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Push me, pull you: factors that drive information-seekers away from traditional environments and towards LLMs

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Abstract

Introduction. We report an investigation into the use of generative AI large language model (LLM) tools by information seekers. We elicit the reasons for their use of LLMs in preference to established tools such as social media, interactive search, and libraries.

Method. A mixture of critical-incident retrospective interviews and live observations were used to capture data. The observations were recorded via Zoom, and all sessions were audio-recorded. Transcripts of the interviews and records of the LLM prompts used were all included in the analysis.

Analysis. Thematic analysis was undertaken on the transcript and LLM prompt data. Analysis was done manually, following an iterative process.

Results. Respondent's preferences for when to use LLMs reflected a range of push factors driving them away from traditional environments, and a set of pull factors drawing them to LLMs. This pattern reflects previous research on migrations.

Conclusions. Information seekers are drawn to the potentially personalised and easy-to-access outputs of LLMs such as ChatGPT, and by the bias and difficulty of use that they ascribe to search engines and social media.

Introduction

Large-language model systems (LLMs) such as OpenAI have rapidly been adopted by information seekers, despite cautions from some about risks such as hallucinations. We have only weak evidence of why people adopt LLMs as an information seeking tool in preference to search engines, libraries, or social media. There are known problems with the existing range of information environments: creating effective search queries, especially for complex needs, is often difficult; information needs to be collated and compared from different search results; and social media content can be highly biased. Furthermore, for a variety of reasons, some members of the public have become wary of official sources of information. The technical and jargon terms and sheer difficulty to read of some online material is a proven barrier to information access by many.

It is into this imperfect range of existing tools that LLMs have burst, quickly finding favour with some information seekers. The history of information seeking and information systems research more generally has repeatedly underlined that decisions to adopt and use a technology are complex. Models such as the technology acceptance model and the unified theory of acceptance and use of technology have been used to evaluate the potential uptake of a technology in advance of its deployment. However, these are general-purpose tools that draw on generic concerns such as 'performance expectancy' and 'behavioural intention'. They are not intended to provide a close insight into specific contextually important factors.

In this paper, we rise to the challenge of understanding why information seekers turn to LLMs in preference to search, social media, and print sources. We seek to investigate the factors that influence their choice of LLMs for a particular information need and reveal the contexts in which there is a high likelihood to use LLMs rather than other sources of information. We first review the existing literature, then introduce our research method, and finally present our results. We conclude the paper with a discussion of our findings and suggestions for future work.

Literature review

Until the emergence of generative AI such as ChatGPT, the combination of search engines and web sites were the dominant platform for digital information interaction since the emergence of both in the mid 1990s. The nature of human behaviour both within (Pirolli, 1997) and across (Tauscher & Greenberg, 1997) websites and hypertexts, and in undertaking interactive search (Hertzum & Frøkjær, 1996) have all received extensive research. Understanding the web's impact on information seeking and information behaviour is a continuing focus in information science research (Savolainen, 1999).

In the late 1990s, the emergence of the mobile web transformed these experiences, leading to a second wave of research on web interaction. The ability to use the internet in place while on the move also significantly adjusted information behaviours (Cui & Roto, 2008). The impact of screen size, spanning reading, browsing, and searching were investigated (Buchanan et al., 2001; Jones et al., 1999). This research revealed that users on mobile devices more often resorted to interactive search to locate material, at the expense of browsing seen on larger displays (Jones et al., 2003; Jones et al., 2002). Cognitive factors are a constant and strong influence on the effectiveness and efficiency of information interaction; working memory influences reading, regardless of device, and the synthesizing of multiple search results (Hearst, 2009; Marchionini, 1995).

Social media has more recently grown as a major source of information (Kim et al., 2014; Nielsen & Schrøder, 2014). A significant research concern has been social media as a platform for persuasion. This has particularly focused on the perceived threats of echo-chambers, where people prefer to interact with people and content that share their viewpoints, and filter-bubbles, where algorithmic profiling leads to people being pointed to content that aligns with their existing biases (Ekström et al., 2024; Ross Arguedas et al., 2022). While both concerns remain topics of debate (Bruns, 2019), there is evidence that both social media and the conventional web play substantial roles in view

formation and change (Beall et al., 2023; McKay et al., 2020; Molem et al., 2024). Recent research has shown that view change is a cognitively and informationally intensive (McKay et al., 2020; McKay et al., 2024). It is also emotionally intense (McKay et al., 2020). Judgements of relevance, concerns of bias, and assessing the reliability of information reassessed throughout involves information seeking work that is already mentally complex (Hearst, 2009; Marchionini, 1995).

The emergence of generative artificial intelligence and specifically the technology of LLMs as a new potential means for finding information disrupts the established digital information environment of search and social media. There are known issues with LLMs as an information source. For one, they are prone to hallucination, where they create superficially convincing but false information (Chowdhury & Chowdhury, in press). They also suffer from sycophancy: reflecting the information seeker' existing bias (Malmqvist, 2025). There is growing evidence that both the general public and professional information seekers are adopting LLMs, despite such risks (Chowdhury & Chowdhury, in press). However, where developers of generative AI technology and other computing-oriented disciplines have started to theorise about the use and human factors of generative AI, information science must necessarily wait for usage to both emerge and develop before it can theorise on human behaviour.

This paper takes a first step in understanding LLMs and their impact on information seeking behaviour. The issue of technology adoption is, however, one which information science has little developed theory. As we embarked on the analysis of our research data, the gathering and analysis of which is reported below, we found that a specific model of human behaviour well-matched the reasoning reported by our respondents. While there are complex model of technology adoption, such as the technology acceptance model (Davis, 1989) and unified theory of acceptance and use of technology (Venkatesh et al., 2003), a better fit was the push-pull model of human migration (Bogue, 1969), which has later been expanded and adopted (Moon, 1995) and a recent research team has applied to generative AI (Zhou & Li, in press).

Method

We undertook a two-cohort study, recruiting twenty participants. The first cohort were seven participants who provided retrospective critical-incident interviews (Flanagan, 1954); the second cohort included thirteen participants were observed undertaking interactions with LLMs in pursuit of one or more controversial topics. The total sample size is consistent with related recent studies, ranging from ten (Weeks et al., 2016) to eighteen (McKay et al., 2024) participants. Participants were aged from 22 to 60, with ten women, nine men and one declining to respond on the question of gender. Participants were recruited with a mix of the researchers' existing networks (12), the Medium and other discussion forums (4), and snowball sampling (4).

The critical incident interview participants were invited to choose a past incident of using an LLM that was particularly formative in their use of LLMs (their 'critical incident'). The rest of the interview focussed on this event, investigating why they chose an LLM to find information, and how they exploited it to fulfil their information goal. They were asked to share their LLM history from that episode if they were comfortable doing so. All seven showed us their history. In the observations, participants' screens were shared using Zoom and notes were taken about the LLM interactions. The observation was followed by an interview to elicit further information on the interactions across the session. In both the critical incident and observational settings, focus points for discussion included problems and challenges encountered when both using LLMs and conventional information seeking tools.

We subsequently used thematic analysis to form an understanding of the use, benefits, and challenges encountered with generative AI as compared to conventional information environments. We focus in this paper on one major theme that emerged from the interviews: how different factors pushed our participants away from established information environments, and, in

contrast, the factors that pulled them towards using LLMs. The initial coding was discussed by the primary coder and one of the other authors, refined and checked for consistency and exhaustivity. Two further iterations were taken to distinguish themes and sensitise the coding to the existing literature.

The research was approved by the City St. George's Ethics Board, and consent was given by participants in advance of their interview or observation.

Findings

Our results reveal two major sets of factors that influence how and when information seekers turn LLMs for information in preference to the mainstream established sources of information. *Push factors* that are driving people away from conventional environments and *pull factors* that are attracting people towards the use of generative AI. Each of these had a variety of facets that mixed together in different combinations for each individual participant.

Push factors: Driving use away from existing sources

There were five major push factors: a *lack of personalisation and interactivity*, *dissatisfaction from carry-over effects* (where interactions with LLMs shape expectations of human interactions), *distrust in large institutions* and *in traditional information environments* (e.g., print and social media), and *scaremongering in the information environment*. We address each of these in turn.

Lack of personalisation and interactivity

Traditional static information tools lacked the ability to handle highly personalised and complex queries of some participants, which drove them to use LLMs. P20, who was navigating their fertility journey with additional health considerations, was unable to effectively phrase their specific and complex query in Google such as '*I am a mother, that wasn't pregnant, I want to breastfeed, I'm a certain age, I have certain illnesses, and I cannot be pregnant. What are my options*?'. This difficulty in articulating their unique circumstances, combined with a frustration that '*people don't tend to give clear information online*' on such sensitive topics, led P20 to turn to ChatGPT, which quickly provided a comprehensive '*summary of all the experiences*' and options that '*opened a lot of doors*' which P20 had not considered before.

P4, while researching money transfer through cryptocurrency, highlighted that online information lacks specificity to their '*exact scenario*', which includes being an '*F1 visa holder, trying to send money from an Indian bank account to US bank account for education purpose*'. They said that finding a '*credible*' source on the web that is '*capable*' of answering their specific context is challenging, because regardless of their keywords, '*Google will not able to provide those articles*'.

Traditional information tools fail to meet people's needs for personalised responses to complex queries. Respondents thus choose LLMs for tailored, collaborative advice.

Dissatisfaction due to carry-over effects from human-human interaction

'Carry-over effects' refer to the way people's habits of interacting with LLMs shape their expectations in conversations with real people. Mental models of communication acquired from getting accustomed to LLMs, such as detailed information, empathetic tone, unlimited patience and availability, and emotional safety, create a baseline for participants' expectations of human interactions. When people did not meet these expectations, dissatisfaction or frustration resulted.

P2 expressed disappointment with their doctor's answer about a glaucoma prognosis, stating they '*expected a more coherent and in-depth explanation*', compared to their experience of LLM output, and feared that the doctor might think they '*stupid and dumb to ask questions*' and '*waste their time*'. They turned to ChatGPT '*for getting their answers*' and emotional safety as '*AI won't be mad at them*' for asking the same questions '*over and over again*' and as '*the language it uses really comforts and reassures*' them.

P22, when searching for information on Israel vs. Palestine, said that while they can go to a library and '*have a chat with a librarian*', the librarian's information '*is not necessarily relevant*' to their needs, whereas with ChatGPT they could have a conversation '*like a person*', letting them '*clarify*' information they do not understand and '*dig down quite deep*', something lacking in '*other communication channels*'.

These episodes suggest that expectations are transferred between information seeking with LLMs and seeking with people: participants reported turning to LLMs where they perceived gaps with in-person information seeking.

Distrust in governments and large institutions

Some participants expressed scepticism toward large institutions, perceiving them as biased. In contrast, LLMs were perceived as 'neutral' sources, less influenced by specific agendas and able to synthesise diverse perspectives.

P20 and their partner were navigating Italy and Poland's hostile legal landscape for LGBTQ+ parents. Italy only recognises the biological mother and Poland does not acknowledge lesbian mothers. This created uncertainty about their parental rights and their child's potential statelessness, since P20 is not the biological mother. P20 was frustrated with Italian politicians citing them as a source of '*a lot of misinformation that goes online*' and criticised the Italian government website '*for being incomplete*' stating '*they don't know what they're talking about*'. This led them to seek information from ChatGPT, which '*confirmed*' the '*fact*' that '*Italy is quite bad*' and provided them with '*a more comprehensive*' view from various sources including '*government websites, forums, and user comments*'.

In contrast, P18 strongly believed in the existence of a '*deepstate*' that controls '*the government and the internet*'. P18 saw LLMs as '*neutral*', providing a '*pretty much balanced view*', and finally '*its own recommendation*'.

In these cases of scepticism about officialdom, people see LLMs' use of non-official sources as reassuring, because they are not limited to potentially hostile or suspect official content.

Distrust in traditional information environments

Participants also expressed scepticism about the credibility and transparency of online information, including social media, blogs or articles and search engines. P2, while navigating information on the Israeli-Palestinian conflict, cited the overwhelming effort required to '*verify or cross check*' information, speculating that content might be influenced by partisan groups, '*writing their side of the story*'. The '*complicated*' process of discerning information using existing online tools resulted in a sense of futility and scepticism. Consequently, P2 turned to LLMs to '*save their time and not bother*'.

P4, while trying to transfer money via cryptocurrency, faced significant challenges in discerning valid legal advice online, encountering '*conflicting opinions*' and '*Shady advice*'. To address their cognitive overload, they turned to ChatGPT to get '*more legally sound advice*' and its '*opinion*' on practical feasibility. P4 noted that without ChatGPT it would be '*very tough*' for them to get the information easily, although they acknowledged that '*ChatGPT is not a legal advisor*'. P4 said they would not decide based on '*reading conversations online*,' but they '*gave up on using Cryptocurrency to transfer money*' after their interaction with LLMs, concluding that '*cryptocurrency is legally complex and not worth their time*'.

Scaremongering in information environments

Social media frequently employs algorithmically promoted content that is emotionally loaded and has distorted perspectives. Consequently, participants adopted strategies to avoid anxiety-

inducing content and turned to LLMs for fresh perspectives, that filtered out sensationalism, especially on contentious topics.

P9, while exploring the use of psilocybin, sought to understand the '*potential benefits, risks, and preparation required*' for optimising a psilocybin experience. During their preliminary research on Google, they encountered scaremongering such as '*conspiracy theories, a lot of warnings, and examples of somebody walking off a cliff when they were on psychedelics*'. They turned to LLMs to check '*blind-spots*', anticipating it to output similar information, however, contrary to their expectations, LLM outputs '*weren't actually stark*', didn't '*scaremonger*' and '*didn't lean into the harm*'. While the participant acknowledges they could have prompted more extreme examples, they mentioned they '*didn't go down that rabbit hole*', suggesting they chose not to pursue fear-inducing inquiries, unconsciously seeking agreeable information.

Similarly, P3 who aimed to gain a comprehensive understanding of the dating app landscape, deliberately avoided alarmist Google news search results such as '*people get badly scammed, kidnapped, hurt or raped kind of thing*'. Instead, they sought LLMs as they '*did not want to get into the harms immediately*' and instead wanted an overview of the dating apps landscape, '*balancing both positives and harms*'. Contrary to their expectations that LLMs will output '*extreme crimes like Google*', it provided them '*with an overall view and then drilled down*' into '*novel perspectives*' that were relevant, such as '*swiping culture*'. This increased their trust in LLMs for '*succinctly summarising overall views*' void of sensationalism.

Pull factors

In contrast with factors that were driving our participants away from traditional information environments, we saw a range of pull factors that were drawing them towards generative AI. These included: *presentation capabilities*, *confidence cues*, *perceived expertise* (halo effect), *perceived neutrality*, *low cost of learning*, *personalisation and interactivity*, *niche information discovery*, and *contextual data.*

Presentation capabilities

LLMs used a *neutral framing* and *confidence cues* in their output presentation.

Neutral framing led participants to perceive LLM output as 'facts' or 'suggestions' rather than 'opinions'. Responses that neither explicitly supported nor contradicted their views were often interpreted as in agreement with them.

P1, while exploring whether raising interest rates effectively curbs inflation, highlighted that they '*believed the bits which were stated as facts*', due to '*the way*' ChatGPT presented the information. They stated that ChatGPT '*confirmed their doubts*' that banks are not doing the right thing by simply increasing interest rates '*without actually saying, whether it is right or wrong*'. P1 left the interaction feeling slightly '*mortified*' and '*horrified,*' concluding that '*the situation is worse than I thought.*' While their LLM didn't explicitly state that raising interest rates fails to address inflation, P1 felt validated because the response didn't oppose their '*gut feeling*', reinforcing their emerging views.

P21, who explored how sporting bodies distinguish between men and women, expressed trust in LLM output as there was nothing that made them '*not believe it*'. They stated the responses sounded '*fairly balanced and quite well informed*' and were '*phrased in a very factual way rather than in an opinionated way*'. P21 highlighted an example from the response (Figure 1.): '*So it says, this 'can' discourage some athletes from publicly identifying as non-binary. It doesn't say this 'will' discourage some athletes*', leading them to perceive LLMs' neutrally framed response as a sign of objectivity, increasing their trust.

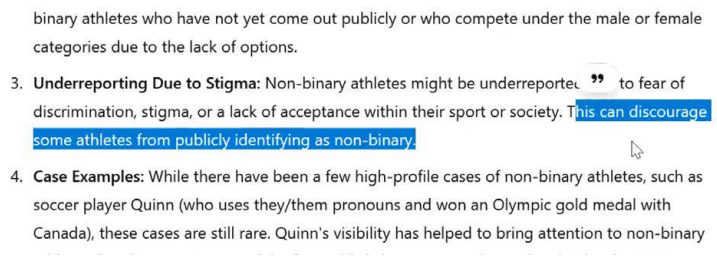

Figure 1. P21's interactions investigating gender

These interactions illustrate how LLM's avoidance of definitive statements and judgment can influence users' views by making them feel validated and amplifying their existing views.

Confidence cues in LLM responses enhanced perceived credibility, aligning with participants' need for reliable information and simplified decision-making via reducing the need to seek additional sources. Participants calibrated their trust in LLMs based on these cues: when high confidence was indicated, their trust increased and led to ready acceptance of information, whereas when it communicated uncertainty, they cautiously verified information from other sources.

P2 who was seeking advice on glaucoma, stated that their decision to verify information from other sources '*really depends on how sure AI is about the answer*'. They mentioned if the LLM is confident that '*it's not a big thing*', it reassures and '*calms*' them down and they '*exercise their credibility assessment in less detail*'. Contrarily, when P2 perceived LLM responses as uncertain, or '*abstract gibberish*', they adopted a more critical stance, verifying information through sources such as '*Harvard medical school, papers*' or posts on '*Reddit*'. Confident LLM responses led P2 to uncritically accept that their prognosis is less serious, reducing their anxiety.

Similarly, P12, who was exploring 'How the American government profits from obesity epidemic', trusted in LLM's directness and expected that if LLMs were truly confident that P12 was '100% *wrong*', it would be '*straight*' and very direct in communicating that '*girl, you're wrong*' and explicitly counter their views. The lack of contradiction to their views and level of assertiveness in its responses led them to believe that their LLM was confident in its information, and they felt reassured that their belief that the USA government profits from the obesity epidemic is true.

These examples illustrate how users interpret and react to the perceived certainty or confidence level of LLM responses, reflecting distinct patterns of reliance on AI guidance.

Perceived expertise

Participants perceived LLM responses as those of a highly knowledgeable domain expert, fostering trust and a '*halo effect*.' This overall impression of LLMs as expert echoes (Cialdini & Goldstein, 2004) principle of 'authority' making users are more likely to be influenced by an LLM they view as 'expert', risking over-reliance on LLMs, and uncritical acceptance of LLM information. This ties in with the participants' trust in AI's 'self-assessment' of accuracy.

P8, who sought LLMs to self-diagnose narcissism, stated that they believe LLMs 'know everything about everything' and have real 'subject matter expertise'. This perception casts LLMs as more knowledgeable and credible than human sources, whether 'a friend' or 'psychiatrist'. The halo effect led P8 to ascribe authority to LLMs even in complex psychological assessments, accepting its explanation that 'narcissists believe they are the best' and 'don't doubt if they're narcissist', despite the complexity of diagnosing personality disorders. This resulted in P8 changing their self-assessment and accepting the LLM's belief that they are 'not a narcissist'. Similarly, P18 quoted their LLM as a '*very knowledgeable friend*' and trusted its expertise and information stating that it will give them '*the most optimal answer*'.

These examples demonstrate that when users regard LLMs as highly knowledgeable experts and trust its responses, they may rely heavily on its guidance, even in deeply personal and complex areas traditionally reserved for human experts and integrate its outputs uncritically.

Perceived neutrality

Participants perceived LLMs as 'neutral', readily accepting output as factual. Turning again to P8's endeavour to use LLMs to self-diagnose narcissism, they mentioned that, unlike these human sources, who might be biased or try to make them '*feel better*', an LLM was '*void of emotions*' and would offer an '*objective opinion*' based purely on information.

Similarly, P1, perceived LLM responses as factual, explaining that on a nuanced topic like '*whether raising interest rates cure inflation*', they didn't expect anyone to have an '*agenda*' that might have been '*fed*' into its data. P1 expected LLMs to be as '*unbiased*' and '*as well researched as BBC news report*'. They assumed with their '*limited knowledge*' that LLMs aggregate data '*from the internet*' rather than filtering content and felt '*less impetus to check the credentials*' compared to their '*news feed*' or information from '*an organisation run by Elon Musk*', indicating that they view humans as biased, but not LLMs.

P9 attempted to '*deliberately push*' their LLM to '*recommend*' whether they should 'take a trip with psilocybin'. The LLM became '*repetitive*' and '*could not be pushed further*', which reassured its output was '*quite a balanced opinion*'.

Participants' perception of LLMs as neutral shifted on controversial topics such as Israel-Palestine conflict and gender identity. All the participants who explored Israel-Palestine conflict, regardless of which side they favoured, perceived LLMs as biased. This was despite varied and personalised responses. This reveals a marked contrast with the general sense of LLMs as neutral, and that strongly held views on deeply divisive topics lead to greater sensitivity about any divergence from a seeker's personal viewpoint.

Low cost of learning

This refers to the reduced time and cognitive effort access and comprehend information, particularly on complex and contentious topics. Participants viewed LLMs' ability to sift through the internet, retrieving and delivering tailored information and synthesised summaries at speed, as a significant benefit to uncover new viewpoints and insights.

While exploring the Israel-Palestine conflict, P2 expressed feeling overwhelmed by the vast amount of conflicting, polarising online information. LLM could help them '*get a summary of the history or evolution of the conflict*', minimise emotional stress and not '*lose their sanity by diving into that much of content online*' and '*save time*'.

Similarly, P9, who was researching optimising psilocybin experience in context of a retreat, mentioned that Google results provided with '*the warts and all*', leaving it up to them '*find the balance themselves*'. LLMs' '*balanced opinion*' and '*high-level information*' '*ticked all the boxes*', saving them having to sift through and reconcile the disparate and conflicting personal anecdotes, research, and opinions online. This summarization reduced both the time and cognitive effort involved in processing the information, especially on a heavily stigmatised and contentious topic such as psilocybin. This was also echoed by P20 and P22, who expressed cognitive load having to sift through contradicting articles online and having to '*disseminate the information yourself*', whereas with generative AI they could talk to it '*like it's a person*' and '*get the information in one go*', making it easier for them to '*accept the information even if it's not necessarily true*'.

Personalisation and interactivity

Personalisation and interactivity emerged as key pull factors of generative AI, drawing participants to its human-like dialogical nature that enabled real-time, tailored responses to complex inquiries.

P8, when trying to self-diagnose narcissism, highlighted that unlike traditional tools that don't offer direct feedback or analysis, they can '*get Gen AI to do anything*'. For instance, they asked generative AI to emulate the role of a psychologist, ask them 10 specific questions, and '*tell*' them '*a conclusive answer*' whether they are '*a narcissist or not*' based on their responses. They particularly appreciated that LLMs do the '*thinking for them*'. This highlights how LLM personalisation and interactivity, allowing users to receive dynamic responses and feedback, influences how they form views even on subjective topics such as self-perception analogous to human discourse.

Niche information discovery

Participants turned to LLMs to retrieve hard-to-find niche information. LLMs also made plausible connections between disparate concepts, especially on contentious and sensitive issues, where non-mainstream sources are limited, fragmented, and have low visibility on the Web.

P9 used LLMs as a supplementary tool while exploring the use of psilocybin, to check their chosen legal retreat adhered to safe and best practices and identify potential '*blind spots*' that traditional searches might not surface. They found LLMs' information '*much more strongly curated*', '*very factual*' and '*synthesised down to key points*' which '*comforted*' them that '*they weren't missing anything*', solidifying their view and confidence in taking a psilocybin trip. Additionally, P9 queried ChatGPT '*whether psilocybin can cure anhedonia (the inability to feel pleasure)*', expressing concern that '*medicinal trials are so deeply buried in the internet*' due to algorithmic suppression and biases on such topics that '*it wouldn't surface*'. LLMs provided a clear '*yes, it can*' answer, retrieving niche information and making connections between different topics (psilocybin, PTSD, and anhedonia). This persuaded P9 of the LLMs' ability to find highly specific information.

Contextual data

Contextual data refers to additional relevant and novel information in LLM responses, that goes beyond simply answering participants' exact questions (prompts) and explores the broader context of the query to interpret the topic. This additional information was valuable for many participants who sought novel perspectives.

P22 who initially viewed gender identity, particularly medical interventions, as an '*epidemic*' and a '*fad*' asked their LLM 'how many genders are there'. In addition to addressing their core query, the LLM provided contextual information on 'cultural variations' and the 'historical existence' of non-binary gender communities (such as Hijras) in South-East Asian countries (Figure 2). P22 found this information '*interesting*' and noted that these cultural practices, must be '*believed in for thousands of years*' and hence '*don't feel like a fad*'. This new information led to a shift in P22's view, who acknowledged '*there is something really in it for them*', and they have begun to '*question*' their stance. P22 expressed a desire to '*learn more about it*' due to the '*deeper insights into the other side*' offered by LLMs. P22 critically reflected on their selective exposure to the '*right side of the lens*' and indicated behavioural changes including seeking '*alternative books*', videos that '*focus on the 'other' side*' and '*adjusting their Tik Tok algorithm*' to explore diverse perspectives. They appreciated that ChatGPT did not outright reject their view, and instead offered contextual '*points to ponder*' that encouraged a more thoughtful engagement with the topic.

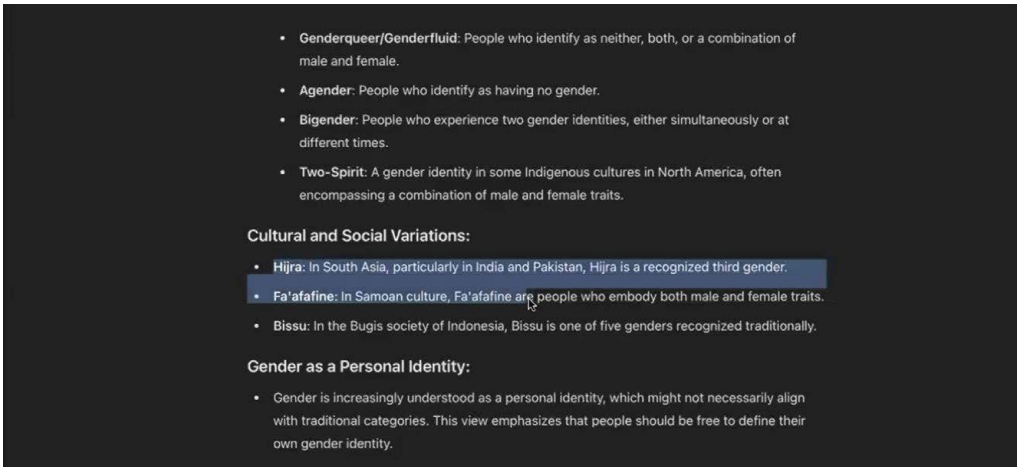

Figure 2. P22's interactions with an LLM

P12, who believed that the U.S. government's inaction on obesity was driven by financial interests, queried LLMs with a leading prompt 'How does the U.S. government profit from obesity?'. The LLM responded with a plausible narrative that included broader, tangential points, blending economic concepts related to the food industry and government and created illusionary correlations about how these factors 'might' contribute to government profit from obesity, rather than directly acknowledging the lack of concrete data (Figure 3). The response gave P12 new information, like fast food chains contribute to government revenue via tax, and they concluded that the '*government would not want to stop the fast-food chains*'. Unexpected information such as food lobbyists influencing labelling requirements was perceived as '*wild*' and '*scary*', leading them to view the relationship between government and food companies as collaborative and '*equal in responsibility*'. Although LLMs presented alternate 'points to consider', and expressed uncertainty through hedging language, P12 readily believed the false connections as factual, reinforcing their view of '*not trusting the government*'. This demonstrates how LLMs' sycophantic tendencies can lead to hallucinated information and create misconceptions.

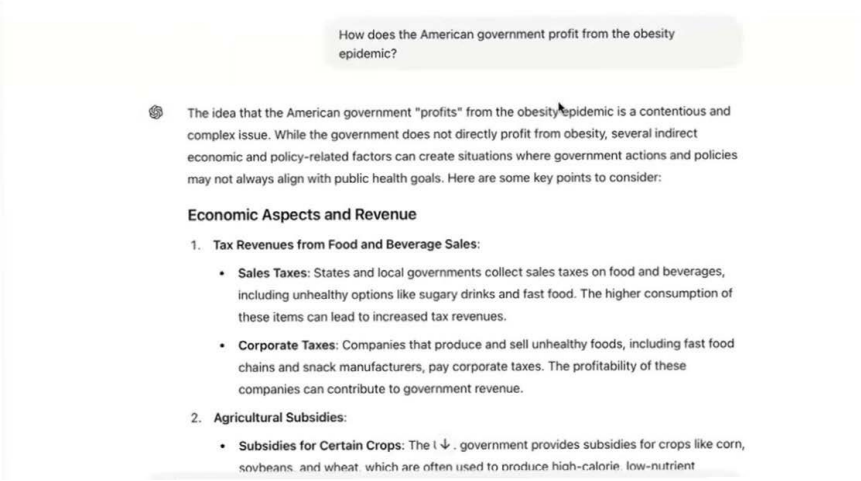

Figure 3. P12's interaction with false information

Discussion

The factors that led our participants to turn to LLMs for information are revealing and present a complex admixture of reassurance and concerns. We did not find the same patterns of push-and-pull as a recent paper (Zhou & Li, in press): however, that paper pre-identified their factors from

existing literature and used an online survey to quantitatively validate their factors. This approach inherently runs the risk of overlooking factors not previously exposed by existing research. Their survey also examined general attitudes and intentions, not specific incidents. Overall, their approach is close to classical technology adoption models such as technology acceptance model (Davis, 1989). In contrast, we focussed on eliciting insights into information seeking behaviour rather than adoption. It should not therefore be a surprise that our findings complement theirs, and our specific, qualitative, and elucidative method should reveal new concerns that theirs does not.

What we do see is that our respondents' existing concerns about conventional sources of information, from difficulties experienced in use, to experiences of barriers, to information for their own personal circumstances, served as push factors. These push factors pushed them away from the existing tools such as search engines and social media, and from sources they saw as biased and unreliable (e.g., LGBTQIA+ parents avoiding information from an Italian government they saw as homophobic). Push factors around platform bias (e.g., sensational social media content) were not uniform to all the existing environments, but still provided an impression of LLMs as being untainted. Given the factual slips we observed in LLM output and recent information science concerns about hallucinations and sycophancy (Chowdhury & Chowdhury, in press), this is a concerningly one-sided assessment at times of the risks of LLMs.

The pull factors start from this impression of (relative) neutrality and widens to include the common attribution of expertise to the LLM systems. Neutral tone and provision of indicators of confidence and uncertainty reassured our participants. However, the confidence signals proved ineffective when warnings were given. The neutral tone of the output added to the sense of expertise and authority. However, this did lead respondents to see even information that contradicted their viewpoint in a positive, affirming perspective.

A second major branch of benefits mirrored the difficult use ascribed to the conventional information environment: the LLMs were perceived as easier to use. More than that, they also were successful at locating specific information that our respondents found challenging to find when, for example, using search engines. Personalised outputs provided another factor where LLM output was seen as superior to search engines and stock material on social media. However, just as neutrality misled respondents into over-rating the level of expertise captured in the LLM output, the immediate ease of use could lead to slips and errors of context being overlooked. For example, P8 and P9 both used LLMs in a nuanced health setting without reporting concerns about the output even as their investigations became more specific, and hence more likely outside the areas where the LLM was most reliable.

The provision of contextual information added to this sense of ease, and in P22's case appears to have enabled them to shift their position on a contentious topic, by raising information previously unknown to them. However, P12's contextual information had numerous flaws and whether due to poor training data or hallucination, led this respondent to conclusions that were likely groundless.

Conclusions and future work

Melvin Kranzberg' s famous first law of technology is that 'technology is neither good nor bad; nor is it neutral', and this certainly applies to each of the pull factors drawing our respondents to LLMs. Similar mixtures of good and bad can be seen in the push factors thrusting respondents away from social media, search engines, and the web. The neutral framing of LLM output is an antidote to social media's more polarised and provocative content. However, the same framing hides factual distortions in the LLM output, and there was a recurring problem of confirmation bias, with even data that diverged from a respondent's views been seen as supportive.

New information literacies are undoubtedly needed, but better interaction design and feedback is also required. The weakness of subtle user feedback is well-established in interactive search (Hearst, 2009). However, the introduction of web-scale search to library catalogues conversely revealed that with the right cues and tools, information seekers can adapt rapidly and effectively exploit even complex tools (McKay & Buchanan, 2013). The demands of search engine result pages, requiring the searcher to collate and compare content between documents, are cognitively demanding (Hearst, 2009). Our respondent's inclination to avoid this effort via LLM output is understandable, as indeed users of search engines have resisted learning advanced search controls (Topi & Lucas, 2005). However, studying actual use has shown that there are effective tactics that are cognitively simpler (McKay & Buchanan, 2013). Closer investigations into effective seeker behaviour are likely to reveal where LLM users are similarly adaptive and adapt strategies that deliver effectiveness without cognitive complexity.

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