause or purpose of this.

To investigate the Round 2 data further, we wrote a software program to look at all visual differences between personas' search results. This led us to look at screen sizes. We did not set out to investigate screen size as a variable in this experiment. Rather, these results were a surprise. A regression analysis revealed a large and statistically significant correlation between screen size and basket price. This analysis does not rule out some other common factor such as the big screens running on more expensive computers. We have not drawn a conclusion in this report as to the cause of this variation, we have only observed a correlation in our test.

CONCLUSION TO EXPERIMENT ONE

We conducted analysis by looking at the products returned from a search term for each site, relevant to that online shop's product range. As we wanted to understand the impact on consumers, we observed what products were presented, in what order, for the top five items, to see how this might affect consumer choice. To understand the impact on price, we created a basket of goods composed of the top five items returned from a search result and determined the total price for the basket. We then developed an average basket price for each persona group. In this way we could compare persona groups search results that were returned.

Overall, we observed differences in presentation and total basket price at some online shopping retailers. We were not able to draw definitive conclusions as to the basis of the different page layouts observed and corresponding total basket price difference. We cannot link them directly to one of our personas. Possible causes of variation could include A/B testing, time, changes inside the retailer's system, among others.

We were not able to see the technology behind what was offered. This is part of the transparency problem of complex technology highlighted in this report. Thus, we cannot definitively determine the actual basis on which differences appeared; we can only describe what we saw and present hypotheses about these observations.

There are many challenges to monitoring this space. In general terms, each company uses its own often proprietary algorithms and/or systems to determine, for example, what will be returned on a search query in its site of the products it carries. This sort of information is sensitive and frequently confidential; it may provide competitive advantage in some settings. The backend developers who have created these systems and run them are often unable to discuss this sort of information in public forums or with researchers due to having signed NDAs.

Another barrier is that the move to online shopping makes it much easier for sellers to change prices quickly – and frequently. In a bricks-and-mortar setting, changing a product's price at a retail chain is an expensive and time-consuming process: think of replacing a single price label at every store across the country for a product. A regulator wants to understand why prices and product offerings are changing. However, when there are more changes happening, more quickly, it is more difficult to measure and to untangle why. Is it A/B testing? Price discrimination? Or just changing stock levels?

Similarly, the shift to online changes the cost of altering product prominence. For example, moving the chocolates with almonds to give it the premium position compared to the mint chocolates is labour-intensive across all the branches of a bricks and mortar chain of stores but costs virtually nothing in an online store. When we ran experiments over just a four-day window in round one, we found differences in offerings in our 'top five' baskets, and variations in average total basket price. Time is a factor. Online shopping environments provide very little friction to change price, range or prominence quickly and frequently.

Consumers often become familiar with the layout of their bricks-and-mortar shop and can therefore find the item they are looking for easily, with many of them conducting only small shopping trips. Online shopping is a different experience for the consumer, and therefore different marketing behaviours, such as A/B testing or product shelf placement, may cause unforeseen impact on the consumer. Whether product steering in an online environment has more ability to coax the customer to less advantageous purchase that steering in a bricks-and-mortar store would prove an avenue for future study.

PART 2: AN OBSERVATIONAL ANALYSIS

THE OBSERVATION

There may be a temptation to equate online shopping with bricks-and-mortar store shopping, as the customer may 'walk' out with a basket of goods, be that as home delivery or an in-person shop.

A major difference between the two experiences is the ability for customers to search. Consumers can search with what they may perceive to be more precision online. Perhaps as result, they expend greater search effort in an online search effort than offline one.[29]

However visible product range is also important for consumer choice. To see many products, a consumer may have to scroll through many screens.

Other concerns may include uncertainty about getting the right item, as reported in a survey of 224 shoppers, comparing traditional and online stores via consumers' perceptions of the performance based on 18 attributes.[30]

One way to measure the product range is to count how many products are visible in a retailer's online versus bricks-and-mortar store. If the consumer is browsing, as opposed to determined shopping, they may scan products and then select, or not.

We conducted an observational analysis in a single event to compare what might be easily visible to a typical consumer visiting a supermarket in Melbourne. To explore this, we visited a food retailer in Melbourne and collected images of what a shopper might see standing in the aisle.

We took an image of a section of the aisle visible directly in front of the consumer. This was done standing at a distance from the supermarket shelf that was with the observer's back close to the opposite shelf in the aisle (approximately 1.4 metres). We weren't trying to inventory all the products offered. Rather, our purpose was to approximate what a consumer might see looking face-on at the shelves and be able to cognitively take in during a brief visit. We took images of 3 different sections of the chocolate shelves. Using photographs to understand physical information behaviour is an approach that has been used in the past by Buchanan, & McKay.[31, 32]

We counted how many unique products were in each eye-sweep image, taken on July 3, 2020. An eye-sweep is what a customer will see if he/she stands with his back close to the opposite aisle, faces the aisle being browsed face-on, and then visually browses the shelves directly in front of him/her. Where there was variation, we took the average of the totals observed per eye sweep as the purpose was to gain an approximation.

The following figures illustrate the eye-sweep. Tags have been removed from the images as the point of this observational research was not to study a particular store venue but rather to compare and examine consumer choice in bricks and mortar versus online shopping.

We then visited the retailer online to see how many screens deep a consumer would have to go in a search of the same category online in order to achieve seeing the same number of products. Products in the online shop were counted if the consumer could have seen the price tag and/or cost per unit of measurement (e.g. per 100g), or could identify a unique product.

The online site was visited from two laptops and a mobile phone (iPhone). In each the browser was expanded to full screen. The default size of text in a web browser was set to 100%, 16 px.[33]

The point of this observational analysis was to gain insight into how the consumer's exposure to breadth of offerings might be compared between bricks-and-mortar shelves into online shopping. We examined 'chocolate' as a category because it enabled us to take several eye-sweep images, each with a distinct product set, and then average the totals. A smaller category of goods would have been more difficult in this methodology.

We did not look at individual products in the bricks-and-mortar store versus the online store, nor prices. The retailer examined is not relevant to the observation; the focus is on the consumer experience not the specific offerings of a specific shop.

Part 2 – Figure 1

Part 2 – Figure 2

Part 2 – Figure 3

OBSERVATIONAL RESULTS

The results of three sample eye-sweep images observations in the 'chocolate' section of a bricks-and-mortar shop were

Image number	Minimum number of unique products in the chocolate shelf
1	63
2	61
3	66
Average	63.3

The variation in the unique product count per image is partly explained by some sections of shelf having large product (a gift box of chocolates) and some having smaller products. The average of the three sets of eye sweeps of counted products was 63.3 chocolate products per eye-sweep.

We then counted how many screens a consumer would scroll through in the same retailers online shopping site in order to see the same number of products.

Within the online interaction, research has shown that the size of screen is one of the important factors in the consumer's Quality of the Experience (QoE), that is 'the degree of delight or annoyance of the user toward applications and service[34]. For this reason, we examined the screen visits required across several different devices, with different sized screens.

		Minimum number of scroll screens to reach 63.3 products observed
1	Laptop 1	23
2	Laptop 2	23
3	Phone	23

The measurement of 'screens' is 'the approximate number of times a consumer must scroll down to get a fresh list of items,' from the top of the website interface where the search bar is located.

Laptop 1 is a MacBook 12-inch, Retina screen. Laptop 2 is a HP Elitebook with a 13.3" diagonal screen. The phone used was an iPhone 11.

For an online shopping experience, the perceived end-to-end quality becomes one of the main goals required by users that must be guaranteed by the network operators and the Internet service providers, through manufacturer equipment. This is referred to as the quality of experience (QoE) notion that becomes commonly used to represent user perception.[35]

Thus, a consumer at the online shop would need scroll down through approximately 23 different screens on laptops 1 (Apple) and 2 (Win), 23 screens on a mobile phone to see the same number of unique products as an eye-sweep image of the same aisle in a bricks-and-mortar shop.

ANALYSIS

This observational analysis illustrates that while an online shop search capability may allow consumers to locate an exact item quickly, range and comparative representation is greatly reduced. For the browsing consumer looking at the range of products, it will take considerably more time and effort to scroll through pages online than to see the same number of unique items browsing shelves at a bricks-and-mortar store. This is why online steerage as a concept is important to explore in more depth.

There is a known disparity between online browsing and in-person browsing. In online browsing, fewer than 10% of users look beyond the first page of search results regardless of whether they are on a mobile phone[36] or a computer[37]. The predominant mental model of online search is that the most relevant results are shown first[38]; users will expect the same from online shopping.

In contrast, during physical browsing people view many hundreds of items with minimal time and effort[39] Consumers have a different kind of agency and control over their viewing when conducting eye-sweeps in a bricks and mortar store compared to being presented with products in the order that an algorithm has determined they should see.

While it is well known that product placement (such as putting high value products at eye-level) is a strategy used by many retailers in a bricks and mortar store to influence choice, this strategy becomes more pointed online. Ordering a product into the first page of search results gives it a significant retail advantage; moving the product out of the first page renders it less visible to all but the most determined shoppers. By contrast, the physical display remains static for a longer period and it is accessible to all, i.e. even with product placement, everyone sees the same product size in a store. The product is not reduced in prominence by a person's device screen size.

Savvy or technologically-engaged consumers can filter searches, or search for a specific item. In this way, hunting for that one single desired known product may be faster and more efficient for some types of consumers online. But it also potentially limits consumer choice even further, in that you cannot find what you don't know exists. Consumer filtering is being applied without perfect knowledge of the set, so they could be filtering other products that they are not aware of, either due to differences in descriptions or poor understanding of the sector. This makes external marketing far more important. i.e. filtering on brands instead of products – Nescafe instead of instant coffee. The savvy shopper may over optimise speed at the cost of choice.

However, where the consumer has a mental image of the product but cannot recall the name, or where the consumer is just browsing and is not sure what they want to buy, the situation may change. An eye-sweep might allow consumers to rapidly scan a wall of products to pluck out the item they recognise but cannot name, rather than having to roll through 20 screens on a phone to find what they wanted because they could not search for it by name. A browsing consumer in a bricks and mortar store can rapidly compare 20 different items in the chocolate category in one eye sweep. Importantly, all those products are next to each other, in close physical proximity. In an online shopping experience, consumers are often only comparing three to four items directly in a side by side comparison. Thus, the ability to directly visually compare a cluster of products may be better in the bricks and mortar setting.

Further research in this area would be useful, particularly with eye-tracking and measurement technology, in order to examine how the shift from bricks and mortar to online shopping influences consumers' agency and choice in practice.

PART 3: OBSERVATION RESEARCH – MONETISING THE CONSUMERS

There has been recent controversy and concern around how social media platforms are used to target consumers and the potential for discrimination against particular groups. Recent reports also suggest a lack of trust in technology companies with users feeling that processes are not transparent. Facebook is one of the largest social media platforms with 2.37 billion monthly active users reported in 2019 and steady increases each year.[40] It is also widely used by organisations of varying sizes to target advertising.

Following the initial exploratory phase and production of a comprehensive report[41] a number of observations were undertaken to explore real-world examples of social media marketing. Particularly, researchers recorded the targeting options presented and any possible issues to consider as is described in more detail below. Two different organisations were observed (for the purposes of this report they will be referred to as Organisation A and Organisation B) with three different marketing campaigns observed.

OVERVIEW OF FACEBOOK MARKETING TOOLS

The Facebook platform uses an auctioning model for targeted marketing, that is, the price for advertising and what the end user sees depends on the audience itself and what other advertising is competing for the same audience.[42]

There are three key ways in which targeted marketing can occur through the Facebook platform,[43] these are:

1. Facebook Ad Manager — this is the simplest form of advertising on Facebook and involves using the tools provided to define an audience based on various interests and demographic factors
2. Facebook Custom Audience — a custom audience can be created using Personally Identifiable Information (PII)
3. Lookalike Audience — this is a newer feature and allows targeting to those that are similar in behaviour, interests or demographic factors to a custom audience

OBSERVATION 1: ORGANISATION A

The aim of the social media campaign was to promote a debt help service. This service is aimed at Aboriginal and Torres Strait Islander peoples throughout Australia who are in need of legal advice about debt and insurance matters.

The campaign itself had a wide target audience as it is aimed at Aboriginal and Torres Strait Islander peoples who themselves are facing debt or financial hardships but also those in community who may be in a position to share the details of the service and refer those in need, this especially includes case workers, medical professionals and others in contact with communities.

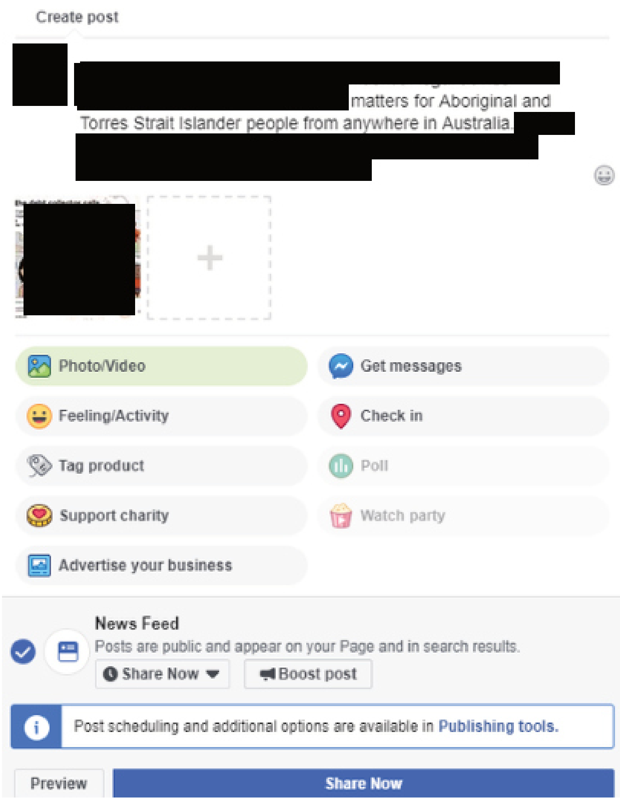
Budget: <$1,000

EXISTING FACEBOOK USAGE

The organisation has a Facebook page which is categorised as a community organisation. They rarely boost posts and mostly look for organic growth and posting directly to pages that may appeal to their audience.

OBSERVATIONS OF SOCIAL MEDIA MARKETING

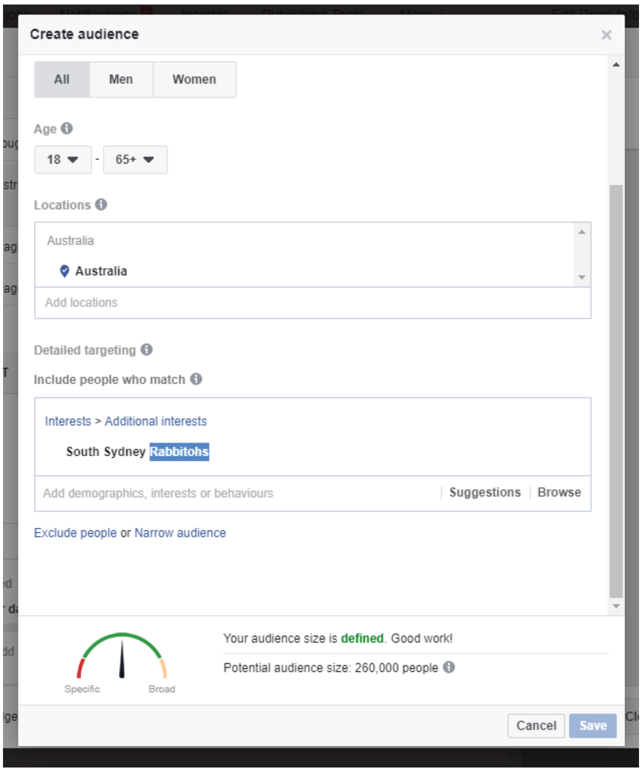
The system allowed an individual post to be created for the page. The post includes text and an image to advertise the service. The creation of the post including the text and image is shown in image 1.



Part 2- Image 1 Screenshot of creating the campaign

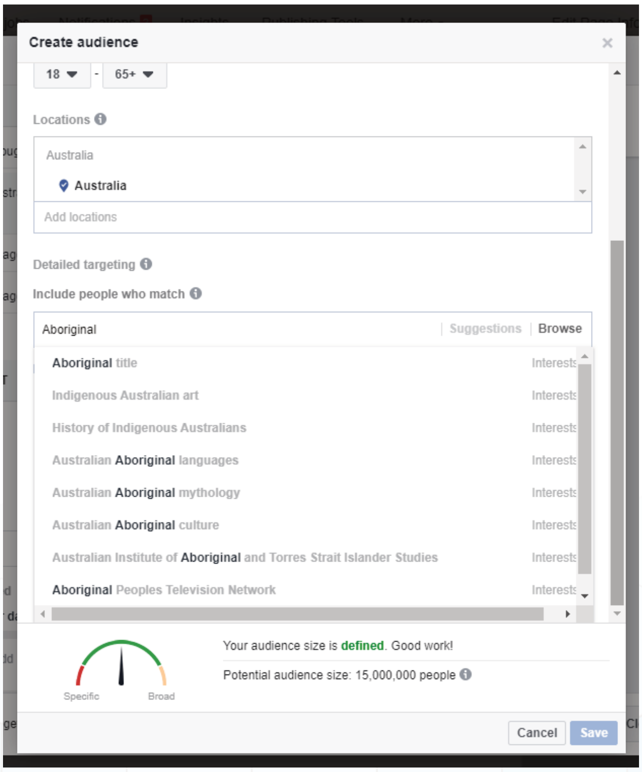
In terms of targeting, the system allowed reaching a particular audience, this mostly related to those identifying as Aboriginal and Torres Strait Islander peoples or working in those communities, some key ways they thought they may be able to target the post included boosting the post to those who also liked the following:

- Sports teams (e.g. South Sydney Rabbitohs as displayed in image 2)
- Land rights
- Aboriginal medical services
- Other services in key communities



Part 2- Image 2 Screenshot of search for 'South Sydney Rabbitohs'

An example of the list of interests given when the term 'Aboriginal' was entered is in image 3:



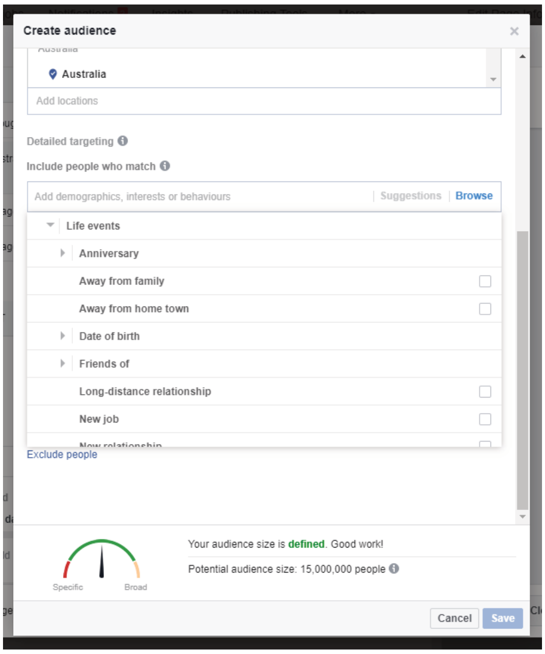
Part 2- Image 3 Screenshot of options when search for 'Aboriginal'

The system also had the potential to target based on the following :

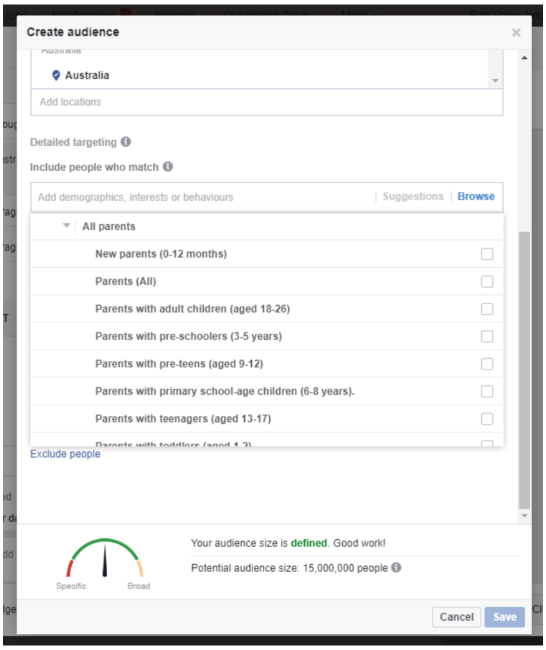
- Geographical area (e.g. Western Sydney)
- Employment status
- Education (available options shown in the screenshot below)
- Income
- Ethnicity

Other targeting options are shown in the following images:

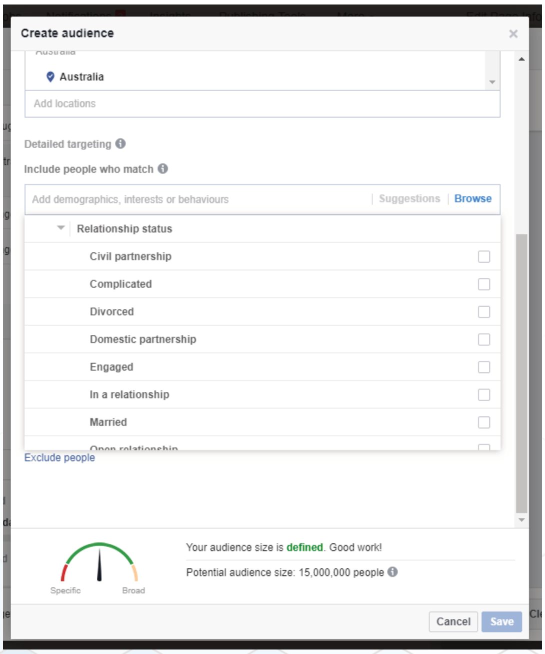
Part 2- Images 4-9 Screenshots of targeting options



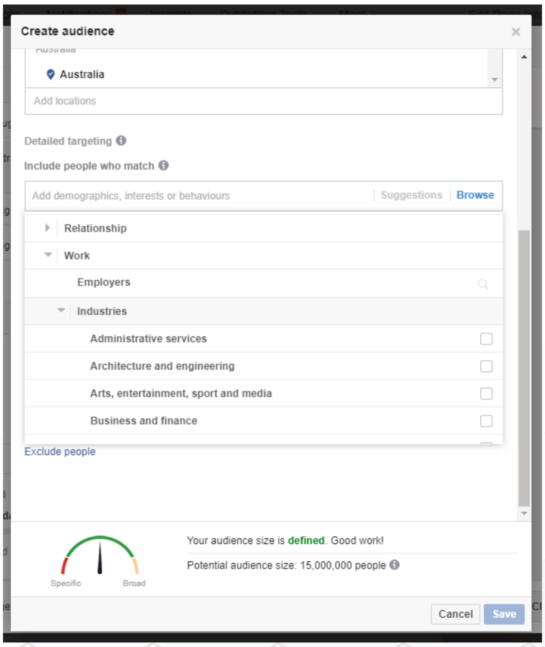
Part 2 - Image 4



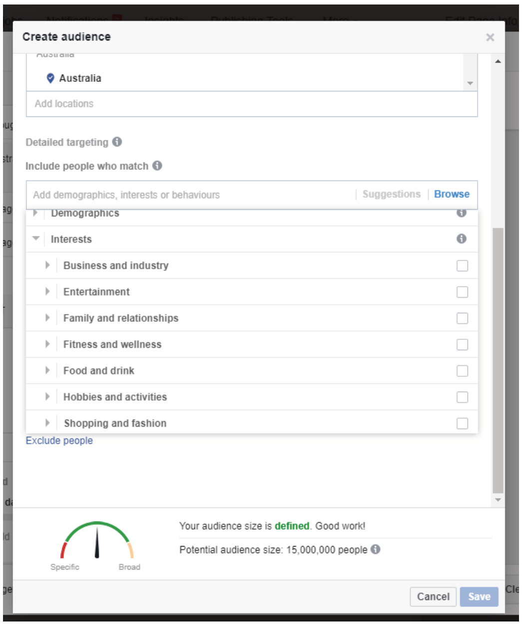
Part 2 - Image 5



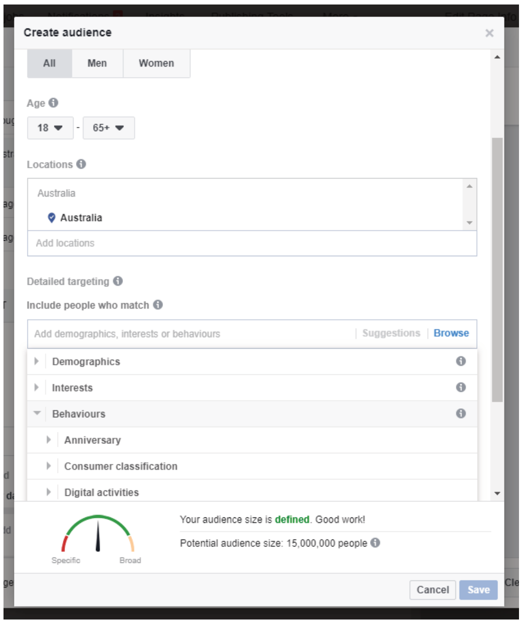
Part 2 - Image 6



Part 2 - Image 7



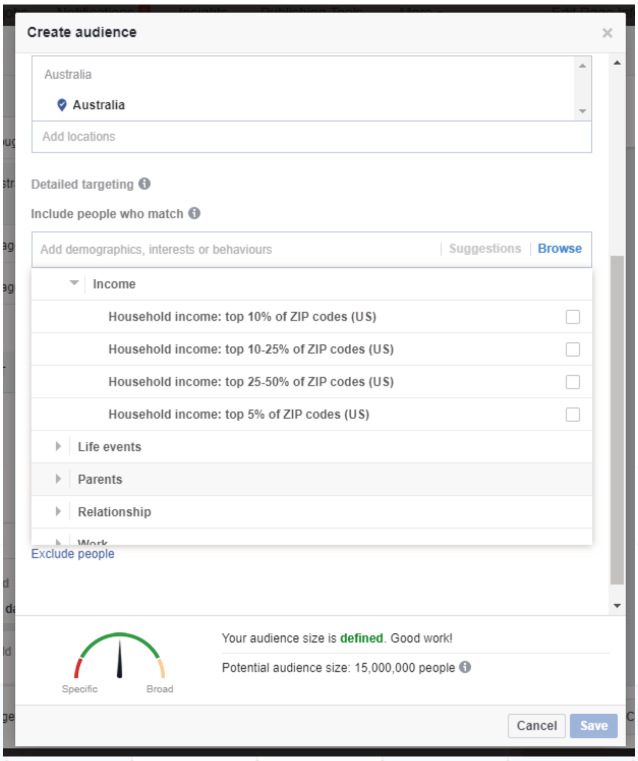
Part 2 - Image 8



Part 2 - Image 9

In Australia, using this particular system to target audiences led to the following issues:

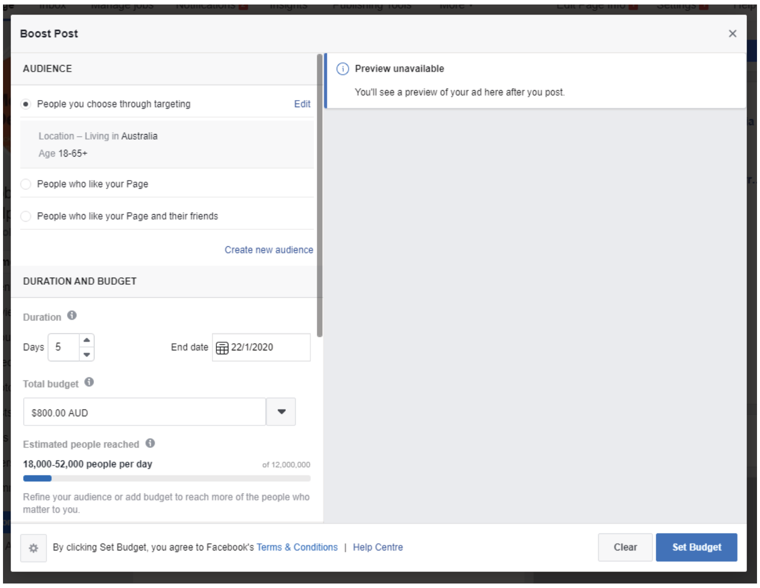
- Many of the characteristics (e.g. ethnicity) were based on US groups as shown image 10
- In targeting specific audiences, they felt the total reach became too narrow
- Some groups/ interests could not be targeted (e.g. Aboriginal Land Right and Medical Centres)



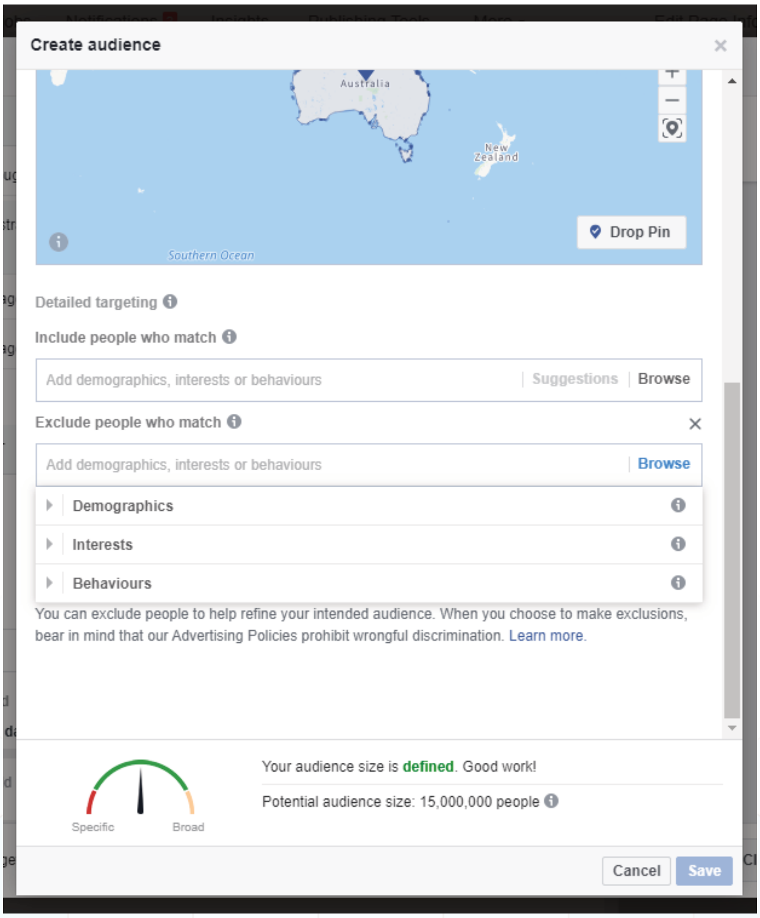
Part 2- Image 10 Screenshot of US-based targeting options

The team had determined that given the current limitations of the technology the best approach would be to target anyone (aged 18–65) in Australia. The following images show the way in which the post was boosted.

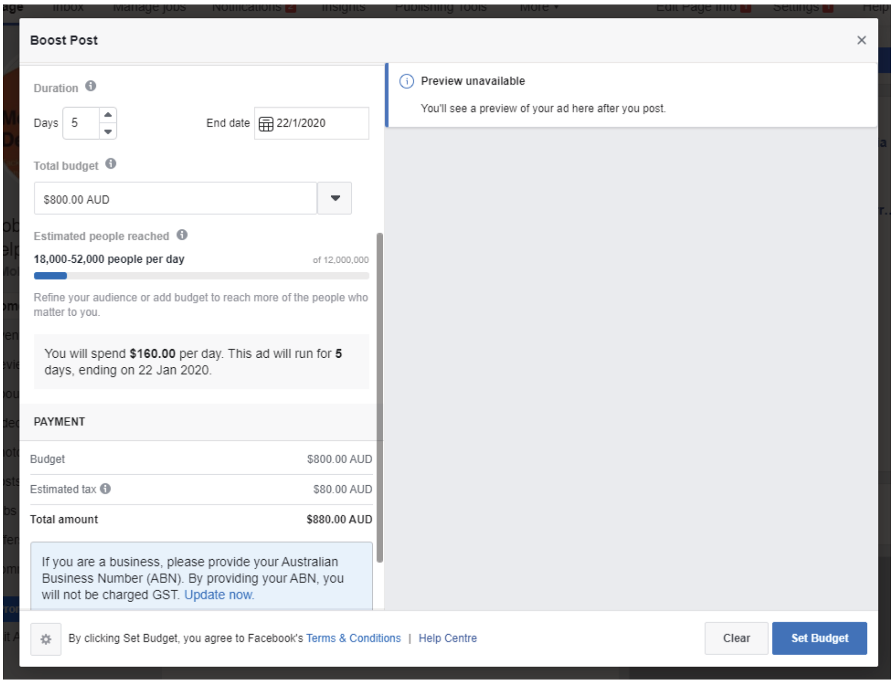
Part 2- Images 11–13- Screenshots of the final targeting selections



Part 2- Image 11



Part 2- Image 12



Part 2- Image 13

They felt this broad approach would lead to a large reach and that the important information would filter to those in need by getting it out to a large enough audience.

OBSERVATION 2: ORGANISATION B PUBLIC EVENT CAMPAIGN

The aim of this campaign was to promote a public event. Specifically, the goal was to get people to sign up to attend the event. The event is targeted at professionals, especially those looking to upskill or change careers.

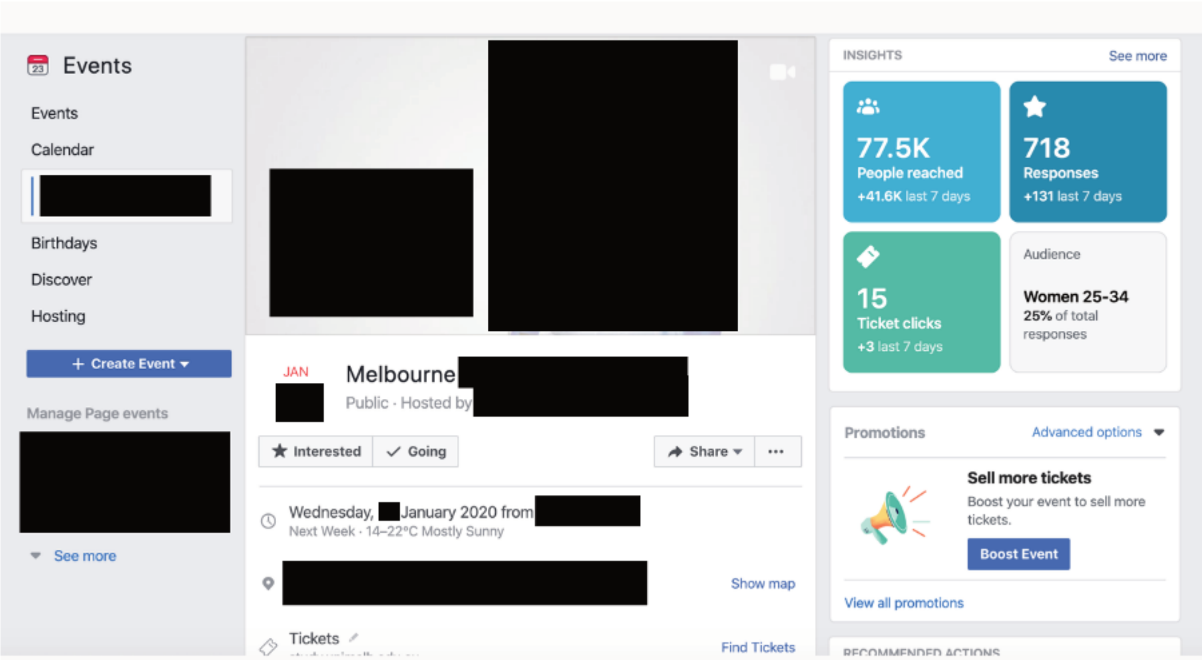
Campaign Budget: >$10,000

EXISTING FACEBOOK USAGE

The organisation has a sophisticated social media marketing plan and program. They regularly boost posts and events and use existing knowledge and audience creation tools to determine where and how to target their posts.

OBSERVATIONS OF SOCIAL MEDIA MARKETING

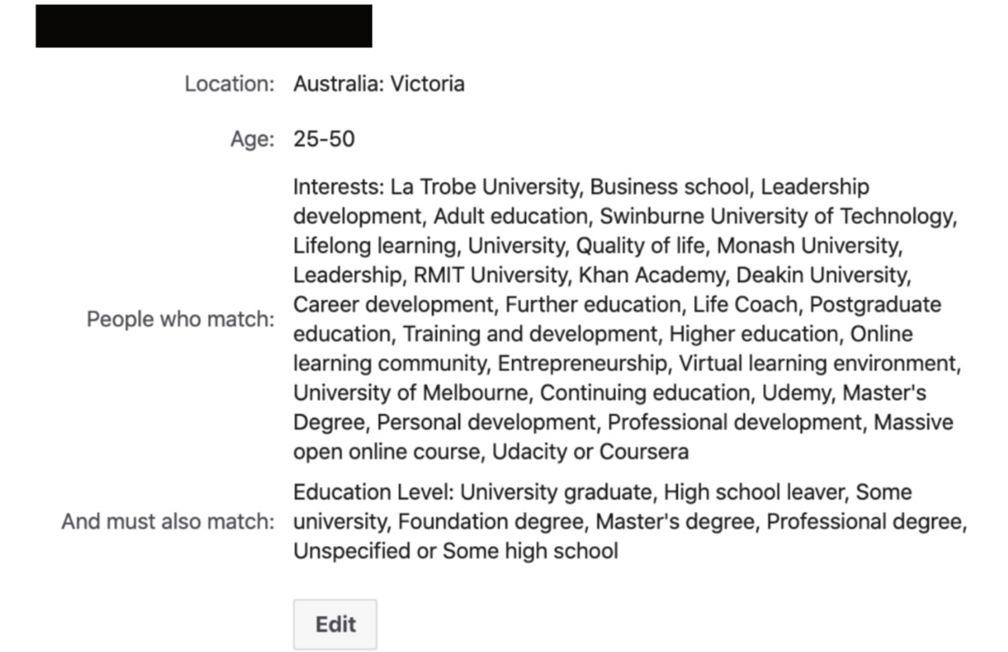
A Facebook event was created for the event. This is shown in image 14.



Part 2- Image 14 Screenshot of the Facebook advertisement

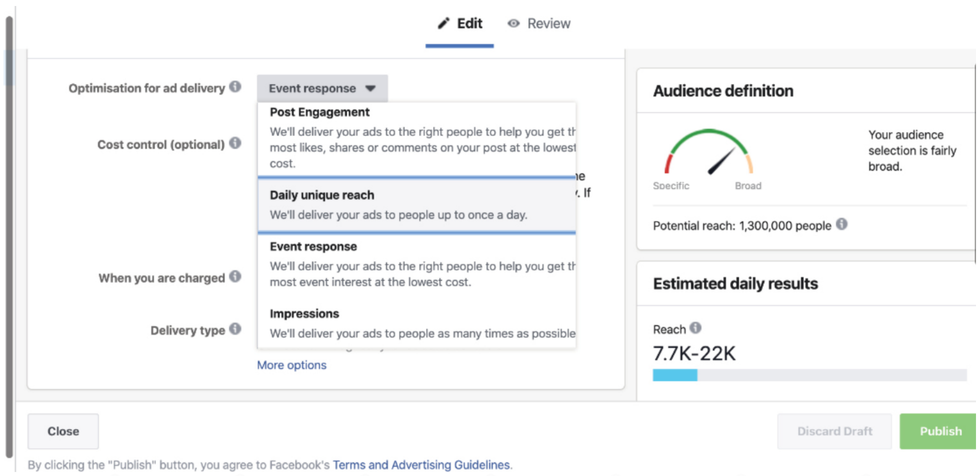
Using existing information and the event brief, it was possible within the system to target people aged 25–50 and located in Australia. It was also possible to include a range of interests (e.g. career development) and education levels for refined targeting of groups.

The full list is shown in image 15 below.



Part 2- Image 15 Screenshot of 'interests' selected for the targeting of the ad

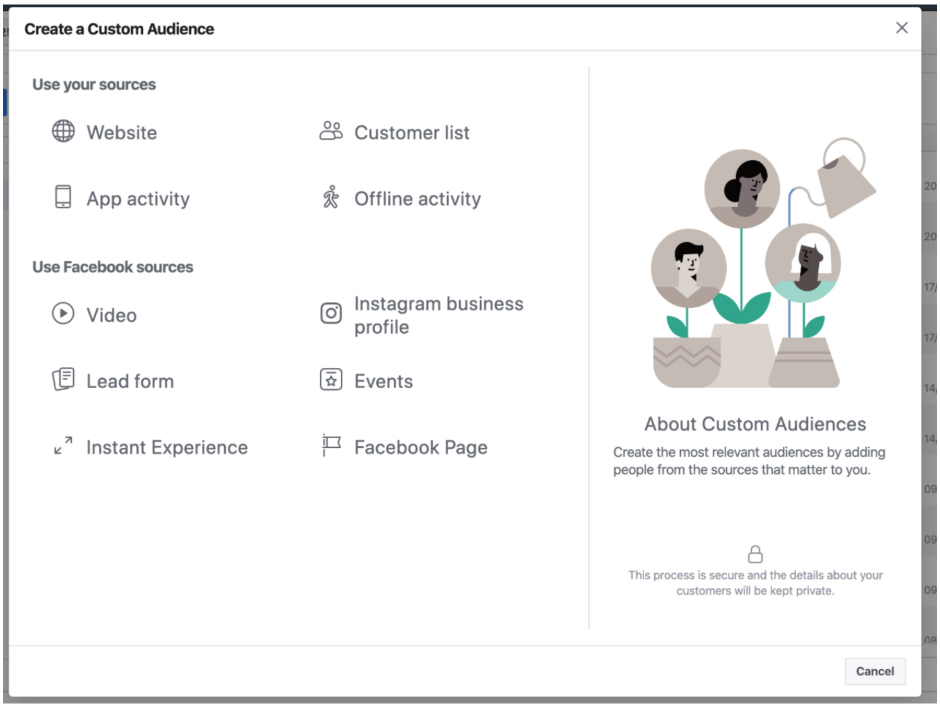
The first phase of the targeting was based on a broader audience while the second phase was to be more targeted. An example of the page shown on Facebook for Business is image 16..



Part 2- Image 16 Screenshot of the Facebook for Business interface

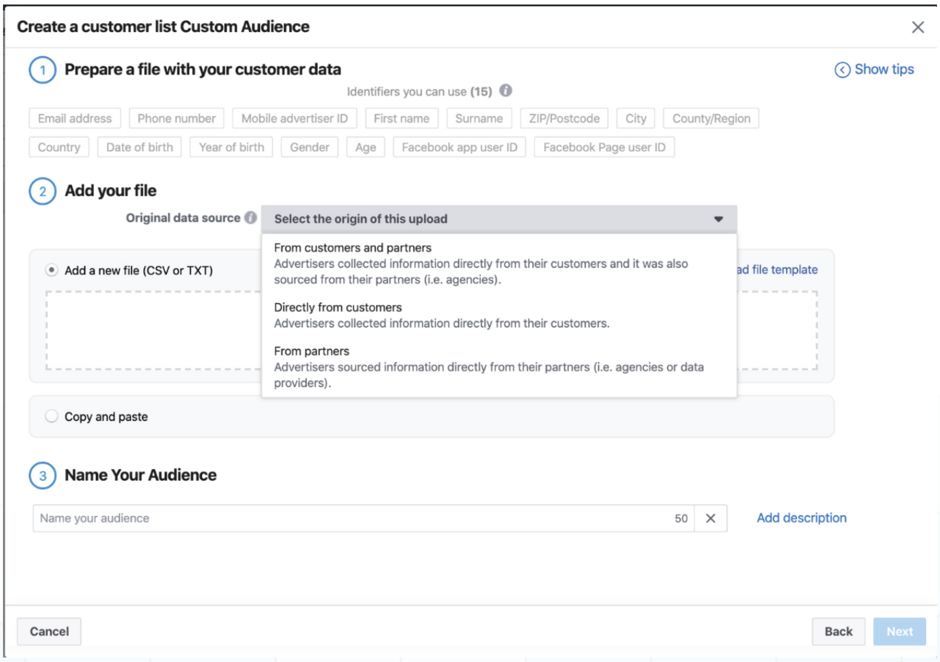
This campaign is similar to many that the organisation had undertaken in the past, so they used key insights from previous campaigns and the already developed audience interests and demographic characteristics.

During the observation, the creation of custom audiences was also shown. As can be seen in image 17 custom audiences can be created using a variety of methods.



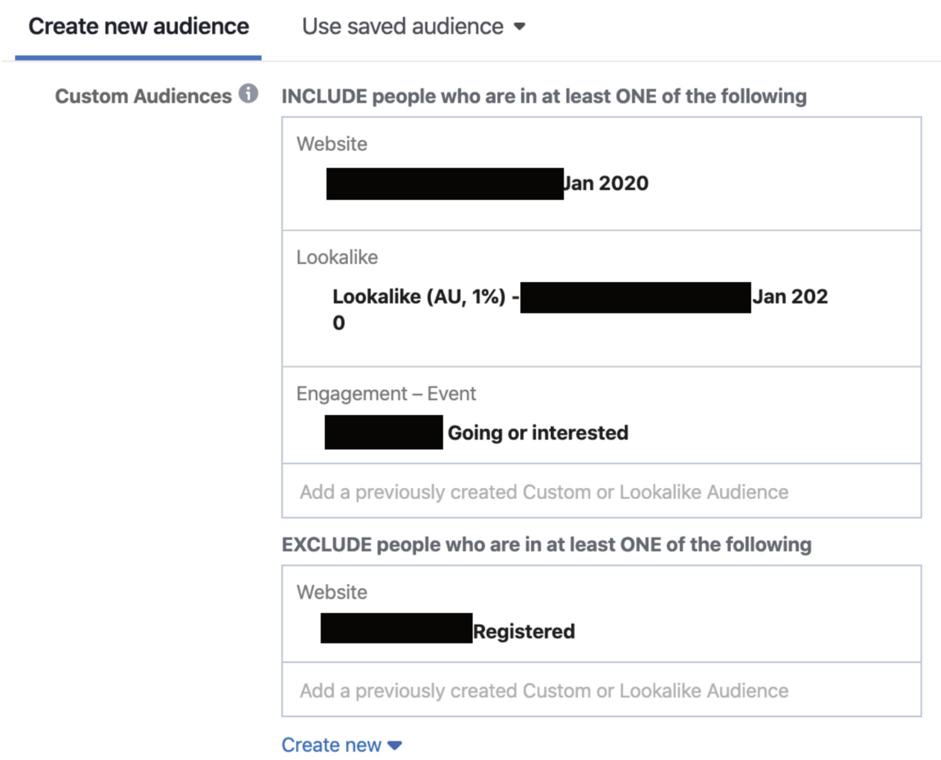
Part 2- Image 17 Screenshot of custom audience options

During this process there is a checkbox whereby the user who is uploading data from another source must define the origin of the data as can be seen in image 18.



Part 2- Image 18 Screenshot of custom audience verification

For the second phase of this campaign, it was also possible to use the system to target those on the custom list as well as those who are considered to be a 'look-alike'. This is shown in image 19.



Part 2- Image 19 Screenshot of the creation of a lookalike audience

OBSERVATION 3: ORGANISATION B NEWS CAMPAIGN

This campaign was aimed at promoting a recent news article. The overall aim was to increase the number of people reading and engaging with the content in the article.

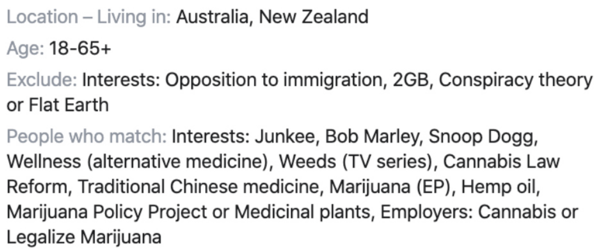
Budget of campaign: >$10,000

EXISTING FACEBOOK USAGE

The organisation publishes and promotes news articles through social media daily. They use knowledge gained from this experience to determine what interests to include related to the topic of each article. They also determine which groups to exclude based on experience to increase the number of genuinely interested readers and decrease the amount of negative and irrelevant commenting.

OBSERVATIONS OF SOCIAL MEDIA MARKETING

The article used for this observation was posted on the Facebook page and discusses cannabis in Australia. In terms of targeting, a number of interests were selected to both include and exclude. These can be seen in image 20.


Location – Living in: Australia, New Zealand

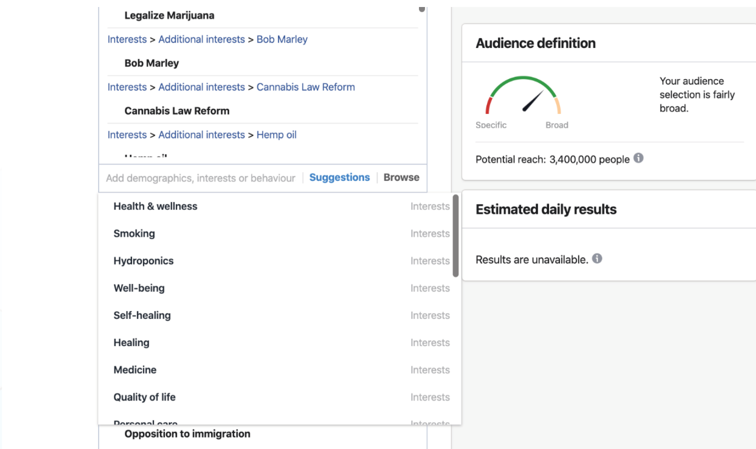
Age: 18-65+

Exclude: Interests: Opposition to immigration, 2GB, Conspiracy theory or Flat Earth

People who match: Interests: Junkee, Bob Marley, Snoop Dogg, Wellness (alternative medicine), Weeds (TV series), Cannabis Law Reform, Traditional Chinese medicine, Marijuana (EP), Hemp oil, Marijuana Policy Project or Medicinal plants, Employers: Cannabis or Legalize Marijuana

Part 2- Image 20 Screenshot of the 'interests' for targeting the article

These were determined based on previous experience as well as suggested interests given by the platform. In image 21 the feature of suggested interests can be seen (e.g. 'Hydroponics' and 'Smoking').



Part 2- Image 21 Screenshot of Facebook suggestions of interests

The post itself was boosted using the Facebook Ad Manager program as seen in image 22. The relevance score of 10 out of 10 and the high click-through rate was seen as evidence of the highly successful targeting of this particular article.

CPC (cost per link click)	CTR (all)	Post engagement	Results	Cost per result	Budget Ad set	Relevance score	Preview link
$0.07	21.57%	937	889 Link Clicks	$0.07 Per link click	$60.00 Lifetime	10	Preview ad
$0.07 Per Action	**21.57%** Per Impres...	**937** Total	**889** Link Clicks	**$0.07** Per link click			

Part 2- Image 22 Facebook statistics of ad performance

KEY FINDINGS

DIFFERENT USER CAPABILITIES

The two organisations have different budgets and levels of sophistication in using online platforms to market to their respective audiences. Using Facebook for Business across many different campaigns, Organisation B have developed complex ways of targeting audiences and have also used both existing data/ knowledge and a trial and error approach to determine the best ways to target various campaigns.

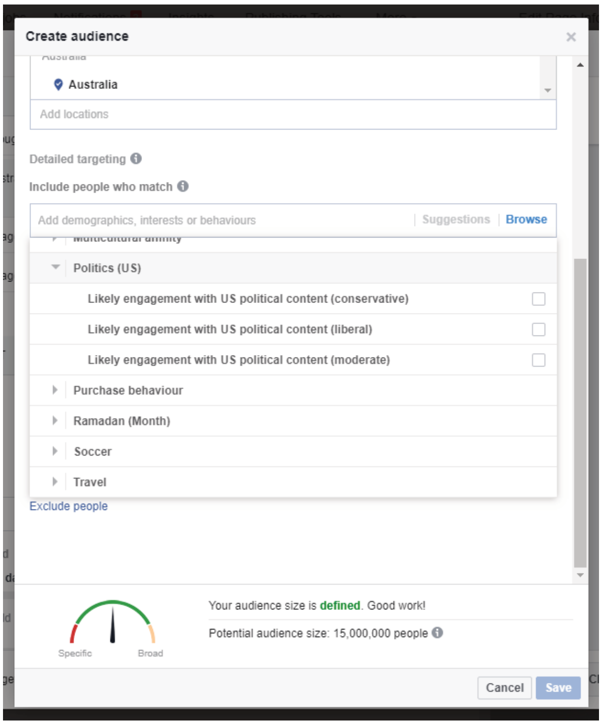
Organisation A in contrast have a more limited budget and use the Facebook platform rather than Facebook for Business to promote their posts. One key issue mentioned was that the Facebook boost page that is accessible to Organisation A as a community group was very limited compared to what is offered on other platforms such as Facebook for Business. Despite the limitations of the more basic version of the marketing tools, it should be noted that these tools are extremely user-friendly, with limited resources and expertise the average user can navigate this process fairly easily and can use the tools to promote to various audiences.

AUSTRALIAN OPTIONS FOR TARGETING

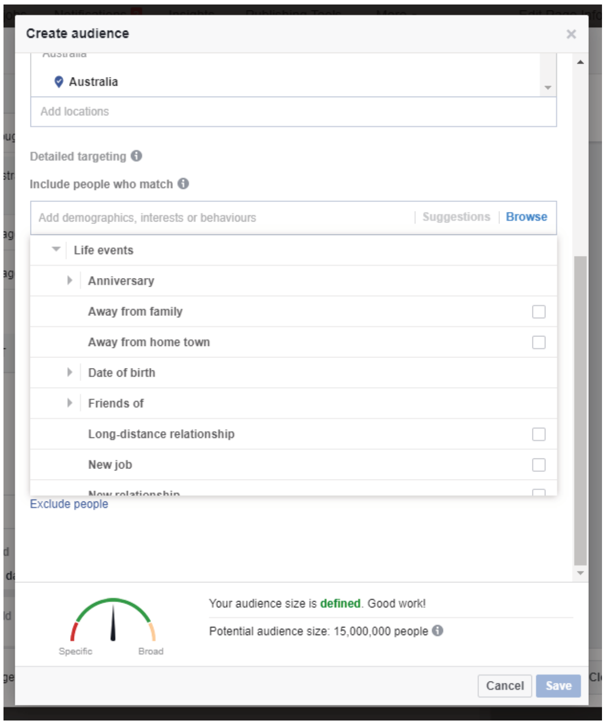
It is evident from the observations that there are some specific methods of targeting that are restricted in Australia.

As can be seen images 23–26 there are a number of options for targeting by ethnicity and income that are available in other countries. There are no existing options for Australia to target in this way. Although the tabs appear (e.g. ‘Multicultural Affinity’) the available options are all US-based.

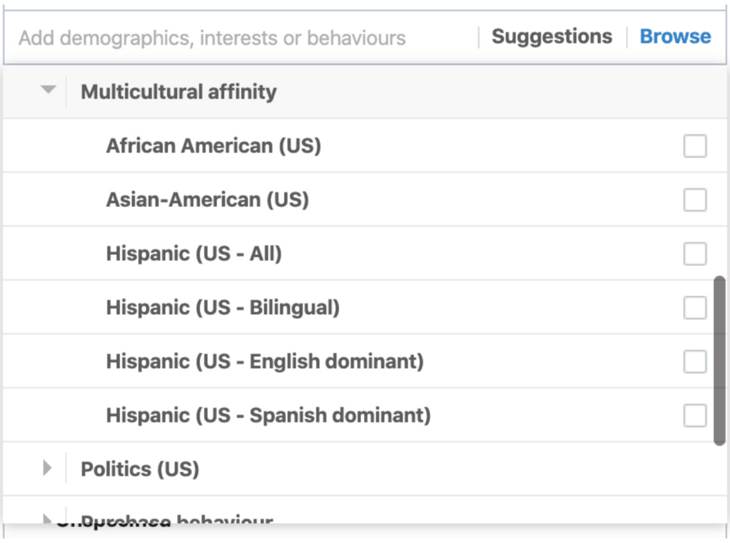
Part 2 – Images 23-26 Screenshots of US and Malaysian-based targeting options not available in Australia



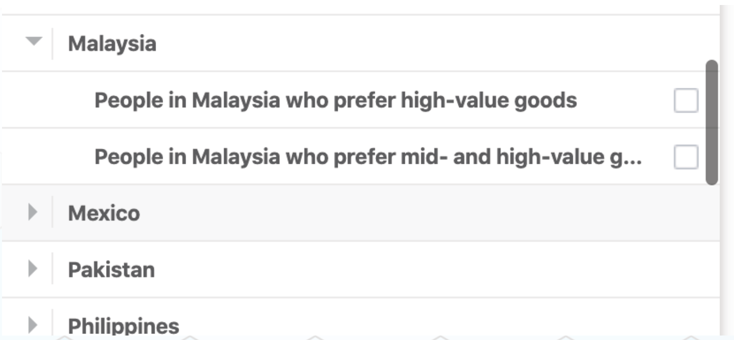
Part 2 – Image 23



Part 2 – Image 24



Part 2 – Image 25



Part 2 – Image 26

'SIDEWAYS MARKETING'

Despite the existing restrictions on direct targeting (e.g. selecting a cultural group) in Australia, it is very possible to use other methods to target specific groups. Although the team at Organisation A ultimately decided to use a broad approach in their marketing strategy there were some key insights into the potential of the existing technology to use indirect methods to target certain groups.

Specifically, it was evident that by using a combination of variables (such as location, income and interests), those of Aboriginal and Torres Strait Islander peoples with low income could be targeted. This raises concerns in terms of creating policies and procedures to protect vulnerable groups, such as people on low incomes, from being targeted using indirect or 'sideways' marketing techniques.

Sideways marketing is where an ad advertisers cannot target an exact desired audience due to restriction or other constraint, so it finds proxy descriptors for the audience and use those, in order to reach the target audience. In this case, cross-referencing a set of other descriptors (e.g. a specific sports team, a geographic area, etc) may allow the advertiser to reach the desired audience of Aboriginal and Torres Strait Islander peoples on lower incomes (or perhaps in financial stress) without using those exact terms that may not be available.[44]

This ability to use multiple interests to target specific groups was even more advanced when looking at Organisations B's campaigns. Some interesting points taken from this observation were the ability to both include and exclude specific interests (e.g. against immigration) and behaviours (e.g. time spent looking at a particular video).

LACK OF VISIBILITY INTO DIGITAL PLATFORM

The social media experts purchasing advertisements commented on the overall lack of visibility into digital platforms for marketing. Specifically, there was no way for them to see how it was determined that an individual had a particular interest or view (i.e. they could select 'career development' as an interest but how Facebook deems a person is interested in career development is completely unknown).

Interests were included or removed seemingly at random for example, at one point in time it was possible to target those interested in well-known Aboriginal and Torres Strait Islander peoples public figures, this option was then removed. The feedback given was that there were constant changes in the capabilities and options for Facebook marketing but how these decisions were made remained unknown. The overall lack of transparency in all of the behind-the-scenes data gathering at Facebook, and defining of individuals and groups, was very clear throughout these observations.

CONCLUSION

Overall, these real-life observations of the way in which organisations use social media are invaluable. They have highlighted key issues of concern that require further attention.

Of particular interest is the potential to target vulnerable groups (and the difficulty in controlling or even exposing this) as well as an overall lack of transparency. We have found that the technological tools have the capability for a degree of 'drill down' targeting that could be used for discrimination in ways that are inconsistent with what would likely be expected by the Australian public. This does not mean there is discrimination. However, the ability to use technology to narrowly focus for consumers search ranges and cross match data creates the possibility for this.

More concerning is the fact that a vulnerable consumer may be narrowly targeted based on their own personal viewing and purchasing habits. In other words, their consumer information can be used against them, in order to manipulate them more effectively.

Targeting of consumer groups for sale of a product is not new. However, doing so with a greatly amplified precision, instantaneously and very cheaply due to the automation of this entire process is new. With the capability to use automated behaviour analysis being newer still. These things converge into a perfect storm of risk for an unfair environment for the consumer, particularly the more financially vulnerable consumer.

If an unscrupulous payday lender can easily identify and target financially vulnerable males of Aboriginal and Torres Strait Islander peoples descent aged 18–25 in a particular region, despite a technology platform not providing a search category for this particular group, what should we do about it? This capability exists, via selecting a set of micro-targeted advertising categories in combination. Thus, this question is worth consideration.

POLICY ISSUES RAISED BY THE RESULTS OF THESE EXPERIMENTS AND OBSERVATIONS

Selecting a set of micro-targeted advertising categories simply by combining categories offered by a technology-based advertiser may now allow persuasion or manipulation of consumers based on race, gender or other criteria that may be illegal or uncomfortable for society as a whole.

The ability to drill down, with such specificity, to narrow groups of consumers and then 'mix and match' across categories is what allows this to happen. The unique nature of the big technology platform, in which consumers not only freely enter in their personal data and preferences (e.g. Facebook) but then also transact significant parts of their lives as well, creates this drill down capability. Proving harm is happening from the existence of this capability is more difficult. This is not because the harm is not happening. It is because we as researchers, and the public more generally, cannot clearly see the data collection, analysis and use – the searching, targeting and advertising– that goes on inside the technology companies' platforms.

Our earlier 2019 report on the *State of the Art in Data Surveillance*[45] illustrates just how extensive this data collection from monitoring has become. This report provides insight into how the data generated from such monitoring can be used by technology companies to 'sell the consumer' to advertisers.

Transparency is one way to prevent the potential to discriminate using these tools. Consumer awareness on these topics has improved more recently, as more consumers have begun to understand how much of their data is being gathered without their permission or knowledge.

REPORT CONCLUSION

Whilst concerns have been highlighted, we recognise that technology offers real value to consumers in a number of ways. Google, Facebook and other social media platforms offer a free service to end users, and highly targeted advertising may have benefits to the consumer.

Technology is moving quickly, and consumers get the benefit of the innovation being driven by this speed. Innovation is important to a healthy economy and providing ever better services for consumers. Technology companies have been at the forefront of innovation for at least two decades, and this has undoubtedly provided valuable services to consumers.

Any regulatory change needs to be careful not to stifle innovation in the technology sector, nor freedom of speech enabled by these technologies in the process, whilst protecting users from the potential harms. The question is whether less desirable uses of technical capabilities by powerful social media tech platform companies would ever be fully seen or known because of the opaqueness at the back end of how their products work for consumers and advertisers.

As the technology for gathering data from consumers online has advanced, so have different jurisdictions' responses, particularly to privacy concerns.[46] Canada began 2020 with a proposal to update its privacy laws and to enhance the power of its information regulator.[47] Prime Minister Justin Trudeau has particularly identified the need to establish new online rights.[48] This follows on Europe's ground-breaking response to personal data privacy concerns in the form of the EU's General Data Protection Regulation that took effect in May 2018. In the US, new state laws, in Vermont[49] in 2019 and in California[50] in 2020 have innovated in forcing greater transparency and accountability on the secretive world of data mining companies, and conferring more rights on consumers. These countries and states provide useful models for Australia in considering how it might address emerging consumer privacy issues.

However, not all consumer data privacy advances have been smooth. India introduced the Personal Data Protection Bill into its Parliament in December 2019. Despite being described as the 'first cross-sectoral legal framework for data protection' in the country, it has been criticised as 'not correctly addressing privacy-related harms in the data economy in India.'

The time to consider regulatory protections for consumers online is before privacy-encroaching technologies become so embedded in online shopping environments that it is difficult to remove or even identify them.

It is not new that traditional advertising may have 'value!' pasted on bold letters above a package price. However, price comparison sites present a different proposition to the end user; they appear to offer an evaluation of the 'best' choice of options 'out there' (e.g. based on price, or some other criteria in the consumer's best interest). There is a disjoin where this is the proposition presented to the consumer, yet this is not necessarily what is going on in the automated selection and presentation of offerings behind the page.

Large datasets can be 'mixed, matched, and massaged'. Predictive analytics based on these are increasingly being applied to automated decision-making about people's lives online (e.g. getting jobs, life insurance, a rental flat). Transparency only helps the consumer get part way up the hill when it comes to understanding the impact.

Giving consumers a single simple 'Press-a-Button' method to delete their data inside the technology giant's data collection repositories – and to instruct the company not to collect more of that personal data going forward is another way, but unlikely to happen without intervention.

Some technology companies have made progress toward this in recent years, but it is still not push-button simple for a consumer to do so.

Giving consumers the right to do this on online shopping sites – again, with push-button ease – would at least give consumers a more level playing field in interacting.

A/B testing may be helpful for retailers, but it creates noise for the consumer and obfuscates clarity on offerings and price-of-product-basket to the consumer. This becomes particularly important where there is decreased transparency to both consumer and consumer protection watchdog due to the use of invisible datasets about the individual consumer, as well as algorithms that are not clear in their functions.

Curation is important, while it can more precisely meet consumer desires, it can also forcibly reduce consumer choice.

The ordering of products also matters in an era of attention deficit. Consumer tendency in a time-poor world to increasingly 'choose by glancing', means that what a consumer is shown first in an online setting can have a strong steerage effect.

Finally, we note that comparator online sites, and other online shopping sites, may imply a 'best choice for you' in a way that walking into a physical market and eyeing a shelf of goods does not. This is important because consumers can wrongly have the impression the site is 'looking after their best interest' when it is in fact offering a different product to one consumer than another. Such an offering may be due to A/B testing, or it could be through advertising dollars paid for a premium position on many consumers' screens at once. In either case, it would be beneficial to the consumer to be made aware this is how the system they are using engages with them. This is not the same as an online bidding site, where everyone can for example see what competitors are bidding for the same product.

Thus, improving standards of transparency – alerting the consumer how the items that are returned to them on a given search have actually ended up there – would be beneficial for the consumer. This is particularly true in an era when more consumers are shopping online out of necessity.

FUTURE RESEARCH

An important contribution of this research work is to identify important areas that might be researched in the future for highest impact and positive benefit to society. The companion report to this work, What We See and What We Don't: Protecting Choice for Online Consumers Policy Report, sets out future research questions in the policy and law areas related to the work in this report.

We identify these possible areas for further technical research:

1. What is the consumer's expectation of internal-to-the-retailer's site search engine output? Does the consumer believe a search for 'oranges' will turn up fresh fruit, and in what order? Does this match actual results returned for a sample of major retailers?

2. What channels for asking product questions do different online retailers provide – and how easy are they to use by consumers?

3. Using eye tracking technology on consumers volunteer participants doing eye-sweeps in categories of products in bricks and mortar stores. Specific questions relate to comparing online shopping to bricks and mortar:

   3.1. In browse mode, how long does it take a consumer to scan a product cluster (e.g. ~ 60 products) to find the desired one in each setting?

   3.2. How well can consumers compare products side by side on or near shelves versus online shopping?

4. How much detailed product information 'at the back of the pack' is available online versus via in person for a reasonable sample of goods? (This might include nutritional, import or other relevant material, including sample sizes of unit of measurement used for the products – e.g.'serving size is 30 grams' etc)

5. Close examination of how different online retailers label their paid product placement goods in search engine results compared to 'normal' goods returned by a category search. Is the terminology used instantly recognisable to the consumer as 'paid-for premium position advertising'?

APPENDIX A: RESEARCH METHODOLOGY

RESEARCH METHODOLOGY FOR PART 1 – PERSONAS TESTING

THE PERSONAS ARE DIGITALLY 'MARKED UP' WITH NEW ACCOUNTS FROM:

- Google / Gmail,
- Facebook
- Twitter

Instagram does not require Age or Gender so was not suitable.

PERSONAS WERE DOCUMENTED AND CREATED FOR THE FOLLOWING TESTS:

TEST 1

- Have social media versus
- Don't have social media

TEST 2

(within 'Have Social Media')

- Age (2 x ages: aged 22 versus aged 66)
- Genders (Male vs Female)

(In Test 2, additional work was done on the personas to give them specific browsing histories.)

- Round Two testing conducted both Test 1 and Test 2. The purpose of two rounds of formal experiments was to test reproducibility and to further examine research areas where informal probe tests had shown variations that were of interest.
- Informal probes were run without the personas before and after the Round One experiment. The probes were visits to the online shopping sites using different browsers, with different settings (e.g. a standard browser on existing deployed devices, 'private browsing', 'incognito' or via Tor Browser, and/or other varied browser histories). The probes included searches of the online shopping sites for wider variety of products that were in the formal experiments. The informal probes were done at different times of the day, and on weekends, over a period of several months, to see if patterns or anomalies of interest emerged. The informal probes were exploratory in nature, not formal experiments. The probes helped to inform the experiments' designs and focal points in both Rounds One and Two.

CONSUMER ONLINE SHOPPING SITES TESTED

1. Coles
2. JB HiFi
3. Booking.com
4. Bunnings
5. Target

BROWSER SET UP, CREATING ACCOUNTS AND PERSONAS

BROWSER SET UP:

The browser set up involved the use of a VPN and web browser's 'incognito mode'. Each persona had its unique IP address randomly attributed in an attempt to remove its effect through randomisation.

When conducting the tests, private browsing modes offered by web browsers ('incognito') proved to be very effective, for the purposes of testing online shopping sites, in allowing us to switch rapidly between personas, erasing previous browsing history, cookies and logging out from all active social media accounts.

Additional information on incognito mode and VPN options is available in the following 'Browser set up' and 'VPN options' sections. Virtual Machines were used to segregate each cohort of personas.

CREATING ONLINE ACCOUNTS:

10 personas of each cohort were created.

There are 3 social media / online platforms per individual persona (Facebook, Google, Twitter) that recorded the factors we wanted to test (age & gender):

WITH SOCIAL MEDIA ACCOUNTS:

Male 22	Female 22	Male 66	Female 66

WITHOUT SOCIAL MEDIA ACCOUNTS:

No Demographic (Control Sample)

A sample size of 10 was to be used for each of the five cohorts. With a total of 50 personas and 120 online/social media accounts created for this experiment.

The accounts were created allowing for rigorous tailoring of our personas.

Accounts on Facebook, Twitter and Google were created with the same user information between platforms for each persona. Common male and female names were used and the emails was created using the form name.surname@gmail.com with the addition of numbers if the email is not available.

PROTOCOL:

1. Create Google account to have a Gmail
2. Create a Facebook account with the Gmail
3. Create a Twitter account with Facebook or Gmail

KEEPING BROWSING HISTORY CONSISTENT BETWEEN PERSONAS (FOR TEST 2):

In order to keep browsing history consistent between the tested demographics, an established list of products to view was created for each subcategory (e.g. 22yo Male). This protocol, that the websites to visit, was based on the personas we were creating. It made use of common articles searched for by the specific demographic. Time spent on each search was specified and, on each page visited uniform mouse sweeping was executed in order to dissipate the effect of mouse tracking.

EXAMPLE OF BROWSING PROTOCOL FOR A 22YO MALE:

Articles (15 seconds per article):

- Pair of young men's bathers
- Shaving cream
- Pair of men's Jeans
- Sports shirt

... And so on

PILOT EXPERIMENT

Before starting the experiment, we used 3 additional websites to test for immediate price differentials or steerage. The protocol was:

1. Start from a fresh incognito mode browser connected to the persona's server through the VPN
2. Connect to all his/her social media accounts
3. Open the selected websites and observe prices and page organization
4. Take a screen capture and carefully store the information. Do this for two different personas.

If no differences are found between the page organization and prices displayed to our different personas, the test were considered insignificant and determined to be No Variation. Any form of price differentials or alternate page set ups/product offering, or steerage based on the factors Age and Gender were viewed as a Variation. If the differences existed but they did not link to specific factor combinations, we looked deeper into the tests made and the persona's used to make an assessment.

COMMENCE EXPERIMENT

UNDERTAKE ROUND ONE (FEBRUARY) TESTING- VISIT SITES

TEST 1:

Use a VPN and set the browser on incognito mode. Visit our targeted websites and record information. Do this twice, changing the IP address.

Use a VPN, set the browser on incognito mode and connect to all social media accounts related to a persona. Visit our targeted websites and record information. Do this twice, changing the IP address and the Persona's social media accounts.

TEST 2:

After having connected all 3 social media accounts and having browsed the pre-specified URL's, open the target websites and record findings. Do this for all personas.

The testing was ideally undertaken by the same person from the same device for each combination of personas. Browsing history and creation of accounts was completed following the protocol described above with all details documented.

UNDERTAKE ROUND TWO (JULY) TESTING- VISIT SITES

The same process was undertaken in the second round of testing. A smaller set of personas was used (15, e.g. three in the Female aged 22 group). We used the same number of persona groups across all cohorts in Round Two testing. We tested the sites of Bunnings, Coles, Target and Booking.com in this round.

For both Round One and Round Two, participants did not log in as users of the online shopping sites. No purchases were made from any retailers as part of this research..

PERFORM ANALYSIS

Following visiting the site, testers saved a copy of the home page screen of each shopping page. The screenshot was assessed in relation to the key areas of interest:

1. variation in price offering of goods, on the basis of single item per offering
2. steerage – the order of goods offered being changed
3. fewer options being presented

This was recorded in an objective manner to allow for analysis. We then assessed the data from each persona combination (e.g. male aged 22 vs female aged 22) to determine if there were any notable differences.

TECHNICAL SETUP

SOCIAL MEDIA / ONLINE ACCOUNT SETUP

Online Platform	Time taken	Information required	Optional information
Google account (Gmail)	2 minutes	- Name - Email - Password -Date of Birth - Gender	- Phone number or second Email
Twitter	2 minutes	-Name - Email or phone - Password	- Photo - Bio - Interests
Facebook	2 minutes	- Name and surname - Email or phone - Dob - Gender	- Photo - Location you live in - City of Birth - Highschool - University - Work - Relationship status

BROWSER SET UP

OBJECTIVE OF THE SET UP:

We wanted to conduct the tests without our different persona's polluting each other and wanted each persona to have a different IP address.

Private Browser Mode (incognito mode):

Key Information:

- The searches you do or sites you visit won't be saved to your device or browsing history.
- Files you download or bookmarks you create might be kept on your device.
- Cookies are deleted after you close your private browsing window or tab.
- You might see search results and suggestions based on your location or other searches you've done during your current browsing session.
- If you sign into your Google Account to use a web service like Gmail, your searches and browsing activity might be saved to your account.
- Does not shield web browsing from an employer. (If using office WIFI for example)

Googles disclosure on Chromes incognito mode:
https://support.google.com/websearch/answer/4540094?co=GENIE.Platform%3DDesktop&hl=en

VPN OPTIONS

Melbourne based:

https://www.personalvpn.com/network/australia-vpn-server-gateways/melbourne/

Multiple international locations:

https://www.expressvpn.com

EXAMPLE OF DOCUMENTATION OF PERSONA CREATION AND TESTING

Persona ID	1
Demographics	Male, aged 22
Social media accounts created	Facebook Google
Browsing history	Date Time Search terms used Site URL Time spent
Test site one	JB Hi-Fi Date Time Total time spent
Test site two	Bunnings Date Time Total time spent

RESEARCH METHODOLOGY FOR PART 2 – OBSERVATIONAL ANALYSIS

AIMS AND OBJECTIVES

The aims of this project are to understand what information is gathered about consumers online, and how that information is used to target advertising and impact on consumers shopping online. This research follows on from a review of the state of the art in consumer data gathering technologies and practices that is entitled **'State of the Art in Data Tracking Technology'**.

KEY QUESTION(S)

- What demographic or other features of consumers can be targeted when purchasing advertising?
- Does this vary by advertising provider?
- Do those purchasing advertising find the options useful?

RESEARCH DESIGN

This work used a contextual enquiry approach (interviews and observations situated in the place of work). We will be observing marketing specialists as they purchase online advertising and asking them about the options they have to tailor and target advertising. Participants will be drawn from two organisations with different target populations so that it is possible to observe purchase of advertising

PARTICIPANTS

These participants have been chosen as they have legitimate reason to purchase online advertising as part of their work. They are different and provide contrast in size, skill level of accessing targeted consumers, and reach.

PARTICIPANT TASKS

Participants were observed and interviewed while conducting their normal work; this method is known as contextual enquiry.[51] This is a technique commonly used in human computer interaction and information systems to understand the work practices of information workers and other individuals.

Data was collected using records of interviews and written notes about the options available for purchasing advertising. Interviews were transcribed and anonymised.

DATA ANALYSIS

Data will be analysed using general inductive coding to understand what options are possible and how they are used by advertisers.[52]

Ethics approval has been granted.

APPENDIX B: ENDNOTES

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