CCCS - ESS ECONOMICS ESSAY COMPETITION 2024

“How should Competition and Consumer Protection rules evolve in the age of Artificial Intelligence?”

By Lukas Lim Kai Zhe & Masuda Marsh Amy Felicity

ABSTRACT

Consumer protection and competition rules are imperative in correcting market failures arising from commercial and intra-business relationships. The development of AI engenders unprecedented problems and novel variants of older concerns that challenge the assumptions upon which present consumer protection and competition rules are built. Hence, the evolution of these rules is non-negotiable—the elephant in the room is "How?".

Following our **Introduction (Section 1)**, **Section 2** of this essay explores what we believe to be the main ways in which AI undermines consumer protection:

1. by enabling malicious manipulation;
2. by facilitating price discrimination; and
3. by harbouring biases.

In **Section 3**, we explain how, with reference to the aforementioned issues in Section 2, the consumer protection regime in Singapore can metamorphose to better safeguard consumers from AI-facilitated fraudulent commercial practices; namely by:

1. correcting for defective consent *vis-a-vis* data provision and trading; and
2. mandating transparency in a two-pronged manner: by mandating disclosures, in specific circumstances, and mandating algorithmic transparency.

Next, **Section 4** elaborates on how AI undermines market competition by:

1. driving algorithmic tacit collusion;
2. facilitating the process of tying and bundling; and
3. increasing the market dominance of existing monopolies.

In **Section 5**, similar to our approach in Section 3, we explain how, with reference to the aforementioned issues in Section 4, the competition regime in Singapore should evolve to better insulate smaller companies from anti-competitive business practices; namely by:

1. building on our proposed solutions in Section 3 to address competition issues; and
2. in relation to Shared AI Systems (SAS), offering an unorthodox conception of mandating the bifurcation of developer firms and adopter firms to avoid conflict-of-interest problems inherent under a unified system.

(268 words)

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1. INTRODUCTION

Artificial Intelligence (AI) emanated from the desire to allow machines to mimic functions of fluid human intelligence: use language, form abstractions and concepts, solve problems previously reserved for humans, and improve themselves (Science and Technology, n.d.).

The sheer volume and variety of data produced daily have virtually cemented AI's role in the future, for it is only by utilising it that we can make sense of 'big data' (Osoba and Welser, 2017). Indeed, the Artificial Intelligence (AI) market is expected to grow to become a trillion-dollar market in the next seven years; this will largely be fueled by its heightened adoption across industries (Bloomberg Intelligence, 2023).

Concomitantly, AI is expected to revolutionise existing commercial and intra-business relationships with continued AI advancement and increasingly creative applications of AI, such that current consumer protection and competition rules will have no choice but to evolve in tandem—if effective protection is to be desired.

This essay will generally proceed with a bifurcation of the two aspects in question: consumer protection and competition. The prejudice that AI could potentially levy on consumer protection will first be explored; followed by an enumeration of the suggested changes in consumer protection rules, in response to the discrete harms identified. The same structure will form the backdrop of our subsequent discussion on competition.

<u>**2. ISSUES (CONSUMER PROTECTION)**</u>

2.1 Malicious Manipulation

Predictive analysis based on user data can reveal, to a reasonable degree of accuracy, the preferences and tendencies of individuals. In the case of advertising, certain messages, which pander to the specific biases or circumstances of individuals, are delivered to individuals in a personalised manner. This, also known as *microtargeting,* is done without the knowledge or consent of said individuals and nudges them to make certain choices that they would otherwise not.

Further, AI-generated synthetic media, or deepfakes, when utilised maliciously, can leverage the trust that consumers of such content have in authoritative figures (*ad verecundiam*) to make ill-informed consumption choices based on fraudulent endorsements.

AI-powered chatbots and voice assistants can also socially engineer their users into making specific decisions. When humanised, assistants powered by Large Language Models (LLMs) can attract increased trust from users (Lemoine and Notebaert, 2011), thereby increasing the credibility perceived by users of the personalised recommendations provided. This is exacerbated by the general aura of objectivity and infallibility our culture ascribes to algorithms (Bogost, 2015).

Such strategies exacerbate the deviation between the economic value perceived by consumers and that which is *bona fide*. This reduces the economic value (per unit price that consumers are willing to pay) that users derive from online services in the name of corporate profits (Petropoulos, 2022).

Manipulation also undermines the decisional autonomy of consumers, especially if the consumer is not privy to the discrete tactical influences employed (Lau, 2022).

2.2 Price Discrimination (PD)

PD is a profit-maximising strategy that involves pricing the same product differently for different consumers based on their willingness to pay (WTP). More specifically, AI virtually allows for first-degree price discrimination by allowing a merchant near-complete access to consumer information. This is based on inferences derived from the aggregated attributes of users whose preferences are known ('*inferences*') (Asthana, 2024), which it can employ to infer a consumer's WTP.

A 2023 study by the Belgian newspaper Dernière Heure revealed that an Uber ride ordered on a smartphone with only 12% battery remaining was 6% more expensive than one ordered on a smartphone with 84% battery remaining (Natelhoff, 2023) as Uber had found that people with lower battery levels were more willing to pay for surge pricing and allegedly exploited this fact by accounting for it in the prices it charged to individual customers.

With PD, prices will converge towards the maximum price consumers would be willing to pay and the overall level of consumer welfare may become far below what it otherwise would be (Armstrong, 2006), as a result of firms, with market power, "unfairly" acquiring the same.

PD also compromises on consumer sovereignty as consumers are deprived of the “opportunity to satisfy those wants at prices not greatly over the costs borne by the providers of the relevant goods and services” (Averitt and Lande, 1997) and therefore, have “the power to define their own wants” (Averitt and Lande, 1997).

2.3 Bias

AI systems are often “black boxes”. The use of AI for decision-making may exploit this opacity and the objectivity of “multi-variable equations” *vis-a-vis* subjective human decisions (Tett, 2014) to legitimise bias already existing in the data (and software) used to train the algorithm, producing results that appear reasonable and nondiscriminatory at face value (Pasquale, 2015).

Additionally, the use of AI for model creation may inductively magnify pre-existing inequalities or discriminations, exacerbating institutional bias, as AI relies heavily on information collected by human systems, which may harbour such biases (Ntoutsi et al., 2020).

The profiling that underpins magnified bias can also enable a business to engage in PD on the *de facto* basis of protected characteristics.

However, more insidiously, consumers of a specific class, who have been selected against, are deprived of options that they can effectively pick from to satisfy their legitimate wants. Crucially, such deprivation does not arise out of anti-competitive practices, but, instead, immutable aspects of themselves.

Worryingly, learning algorithms can also implicitly reconstruct sensitive fields via *inferences* and use these probabilistically inferred proxy variables for discriminatory classification (Raghavan and Barocas, 2019). This threatens to undermine decades of progress in outlawing the consideration of protected characteristics in decisions.

3. SUGGESTIONS (CONSUMER PROTECTION)

3.1 Correct for Defective Consent *vis-a-vis* Data Provision and Trading

The Consumer Protection (Fair Trading) Act 2003[1], like most international consumer protection laws today, is founded upon the libertarian 'notice and consent' doctrine, ie. that if consumers have been put in a position to make informed and meaningful choices (Nehf, 2019), any harm agreed to by consumers cannot be held against businesses.

[1] https://sso.agc.gov.sg/Act/CPFTA2003

Worse, the Personal Data Protection Act of 2012[2] relies on data subjects' *prima facie* consent or voluntary provision as a basis for lawful processing. It does not account for instances where such consent is not fully informed.

However, in today's digital environment where businesses can inundate us with dozens of pages of terms and conditions designed to insulate against liability of virtually any form for the simplest online transactions and threaten possibly deny access to a perceptibly 'necessary' service, *prima facie* assent must be rejected and 'supplanted by responsible contracting practices mandated by law' (Nehf, 2019).

Excessively lengthy disclosures and coercion are merely some of the many dark patterns[3] employed today to exact defective consent; others include misleading language or design choices (Jarovsky, 2022), as well as, specifically concerning privacy, liberal default data-disclosure settings and hindrances to privacy-protective actions (Jarovsky, 2022).

A solution to this would be to outlaw, or, at the very least, impose restrictions on the use of, the aforementioned dark patterns in fair trading laws and data protection regulations, such that businesses would be under the legal obligation to refrain from employing the same. Such measures would allow the customer and data subject to better appreciate,

[2] https://sso.agc.gov.sg/Act/PDPA2012
[3] User interface design choices that manipulate the data subject's decision-making process, via cognitive biases, in a way detrimental to his or her privacy and beneficial to the service provider (Jarovsky, 2022)

at the time of collection, the nature of the product under consideration and the extent of data-sharing that they have licensed. The benefits of this are two-fold:

i. ***bona fide*** **consumer sovereignty would be upheld in the decision to participate in a consumer transaction** by having malicious manipulation outlawed insofar as the exploitation of particular cognitive biases is involved; and
ii. ***bona fide*** **consumer sovereignty would be upheld in the decision to disclose data** as consumers would be better positioned to foresee the discrete risks involved in data disclosures, thereby being empowered to take reasonable precautions against those risks. In assuming consumer rationality, businesses would be denied the data required for malicious manipulation and biased decision-making.

3.2 Mandate Transparency

3.2.1 Mandatory Disclosures

At present, first-degree price discrimination (1PD) is not illegal in Singapore; nor is the decision to prohibit it an obvious one. This is because 1PD can improve access to goods and services by less well-to-do consumers, via cross-subsidy, and is arguably a mere manifestation of corporate ingenuity.

Instead, a less contentious and invasive solution would be to mandate that companies inform consumers when they are being profiled, of the data utilised for such profiling, and when they are subject to personalised pricing strategies, based on such consolidated profiles (Davola, 2023).

Similarly, as outlawing dark patterns that are minimally pervasive and deleterious, deep fakes, in general, and the use of LLM assistants in advertising, mandating disclosures to such ends remains sensible.

In addition, to avoid exacerbating the already entrenched problems of ‘disclosure overload’ (Winter, 2019) and dark patterns online, the brevity, visibility, and clarity of such disclosures must be upheld by law.

The presence of reasonably comprehensible disclosures will allow consumers to be made cognisant of the discrete, and otherwise opaque, profit-maximising strategies of corporations and not be opaquely misled to their detriment *vis-a-vis* footing a higher price and participating in an otherwise adverse transaction.

3.2.2 Algorithmic Transparency

In the earliest AI systems, manual algorithmic testing, while tedious, served as a feasible strategy for uncovering glitches (Wulf and Seizov, 2022) and faulty reasoning.

However, in pursuing greater speed and data processing power, AI systems have become exceedingly complex. Humans can no longer turn to menial methods for testing each critical decision chain.

In addition, the capability of AI systems to 'spot patterns, correlations, and different dimensionalities in the [large] data sets they observe' and uncover insights beyond conventional human imagination (Wulf and Seizov, 2022), underpins the problem of 'unknown unknowns', such that humans may not even be privy to the aspects that such manual tests should encapsulate.

To this end, future regulations should mandate the attachment of 'explanators'—algorithms that seek to reconstruct the inner workings of 'black box systems' by 'asking' them a range of questions and comparing the results produced with the input offered (Cassauwers, 2020). The reports produced by such 'explanators' should form the cornerstone of strict AI auditing standards.

This approach is, compared to decreeing the use of 'white box systems', far more facilitative of AI advancement as 'white box systems' are, by design, less powerful than their 'black box' counterparts (Cassauwers, 2020).

4. ISSUES (COMPETITION)

4.1 AI Driving 'Algorithmic Tacit Collusion'

Algorithmic tacit collusion refers to the capability of algorithmic pricing agents to independently engage in tacit collusion, which reduces market competition, without human intervention (Dou et al, 2024). These pricing algorithms require a profit aim, profit-maximising or otherwise, to be set before achieving it in the most efficient manner (Caforio, 2022), and what lies at the heart of it is AI (Tableau, n.d.).

Figure 1: Impact of Algorithms on Collusion

Relevant factors for collusion		Impact of algorithms on the likelihood of collusion
Structural characteristics	Number of firms	±
	Barriers to entry	±
	Market transparency	+
	Frequency of interaction	+
Demand variables	Demand growth	0
	Demand fluctuations	0
Supply variables	Innovation	-
	Cost asymmetry	-

Note: + positive impact; - negative impact; 0 neutral impact; ± ambiguous impact.

As seen in Figure 1 (OECD, 2017), algorithms have substantially increased market transparency and the frequency of interaction of firms. This is the result of AI algorithms' ability to increase the availability of data and make predictions about rivals' actions (OECD, 2017).

Increased market transparency and increased communication between market players allow them to access the same information about each other's price and production decisions, making it easier for them to coordinate their actions and reach agreements on pricing and output levels (Bundeskartellamt, 2016).

Additionally, increased market transparency comes along with a reduction in strategic uncertainty of tacit collusions, alluring firms in a market to collude. Collusive agreements can be problematic as firms could unfairly deviate from the anti-competitive agreement for their profits (OECD, 2021). Monitoring algorithms, in particular, can oversee the actions of colluding firms, making it easier to uncover deviations and hold parties accountable, thereby alleviating the issues surrounding collusive agreements and making it more attractive for firms to partake in (OECD, 2021).

4.2 AI Facilitating Tying and Bundling

Tying occurs when a firm with market power only sells a specific item (tying good) together with another item (tied good), allowing it to leverage market power across products (Evans and Salinger, 2005). A second monopoly in the market of the latter goods is established, thereby suppressing competition.

As mentioned, AI allows companies to better understand customer idiosyncrasies—facilitating the creation of personalised offers that are more attractive to customers and increasing the likelihood of successful tying strategies. Furthermore, AI can help companies automate the process of identifying and creating bundled offers (DiLoreto and McCartney, 2022); it is now quicker and cheaper for companies to carry out tying. Indeed, E-commerce has allowed customers today to be induced into buying additional products at discounted prices immediately after purchasing one or some of the available products, i.e. sequential bundling (Gayer et al, 2021). As such, AI facilitates tying, indirectly undermining market competition.

4.3 Increased Market Dominance

AI is a capital and information-heavy field (Run:ai, n.d.), making it sensible that larger companies with substantial funding and technical expertise, which tend to be the tech giants (Marr, n.d.), have a higher possibility of developing successful AI systems. The concern is when dominant market players manipulate their AI systems to intentionally stifle competition.

An example to illustrate this would be the American Airlines smart travel reservation booking system, SABRE. The US airline industry is an oligopoly, with American Airlines being one of the four companies to dominate the market (Segal, 2024), and SABRE's default information sorting behaviour took advantage of typical user behaviour to create a systematic anticompetitive bias for American Airlines. SABRE's interface design was made possible through AI—flights from American Airlines were always presented on the first page of the ranked flight options, even when other airlines had cheaper or more direct flights. Nonpreferred flights were often relegated to the second and later pages, which consumers rarely reached (Friedman and Nissenbaum, 1995). This resulted in the enhanced popularity of American Airlines at the expense of other airlines, especially because 90% of the tickets booked by consumers are booked by the first-page display (Friedman and Nissenbaum, 1996). Though SABRE was promoted as an application for all airlines, it promoted American Airlines specifically, reducing market competition.

Sabre's case demonstrates how large firms with substantial market power can develop the AI systems that are adopted by rivals, reducing competition much to their advantage—a paramount issue that AI imposes on market competition.

<u>5. SUGGESTIONS (COMPETITION)</u>

5.1 Mandating Transparency & Implementing Auditing Standards

Singapore's Competition Act 2004[4] aims to address the issues above by prohibiting anti-competitive agreements, decisions, and practices (Section 34) and the abuse of dominant positions (Section 47). CCCS, under the act, is then allowed to conduct investigations if these sections have been infringed.

Firstly, a key limitation of Singapore's competition laws is the difficulty in detecting and proving AI algorithm-facilitated collusion. Collusion allegations require tangible proof of an agreement, but, because AI algorithms can autonomously adjust prices, share information, and other parameters based on market conditions without market players meeting to communicate (Tyler, 2024), it is much more difficult for CCCS to pinpoint AI-facilitated collusive agreements and undertake investigations. Hence, it is not only in the context of consumer protection that transparency is critical. Transparency of AI is also paramount for CCCS to identify AI-facilitated collusive agreements.

[4] https://sso.agc.gov.sg/Act/CA2004

Our suggestion is hence to pair mandatory transparency with the introduction of strict auditing standards. This would allow CCCS to regularly audit companies' AI algorithms to ensure compliance and identify anti-competitive collusions.

5.2 Data Provision

Feeding off Section 3.1, outlawing the aforementioned dark patterns in fair trading laws and data protection regulations results in businesses being denied the data required for malicious manipulation and biased decision-making. This limits the likelihood of successful tying and bundling strategies as companies now have less consumer information to infer their preferences from.

5.3 Establishing A Divide Between Developer Firms ('Developer') and Adopter Firms ('Adopter') *vis-a-vis* Shared AI Systems (SAS)

Shared AI systems (SAS), such as SABRE, are AI systems adopted by one or more firms unless the shared use of the system arises out of a joint venture. SAS are often distributed for a fee.

At present, it is common for a single firm to both develop and employ SAS.

In being acquisitive, the firm can either:

(1) Maximise the royalties derived from the **adoption of its SAS by rival firms**; or

(2) Employ SAS to **maximise the demand** for its products, in particular.

However, a profit-maximising firm would elect to straddle both sides; it would manipulate the algorithmic formulae underpinning the SAS to favour its products while maintaining the facade that the SAS is fair to all (see Section 4.3). Hence, the firm exploits the reliance of rival firms on its SAS to undermine free and fair market competition.

By bifurcating the development and adoption of SAS, such that a Developer of SAS will not be, in law, permitted to adopt the SAS to augment demand for its products, a Developer will be prohibited from earning profit through (2), thereby alleviating the clear conflict, which exists under a non-bifurcated system, between a firm's profit-maximising objective and broader competition ideals.

Additionally, by mandating that a Developer also be subject to fair distribution obligations, an avaricious Developer will also be compelled to promote the widespread adoption of its SAS. This opens up opportunities for newer companies to enter the market and smaller companies to compete with larger, more established firms. This is because these smaller and newer companies can now access and incorporate cutting-edge AI systems into their operations, without needing to engage in the resource-intensive activity of developing AI systems from the ground up.

6. CONCLUSION

The proliferation of AI in the digital age runs the risk of facilitating noxious ramifications to consumer protection and market competition. In advancing consumer protection and market competition rules, however, it is essential that Singapore's status as a hub for AI advancement is also considered. A safe general rule of thumb would be to proceed measuredly; make law in reference to proven or proximately imminent problems, and not far-fetched hypotheticals. If there is any government that could do it, it would be Singapore's.

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