ADM+S
ARC Centre of Excellence for **Automated Decision-Making and Society**

AI and Automated Decision-Making in News and Media

Key technologies and emerging challenges

FOCUS AREA REPORT 01

In the spirit of reconciliation, we acknowledge the Traditional Custodians of Country throughout Australia and their connections to land, sea and community. We pay our respect to their Elders past, present and emerging, and extend that respect to all Aboriginal and Torres Strait Islander peoples today.

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ABSTRACT

Automated systems and processes are a common feature of the news and media environment. This report introduces four key examples: search, recommendation, automated content moderation and curation, and advertising technology (AdTech). We provide a basic explanation of how these systems work at the technical level and show how they operate in context, drawing on examples and case studies across news and media. We then map emerging challenges associated with the use of each technology across the news and media environment, drawing on peer-reviewed research from multiple disciplines. The findings and outcomes of current research in this area from the ARC Centre of Excellence for Automated Decision-Making and Society are featured throughout. We end by identifying several critical areas where future work is needed to help ensure the safe and responsible deployment of automated systems across news and media.

INTRODUCTION

From the steam presses of the early nineteenth century onward, automation has been a transformative feature of the news and media industry. This report describes the latest phase of media automation, driven by recent advances in artificial intelligence (AI). This current phase is characterised by a striking feature: machines are now intimately involved in making decisions about how our news and media are created, distributed and received.

In the last few decades, once-novel technologies have become ordinary: search engines find newsworthy information, recommender systems curate it, automated markets buy and sell advertising, and social media platforms are managed by content moderation and curation systems. Although humans remain involved in this process, they work alongside and within automated systems.

Automation may bring about a more diverse and dynamic media system, but these benefits must be weighed against the risks to democracy and civic life. A better public understanding of this current phase of media automation is essential. In a fast-moving landscape, there is much that policymakers, industry participants, researchers and citizens need to know.

Table 1. Summary of automated systems and their challenges

Automated system	Emerging challenges
Search	+ Competition in web search + Autocomplete biases + Misinformation and disinformation in search results + Source diversity
Recommendation	+ Organisationally siloed deployment of recommender systems + Ensuring that recommendation accounts for equality, fairness and diversity + Relating to transparency, risk assessment, risk mitigation, and data access and scrutiny
Moderation and Curation	+ Cultural differences and geopolitical conflicts informing moderation and curation decisions + Ongoing challenges with electoral and health disinformation, political bias, gender-based violence, deepfakes, image-based sexual abuse, and coordinated interference from state-sponsored actors and other groups.
AdTech	+ Automated ad blacklisting and its unintended consequences + The rise of first-party data and its impact on advertising models + Iterative targeting through pattern-mining

In this report, we outline four critical examples in this area: search, recommendation, moderation and curation, and advertising technology (AdTech). We describe how these systems work and where we encounter them, as well as the associated problems and possibilities. We outline a series of emerging challenges for each automated system, drawing on peer-reviewed research from multiple disciplines. We summarise these in Table 1.

Finally, we focus on two key emerging issues: the use of generative AI and the challenges of evaluating automated media.

At the ARC Centre of Excellence for Automated Decision-Making and Society (ADM+S), we are actively working on research projects and initiatives to better understand the effect of automation on news and media. The report also highlights the diverse range of multidisciplinary ADM+S research projects that address many of these emerging challenges. These projects demonstrate our ongoing commitment to produce outcomes that support ethical, responsible and inclusive automated decision-making.

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01. SEARCH ENGINES IN NEWS AND MEDIA

What are search engines?

Search engines shape how we navigate the internet, influencing how we collectively remember events and communicate.

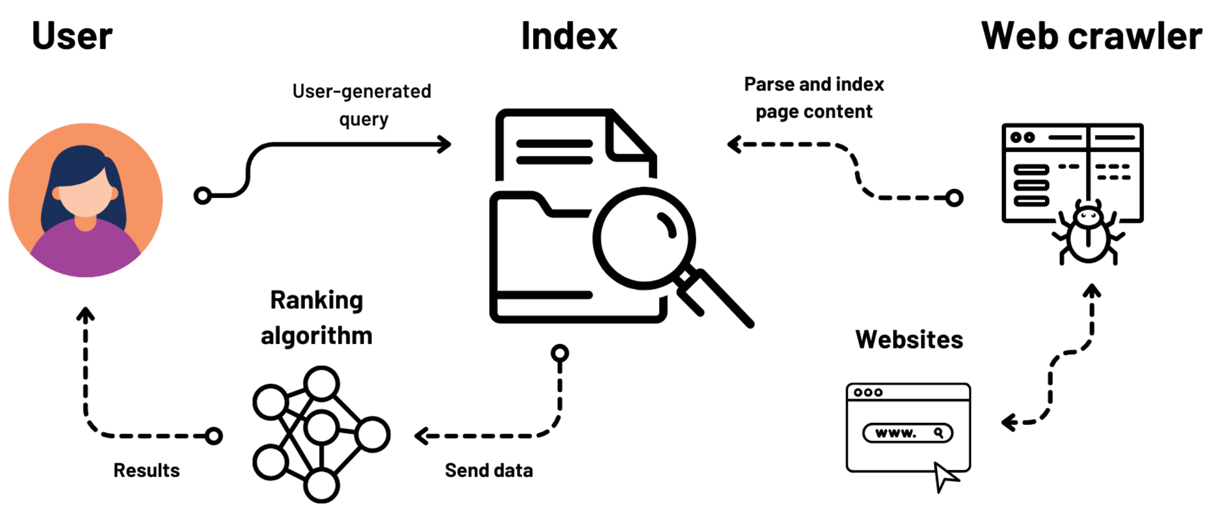
At the most basic level, **search engines index content** and allow people to search for specific keywords. The most well-known examples of search engines are those that search the web, but we also frequently encounter search engines when we use email or search for items on an online store. When people use a web search engine, they are searching a particular index of the web rather than searching the web directly. This index is built through automated programs called web spiders, crawlers or bots. These automated programs record all the words that appear on a website, search for and follow any hyperlinks included on the site, and repeat the process of recording words to create a large and constantly growing index that is queried every time a person enters search terms into the search engine.

A **crucial function** of search engines is **ranking**, where algorithms determine the position at which a webpage appears in the search engine's results pages. Parameters such as relevance, authority and trustworthiness, content quality, user engagement metrics and technical optimisation dynamically inform which results are featured first. PageRank, an important factor in Google's early search algorithms, was developed based on the idea that a webpage's importance can be determined by the number and quality of links that direct to it.

Where do we encounter search engines?

As of May 2023, 93.12% of all search queries conducted across all search engine providers take place through Google (Oberlo, 2023). Alphabet—Google's parent company—invests significant resources into the smartphone and tablet industry and pays

Figure 1. How search engines work

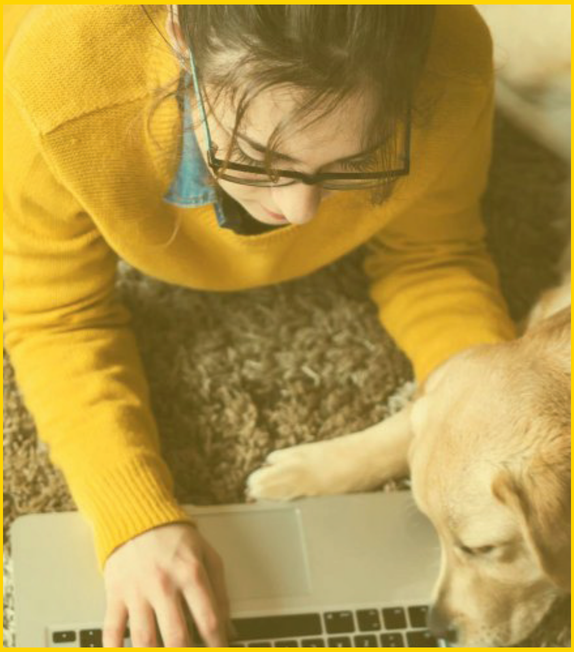


other companies such as Apple to maintain Google Search as the default search engine on their devices (Duffy, 2020). Google has a monopoly on the web search engine market (Sterling, 2016), with exceptions such as Baidu in China and Yandex in Russia. Meta-search engines such as DuckDuckGo and Dogpile also rely heavily on Google's search results (Graham, 2023).

Voice search has grown in popularity, first in smartphones and then in smart speaker devices, such as Amazon's Alexa, Apple's Siri, Google Assistant and Microsoft's Cortana. Google Assistant is available on more than one billion devices, but Siri leads the smartphone voice assistant market share with 45.1% ownership (Gajić, n.d.). Search results are delivered audibly or displayed on screen, depending on the device being used. Voice search **underperforms** across **tonal languages** (e.g., Mandarin Chinese, Thai or Vietnamese), **morphologically complex languages** (e.g., Finnish, Hungarian or Arabic) and **low-resourced languages** with limited available linguistic resources and training data, which often receive less attention in terms of research and development (Khurana et al., 2023).

Emerging challenges

The market dynamics of web search engines continue to present questions about the scope of competition. In the early phase of the commercial web, a significant number of search engines appeared, including Excite, Yahoo!, Lycos, Alta Vista and Ask Jeeves. Google was introduced in 1998 and rapidly grew its market share; by 2010, outside Russia and China, only Google and Microsoft were offering independent search at scale, with search engines such as DuckDuckGo and Yahoo! syndicating results from Google or Microsoft's Bing. Amazon's A9 search portal was introduced in 2004 and withdrawn in 2008. This strong market share can be explained by three factors. First, the barriers to entry for new web search engines are high. Web search engines are dynamic systems operating at a global level, involving massively distributed computationally infrastructure and substantial human resources. Second, search engines have been integrated into the design of web browsers (where we are accustomed to searching in the address bar) and into operating systems, especially for smartphones. The commercial arrangements with device manufacturers and platforms that underpin the integration and pre-installation of Google Search are now at



How you search matters.

Launched in late July 2021, the Australian Search Experience is an ADM+S project that helps us understand how search engines operate. The project takes a citizen science approach to investigate the search results and rankings produced by leading search engines for a wide range of search topics; it relies on data donations from the general public made through a browser plug-in available for the desktop versions of leading web browsers, including Google Chrome, Mozilla Firefox and Microsoft Edge.

This research aims to assess the extent to which search results are personalised by leading search engines and their algorithms based on the profiles established by these search engines for their different users. It compiles and analyses the search recommendations encountered by a wide range of genuine users across prominent digital media platforms for a variety of generic and specific topics over a period of time.

In collaboration with AlgorithmWatch (an ADM+S partner organisation) and building on the browser plug-in developed for a study in 2017, the Australian Search Experience addresses these limitations and translates the data donation approach to the Australian context. Over 12 months, 350 million search results were collected from more than 1,000 citizen science participants. In July 2022, the Australian Search Experience moved from the data donation phase to the data analysis phase.

The preliminary findings for Google News search results show limited evidence of personalisation, with news and information sources recommended for particular searches mainly influenced by the search topic. The research team is now exploring the diversity of news outlets in the dataset, aiming to identify how much local and national news is featured in the Google News results. The project will also reveal whether particular news outlets appear more often than others. By examining search results across Google News, Google Search, Google Videos and YouTube to understand how different Google services and platforms operationalise 'authoritativeness' across socio-cultural issues and over time, the project focuses on the top-ranked sources for each service or platform and reflects on issues of media diversity in relation to these results.

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issue in an antitrust case in the United States. Third, due to the central place of search engines in the web media ecosystem, search dominance is closely tied to market power in search advertising in particular and web advertising in general. We discuss AdTech further below.

Concerns over biases in Google's autocomplete function are well documented in the academic literature on court rulings regarding Google's legal liability for defamatory suggestions and the societal effects of the stereotypes that these suggestions perpetuate (Graham, 2023). An AlgorithmWatch report found that search engines returned almost one slanderous suggestion for each query and a false statement for every other query; the report also found that Yahoo! produced more inappropriate suggestions compared with Google, Yandex and Bing by a wide margin (Kayser-Bril, 2020). Researchers have also noted the cultural effects of harmful stereotypes perpetuated by autocomplete suggestions (Baker & Potts, 2013; Noble, 2018).

The subject of what search engines should present is actively debated. One view is that search engines should be built and maintained to reflect an objective, neutral and universal outlook on the world. An alternative position calls on search engines to reflect relativistic truths, which requires results to be personalised and aligned to user interests or a specific context. A third position calls for search engines to proactively mitigate the harms associated with historical biases, such as those associated with race and gender (Noble, 2018). Relevance—the value with which search engines are built and maintained—constitutes 'multiple competing sets of interest, each intersecting with economics, power relations, and politics' (Graham, 2023, p. 136). Emerging questions around search engine personalisation through pattern recognition, which relies on large-scale behaviour tracking to identify relationships between different kinds of behaviours, are being investigated alongside questions about profile-based personalisation.

Longitudinal research that tracks changes in search results presents various methodological challenges due to the opaque nature of proprietary technologies, driven by market competitiveness, privacy concerns, legal constraints and the complex nature of search engines as socially embedded automated systems. Search results generated by one machine in one location may not be the same as another machine under different circumstances, even soon after the initial query. This is because search results are based on hundreds of contextually dependent signals that are specific to each search (Hargittai, 2007). Search engine recommendations change over time as new information is received and indexed, but the processes by which such changes are made remain unknown, as well as the mechanisms for vetting the information provided and the speed of such changes. In the context of fast-moving events such as natural disasters and political crises, it could lead—at least temporarily—to recommendations that promote misinformation and disinformation.

Recent studies have sought to overcome some of these problems by implementing innovative new data-gathering methods. A German exploratory study used a small number of artificial Google accounts that were given unique personas or specific interests and found very little evidence of personalisation in Google News (Haim et al., 2018). A similar study from the United States by Nechushtai and Lewis (2019) used Amazon's Mechanical Turk system to hire 168 human clickworkers who regularly searched for political topics and also found little variance in the Google News search results. Both studies noted that Google News generally presents news only from a very limited selection of sources: 'the news experience that Google News constructed for users … is highly concentrated, empowering a handful of prominent outlets and marginalising others' (Nechushtai & Lewis, 2019, p. 302).

Can I get a fact check?

Intelligent assistants such as Google Assistant, Amazon Alexa and Apple's Siri allow users to perform simple operations via voice commands (e.g., 'What's the weather today?').

A major challenge in voice search is that search engines are selective in the information they return (Amigó et al., 2022). As a result, it is harder for voice assistants to present complex information and users' search needs are only partially satisfied—that is, the search result may only present one side of the story (Kiesel et al., 2021; Spina et al., 2021).

ADM+S collaborated with RMIT ABC Fact Check to improve presentation strategies for fact checks through voice-enabled assistants (Hettiachchi et al., 2023; Spina et al., 2023). The results revealed that, when designing fact-checked content for voice-enabled interfaces, it is vital to ensure the information presented is clear, concise and personalised, as this will foster perceived trust towards the organisation and the author (Hettiachchi et al., 2023).

The recent uptake of conversational systems based on generative AI, such as OpenAI's ChatGPT, can provide opportunities to improve the 'naturalness' of voice search interactions. However, it also makes some of the challenges identified in conversational search even more important: responses generated by systems using large language models will still need to be combined with other technologies (e.g., information retrieval techniques) to help users better understand the provenance, authority and trustworthiness of the information consumed via voice-enabled systems.

02. RECOMMENDER SYSTEMS IN NEWS AND MEDIA

What are recommender systems?

Recommender systems use data and machine learning to suggest products, services and content to people based on their prior activities and those of other users. These systems are also influenced by business models and content moderation rules. One key use of this technology across the news and media sector is to personalise the content that websites and platforms present to audiences.

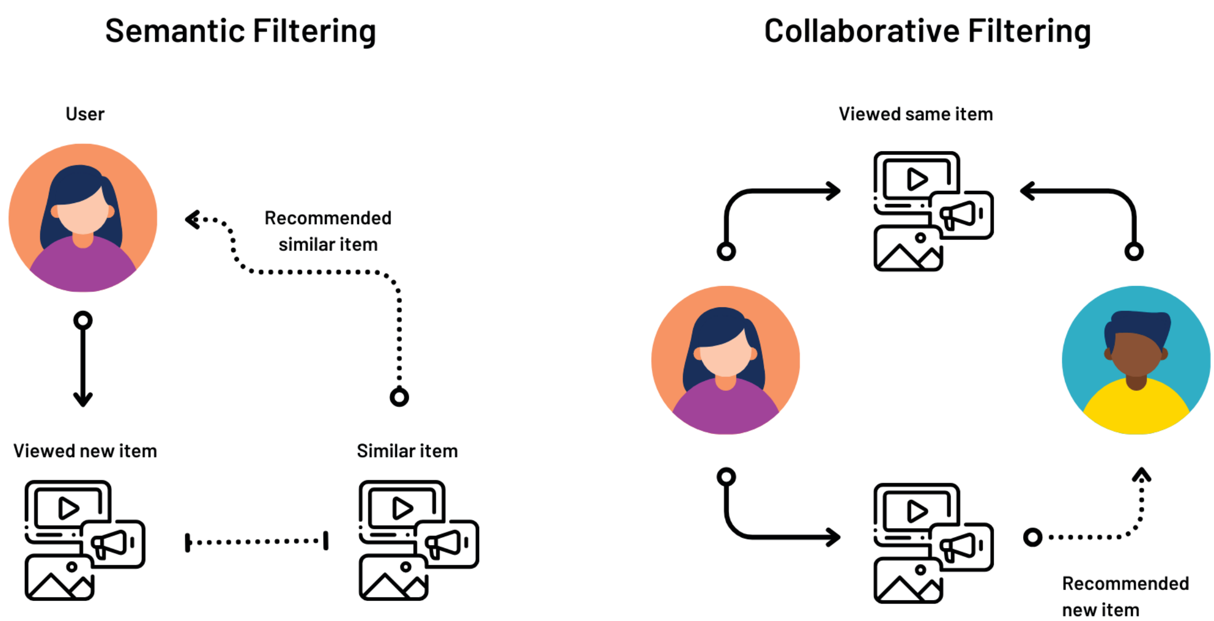
In terms of the technical operation of recommender systems, there are two dominant methods currently in use. The first is **semantic filtering**, which draws on the previous behaviour of the user, such as search activity, to recommend new items.

The second is **collaborative filtering**, where items are recommended based on the tastes of similar users.

Although a range of other considerations are becoming important, the main focus of recommender system improvement is **accuracy**—that is, the extent to which the recommender system is able to predict users' behaviour in engaging with the recommended content and the quality and relevance of the content (Gunawardana & Shani, 2009).

As recommender systems become increasingly central to the news and media environment, designers are considering alternative approaches to optimisation. For instance, **novelty** is an important attribute that captures whether a particular content item has already been recommended to

Figure 2. Semantic vs collaborative filtering



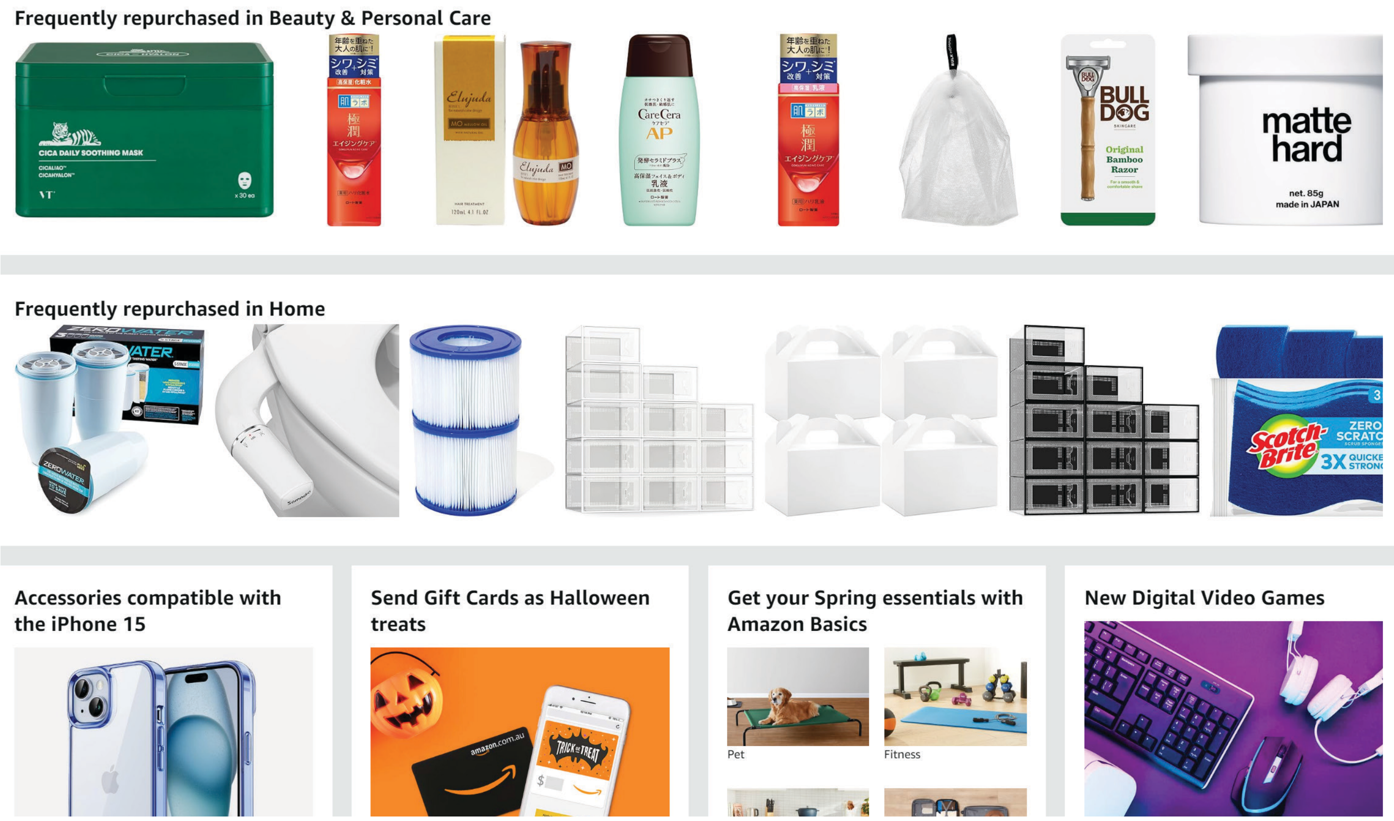


Figure 3. Product recommendations on Amazon homepage

the user (Vargas & Castells, 2011). This is vital for news because users rarely read any news item twice. Currency is an important aspect of novelty for news, where the system generally needs to recommend the latest news rather than something from the archives. **Serendipity** is also a useful attribute, which includes aspects of relevance, novelty and surprise (Kotkov et al., 2016). This allows systems to present an item that users might not have expected to find but is still engaging, new and relevant. There are also active discussions about how to best understand **diversity**. Technically, diversity is the degree of 'dissimilarity' among recommended items (Raza & Chen, 2020), but some are trying to broaden this definition to account for media policy goals. Ensuring that recommender systems balance the interests of users, the metrics selected by operators and broader democratic commitments to surfacing content from a range of voices remains an ongoing challenge (Helberger, 2019).

Where do we encounter recommender systems?

Recommender systems are found across the news and media environment, playing a major role in familiar platforms and services, such as Netflix, Amazon, Spotify, TikTok, Instagram, smart TVs and news websites.

For many social media platforms, recommendation is at the heart of their operations. For instance, when someone opens the TikTok app, they are essentially opening a recommender system, better known as the For You Page (or FYP). In a similar fashion, much of Facebook's activity centres around the News Feed, another recommender system. These recommender systems allow Meta to parse the thousands of posts one can possibly see when browsing Facebook to view interesting or engaging content (Lada et al., 2021).

Recommendation is also critical for entertainment platforms. Perhaps the most infamous recommendation system in this sector is found on Netflix, which presents content to viewers based on 'viewing

Socially responsible recommendation on Amazon Bookstore and Twitch

ADM+S PhD candidate Louisa Bartolo is examining the question of what socially responsible algorithmic recommendations on cultural and entertainment digital platforms might entail.

Bartolo examined data to empirically investigate recommendations on two different digital platforms: Amazon Bookstore and the streaming platform Twitch.

For Amazon, she identifies which history-related books emerge as 'winners' due to algorithmic recommendations. For Twitch, she explores how the recommendations on the platform home page show content by streamers self-identifying as transgender, who face structural disadvantages both on and off the platform.

She offers pragmatic suggestions to platforms about working towards more socially responsible recommendations. These suggestions will be useful to the variety of regulatory bodies increasingly being tasked with overseeing these systems.

history, demographic and location data' (Lobato, 2018, p. 251). Netflix is also now offering a top-10 list to subscribers, showing popular shows in the user's location.

Spotify, another popular entertainment platform, uses recommendation systems in various ways. Some of the most prominent examples include its radio feature, which allows users to listen to similar music, and Discover Weekly, which offers a curated playlist of new songs. Recommendation systems are evident across the entire Spotify platform, from loading the application and being presented to various albums and songs to the numerous playlists offered based on specific genres or moods.

Recommendation systems are also becoming part of our living rooms. Although we tend to associate algorithms with major technology platforms, smart TVs are also supported by recommendation systems. When we turn on a new television, we are presented with suggestions for shows and apps to watch content on (also see 'Breakout box: Investigating video recommender systems').

In terms of news, recommendation systems operate in a variety of contexts. A longstanding example involves listing the most popular or most viewed news articles on a news website. Recently, user-driven recommendation has become common; for instance, News Corp Australia subscribers can choose to have news 'about specific subtopics such as [the] Collingwood Football Club' automatically recommended to them (Mediaweek, 2021). At the more extreme end, Scandinavian publisher Schibsted has introduced an automated content management system across its publications, which allows automatic systems to perform some of the curational work previously conducted by editors (Shevchenko, 2021).

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Investigating video recommender systems

ADM+S Associate Investigator A/Prof. Ramon Lobato (RMIT) is investigating automated content curation in video services and devices with his collaborator Dr Alexa Scarlata.

They have found that the use of automation is widespread and growing, encompassing not only algorithmic content recommendations but also content delivery, optimisation, quality of service and payments.

However, many key decisions, such as integrating apps within smart TVs, continue to be made by humans due to business negotiations, cultural value or popularity.

A key focus for Lobato and Scarlata is the use of smart TVs in Australia. Through device testing, they found that smart TV operating systems are evolving in ways that warrant policy attention. Business practices such as self-preferencing, partner preferencing, search and recommendation bias, poor integration of third-party apps and prioritisation of advertiser content create a challenging discovery environment for local content and services. A nationally representative survey conducted in December 2022 revealed that more than half of Australian users cannot tell the difference between advertisements and recommendations in smart TV interfaces.

Figure 4. Smart TV testing lab at RMIT

Emerging challenges

The development and deployment of recommender systems can be organisationally siloed, with the design of these tools often placed in the hands of technical teams and marketing (Mitova et al., 2023) or substantially outsourced to cloud services such as Amazon. Ensuring that a wide variety of internal and external stakeholders can provide input into the design and rollout of these systems remains an ongoing challenge.

Recommendation also allows for greater personalisation, which raises additional issues. Questions of equality, fairness and diversity create difficult challenges for platforms and regulators (Deldjoo et al., 2023). In the music context, for instance, some genres are characterised by a very strong gender bias, and it is difficult for female artists to obtain similar levels of attention as their male counterparts. In attempting to make the music industry more equitable, should platforms amplify music by female artists to music listeners who have a pattern of only listening to male artists? Music platforms primarily use human-curated playlists to address issues of inequality among their creators, with Spotify creating playlists to amplify First Nations, female-identifying and LGBTQIA+ artists.

Although concerns about network-based 'filter bubbles' have been debunked (see Bruns, 2019), there are still ongoing challenges associated with balancing the need to give people the content they already know they want and exposing them to a variety of content that they might otherwise not encounter. Such tensions raise a series of wider social questions about these systems:

+ Should Spotify recommend at least some Australian music to Australian accounts regardless of user interest?
+ Should Australian smart TVs prioritise free-to-air channels, even if the user predominantly uses streaming services?
+ Should news websites present breaking news and political updates, even if the user is only interested in sports and business?

These questions around diversity and personalisation are being actively discussed by industry, researchers, policymakers and regulators.

Countries are already anticipating possible risks associated with recommender systems and introducing legislation in response. The European Union enacted the Digital Services Act 2022, which regulates intermediary service providers and stipulates that recommender systems must comply with requirements relating to transparency, risk assessment, risk mitigation, and data access and scrutiny (sections 27, 34, 35, 38, 40 and 44). In April 2023, the European Commission designated 19 platforms as very large online platforms, and recommender systems will now face the strictest level of regulation. China has also introduced interventionist reforms, enacting the Internet Information Service Algorithmic Recommendation Management Provisions in March 2022. A particular emphasis is being placed on the inspection of 'large-scale websites, platforms, and products that have larger public opinion properties or capacity for social mobilisation' (Webster, 2022). To date, Australia is not planning to directly regulate recommender systems.

Designing considerate and accurate recommender systems

ADM+S researchers are exploring how recommender systems can not only balance the needs of users and platforms but also how they can consider the interests of third parties. For example, Airbnb properties can influence nearby residents and hotels, and Google Maps can cause traffic bottlenecks due to recommended routes.

A project is currently underway to design considerate and accurate recommender systems. ADM+S researchers are working with the e-scooter company Lime on an ongoing trial in Melbourne. They are investigating how recommendations associated with e-scooters have influenced cyclists, pedestrians, councils and planning, public transport and local businesses (Kegalle et al., 2023).

This involves developing new hybrid approaches by drawing on quantitative data science and qualitative studies. Field experiments are planned to observe live e-scooter trips from participants and in-context surveys of riders and other stakeholders who are affected by these trips.

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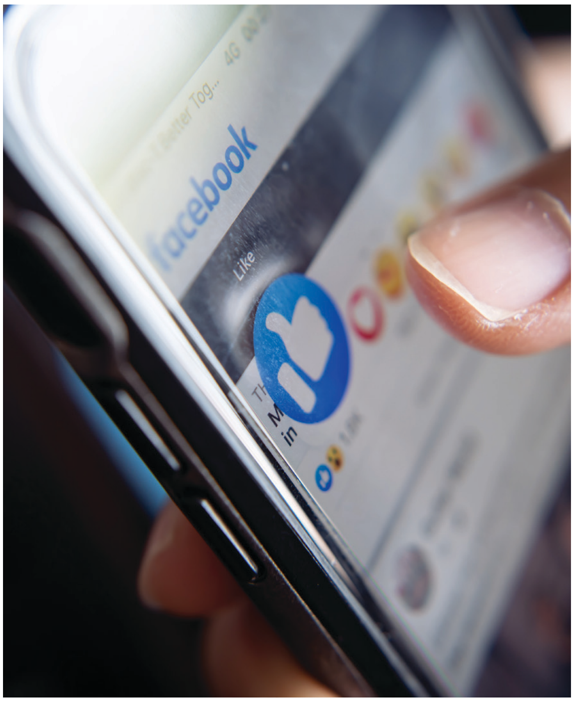
03. AUTOMATED CONTENT MODERATION AND CURATION

What is automated content moderation?

The work of organising and sanitising user-generated content is both controversial and routine for the platform-dominated digital media environment. Moderation refers to the work of removing or limiting the visibility of content that contravenes the rules of a platform (Gillespie, 2018).

Digital platforms have developed extensive and complex sets of rules about acceptable content and conduct, but many of them are difficult to enforce automatically. Historically, human moderators (often based in low-income countries) have played an invaluable but largely invisible role in reviewing user-generated content posted to major platforms (Roberts, 2019).



Leading digital platforms have automated a great deal of moderation work. Regardless, the content moderation value chain undoubtedly still involves human workers undertaking 'ghost work' (Gray & Suri, 2019). This includes everything from data labelling to fact-checking (Montaña-Niño et al., 2023). Each phase in the development of content moderation policies and tools has been primarily driven by waves of public controversy over content that was left up for too long or wrongfully removed. Over the last two decades, these 'shocks' (Ananny & Gillespie, 2016)—and the resulting mounting regulatory pressures—have pushed platforms to refine their policies and develop more sophisticated processes.

Where do we encounter content moderation?

Content moderation is complex: individual platforms develop bespoke processes, each of which automates some part of the central challenge of identifying, removing and reviewing content. Automated moderation tools used in various combinations by platforms include:

- **Filtering:** content moderation systems use relatively blunt filtering approaches that prevent individuals from using certain keywords or phrases in their posts and searches.
- **Identifying inauthentic behaviour:** major platforms analyse the source and content of incoming posts to prevent spammers from sending bulk commercial messages and coordinate

attempts to manipulate the platform and its users.

- **Hash matching or proactive filtering:** for child sexual abuse material and extremist propaganda, platforms and governments around the world have established shared databases of known unlawful content. When new material is uploaded to a major platform, it is almost always screened for a potential match to previously detected content. Over time, hash matching tools have been improved to allow platforms to automatically prevent people from distributing not just identical content but also edited versions of existing content that have been manipulated or distorted to bypass the filters.
- **Copyright takedowns:** copyright law around the world requires digital platforms to implement a 'notice and takedown' system. The system allows copyright owners to request that platforms remove content that infringes their rights. To address the vast scope of alleged copyright infringement online, copyright enforcement companies have developed automated search tools that generate copyright infringement notices in bulk. For instance, YouTube was forced to develop automated systems to respond to the millions of incoming requests it received each day (Urban et al., 2017).
- **Copyright matching:** in seeking partnerships with media companies, digital platforms have developed tools that automatically detect potential copyright infringement in user-uploaded content. YouTube's Content ID is the most well-known copyright matching system, but other platforms have their own systems to screen content on their networks, and smaller platforms use third-party services such as Audible Magic. These tools are similar to hash matching tools: film and television studios provide reference copies for every item in their catalogues, which are processed and used by platforms to compare audiovisual content uploaded by users.
- **Queue prioritisation:** platforms receive a very large number of complaints from users, and they use automated systems to triage incoming complaints according to potential severity and reach.
- **Automated detection:** platforms shifted to embrace automated detection tools during the COVID-19 pandemic. Prior to the pandemic, major digital platforms trained classifiers on the outputs of their human moderators, but these systems were primarily used to prioritise content for review, not to replace flagging or enforcement. When COVID-19 infections threatened to shut down call centres, the largest platforms started using machine learning classifiers to detect potential policy breaches. Initially, these classifiers performed poorly; for example, though classifiers could easily detect spam, they struggled to correctly interpret hate speech. Platforms invested significantly in their improvement, and content policy classifiers are now in heavy mainstream use. As performance improves, classifiers can take direct action before users have observed the content in question, including prioritising material for review, automatically enqueuing content that has not yet been flagged by human users and automatically removing content before any complaints are made.

Production and distribution of online sexual health content

ADM+S PhD candidate Joanna Williams' thesis explores why sexual health organisations do not produce social media content that aligns with the digital and sexual cultures of young Australians.

Williams interviewed social media workers from 12 sexual health organisations concerning their experiences of producing and distributing content on Instagram and Facebook. She analyses how Meta's content moderation policies represent sexual health content.

Her work demonstrates that Meta's arbitrary and ad hoc automated content moderation practices significantly constrain the content that sexual health organisations produce. The ever-present threat of reduced visibility and reach causes workers to dedicate significant time to navigating Meta's opaque content moderation systems. This reduces the time they can spend on understanding the digital and sexual cultures of young people and producing content.

Her research provides concrete examples that can be used to advocate for Meta to reduce the erroneous removal of sexual health promotion content. She is also developing practical strategies that build the capacity of the sexual health sector to navigate automated content moderation.

- **Reach reduction:** platforms have started to embed content moderation decisions in their ranking and recommendation systems to reduce the visibility or availability (Zeng & Kaye, 2022) of 'borderline' content—that is, content that is not clearly prohibited but is nonetheless controversial (Gillespie, 2022).
- **Prompts, nudges and friction points:** many platforms now employ various forms of behavioural nudges and technical barriers that are designed to reinforce the platform's rules. Platforms use a range of nudging interventions that inform users of issues associated with search terms, direct users to helplines and resources or provide warnings or barriers to entry. These interventions take the form of labels, notices, notifications and warnings, and they are primarily used to nudge the user to obtain further information or reconsider viewing or posting the content. They are often found on content that borders between documenting harmful behaviour and being informative in nature. For instance, TikTok provides labels with links to local resources on content that discusses eating disorders and mental health concerns.

Emerging challenges

Controversies over content moderation have escalated in recent years. These issues are contested, involve difficult trade-offs and invoke major cultural differences and geopolitical conflicts. Governments around the world are currently introducing regulatory regimes to influence how technology companies moderate. Most prominently, the Digital Services Act 2022 (EU) creates new obligations on platforms and new rights for people subject to automated content moderation decisions. Other regulations address specific types of content moderation problems, including electoral and health disinformation, political bias, gender-based violence, deepfakes and image-based sexual abuse, and coordinated interference from state-sponsored actors and other groups.

These issues will continue to be relevant due to the rapid pace of development in machine learning and global interest in these topics. The bulk of moderation work is moving from large numbers of low-paid human moderators towards automated classification and review. New foundation models, including large language models and multimodal systems, are likely to present major improvements in the ability of automated systems to understand context, which is one of the most controversial and difficult challenges in moderation. Progress is also visible in the extension of classification capabilities to different languages, regional dialects and different cultural contexts, though progress is still relatively slow here. Concerns around these emerging curation practices are only beginning to emerge. As the role of automation in shaping discourse and culture becomes more visible, there is likely to be more global interest in influencing how decisions about curation are made, who makes them and when they are open for public contestation.

Tackling everyday online misogyny

ADM+S PhD candidate Lucinda Nelson's research addresses the challenges of responding to the subtle, 'everyday' manifestations of online misogyny on social media platforms.

In her PhD, Lucinda analyses the qualitative and quantitative data sourced from discourses about the Depp v. Heard trial on Twitter, YouTube and Reddit. She examines how misogyny can be hidden in 'civil' language, which is difficult to classify accurately using current automated tools, and the role of platform policies and technical affordances in the spread of everyday online misogyny. She also investigates the role of monetisation in the creation and amplification of everyday misogynistic content.

Through this analysis, Lucinda aims to identify distinguishing features of everyday online misogyny that could be used in automated detection and content moderation systems. She also aims to provide practical recommendations about technical and policy changes that could help reduce the prevalence of misogyny on social media platforms.

04. ADTECH IN NEWS AND MEDIA

What is AdTech?

AdTech systems automate the buying, selling, placement and measurement of online advertising.

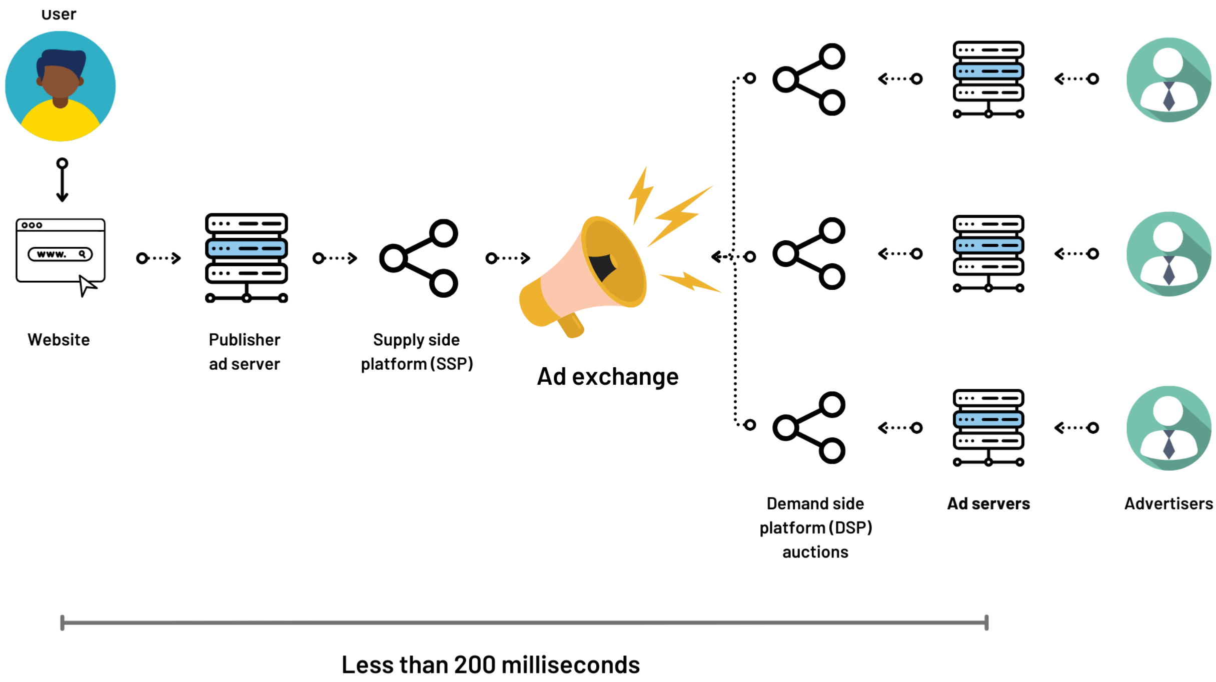
Advertisers do not want to pay for everyone to see their advertisement—only the people they think are likely to be persuaded by it. These people are referred to as 'targets', and serving advertisements to less relevant audiences is known as 'waste' (Turow, 2011). Choosing the right media channels, paying the right price and measuring the result is a great deal of effort, and AdTech allows the sector to automate much of this work.

The most common form of AdTech is programmatic advertising. Programmatic advertising uses automation to auction website advertising space to advertisers who want to place an advertisement. Demand-side platforms conduct auctions between multiple advertisers seeking to place an advertisement through a sell-side platform. The sell-side platform processes the winning bidder, who can then show their advertisement to the audience. The entire process, illustrated in Figure 2, occurs in fractions of a second. Auctions are increasingly being incorporated into advertisement exchanges, which form part of the sell-side platform.

Where do we encounter AdTech?

AdTech underpins the commercial internet. However, in contrast to the other technologies outlined in this report, most media consumers do not directly interact with AdTech—only the end result of the bidding process is observable. After the frantic automated bidding of an online

Figure 5. A simplified programmatic process. Source: Thomas and Kininmonth (2022) .



advertising auction, we might scroll past a vaguely relevant advertisement as we browse social media, read the news or scroll through search results. However, this description underlines just how important AdTech is to our modern online experience. Although its operations may be opaque or invisible to us, the results of AdTech are everywhere, and AdTech itself is central to the online media economy, including major digital platforms, small businesses, not-for-profits and the public sector.

Emerging challenges

Ad blacklisting

Online advertising systems can place advertisements alongside all types of content, and because of this, companies are increasingly concerned about where their advertisements end up. Brands obviously do not want to be placed against extremist, offensive or discriminatory content. However, each industry may also have specific requirements. For example, a car manufacturer may not want its advertisements placed next to news of a recent car crash or a grassroots campaign against the dominance of cars in urban environments.

In response to these concerns, various online intermediaries have offered to help advertisers manage their 'brand safety'. Although these companies claim to use advanced AI, the most common tactics involve automating blacklists of words to ensure that, even when an advertiser wins an auction, brand safety intermediaries will simply stop advertisements from being uploaded to a website. The problem is that these lists are relatively unsophisticated and can immediately cause minor problems for media organisations and content creators relying on advertising revenue. For example, the term 'pandemic' is often on blacklists, which, during the COVID-19 pandemic—the first global pandemic in over 100 years—caused a flash automated advertising collapse in the news sector (Sweney, 2020). 'Brand safety' requirements to avoid association with sexual content can also discriminate against LGBTQIA+ content creators on social media entertainment platforms such as YouTube.

The rise of first-party data

The online advertising system was largely built around the 'cookie', a technology in common use since the mid-1990s that collects user behaviour information on a website: the links they click on, the things they type and even how long they spend there (WebWise, 2012). This somewhat obscure standard has been the backbone of the online advertising industry for years and has allowed behavioural advertising to flourish. Put simply, when a user searches for shoes, it is the reason why shoes continue to be advertised to them. However, growing concerns about privacy have caused major web browsers to stop supporting cookies. Apple has already blocked third-party cookies in its Safari browser, and Google is planning to deprecate cookies in 2024.

In response, major international news organisations are developing in-house advertising platforms. The New York Times, The Guardian and other outlets are investing in bespoke advertising platforms (Meese, 2023). These platforms collect first-party data, which are voluntarily captured from readers and subscribers, usually through a log-in mechanism. What is interesting about this development is that news organisations now have some capacity to step away from the wider programmatic environment. Automation is still part of these bespoke products, but the owners of in-house platforms have much more control.

From targeting to 'vibes'

Online advertising relies on vast pools of personal data. Although advertising has always relied on a tacit understanding between audiences and advertisers to access news and media, a significant amount of personal data are collected, which allows companies to better align their advertisements with specific audiences. People have now become familiar with the concept of advertisement targeting, where advertisers draw on behavioural data to identify relevant audiences.

ADM+S researchers have found that advertising models now go well beyond simple targeting (Carah et al., 2023). Advertisers are building models that iteratively update their audience based on which consumers engage with their content and who makes purchases. Instead of relying on established demographic criteria, these efforts are predictive and known as pattern mining. Machine learning is a common tool used for these activities.

Machine vision is also becoming prominent in predicting associations between advertisements and audience interests, including through clustering and analysing user-created content.

Both marketers and social media platforms engage in visual pattern mining to better identify advertising opportunities. For example, Coca-Cola used an image-recognition algorithm to identify people on social media who were drinking competitors' products and subsequently targeted them with advertisements (Dua, 2017). Meta has also held a longstanding patent for a similar technology (Mitchell et al., 2015). Generative AI technologies are likely to be incorporated into these iterative processes in the future.

The Australian Ad Observatory

The use of custom targeted advertising poses many potential social harms, such as the reintroduction of historical forms of discrimination (e.g., targeting job or housing advertisements by race or gender), the propagation of racist or gender stereotyping and the spread of false and harmful information. Because these advertisements are personalised and ephemeral, they are also difficult to observe or 'dark'. Dark advertisements continue the trend away from mass advertising, which is available to large audiences and subject to public scrutiny.

At the Australian Ad Observatory, building on work by AlgorithmWatch, ProPublica and New York University, the ADM+S has developed novel citizen science approaches through a national data donation and analytics platform to address the challenges posed by dark advertisements. The Australian Ad Observatory has already collected over 700,000 advertisements from 2,000 volunteers but is still looking for more people to sign up. A large pool of diverse participants of different ages and backgrounds and from different parts of Australia will help us better understand how particular groups in society are being targeted with particular types of advertisements.

The ABC recently partnered with the Australian Ad Observatory to find gambling advertisements that were illegally targeting Australians on Facebook. Through the Australian Ad Observatory, the Consumer Policy Research Centre has uncovered online advertisements that use vague and misleading environmental and sustainability claims in their messaging to consumers. The Australian Ad Observatory will also work with the Foundation for Alcohol Research & Education to further analyse the content of alcohol advertisements on social media.

admscentre.org.au/adobservatory

LOOKING AHEAD

The rise of generative AI

Generative AI encompasses systems with the ability to produce original and creative content across various mediums, such as text, images and audio. Unlike discriminative AI systems (conventional AI), which primarily analyse existing data to make classifications or recommendations, generative AI systems generate entirely new content autonomously (Bell et al., 2023).

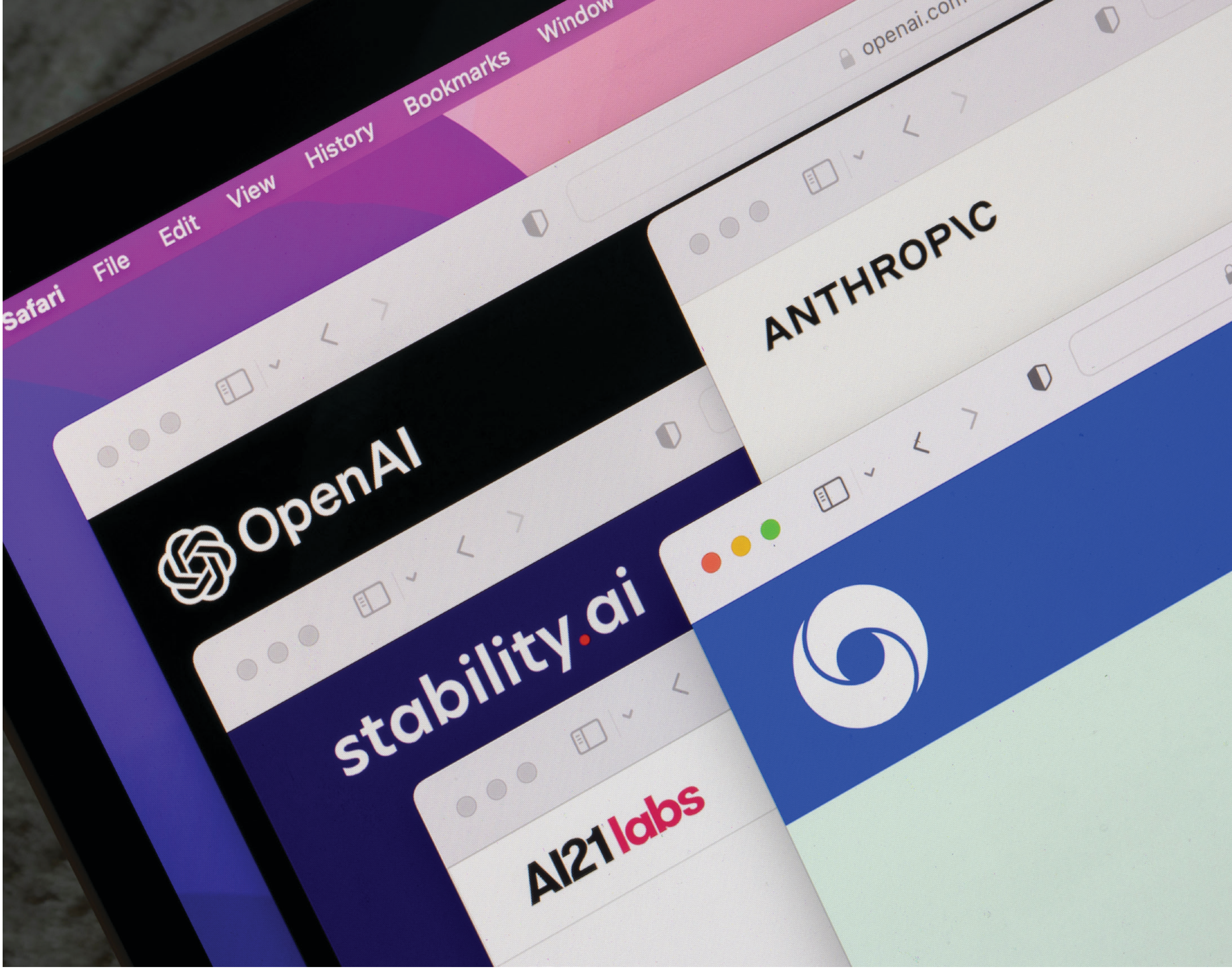
Constructing a generative AI system involves gathering extensive amounts of pre-existing data and training the machine learning system to recognise and replicate the underlying patterns within that data. The generative AI system then leverages the acquired knowledge from these foundation models to produce a range of new outputs.

Most people do not engage directly with foundation models. Instead, they encounter new types of services, applications and businesses that use them in the form of chatbots, enhanced applications (e.g., search) and subscription services such as ChatGPT.

The news and media sector has mainly focused on the threat that generative AI poses to employment and established working arrangements; these are issues concerning the wider creative economy. Rod Sims, the former chairperson of the Australian Competition and Consumer Commission, has suggested that generative AI bots (including ChatGPT) should be designated under the News Media Bargaining Code and that AI companies such as OpenAI should pay to access online content (Buckingham-Jones, 2023). Generative AI was a central issue in the recently concluded screenwriters' strike in the United States. The Writers Guild of America did not oppose the use of tools such as ChatGTP, but it secured agreements that such tools could not be recognised as writers and that their use:

+ could not be required by a studio
+ could not reduce a writer's credit or payment if, for example, they were used to generate draft material
+ would be permissible for a writer with the studio's agreement and without any reduction in a writer's credit or payment.

The screenwriters' settlement with the studios foreshadows the extensive use of generative AI in the screen industries, but only insofar as writers share the benefits of the technology and have some control over



its use. Some reports (see Cho, 2023) have noted that the revenue-sharing deal with the writers preserves the intellectual property interests of the studios, as works created by an AI are considered not to be protected by US copyright law.

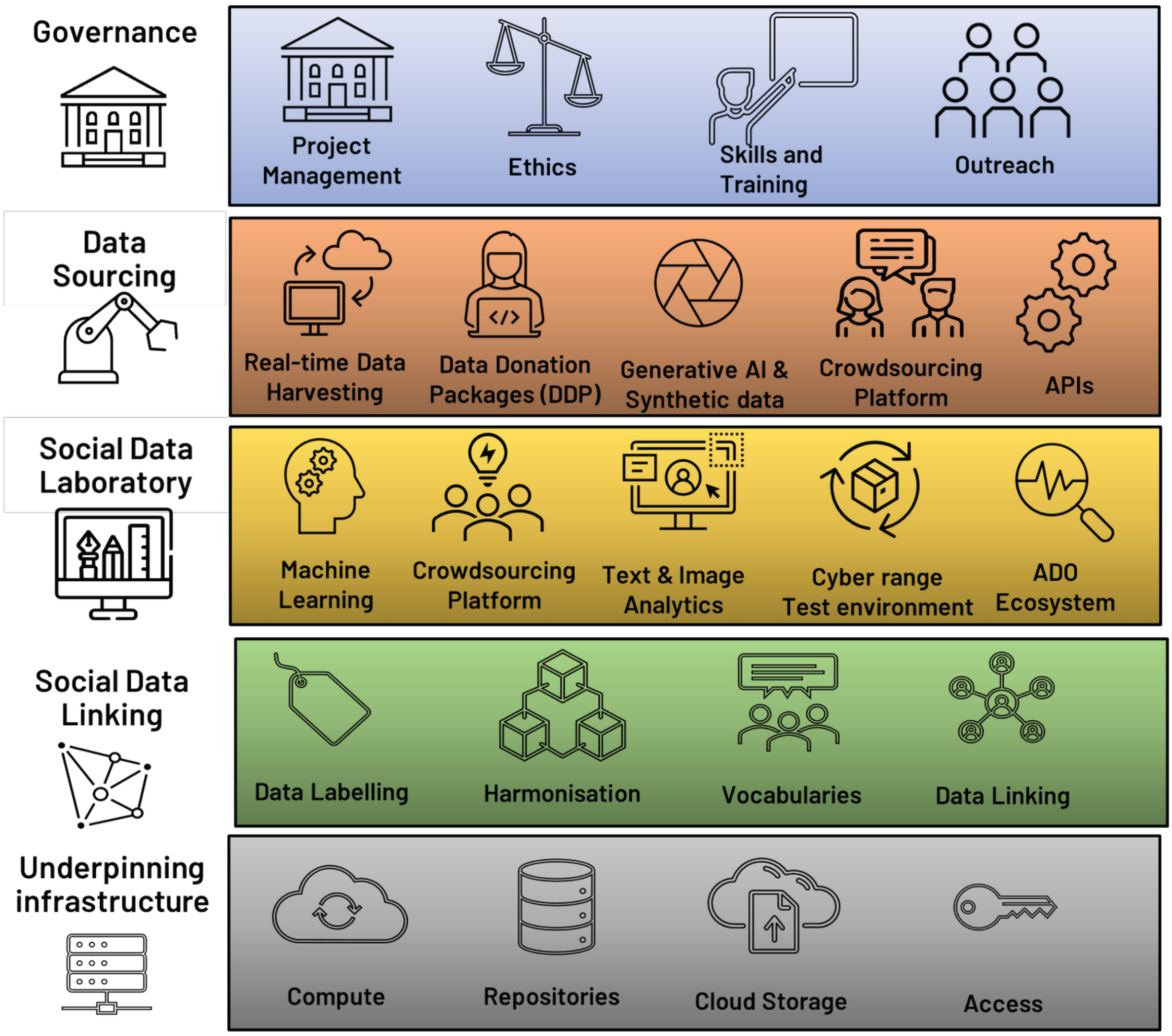
Other challenges are associated with generative AI. These include the need to establish internal organisational policies around the use of generative AI, understanding any cultural biases that may reside within the foundational dataset and learning how audiences engage with these new forms of synthetic content. ADM+S will be releasing a working paper on generative AI soon.

ADM+S researchers are also working on prototyping and evaluating methods to remove harmful generative capability from foundation models. Rapid progress in AI has been made possible by a trend in AI development where one general 'foundational' model is developed (usually using a large dataset from the internet) and then adapted many times to fit diverse applications rather than beginning from scratch each time. Although this method of automated decision-making development is time and cost effective, it comes with the risk of 'baking in' negative tendencies at the foundational layer, such as creating toxic content, misogyny or hate speech, which subsequently spreads to each downstream application. The toxicity scalpel project, led by Dr Aaron Snoswell and colleagues, examines how language models used in automated decision-making systems might be improved by making modifications at the foundation model stage rather than at the application level, where computational interventions, social responsibility and legal liability have historically been the focus.

New tools for evaluating and understanding automated media

Although online platforms play an increasingly critical role in our social and economic lives, we are often unable to observe their operations and social effects. The Australian Social Data Observatory (ASDO) is a proposal developed by researchers at the ADM+S and the Australian Research Council Centre of Excellence for the Digital Child in consultation with researchers, research centres, institutions and industry partners across Australia and the world. ASDO will use innovative methods of collecting and analysing data (e.g., data donations and crowdsourcing) combined with machine learning, natural language processing and other tools to support research on critical national issues, such as the distribution of misinformation and the communication flows in emergencies and humanitarian crises. The ASDO is currently consulting with the Australian Council of Learned Academies, industry and civil society organisations, government agencies, collecting institutions and research organisations.

Figure 7. ASDO technology overview



The mirror world project is one example of the potential benefits of building out research infrastructure. The project was a pilot experiment led by ADM+S Chief Investigator Prof. Chris Leckie, where a test environment for a social media platform was developed. It used OpenAI's GPT-3 service to generate messages on a variety of topics with different sentiments and stances. These messages were then run through a local emulation environment of Twitter (now 'X') to test the effect of mis/disinformation. The ASDO can expand on this work to build a test environment or social 'cyber range' for testing and analysing a range of issues already occurring on digital platforms. These test environments are often used in cyber security to test issues in a contained environment. In a similar way, researchers involved with the ASDO believe we need a social test environment or 'cyber range', a national research infrastructure to test and analyse digital platforms and social media content to reduce harms, anticipate problems and support positive outcomes from digital platforms.

CONCLUSION

This report has provided an overview of the latest research around automated decision-making across news and media, drawing on multidisciplinary research and ADM+S projects. We focused on four well-established technologies—search, recommendation, automated content moderation and curation, and AdTech—and outlined several emerging challenges associated with their use across news and media.

ADM+S researchers are actively working on these problems. The broad outline signals where future research is heading in this area. We see a greater need for investment in research and evaluation tools and infrastructure, a growing focus on the importance of generative AI, as well as the deployment of innovative methods such as social 'cyber range'. Of course, these are tasks for the broader research community. By fostering collaboration among researchers, industry partners and civil society organisations, we aim to create a robust ecosystem of informed stakeholders dedicated to shaping the future of news and media.

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