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ALGORITHMIC CONSUMERS

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I. INTRODUCTION

Your automated car makes independent decisions on where to purchase fuel, when to drive itself to a service station, from which garage to order a spare part, or whether to rent itself out to other passengers, all without even once consulting with you. Another algorithm synchronizes health-related data from sensors placed on your pet with data from sensors placed in its food bag and data regarding pets' seasonal illnesses. When the pet food runs low, the algorithm automatically seeks the best deal and orders food of a kind which best fits your pet's needs.

Science fiction? No longer. The next generation of e-commerce, researchers say, will be conducted by digital agents based on algorithms that can handle entire transactions: from using data to predict consumers' preferences, to choosing the products or services to purchase, to negotiating and executing the transaction, and even automatically forming coalitions of buyers to secure optimal terms and condi-conditions.[1] Human decision- making could be completely bypassed. Such algorithms might be written by consumers for their own use or supplied by external firms.[2] We call these digital assistants "algorithmic consumers."

This is not a huge technological leap. The future is already here. In some industries, such as stock trading, algorithms already automatically translate their results into buying decisions.[3] Intelligent personal assistants, such as Google Assistant,[4] Amazon's Echo,[5] and Apple's

1. *See, e.g.*, Minghua He, Nicholas R. Jennings & Ho-Fong Leung, *On Agent-Mediated Electronic Commerce*, 15 IEEE TRANSACTIONS ON KNOWLEDGE & DATA ENGINEERING 985, 985–90 (2003).

2. *See, e.g.*, CHRISTOPHER STEINER, AUTOMATE THIS: HOW ALGORITHMS CAME TO RULE OUR WORLD (2012); Theo Kanter, TEDx Talks, *Ambient Intelligence*, YOUTUBE at 15:13 (Feb. 3, 2016), https://www.youtube.com/watch?v=1Ubj2kIiKMw [https://perma.cc/9VAU-P2Z2]; Don Peppers, *The Consumer of the Future Will Be an Algorithm*, LINKEDIN (July 8, 2013), https://www.linkedin.com/pulse/20130708113252-17102372-the-consumer-of-the-future-will-be-an-algorithm [https://perma.cc/ZW3G-23FQ].

3. A relatively early example involves two MIT Media Lab projects that date back to 2000–2002. Impulse and MARI (Multi-Attribute Resource Intermediary) were applications in which a shopper could set preferences for product types, prices, and other considerations (for example, availability of a warranty or manufacturer's reputation). The system negotiated with potential sellers and alerted the shopper if a deal was reached. Deals were concluded subject to the buyer's confirmation. S. Keegan, G.M.P. O'Hare & M.J. O'Grady, *Easishop: Ambient Intelligence Assists Everyday Shopping*, 178 INFO. SCI. 588, 589–90 (2008); Gaurav Tewari, Jim Youll & Pattie Maes, *Personalized Location-Based Brokering Using an Agent-Based Intermediary Architecture*, 34 DECISION SUPPORT SYS. 127, 127–30 (2002).

4. *Google Assistant*, GOOGLE, https://assistant.google.com/ [https://perma.cc/L44Q-QHE4].

5. Greg Miller, *Amazon Echo: The World's Smartest Assistant*, WALL STREET DAILY (Aug. 4, 2015, 4:00 AM), https://www.wallstreetdaily.com/2015/08/04/amazon-echo-assistant/ [https://perma.cc/9H3P-8EVU].

Siri,[6] perform tasks for individual users, based on users' inputs (such as scheduling constraints) and a variety of online sources (such as weather or traffic conditions). Consumers can already purchase a washing machine from the W9000 series developed by Samsung and IBM, which uses IBM's ADEPT (Autonomous Decentralized Peer-to-Peer Telemetry) technology to make autonomous orders and payments (like buying detergent) and then update the owner via a smartphone.[7] This technology, revealed in 2015, exemplifies what is known as the Internet of Things ("IoT"), whereby connected devices automatically handle myriad day-to-day tasks.[8] With the advent of these technological changes, many people envisage that algorithmic consumers will become the rule rather than the exception for an exponentially increasing number of transactions — realizing a vision of a world where "humans do less thinking when it comes to the small decisions that make up daily life."[9]

Algorithmic consumers have the potential to dramatically change the way we conduct business, as well as the competitive dynamics of the market. Consumers in this ecosystem do not make purchasing decisions directly, but instead outsource such tasks to algorithms, thereby minimizing the direct role they play in purchasing decisions. The use of algorithmic consumers also affects market demand and trade conditions. This is partly because algorithmic consumers can significantly reduce search and transaction costs, help consumers overcome biases and enable more rational and sophisticated choices, and create or strengthen buyer power. More importantly, algorithms may even influence consumer purchasing decisions, potentially distancing them from the subjective choices of individual users. Such effects may have profound impacts on market demand, as well as on suppliers' marketing strategies, trade terms, and product offers.

These developments raise new and important conceptual and regulatory issues. Indeed, some of the most fundamental conceptions about how markets operate may need to be reevaluated. Will it still

6. Sheetal Reehal, *Siri — The Intelligent Personal Assistant*, 5 INT'L J. ADVANCED RESEARCH IN COMPUTER ENGINEERING & TECH. 2021, 2021 (2016).

7. Stan Higgins, *IBM Reveals Proof of Concept for Blockchain-Powered Internet of Things*, COINDESK (Jan. 17, 2015, 7:12 PM), http://www.coindesk.com/ibm-reveals-proof-concept-blockchain-powered-internet-things [https://perma.cc/4UE5-77WU]; IBM INSTITUTE FOR BUSINESS VALUE, IBM, *ADEPT: AN IOT PRACTITIONER PERSPECTIVE* 13 (Draft Copy for Advance Review, Jan. 7, 2015), http://www.scribd.com/doc/252917347/IBM-ADEPT-Practictioner-Perspective-Pre-Publication-Draft-7-Jan-2015 [https://perma.cc/87UL-ZPT6].

8. *See* OECD, DSTI/ICCP/CISP(2015)3/FINAL, THE INTERNET OF THINGS: SEIZING THE BENEFITS AND ADDRESSING THE CHALLENGES 9 (May 24. 2016).

9. Danny Yadron, *Google Assistant Takes on Amazon and Apple to Be the Ultimate Digital Butler*, THE GUARDIAN (May 18, 2016, 2:17 PM), https://www.theguardian.com/technology/2016/may/18/google-home-assistant-amazon-echo-apple-siri [https://perma.cc/EZ4V-79HY].

make sense, for example, to speak about consumer choice when preferences are defined, predicted, and shaped by algorithms? How will market demand and supply be affected? Regulators must reevaluate their tools to deal more effectively with market and regulatory failures that may arise in this ecosystem. Such issues will soon become fundamental for e-commerce, making an examination of the posed regulatory challenges essential and timely.[10]

Despite these potentially game-changing technological developments, most of the literature on commercial algorithms focuses on the use of algorithms by suppliers (such as Google, Uber, Amazon, and Target).[11] Much of this literature emphasizes the role of algorithms in collecting and analyzing information about consumers' preferences, enabling firms to better compete for their attention and to create more efficient and profitable marketing campaigns.[12] Another stream of literature deals with the potential use of algorithms to more easily facilitate collusion or oligopolistic coordination among suppliers.[13] Interest in consumers is mainly restricted to their role as a resource for information ("consumers as products") and as a target for marketing campaigns.[14] The sparse literature on the use of algorithms by consumers has treated them as tools to help consumers compare price and quality, predict price and market trends, make expedient decisions under uncertain conditions, make better-informed choices, and strengthen competitive pressure overall.[15] This literature disregards the possibility that at a certain point consumer deference to algorithms may result in those algorithms bypassing consumer input altogether.

Our Article seeks to fill this void. We address the changes in market dynamics that can be expected given imminent technological developments, as well as the implications for regulation of a reality in which consumers routinely make purchasing decisions via algorithms.[16] In particular, we ask whether human consumers may benefit from what algorithmic consumers have to offer and what kind of regu-

10. *See* Kevin D. Werbach, *The Song Remains the Same: What Cyberlaw Might Teach the Next Internet Economy*, 69 FLA. L. REV. (forthcoming 2017) (manuscript at 30–31), *available at* https://papers.ssrn.com/sol3/papers2.cfm?abstract_id=2732269 [https://perma.cc/2QJQ-X5TY].

11. For the seminal article see Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition* (Univ. of Oxford Ctr. for Competition Law & Policy, Working Paper No. CCLP(L)40, Univ. of Tenn. College of Law, Research Paper 267, May 2015). *See also* ARIEL EZRACHI & MAURICE E. STUCKE, VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY 11–21 (2016).

12. *Cf.* David Evans, *Attention Rivalry Among Online Platforms*, 9 J. COMPETITION L. & ECON. 313, 313–15 (2013).

13. Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 2.

14. *See* Evans, *supra* note 12, at 313–14.

15. EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 11, at 191–202.

16. *See also* Werbach, *supra* note 10, at 42.

lation, if any, is needed in order to ensure that users are not harmed by the coming changes.

Part II first explores the potential benefits and harms of algorithmic consumers, and the way these advances affect the competitive dynamic in the market is explored in Part III. Such an exploration is essential to articulate the changes introduced by this new technology. Part IV then analyzes the implications of such technological advances on regulation, with a special focus on the tools needed to ensure that algorithmic consumers bring about the benefits they promise. In particular, we identify three main regulatory challenges that arise in this regard: reducing barriers to reaching consumers; reducing barriers to access to relevant data; and dealing with exclusionary conduct by competing algorithms via conduct such as bundling, price parity, or exclusivity contracts.

II. TECHNOLOGICAL BACKGROUND

How do algorithmic consumers affect other consumers' choices? How, if at all, does the algorithm's decisional procedure differ from human purchasing decisions? This Part explores these questions in light of technological changes that have facilitated a much wider and more sophisticated use of algorithmic consumers.

A. What are Algorithmic Consumers?

Algorithms are structured decision-making processes that employ a set of rules or procedures, such as a decision tree, to automatically supply outcomes based on data inputs and decisional parameters.[17] In a broad sense, we all use algorithms in our daily lives. For example, when people decide what to eat, they use data inputs (for example, how hungry I am, what foods are available, how healthy or tasty each option is) and weigh each one in order to reach an outcome that most accords with their preferences (for example, I'll have the salad even though the chocolate cake looks more appealing, because I want to eat something healthy).

Coded algorithms do the same. They use a predetermined decision tree which assigns weights to decision parameters in order to suggest the optimal decision given a particular set of data and circumstances.[18] The decision parameters and their weights are set by algorithms' designers so as to optimize users' decisions. More advanced algorithms employ machine learning, the process by which an algorithm learns from its own analyses of previous data how to refine and

17. *See, e.g.*, THOMAS H. CORMEN, CHARLES E. LEISERSON, RONALD L. RIVEST & CLIFFORD STEIN, INTRODUCTION TO ALGORITHMS 5 (3rd ed. 2009).

18. *See, e.g.*, *id.* at 192–93, 843–49.

redefine its decision parameters (for example, determining each consumer's optimal level of risk aversion),[19] freeing the algorithm from predefined preferences. For instance, based on a consumer's past actions an algorithm may conclude that the consumer likes to purchase products similar to those bought by her close friends, and change the decisional parameters accordingly.

A wide variety of algorithms already help consumers make decisions in market transactions. At the most basic level, algorithms offer consumers information relevant to their choices. Some simply collect and organize relevant information provided by suppliers, such as Kayak, Expedia, and Travelocity, which offer information on flight prices and schedules. Others offer information about quality, such as rating services TripAdvisor and Yelp. More sophisticated algorithms use data analytics to enable price forecasting.[20] Still others use consumers' characteristics and past revealed preferences to narrow down the options, presenting only those assumed to be most relevant, such as is done by online dating services OKCupid and Tinder. Such algorithms serve as tools to enhance consumer choice by aggregating and organizing relevant data so as to help the consumer make an informed decision. But the ultimate decision is still made by the consumer, based on the information provided.

The new generation of consumer algorithms can take such services a step further, making and executing decisions for the consumer by directly communicating with other systems through the Internet. The algorithm could automatically identify a need, search for an optimal purchase, and execute the transaction. In the pet food example, a specialized algorithm would collect data from the pet and its food bag to determine whether it is time to replenish the supply, and could also consider the actual nutritional needs of the particular pet. Decisional parameters to be included in the algorithm may also include real-time data predicting seasonal disease risks, temporary shortages of ingredients, and predictable price changes. Once a choice has been made, based on the data analysis, the algorithm may automatically make an order and arrange for payment and delivery,[21] with the assistance of intelligent online software agents ("shopping bots").[22]

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19. *See, e.g.*, OECD, DATA-DRIVEN INNOVATION FOR GROWTH AND WELL-BEING: INTERIM SYNTHESIS REPORT 4 (2015). For examples of machine learning already used in algorithms, see Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 2.

20. For example, Decide.com was a web service that forecasted the likelihood and the amount that the price of a certain product would change in the near future. *See, e.g.*, Sarah Perez, *Decide.com's Shopping Engine Now Tells You What to Buy, Not Just When to Buy It*, TECHCRUNCH (July 31, 2012), https://techcrunch.com/2012/07/31/decide-coms-shopping-engine-now-tells-you-what-to-buy-not-just-when-to-buy-it/ [https://perma.cc/ABF9-DEAH].

21. *See* Mike Power, *What Happens When a Software Bot Goes on a Darknet Shopping Spree?*, THE GUARDIAN (Dec. 5, 2014, 8:56 AM),

A recent and provocative example of such a shopping bot involves the Random Darknet Shopper, which was used in an art project displayed at a gallery in St. Gallen, Switzerland in 2015.[23] For the duration of the exhibition, the artists gave the bot a weekly budget of $100 and sent it to shop on the Darknet[24] — a network of unindexed and typically anonymous online black markets.[25] The bot chose items and had them sent to the artists by mail, without the artists knowing in advance what would be purchased; the ordered items were then displayed in the exhibition.[26]

This rise of algorithmic consumers is facilitated and accelerated by the combined effect of technological capabilities and consumer demand. Technological advances in artificial intelligence, big data collection, storage, and analytics have made algorithms much more convenient and powerful than ever before.[27] Meanwhile, the exponentially increased volume of data available,[28] which challenges the human cognitive capacity to process the relevant information, has made the ability of algorithms to sort through relevant data ever more important.[29] Demand for such services is also increasing because they free up time for consumers to handle matters that truly require human discretion, such as time spent on work, family, and friends. The idea of relying on another's choice is not new. Book clubs, which choose and send their members a book each month, illustrate this type of relationship. Algorithmic consumers simply replace humans in making such choices.

Figure 1 depicts the decision-making process of algorithmic consumers. We suggest that algorithmic consumers can be involved in all stages of the transaction.

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https://www.theguardian.com/technology/2014/dec/05/software-bot-darknet-shopping-spree-random-shopper [https://perma.cc/AL93-HT33].

22. *See* Prashant R Nair, *E-Supply Chain Management Using Software Agents*, CSI COMM., July 2013, at 14 ("The intelligence of an agent refers to its ability of performing tasks or actions using relevant information gathered as part of different problem-solving techniques such as influencing, reasoning, and application specific knowledge. Agents can behave autonomously or proactively.").

23. Power, *supra* note 21.

24. *Id.*

25. *See Primer on DarkNet Marketplaces: What They Are and What Law Enforcement Is Doing to Combat Them*, FBI (Nov. 1, 2016), https://www.fbi.gov/news/stories/a-primer-on-darknet-marketplaces [https://perma.cc/7N2W-4HLK].

26. Items purchased by the bot included ten ecstasy pills, a baseball cap-mounted hidden camera system, a fake Louis Vuitton handbag and 200 Chesterfield cigarettes. The exhibits were seized by authorities after the exhibition closed. Power, *supra* note 18.

27. *See, e.g.*, EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 11, at 11–21.

28. *See, e.g.*, Yun Wan, *The Evolution of Comparison-Shopping Agents*, *in* AGENT SYSTEMS IN ELECTRONIC BUSINESS 25, 26 (Eldon Y. Li & Soe-Tsyr Yuan eds., 2008).

29. *See* NIVA ELKIN-KOREN & ELI M. SALZBERGER, LAW, ECONOMICS AND CYBERSPACE: THE EFFECTS OF CYBERSPACE ON THE ECONOMIC ANALYSIS OF LAW 70, 94–96 (2004) (arguing that while the costs of retrieving information in cyberspace may fall, the cognitive barriers on individual choice are likely to become stronger).

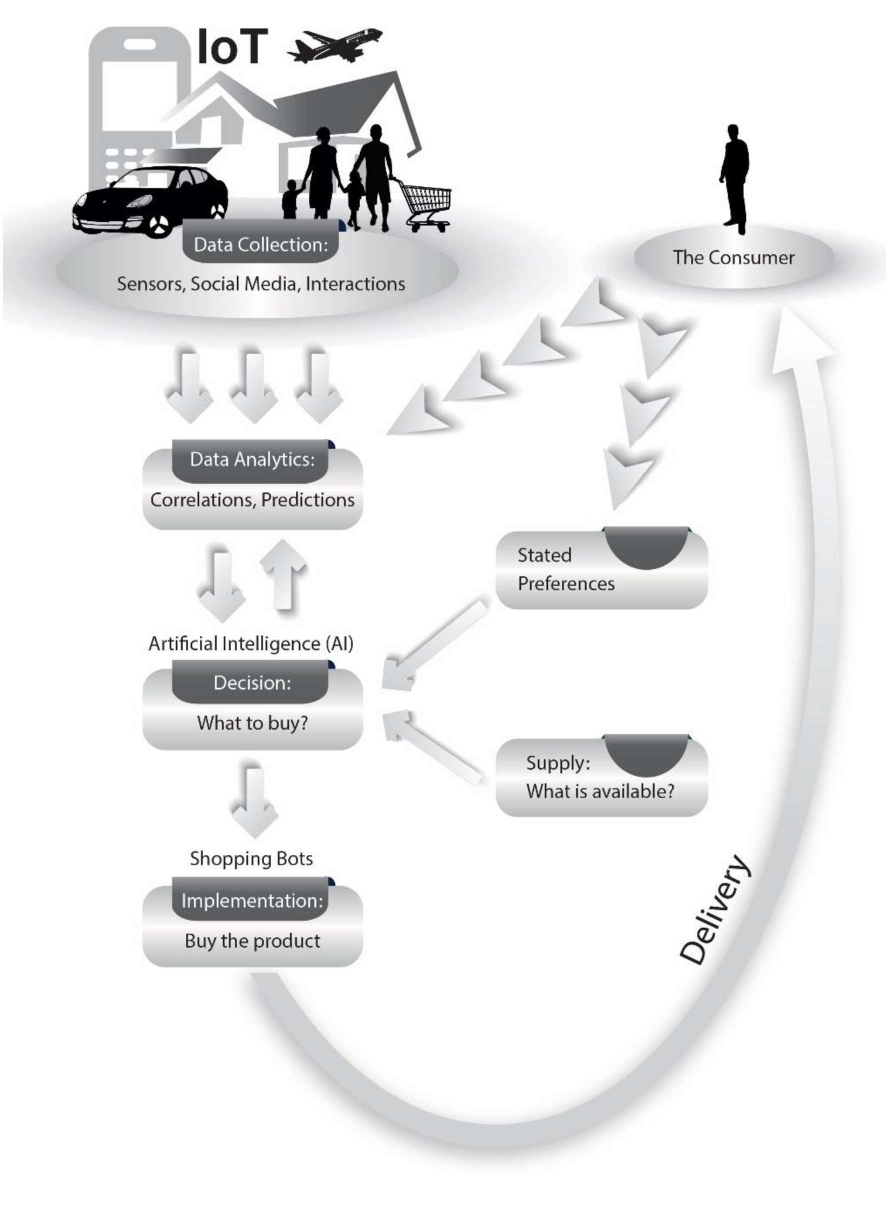

Figure 1: Decision-Making Process of Algorithmic Consumers

The first stage involves data collection, which is necessary to determine the consumer's needs and preferences, and to identify available purchase options. Data can come directly from the user in the form of explicitly stated preferences or from specialized sensors (for example, wearable sensors such as Fitbit). It can also come from diverse external data sources, including suppliers' websites, social media, video-sharing sites, sensors, and user data ancillary to online performance (such as transactions, email correspondence, searches, and reading habits). The relevant data is collected, updated, stored, and organized to provide an informed, accurate, and comprehensive data set needed for the next step. It is noteworthy that the same data used by suppliers to determine consumers' preferences can also be integrated into the algorithmic consumer's decision tree to make decisions that better serve the consumer.

The second step is data analytics, in which the algorithm analyzes the relevant data to identify consumer preferences and to establish and compare the purchase options in any given situation. The data analyzed will potentially include consumers' personal data. For example, a consumer's recent adoption of a second pet may lead to a prediction that the consumer's need for pet food will double. Analysis may also involve data from other sources to make better choices, such as the special needs of the breed of the adopted pet.

The third step is decision-making. Purchasing decisions are made in accordance with the algorithm's decision tree based on the data analysis performed in the previous step. The consumer's needs, stated and/or revealed preferences, as well as the information about supply options is combined. The purchasing decision may then be fed back into the database, in order to ensure that future decisions are compatible with it.

The final stage is implementation**.** The algorithm may employ and direct shopping bots to perform all stages of the transaction, including negotiating a deal, placing the order, signing a contract, paying, and arranging delivery.

None of the foregoing implies that human shopping will completely disappear. In fact, the act of shopping fills important needs, at least for some consumers, including social interaction and the pleasure to be had from choosing a specific product, like a piece of jewelry.[30] Nonetheless, even consumers who enjoy shopping may prefer to employ algorithmic consumers for certain more mundane products, like pet food. Some might even prefer to have algorithms make all of their consumption decisions.

30. *See, e.g.*, Yiannis Gabriel, *Identity, Choice and Consumer Freedom — The New Opiates? A Psychoanalytic Interrogation*, 15 MARKETING THEORY 25, 27 (2015) (consumer choice has become an opiate for contemporary society, since consumption and consumerism offer immediate gratification, compensating for discontents arising from the lack of control over many aspects of life).

B. The Benefits and Risks of Algorithmic Consumers

Despite the overall similarity between the decision-making processes of humans and algorithms, algorithms differ from human decision makers in important ways. As we shall see, while algorithmic consumers reduce, and sometimes even eliminate, some limitations on consumers, they exacerbate other types of limitations.[31] Identifying these differences is necessary to explore their potential implications for market dynamics and social welfare, and to design appropriate regulatory responses. These differences are outlined below.

1. Virtues of Algorithmic Consumers

Consumer choice involves several steps: determining the parameters for the decision; comparing available options based on those parameters; making a choice; and transacting with the chosen supplier. As elaborated below, algorithms may reduce the costs and increase the quality of each of these steps by potentially making speedier, more sophisticated, less expensive, and less biased purchasing decisions.

The most basic advantage of algorithms is that they enable a speedier decision. Given any number of decisional parameters and data sources, computers can apply the relevant algorithm far more quickly than the human brain, especially if the decision tree involves a large number of decision parameters that need to be balanced or many data inputs that must be analyzed or compared. Assume, for example, that it is worth a consumer's while to spend up to two hours finding the best deal for a certain product. If she has to locate the relevant information herself, she might be able to check and compare some number of offers. An algorithm may be able to compare a vastly greater number of offers in the same time. Automatic acceptance of the algorithm's suggestion saves the consumer even more time. This might be especially important in some transactions, such as trading in the stock market or booking a soon-to-depart flight. Furthermore, many consumers will presumably prefer enjoying free time to spending time on decisions that are not financially or otherwise meaningful.

A second advantage of algorithms involves their analytical sophistication. Advances in data collection, storage, synthesis, and analysis have ushered in the age of big data, which enables algorithms to integrate numerous variables into their decision tree. This provides a

31. Note that some of the characteristics explored below also relate to algorithms that only perform the search function and do not execute the transaction. Observe, however, that the more reliable the searches performed by algorithms, the stronger consumers' incentives may be to rely on them without checking the accuracy of their suggestions, effectively using them as algorithmic consumers. Therefore, the benefits of better searching by algorithms are relevant to our analysis.

level of sophistication that usually cannot be achieved by the human mind alone. It is not that humans cannot perform these tasks, but it might not be worth their while to do so, given the time and effort involved. An interesting example is Farecast, an algorithm that predicted price changes in flight costs with an accuracy above 70% — a feat it accomplishes by analyzing fifty billion previous airfare data inputs.[32]

Artificial intelligence tools for machine learning, data mining, online analytical processing, business performance management, benchmarking, and predictive analytics also strengthen the algorithm's analytical capabilities. Interestingly, such data analytics tools might identify preferences of which consumers themselves are unaware. For example, a consumer thinks her budget goes mainly toward healthy food, but in fact she spends a lot of money on chocolate. It might also enable the algorithm to identify, and even predict, a consumer's future preferences. If a consumer likes to follow certain social trends, for example, the algorithm may identify this behavioral pattern as well as the trends that emerge from the relevant data. Data scientists indeed argue that algorithms can teach us things we don't know about ourselves.[33] As Google's chief economist, Hal Varian, recently explained in relation to Google's personal algorithmic-based assistant, Google Now, "[Google] should know what you want and tell it to you before you ask the question."[34]

Sophistication can also relate to additional parameters in the decision-making process, thereby expanding the dimensions of offers to be compared. For example, algorithms may analyze offers in languages that the consumer does not understand and identify legal problems that she might overlook.[35] Indeed, algorithms can potentially "read" contractual terms, thereby avoiding at least some contractual limitations that human consumers might fall into due to time, language, or information constraints.[36] Similarly, algorithms might more easily cope with cultural differences in transacting.

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32. *See* Damon Darlin, *Airfares Made Easy (or Easier)*, N.Y. TIMES, July 1, 2006, http://www.nytimes.com/2006/07/01/business/01money.html [https://perma.cc/2ZPF-FWK7].

33. *Cf.* James Max Kanter & Kalyan Veeramachaneni, *Deep Feature Synthesis: Towards Automating Data Science Endeavors*, *in* IEEE INT'L CONF. ON DATA SCI. & ADVANCED ANALYTICS 7 (2015) (reporting on an experiment in which the algorithm better predicted human behavior than humans).

34. Hal R. Varian, *Beyond Big Data*, 49 BUS. ECON. 27, 28 (2014).

35. For an example of a methodology and technical tool using natural language processing to identify and measure ambiguity in website privacy policies, see Joel R. Reidenberg, Jaspreet Bhatia, Travis D. Breaux & Thomas B. Norton, *Ambiguity in Privacy Policies and the Impact of Regulation*, 45 J. LEGAL STUD. S163, S165–77, S183–84 (2016).

36. *See* OREN BAR-GILL, SEDUCTION BY CONTRACT: LAW, ECONOMICS AND PSYCHOLOGY IN CONSUMER MARKETS 18–19 (2012); OMRI BEN-SHAHAR & CARL E. SCHNEIDER, MORE THAN YOU WANTED TO KNOW: THE FAILURE OF MANDATED DISCLOSURE 7–9 (2014); Yannis Bakos, Florencia Marotta-Wurgler & David R. Trossen,

Interestingly, algorithms need not apply only to one product or group of products, but might help consumers make parallel decisions with regard to a large number of products, choosing among them in keeping with given preferences and a given budget. Algorithms might even calculate for the consumer the minimal budget needed for a certain lifestyle, thereby affecting consumers' choices with regard to the number of hours they work (for example, of overtime or on freelance projects).

Third, algorithms can reduce information and transaction costs. This can occur at any stage of the decision-making process. Let us illustrate this with the first stage of the process, determining the parameters for the decision. Many tools exist to aid this stage. For example, the algorithm can offer each consumer a menu of decision parameters to choose from.[37] But more importantly, as noted above, algorithms can autonomously define the decision parameters for each consumer, based on the preferences manifested through her actions. Such technology has already been used by some online retailers, such as Amazon, which makes marketing suggestions based on past purchases and items determined to be similar to those past purchases.[38] The dating site OKCupid refines consumer choices based on answers to questions designed to calculate compatibility between dating mates,[39] and Pandora refines its selection of songs for each consumer based on her past preferences (a process called "self-customization").[40] An algorithm need not know consumers' precise preferences; often, data regarding relative choices would be sufficient; for instance, an algorithm could use the rule: A is preferred to B, B is preferred to C, and thus A is preferred to C.[41] These techniques reduce informational costs. Costs can be further reduced if a similar search is performed for more than one consumer. Such searches need not be

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Does Anyone Read the Fine Print? Consumer Attention to Standard-Form Contracts, 43 J. LEGAL STUD. 1, 4 (2014); Florencia Marotta-Wurgler, *Does "Notice and Choice" Disclosure Regulation Work? An Empirical Study of Privacy Policies* 5 (Univ. of Mich. Law Sch., Law & Econ. Workshop, Apr. 16, 2015), https://www.law.umich.edu/centersandprograms/lawandeconomics/workshops/Documents/Paper13.Marotta-Wurgler.Does%20Notice%20and%20Choice%20Disclosure%20Work.pdf [https://perma.cc/QR2F-XNJV].

37. For example, dating sites request the user to determine what decisional parameters are most important to him in choosing who to date.

38. Greg Linden, Brent Smith & Jeremy York, *Amazon.com Recommendations Item-to-Item Collaborative Filtering*, 7 IEEE INTERNET COMPUTING 76, 78–79 (2003).

39. Christian Rudder, TEDEd, *Inside OKCupid: The Math of Online Dating*, YOUTUBE at 2:50 (Feb. 13, 2013), https://www.youtube.com/watch?v=m9PiPlRuy6E [https://perma.cc/S2FD-BGCM].

40. Barb Gonzales, *How Pandora Creates Stations and How to Customize Them*, LIFEWIRE, (Sep. 6, 2016), https://www.lifewire.com/how-pandora-creates-stations-1847393 [https://perma.cc/H3BA-BTP8].

41. For a discussion of relational preference handling by algorithms, see, e.g., Ronen I. Brafman, *Relational Preference Rules for Control*, 175 ARTIFICIAL INTELLIGENCE 1180, 1180–81 (2011).

simultaneous, since the algorithm may be able to cache the results for future use. Also, the algorithm's capacity to perform its task is limited only by technology; it is never tired or stressed.

Fourth, algorithms can avoid consumer biases. As numerous studies have shown, humans suffer from biases that lead to non-optimal decisions. Consumers are often swayed by non-relevant factors such as the color of a product's packaging, or information they have just heard.[42] Indeed, human choice is often constructed ad hoc during a choice and shaped by context-specific factors.[43] These factors need not affect the algorithm, unless, of course, we choose to include them in the decision tree. Algorithms can also avoid biases based on routine. For example, a consumer always buys one kind of pet food without checking whether alternatives better meet her needs.

Similarly, algorithms may overcome manipulative marketing techniques, which "play upon people's insecurities, frailties, unconscious fears, aggressive feelings and sexual desires to alter their thinking, emotions and behaviour."[44] For example, an algorithmic consumer will not be tempted into buying chocolate from the display stand next to the cashier just because it cannot fight the temptation. Nor will it be subject to "subliminal stimulation."[45] Furthermore, it will not be subject to at least some elements of what some call the "new mind control" — manipulations by social media and websites.[46] This is not to say, of course, that algorithms might not be subject to new forms of manipulation, some of which could be avoided by human purchasers.[47]

Additionally, the ability to automatically translate the algorithm's choice into a positive action may generate some positive psychologi-

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42. *See, e.g.*, Jesper Clement, *Visual Influence on In-store Buying Decisions: An Eye-track Experiment on the Visual Influence of Packaging Design*, 23 J. MARKETING MGMT. 917–18 (2007) ("90% [of consumers] make a purchase after only examining the front of the packaging and without having the product in the hand"); *see also* Milica Milosavljevic, Vidhya Navalpakkam, Christof Koch & Antonio Rangel, *Relative Visual Saliency Differences Induce Sizable Bias in Consumer Choice*, 22 J. CONSUMER PSYCHOL. 67, 67 (2012); Rita Kuvykaite, Aiste Dovaliene & Laura Navickiene, *Impact of Package Elements on Consumer's Purchase Decision*, 15 ECON. & MANAGEMENT 441, 441, 446 (2015).

43. *See, e.g.*, THE CONSTRUCTION OF PREFERENCE 1–2 (Sarah Lichtenstein & Paul Slovic eds., 2006). For a specific example of bias and how it affects competition and welfare, see Michal S. Gal & Daniel L. Rubinfeld, *The Hidden Costs of Free Goods: Implications for Antitrust Enforcement*, 80 ANTITRUST L.J. 521, 528–540 (2016).

44. Robert Epstein, *The New Mind Control*, AEON (Feb. 18, 2016), https://aeon.co/essays/how-the-internet-flips-elections-and-alters-our-thoughts [https://perma.cc/VQ3S-TU3H]; *see also* Ryan Calo, *Digital Market Manipulations*, 82 GEO. WASH. L. REV. 995, 1010 (2014) (big data increases the ability to detect and manipulate consumer's vulnerabilities).

45. Epstein, *supra* note 44. Unless, of course, it relies on data created by humans who do have these biases.

46. *Id.*

47. *See infra* Section II.B.2. This may happen if the algorithm's vulnerabilities are known and are exploited by suppliers.

cal effects. For example, the fact that consumers do not need to engage in some otherwise burdensome decisions may increase their level of happiness.[48] Finally, the fact that the algorithm operates au-automatically can increase the use of online options by consumers who fear the Internet, or who do not know how to take advantage of online purchase opportunities. It thereby increases equality among consumers.

2. New Harms and Risks

Algorithmic consumers might also generate new harms and risks, such as: limiting consumer choice and autonomy; increasing consumers' vulnerability to inefficient decisions made on their behalf and to cyber-security harms; and creating negative psychological and social implications.

As we elaborate elsewhere, one major implication of using algorithmic consumers is a reduction in consumers' autonomy.[49] The new generation of algorithms distances consumers from actual purchase choices. The consumer voluntarily gives up the ability to affect the final purchasing decision, beyond determining which algorithm to use and possibly selecting which decision parameters to apply. That is, while the consumer chooses the algorithm, the algorithm selects the product, so the consumer is always one step removed from the consumption decision.

One may contend that the consumer is exercising her autonomy at a higher level by choosing which algorithm to use. Moreover, algorithms can be designed to allow the consumer to intervene at any step of the process, from changing the decision parameters (for instance, whether the color of the package matters) to potentially declining the algorithm's suggestion. Yet much depends on the algorithm's transparency to the consumer. The algorithm could be a black box — a credence good[50] — especially if machine learning is applied to shape the algorithmic choice or if the decision-making process involves complex trade-offs. The consumer's motivation as well as ability to verify that the algorithm's decision best promotes her preferences may

48. *See, e.g.*, Barry Schwartz, TED Talks, *The Paradox of Choice*, YOUTUBE at 8:00 (Jan. 16, 2007), https://www.youtube.com/watch?v=VO6XEQIsCoM [https://perma.cc/NC2P-4BHV].

49. *See* Michal S. Gal, Technological Challenges to Choice 24 (Feb. 19, 2017) (unpublished manuscript) (on file with the HARV. J.L. & TECH.).

50. A credence good is defined as a type of good with qualities that cannot be observed by the consumer after purchase, making it difficult to assess its utility. *See* Uwe Dulleck & Rudolf Kerschbamer *On Doctors, Mechanics, and Computer Specialists: The Economics of Credence Goods*, 44 J. ECON. LITERATURE 5, 5–6 (2006). Typical examples include expert services such as medical procedures and automobile repairs and goods such as dietary supplements. *See id*. at 6.

also be low.[51] In most cases, consumers will display a pattern of conduct similar to that seen in relation to online contracts: accepting the algorithmic choice as default, without delving into the details and checking whether an optimal choice was made.[52]

A related limitation involves consumer choice. The algorithmic choice may not always accurately reflect consumers' preferences. To establish the significance of this welfare challenge, we offer some examples of constructed consumer choices that do not reflect their true preferences. One reason is inherent limitations of computer coding. For instance, algorithms might not (as of yet) be able to recognize and relate to certain nuances that humans intuitively understand. While such nuances might not be important in many transactions, they could be essential in others. Accordingly, most of us would probably not want an algorithm to automatically choose our partner in business or in life, and possibly also not our wedding ring.

Alternatively, the algorithmic decision might be based on incorrect assumptions embedded in the code by the designer (for example, the assumption that one's preference for a certain type of pet treat last week implies the same preference this week); or it may arise from the algorithm's data analysis. As suggested by Solon Barocas, Sophie Hood, and Professor Malte Ziewitz, "algorithms embody a profound deference to precedent," drawing on past behavior to predict future preferences.[53] Consequently, demand as set by the algorithmic consumer might be, at least to some extent, more self-perpetuating and path-dependent than human-based demand would otherwise be.[54] Furthermore, even if the algorithm recognizes and attempts to follow a consumer's behavioral pattern for sometimes making a completely different choice (for instance, today I wish to wear pink and orange), it will be difficult for it to establish when exactly to suggest such a choice to the consumer. Such path dependence may be strengthened by two additional effects. First, if the algorithm's decisions are fed back into the database, the consumer's path dependence will be further reinforced. Second, if algorithmic choices indirectly affect other consumers' choices, whether they are made through an algorithmic consumer or not, then incorrect choices may be further perpetuated and intensified.

This vulnerability to biases and errors embedded in the code or drawn from the data is not easily overcome. A consumer who is unaware of such assumptions will likely also be unaware of any choices

51. Interestingly, other algorithms might also be created to perform this task.

52. *See* BEN-SHAHAR & SCHNEIDER, *supra* note 36, at 10.B

53. Solon Barocas, Sophie Hood & Malte Ziewitz, *Governing Algorithms: A Provocation Piece*, *in* GOVERNING ALGORITHMS 8 (Mar. 29, 2013), http://governingalgorithms.org/resources/provocation-piece/ [https://perma.cc/D2YN-ES7K].

54. *Id.*

she has forgone. This type of failure, involving unknown unknowns, is likely to be difficult to fix. Consumers may find it increasingly difficult — or not worth their time — to exercise oversight over sophisticated and opaque systems.[55] Further, as algorithms become more complicated, even the coders might not completely understand the algorithm's decisional parameters.[56] In some cases, nonetheless, deference to human choice by changing the parameters for the algorithm's choice may limit such vulnerabilities (for example, instructing the algorithm to buy another dog treat today).

Another potential problem created by algorithmic consumers is the increased vulnerability of the consumer to certain harms. One major concern is vulnerability to the risks associated with the digital world in areas like privacy and cyber-security. Algorithmic consumer systems are likely to collect, record, and aggregate immense volumes of personal data.[57] Security failures may allow access of unauthorized parties to private data, which may then be used without consumers' consent.

Additional concerns abound, including manipulation and control of consumers' choices by the algorithm's designer or owner, further elaborated in the next Part. So far, we have assumed that the algorithm has only the consumer's best interests at heart. But at least in some instances, algorithms might be manipulated in ways which do not necessarily promote the consumer's welfare. As Facebook recently demonstrated in a controversial experiment on emotional contagion, algorithms may even shape the way we feel.[58] When human judgment is replaced by non-transparent code, consumers are harder pressed to protect themselves against such manipulation due to their inability to understand, decipher, and challenge algorithms.

The use of algorithmic consumers may also carry with it potentially negative psychological implications. Will consumers necessarily be happier in a world in which most decisions are made for them by machines? How will people feel about purchasing decisions made on

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55. *See, e.g.*, Elizabeth Nixon & Yiannis Gabriel, *'So Much Choice and No Choice at All': A Socio-Psychoanalytic Interpretation of Consumerism as a Source of Pollution*, 16 MARKETING THEORY 39, 46–47 (2015) (some consumers can view the marketplace as "draining" and a source of "physiological ill health").

56. Facebook provides an interesting example: The firm reportedly had difficulty changing the parameters of its own news feeds because so many coders were involved in the creation of its algorithm. *Cf.* Bernhard Rieder, *Studying Facebook via Data Extraction: The Netvizz Application*, *in* PROC. OF THE 5TH ANN. ACM WEB SCI. CONF. 346 (2013).

57. *See, e.g.*, Shoshana Zuboff, *Big Other: Surveillance Capitalism and the Prospects of an Information Civilization*, 30 J. INFO. TECH. 75, 78–79 (2015).

58. Adam D. I. Kramer, Jamie E. Guillory & Jeffrey T. Hancock, *Experimental Evidence of Massive-scale Emotional Contagion Through Social Networks*, 111 PROC. NAT'L ACAD. SCI. 8788, 8788–90 (2014); *see also* Vindu Goel, *Facebook Tinkers with Users' Emotions in News Feed Experiment, Stirring Outcry*, N.Y. TIMES (June 29, 2014), https://www.nytimes.com/2014/06/30/technology/facebook-tinkers-with-users-emotions-in-news-feed-experiment-stirring-outcry.html [https://perma.cc/V49G-TJMZ].

their behalf when they do not know or understand the parameters used? And what will consumers do with their spare time? How will they be affected by the loss of the social interactions that often accompany shopping? Such matters are beyond our expertise, but our intuition suggests that the effect on well-being might not all be positive, even if our lives are more efficient and the "correct" decisions are made.

Finally, algorithms can accelerate economic and political inequality: "Those who own the robots and the tech are becoming the new [landlords]."[59] Indeed, as elaborated in Sections III.A and III.B below, once algorithms become important market mediators connecting between suppliers and consumers, their creators or operators can potentially (ab)use their market power in order to increase their profits at the expense of consumers or even suppliers.[60]

Some of the effects elaborated above — positive and negative — might be further strengthened by the use of robots and smart devices. Technological developments in robotics already enable machines to perform many more actions than ever before in many spheres, including in homes and offices. In our pet food example, once the pet food has been delivered to the consumer's doorstep, a robot might collect it and put it in the cupboard, freeing the consumer from even this task. Engineers envisage that as technology develops further, the abilities of personal-use robots will be largely determined by their software rather than their hardware, as has occurred with smartphones.[61] Smart devices may also facilitate enforcement of contractual obligations in the digital world, thereby further limiting the need for human intervention.[62]

III. EFFECT ON MARKET DYNAMICS AND ON WELFARE

The above analysis shows that algorithmic consumers create a host of intriguing effects, many of which hold promise to benefit consumers. In this part of the paper we explore the market dynamics created by algorithmic consumers — the causal links among algorithms,

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59. Izabella Kaminska, *Time to Take Basic Income Seriously?*, FT ALPHAVILLE (June 17, 2013), http://ftalphaville.ft.com/2013/06/17/1536022 [https://perma.cc/A93V-XLUA].

60. The ability of a supplier or group of suppliers to maintain price above the price that would exist in a competitive market is referred to as market power. William M. Landes & Richard A. Posner, *Market Power in Antitrust Cases*, 94 HARV. L. REV. 937, 937 (1981).

61. *See, e.g.*, Chris Anderson, MAKERS: THE NEW INDUSTRIAL REVOLUTION 17–18 (2012) (explaining how the creation and design of physical goods is becoming increasingly software based); Mark A. Lemley, *IP in a World Without Scarcity*, 90 N.Y.U. L. REV. 460, 480–481 (2015).

62. *See, e.g.*, Varian, *supra* note 34, at 30 ("What happens if [a car buyer] stop[s] sending in the monthly payments? . . . Nowadays it's a lot easier just to instruct the vehicular monitoring system not to allow the car to be started and to signal the location where it can be picked up.").

competition, market players, and social welfare — in order to determine whether we can rely on the market to bring about the potential benefits and limit the harms of these developments. The analysis will also aid us in locating market and regulatory failures, an essential prerequisite for regulatory policy, which is the focus of Part IV.

To explore the numerous effects of algorithmic consumers on market dynamics, we start with a simple case, which assumes that markets are competitive, and gradually relax this assumption. We also assume that algorithmic consumers are provided and controlled by external firms, thereby acting as agents for the consumer.[63] When the algorithm is written or controlled by the consumer herself, some of the effects on consumers analyzed below are mitigated.

A. Effects on Consumers

One of the most important effects of algorithmic consumers on market dynamics is their ability to significantly alter consumer demand. A fundamental question is how these changes in the demand curve will affect consumer welfare. The most basic effect is a reduction in cost and/or an increase in quality (depending on the preferences set by the consumer) in the products purchased. Such increased quality need not be limited to economic efficiency, but may include other dimensions that the consumer values, such as privacy and sustainability.[64] Algorithms can be coded either to shadow the consumer's choices, simply carrying them out in a more efficient manner, or to improve these choices within the framework of the consumer's preferences (for example, overcoming biases). The latter, of course, has a more significant effect on consumer choice.

The size of these effects depends on the extent of advantages enjoyed by consumers. Three cumulative parameters determine this extent. The first is the comparative advantages of algorithms over human-led transactions. The analysis above sought to highlight the advantages, as well as the limitations, of algorithmic consumers compared with human transactions. It was shown, for example, that at least certain types of transactions can be executed by an algorithm in a quicker, less costly, more efficient, and more sophisticated manner.

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63. *See, e.g.*, Lauren Henry Scholz, *Algorithmic Contracts*, 20 STAN. TECH. L. REV. (forthcoming 2017) (manuscript at 11), *available at* https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=2747701 [https://perma.cc/4C8F-FZC7].

64. Such added value is a prerequisite for the use of algorithmic consumers, at least under the assumption that consumers can compare trade terms with and without the use of such algorithms. However, one might be skeptical about this assumption. Algorithmic consumers have emerged partly as a response to data overload and the immense number of choices presented to consumers, which are simply impossible to process manually. Therefore, consumers may find it difficult to fully understand the decision-making process which leads to any particular choice, and hence to weigh the parameters considered by different algorithms in reaching that choice.

The extent of these effects depends, inter alia, on the type of transaction, such as whether the consumer has already made similar decisions in the past or whether the decision involves new and sophisticated parameters, and the type of algorithm and input used, such as the level of the algorithmic analysis and the scope of data the algorithm can access and analyze.

The second parameter is the market power of the algorithmic consumer vis-à-vis the suppliers of products and of inputs necessary for the successful operation of the algorithm. Generally, the stronger such market power, the greater the benefits from the transaction that can potentially be passed on to consumers. Strong algorithmic consumers might also partly counter the market power of some suppliers. This is especially true with regard to small consumers, who could not otherwise easily protect themselves against suppliers' power. Still, as elaborated below, buyer power can sometimes have negative effects on welfare.

The third parameter is the percentage of the reduced costs or increased value created by the algorithm that is passed on to the consumer. This depends mainly on the market power of the algorithm's provider vis-à-vis the consumer, and is only relevant when the algorithm is not created or operated by the consumer.[65] The stronger the algorithm provider's market power, the smaller the benefit that will be passed on to the consumer. Such market power rests on several parameters, all relating to the height of entry barriers. These may include the number of competing algorithmic consumers available in the market, the algorithm's comparative advantages, and the costs of switching to another algorithm. With respect to the latter, the personal data accumulated by a specific application on each user may create an important barrier. If the data cannot be used by another platform, due to limitations on data portability, the cost of switching to another algorithm, and losing this personal history might be prohibitively high. In fact, access to rich, fresh, diversified, and dense data on the particular consumer, as well as to data on other consumers and supply offers, may be crucial for the success of any particular algorithmic consumer.[66] The more unique the data, and the more essential for making an

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65. Such control might be manifested in many different ways. One possibility is a mandatory requirement that a predetermined percentage of the avoided costs will automatically be transferred to the algorithm's coder or operator, as is done by online travel agents like Expedia and Booking.com. *See, e.g.*, Trefis Team, *What's Driving Expedia's Stock?*, FORBES (Jan. 4, 2013, 4:40 PM) https://www.forbes.com/sites/greatspeculations/2013/01/04/whats-driving-expedias-stock/#278db5d2359b [https://perma.cc/49G3-EZ5D]; Dennis Schaal, *How Booking.com Turned the Other OTAs into Converts*, SKIFT (Jun. 25, 2012, 9:02 AM), https://skift.com/2012/06/25/how-booking-com-conquered-world [https://perma.cc/3A9K-STKM].

66. For access barriers into big data markets see, e.g., Daniel L. Rubinfeld & Michal S. Gal, *Access Barriers to Big Data*, 59 ARIZ. L. REV. (forthcoming 2017), *available at* https://works.bepress.com/daniel_rubinfeld/85/ [https://perma.cc/QL55-AD8B].

optimal purchasing decision, the stronger the market power of the player who has access to such data. This, in turn, implies that competition among algorithmic consumers might be at least partially affected by access to data. The ability of the consumer to compare the relative qualities of competing algorithms, as well as the default option available on her digital platform, will also influence the algorithm provider's market power. In the sections below, we further explore some parameters that affect the ability and incentives of algorithmic consumers to pass on the benefits they create to consumers.

Interestingly, multi-task algorithms, which make decisions over a range of products, might completely change the overall bundle that the consumer purchases. For example, if the algorithm is looking for a leisure activity for the weekend, it might compare for the consumer the overall utility of reading a book, going to a show, or meeting a good friend. This, in turn, might expand the boundaries of substitutability and market definitions as we use them in some regulations. Such algorithms may also have a wider effect on market dynamics than a uni-task algorithm.

B. Effect on Suppliers

How do algorithmic consumers affect the conduct of suppliers, if at all? A major effect involves increased competitive pressures. Since algorithmic consumers can compare a larger number of offers, competition may become stronger. Furthermore, the dimensions on which competition will take place may expand, since algorithms can check and compare many more variables. For example, since algorithms are more likely than humans to check and rate contractual terms, given the significantly lower costs they incur in doing so relative to human consumers, suppliers will have stronger incentives to improve the contractual terms they offer and make them fairer. Observe that some of these changes might also create positive externalities for consumers who do not use algorithms.

The rise of algorithmic consumers will likely also motivate suppliers to create new types of data that algorithms can use in their decision processes. For instance, algorithms can be coded to check parameters relevant for assessing the risk levels posed by potential suppliers, such as their transaction history or how long their websites have existed. In response, suppliers will have to develop better tools to signal the reliability of transacting with them, and allow algorithms to make more informed decisions.

Algorithmic consumers may also affect suppliers' marketing tools. Algorithms are immune from biases that influence consumers, such as the color of a product's packaging. Hence, in the future, suppliers are likely to invest less in marketing that caters to such biases and more in providing information on the product's qualities in ways that can be observed by algorithms. Targeted ads, which are sent to the consumer at times when she is most likely to make a relevant consumption decision,[67] will also become less relevant, although they might still be used to convince the consumer to alter her stated preferences. Finally, since more transactions will be digital, fewer physical stores and more virtual ones will be needed, thereby saving on the costs of physical infrastructure and sales personnel. While this trend is already taking place,[68] algorithmic consumers will intensify it.

Furthermore, the ability to save the transaction history of all users provides the algorithm with a long memory over numerous transactions, thereby reducing suppliers' incentives to shirk on one-time transactions with each consumer.

At the same time, suppliers might also seek ways to manipulate the choices made by algorithms in ways that exploit their shortcomings, such as blind spots and inefficient decisional parameters. This may lead to a technological race between consumers and suppliers, each bent on developing systems that are able to identify the other's shortcomings while fixing its own blind spots.

How will these changes affect the ease of entry of new suppliers, which could, in turn, increase competition? The answer is manifold. On the one hand, path dependency in algorithmic consumers (heavy reliance on the trajectory of past purchasing decisions), as well as suppliers' reliability based on past transactions, might give preference to established suppliers. On the other hand, new suppliers might be able to enter the market more easily if reputation and past transactions, as well as physical infrastructure, are given lesser weight than parameters such as price and quality.[69] Also, the expanded dimensions of competition that algorithms can check may ease the entry of new firms. In addition, transparency of a widely-used algorithm's decision parameters might make it easier for new suppliers to assess how much they need to invest in higher quality or lower prices in order to enter profitably, thereby reducing uncertainty and facilitating entry.

A subtler yet important effect on entry and expansion decisions of suppliers involves biases. As long as some level of economic irrationality is expected from consumer choices, some suppliers can make what otherwise seem irrational entry decisions, and still succeed. But

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67. Through the consumers' smartphone or smart glasses, for example.

68. *See, e.g.*, Darrell Rigby, *The Future of Shopping*, HARV. BUS. REV. (Dec. 2011), http://www.wipro.com/documents/the-future-of-shopping.pdf [https://perma.cc/Q25A-G5J6].

69. The literature on discrimination emphasizes that one of the benefits of big data, which is an essential input into algorithmic consumers, is that it opens up opportunities for segments of the population which would otherwise be categorized as risky. *See, e.g.*, FTC, BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? 5–8 (Jan. 2016). An analogous effect can occur with regard to new suppliers.

once consumer choices become automated, irrational choices by consumers cannot be relied on. This in turn will affect the type of suppliers that will enter or expand in the market. As Professor Avishalom Tor argues, the welfare effects of such a change are not straightforward. It might even have negative effects on dynamic efficiency, if important inventions are not based on rational decisions regarding investment and entry.[70]

Another interesting twist on market dynamics derives from the idea that algorithmic consumers could include decisional parameters designed to eliminate or at least reduce some market failures in the long run. Algorithms are sufficiently flexible to include considerations such as long-run effects on market structures that might harm consumers, and even environmental considerations. For example, an algorithm might be able to recognize below-cost predatory pricing which will harm market dynamics in the long run, and respond by spurning the monopolistic supplier, even when the price offered is the lowest available. Likewise, it might recognize the existence of a cartel or of oligopolistic coordination and refrain from doing business with those suppliers until prices are lowered. Or it might always buy some portion of its goods from at least one new source, to strengthen incentives for new suppliers to enter the market. Of course, including such decisional parameters requires more sophisticated modeling and analysis of market conditions and their effect on welfare, but given advances in economics and in data science, they are becoming easier.[71] Such developments could improve market dynamics and eliminate some market failures without the need for regulatory intervention.

C. Effect of Algorithmic Interactions

So far, we have focused on how suppliers interact with algorithmic consumers generally, without relating to the methods through which they make their offers. Let us now add another factor to the analysis: suppliers operating through decisional algorithms — a practice already commonplace in many industries.[72] A well-known example is Uber's surge pricing algorithm, which sets the price for a taxi ride at any given time based on the availability of supply relative to

70. *See, e.g.*, Avishalom Tor, *Boundedly Rational Entrepreneurs and Antitrust*, 62 ANTITRUST BULL. (forthcoming 2017) (manuscript at 42–43), *available at* https://papers.ssrn.com/sol3/papers2.cfm?abstract_id=2841515 [https://perma.cc/5VK9-D45Z].

71. For the level of sophistication of algorithms, see Sameer Dhanrajani, *Changing Face of Algorithms — Sophistication in Analytics Tools & Techniques Leading to Fluid and Agile Enterprise Decision Making*, DEMYSTIFYING DATA ANALYTICS, DECISION SCIENCE & DIGITAL (Feb. 13, 2017), https://sameerdhanrajani.wordpress.com/2017/02/13/sameer-dhanrajani-changing-face-of-algorithms-sophistication-in-analytics-tools-techniques-leading-to-fluid-and-agile-enterprise-decision-making/ [https://perma.cc/7QD4-CBH8].

72. *See, e.g.*, EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 11, at 15.

demand.[73] This algorithm became famous when a New York City Uber driver, using the algorithm, charged the cookbook author Jessica Seinfeld $415 to drive her two children to nearby events during a snowstorm in 2013.[74] When Uber was criticized, its CEO responded, "We are not setting the price. The market is setting the price . . . . We have algorithms to determine what that market is."[75] Other examples abound.[76]

The use of algorithms by suppliers as well as consumers could completely change the dynamics of the interaction between them, and indeed, could affect even the very concept of negotiation. Algorithmic decision makers used by suppliers will need to be designed to generate the best response to extremely structured and rapid checks and comparisons of their offers. Moreover, the race between the two sides to identify and exploit each other's shortcomings could lead to an "algorithm war," the winner of which will enjoy a larger share of the transactional pie. Also, the use of algorithms on both sides will most likely reduce both parties' transaction costs, a fact which can also translate into lower costs for consumers.

D. Increased Buyer Market Power

Algorithmic consumers can also aggregate consumers into buying groups. This can be done through the creation of a buying platform operated by one algorithm, or by several algorithmic consumers joining forces. The available technology makes the formation of buying groups easier than ever. How might this fact affect market interactions and dynamics?

Algorithmic buying groups may reduce the ability of suppliers to learn about, or to use to their advantage, information regarding each user's preferences by aggregating the choices of different consumers into one virtual buyer (what might be called anonymization through aggregation). Indeed, once consumers are aggregated into sufficiently large consumer groups, suppliers will lose the ability to collect information on consumers' individual preferences with regard to products bought through the group, and to discriminate among them based on each consumer's elasticity of demand.[77] For instance, a seller might

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73. Marcus Wohlsen, *Uber Boss Says Surge Pricing Rescues People from the Snow*, WIRED, (Dec. 17, 2013, 6:30 AM), https://www.wired.com/2013/12/uber-surge-pricing/ [https://perma.cc/33TU-5QGP].

74. Jessi Hempel, *Why the Surge-Pricing Fiasco Is Great for Uber*, FORTUNE, (Dec. 30, 2013), http://fortune.com/2013/12/30/why-the-surge-pricing-fiasco-is-great-for-uber/ [https://perma.cc/FYC6-XRRH].

75. Wohlsen, *supra* note 73.

76. *See, e.g.*, EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 11, at 13–17.

77. *See, e.g.*, Samuel B. Hwang & Sungho Kim, *Dynamic Pricing Algorithm for E-Commerce*, *in* ADVANCES IN SYSTEMS, COMPUTING SCIENCES AND SOFTWARE ENGINEERING 149 (Tarek Sobh & Khaled Elleithy eds., 2006). For a discussion of the wel-

price discriminate by charging a law professor more for the same law book than a student, given that the former generally has greater financial means with which to buy law books. The loss of this ability, in turn, could increase consumers' welfare, if suppliers are forced to set a lower price for all. It may also reduce privacy concerns.[78] However, in some situations it might also affect welfare negatively, for example, by limiting the ability of some flexible-demand consumers to enjoy lower prices, or by limiting consumers' exposure to personalized offers for products they would otherwise not be aware of but would like to consume.[79]

Algorithmic buying groups can also solve some collective action problems,[80] and create and strengthen consumers' buyer power.[81] The question then arises, how does increased buyer power affect welfare and the balance of powers in the market? Might the increased buyer power simply involve a transfer of wealth to consumers, so that a larger part of the benefits from the trade favor consumers rather than suppliers? This question is not new. It has arisen, inter alia, in the context of purchasing cooperatives and joint buying groups.[82] Federal antitrust enforcement agencies have held that such groups may be assumed to create pro-competitive effects, as long as "the purchases account for less than 35 percent of the total sales of the purchased product or service in the relevant market."[83] We see no reason to exempt algorithmic buying groups from these rules. Yet algorithmic consumers may make buying groups more relevant and powerful than

fare effects of price discrimination, see, e.g., R. Preston McAfee, *Price Discrimination*, *in* 1 ISSUES IN COMPETITION LAW AND POLICY 465, 480–83 (ABA Section of Antitrust Law 2008).

78. Individually used algorithms might also apply technological strategies to ensure consumers' privacy, thereby creating similar effects. For privacy concerns resulting from the collection of data on consumer habits, see, e.g., MAURICE E. STUCKE & ALLEN P. GRUNES, BIG DATA AND COMPETITION POLICY 51–66 (2016).

79. EXEC. OFFICE OF THE PRESIDENT, BIG DATA AND DIFFERENTIAL PRICING 4–5, 12 (Feb. 2015).

80. This assumes, of course, that those using the algorithm have the flexibility necessary to wait until the supplier changes its terms. Nonetheless, a supplier anticipating the market power of an algorithmic consumer might change its terms a priori.

81. Buyer power refers to the ability of buyers to influence the terms of trade with their suppliers. Joint buying algorithms may generate significant market power for consumers if a significant percentage of buyers makes their purchases through them. *See* OECD, DAF/COMP(2008)38, MONOPSONY AND BUYER POWER 9 (Dec. 17, 2009). Buyer groups are established in order to take advantage of economies of scale and scope. Peter C. Carstensen, *Buyer Cartels Versus Buying Groups: Legal Distinctions, Competitive Realities, and Antitrust Policy*, 1 WM. & MARY BUS. L. REV. 1, 13–14 (2010).

82. *See, e.g.*, OECD, DAF/COMP/WD(2008)79, ROUNDTABLE ON MONOPSONY AND BUYER POWER: NOTE BY THE UNITED STATES 5 (Oct. 13, 2008).

83. *Id.* at 5 (quoting U.S. DEP'T OF JUSTICE & FTC, STATEMENTS OF ANTITRUST ENFORCEMENT POLICY IN HEALTH CARE 54 (Aug. 1996)).

ever, and bypass the limits set by the agencies. Therefore, the question of the effect of such power on welfare becomes more relevant.[84]

An OECD roundtable identified several potential ways in which buying groups might harm consumers.[85] This is not the place to test the accuracy of these theories, but simply to note their acceptance by at least some competition authorities around the world.[86] One theory focuses on reduced incentives for suppliers to invest in productive or dynamic efficiency, if consumers enjoy a large part of the investment.[87] When those joining together are also competitors, as opposed to end consumers, another potential harm arises: competitors might use the joint buying algorithm(s) to collude on other aspects of their businesses. In fact, algorithms can make collusion easier, since they can relatively easily store, compare, and analyze the buying requests of each member of the joint buying venture.[88] These potential harms should be balanced by algorithmic consumers' potential ability to counteract the negative effects of algorithmic suppliers' market power on consumers.

Another concern focuses on the ability of algorithmic consumers with market power to erect or increase artificial entry barriers, thereby limiting competition with other algorithmic consumers.[89] For instance, they can compel their users not to switch to a competing algorithm (thereby creating downstream foreclosure), or they can coerce suppliers not to supply products to competing algorithms (thereby creating upstream foreclosure).[90] Another example involves price parity — mandating the supplier not to sell to anyone else at lower prices. Algorithmic consumers have an incentive to ensure price parity because of the increased benefits they can enjoy from trade with consumers when competition is limited, as well as a reduced need to invest in ensuring their algorithm works best and in keeping up with technological changes. This, in turn, reduces the benefits enjoyed by consumers.

Algorithmic consumers can also abuse their buyer power to limit competition among suppliers. Interestingly, exclusion might be achieved covertly, by coding the algorithm in accordance with decision parameters which give little weight to the offers of an otherwise

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84. Antitrust law is mostly tolerant towards buying groups, even when these hold a significant share of the input market. Carstensen, *supra* note 81, at 37.

85. *See* OECD, *supra* note 81, at 9–12.

86. *Id*.

87. *Id*. at 11–12.

88. For the ability of algorithms to make collusion easier, see, e.g., EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 11, at 35–81.

89. *Id.* at 30–32.

90. Downstream foreclosure means foreclosing access to one's customers; correspondingly, upstream foreclosure means foreclosing access to one's sources of supply. Christodoulos Stefandis, *Downstream Vertical Foreclosure and Upstream Innovation*, 45 J. INDUS. ECON. 445, 445 (1997).

efficient supplier.[91] Note, however, that excluding suppliers could clash with the interests of algorithmic consumers. Excluding suppliers who might make a better offer, or who might at least strengthen competitive pressure on other suppliers, could reduce the algorithm's market value. Accordingly, incentives to engage in such exclusionary conduct will generally be limited by market forces. Incentives might change when that exclusion creates market value — for example, when consumers wish not to patronize certain firms (for example, firms which exploit child labor) and are willing to give up otherwise better offers, or when the algorithm's operator is also competing in the market for the supply of products.[92]

These concerns regarding the abuse of market power by algorithmic consumers are exacerbated by the high entry barriers into the market for (some) algorithmic consumers, which we explore in the next section.

E. Barriers to Competition in Digital Markets

So far our analysis has focused on consumers, algorithmic consumers, and suppliers, largely disregarding the intermediaries that connect them or the firms that provide the inputs they need. However, once we expand our point of view accordingly, market dynamics change.

The following discussion addresses two points of control which could critically shape algorithmic consumers' conduct: access to potential users and access to data. By the latter, we mean the ability to collect and analyze data that is relevant to the transaction, including data on the preferences of particular consumers. As we shall show below, currently both points of control may exhibit high entry barriers.

Digital markets suffer from a high level of concentration. Currently a handful of digital intermediaries with mega platforms control effective points of access to potential users. These include smart devices (iPhone and Kindle), operating systems (iOS and Android), application stores (Apple Store and Google Play) and browser entry points (Google Search and Facebook). The high level of concentration is largely due to network effects, created when the value for each consumer of using the platform rises in parallel with the number of others

91. Assume, for example, that the most efficient supplier sells its product only in given quantities. If the algorithm's parameters limits purchases of packages of such quantities, even if this parameter is not necessarily important to the user, then the most efficient suppliers' offers might not be chosen by the algorithm.

92. This paper assumes that suppliers, buyers, algorithm providers, and algorithm operators are separate entities, operating at different levels of the supply chain. Once this assumption is relaxed, additional competitive issues arise. While these are intriguing, they are beyond the scope of this paper.

using the system.[93] These network effects are further increased by the network effects of big data.[94] By converging control of content, access, and online distribution channels, large networks enjoy inherent competitive advantages in access to an immense volume of users' personal online data.[95]

This situation has several implications for the likelihood of competition in the market for algorithmic consumer applications. Most importantly, access to such intermediaries is currently essential for most suppliers of algorithmic consumers, since they generally need to go through these middlemen to reach their users (for example, through an app store) or to collect the relevant data (for instance, through a search application). As a result, digital intermediaries may affect which algorithmic consumers reach potential users, and on what terms.

Alternatively, and perhaps more realistically, mega platforms may attempt to provide and control algorithmic consumers by themselves, given that such algorithms are likely to become consumers' gateway into the digitized world.[96] This conjecture is strengthened by the fact that algorithmic consumers can obscure each individual consumer's preferences by aggregating all of them, thereby limiting the incentives of platforms whose value depends on such data to grant access to such applications. The more important the access through the intermediary or to the unique data held by it, the more likely that the handful of mega platforms dominating digital markets will attempt to control that access. This, in turn, might further fortify the mega platform's market power and increase entry barriers into the markets for both mega platforms and algorithmic consumers.[97]

Indeed, the major digital platforms are already racing to develop the best digital shopping assistant.[98] Furthermore, one of the strategies used by some mega platforms to lure consumers to their applications

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93. NICOLAI VAN GORP & OLGA BATURA, EUROPEAN PARLIAMENT DIRECTORATE-GEN. FOR INTERNAL POLICIES, POLICY DEP'T A: ECON. & SCI. POLICY., IP/A/ECON/2014-12, *CHALLENGES FOR COMPETITION POLICY IN A DIGITALISED ECONOMY* 8 (July 2015).

94. Big data exhibits several types of network effects: those arising from the use of a product by many others; trial-and-error and learning-by-doing effects; and scope-of-data and spillover effects in multi-sided markets. *See, e.g.*, STUCKE & GRUNES, *supra* note 78, at 162–99; Rubinfeld & Gal, *supra* note 66, at 17–18.

95. Some jurisdictions are conducting investigations into the anticompetitive effects of these intermediaries. *See, e.g.*, STUCKE & GRUNES, *supra* note 78.

96. *Cf.* Ariel Ezrachi & Maurice E. Stucke, *Is Your Digital Assistant Devious?* (Oxford Legal Studies Research Paper No. 52/2016; Univ. of Tenn. Legal Studies Research Paper No. 304 Aug. 23, 2016), *available at* https://papers.ssrn.com/sol3/papers2.cfm?abstract_id=2828117 [https://perma.cc/2VWT-VLJW].

97. EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 11, at 191–92.

98. *See* Mark Prigg, *Apple Unleashes Its AI: 'Super Siri' Will Battle Amazon, Facebook and Google in Smart Assistant Wars*, DAILY MAIL (June 13, 2016), http://www.dailymail.co.uk/sciencetech/article-3639325/Apple-unveil-SuperSiri-Amazon-Google-smart-assistant-wars.html [http://perma.cc/8K3Z-6HF5].

is to create multi-task algorithms, which combine many functions, including services such as organizing the user's calendar, issuing reminders of scheduled meetings, advising the user to take an umbrella when rain is forecast, and calling contacts at the user's request ("digital butlers").[99] Algorithms like Siri and Google Assistant already perform many of these tasks free of charge, and in the near future it is envisaged that they will perform many more, including purchasing decisions (extending the example given by Google: "Find my daughter a Spanish tutor").[100] Accordingly, firms like Google and Apple have evolved from mainly being intermediaries in two-sided markets between advertisers and consumers to operating as multi-tasking agents that combine a multitude of services, including algorithmic consumers.

This technological tying of services may (partially) mitigate the loss of power resulting from the scenario elaborated below in which digital intermediaries might become less important as a source of big data and of reaching suppliers. It also gives those intermediaries inherent advantages that create entry barriers into their markets. First, because of their current dominant position over existing platforms, their digital butlers become the default option. This, in turn, creates a large base of users and raises switching costs. Second, their ability to combine many tasks, including some already provided for free (like displaying maps), creates an advantage relative to a uni-task algorithm. This advantage will be strengthened by the ability of these digital butlers to serve as a one-stop shop for making interconnected decisions. Third, the range of their services allows these intermediaries to accumulate more data on each user. This enables them to create better user profiles, which in turn enables them to act as better algorithmic consumers.[101] Fourth, and relatedly, the fact that such intermediaries currently serve as major gateways to the digital world enables them to accumulate more data. To the extent that data about other users (as opposed to data about each particular user) is important for the functioning of an algorithmic consumer, this might further increase entry barriers.[102] Therefore, the roles of algorithmic butlers and algorithmic consumers reinforce each other and raise entry barriers for other firms in the market for algorithmic consumers. If so, users might

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99. This term was coined by Danny Yadron. *See* Danny Yadron, *Google Assistant Takes on Amazon and Apple to Be the Ultimate Digital Butler*, THE GUARDIAN (May 18, 2016), https://www.theguardian.com/technology/2016/may/18/google-home-assistant-amazon-echo-apple-siri [https://perma.cc/VVE3-Z3NR].

100. *See id*.; Google Developers, *Google I/O Keynote — 2016*, YOUTUBE at 24:50 (May 18, 2016), https://www.youtube.com/watch?v=862r3XS2YB0 [https://perma.cc/WD5N-QBJC].

101. *See* EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 11, at 195.

102. *Id.*

be inclined to have these platforms also make purchases for them.[103] Much depends, however, on the perceived interests of such bundled algorithmic butlers in the eyes of consumers. Should they be perceived as furthering mainly the interests of their suppliers and not those of consumers, consumers might prefer to use algorithmic consumers written solely for their benefit.[104]

An interesting question is how this market structure will affect the supply of goods. Data on consumers' actual and predicted preferences could generate a significant competitive edge for any suppliers that collaborate with the mega platforms, because those suppliers will be better able to predict and cater to consumer demand. Consequently, control over consumer data may enable platforms supplying algorithmic consumers to leverage their power so as to partially control the supply of goods. This would actually result in significant power over both demand and supply. Another troubling possibility is that a mega platform could come to control both consumer algorithms and some suppliers. The risk is that the platform might use algorithmic consumers to shape demand to match their own supply. More subtle effects might also arise. For instance, even when the mega platform does not control suppliers, it might change consumers' choices if doing so gives it an advantage in other aspects of its operations.[105]

Based upon these current features of digital markets, Professors Ariel Ezrachi and Maurice Stucke offer a pessimistic vision. They suggest an inevitable path by which the control of consumer algorithms falls into the hands of existing intermediaries, leading to decision-making that will not necessarily further consumers' welfare.[106]

We are not so pessimistic, at least not in the long run. Rather, technology is a bit like a phoenix, reinventing itself time and again, sometimes with the assistance of correctly structured regulation. Degrees of power and methods of control may change so as to introduce more competition. Just as points of control have historically moved from the individual computer to the Internet, new technological developments mean the latter could soon lose some of its power. Most importantly, the Internet of Things may change the locus of data needed for the operations of algorithmic consumers from the Internet towards more physical, and possibly less concentrated, loci (such as smart homes, smart cars, smart appliances, and smart clothes). This, in turn, might shift at least some power away from existing Internet in-

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103. *Id*. at 194.

104. One way to indicate such incentives is to base the algorithmic provider's revenues on a percentage of the cost savings it generated.

105. For example, the algorithm could experiment with how users react to choices which do not precisely fit their preferences, but which might increase the mega platform's revenues. See, by way of analogy, the Facebook experiment on how changes in users' news feeds affected their emotions. Kramer, Guillory & Hancock, *supra* note 58, at 8788–90.

106. *See* EZRACHI & STUCKE, VIRTUAL COMPETITION, *supra* note 11, at 194–97.

termediaries.[107] Firms like Google have already started to expand into markets which provide them with information from physical infrastructure, such as smart home devices and smart cars. This "sensor-control war," however, will not be an easy one for the existing mega platforms to win, as it is hard to imagine one firm controlling all or most of the sensors embedded in numerous physical sources. Such a change might, however, also create new entry barriers. One potential barrier might include intermediary digital systems which connect the data gathered from "things" to create a "collaboration of things" in what some call the "internet of everything," a ubiquitous connectivity of people, devices, data, machines, and processes.[108] In such a world, those controlling the connectivity platform might possess significant market power.

Interoperability between data sources (either mandated or market-driven) might also change the points of control. Moreover, where the data necessary to make a decision on behalf of the consumer need not be vast or varied, and the decisional parameters are quite transparent, there may well be a place in the market for the creation of algorithmic consumers which are not operated or controlled by the intermediaries. Finally, technological changes may also reduce barriers to the execution of transactions. Rather than go through suppliers of search services, in some instances algorithmic consumers might potentially interact directly with suppliers through the Internet.

All of this does not imply that new technologies or market structures will necessarily overcome all the limitations to the efficient operation of algorithmic consumers. However, it does shed new light on how markets are likely to operate in the future, and potentially opens the door to less concentrated market structures. Much depends on the new business models that would be adopted in response to the change in the loci of control of data.

To summarize Part III, algorithmic consumers may significantly affect market dynamics, altering both demand (consumers' choices) and supply (changing many dimensions of suppliers' conduct). Such algorithms have the potential to create positive effects on consumer and social welfare. By increasing competition among suppliers, algorithms are likely to increase allocative, productive, and dynamic efficiency, which in turn should lead to lower costs and higher quality products. They can also assist consumers in fulfilling other preferences, such as increased privacy and sustainability. Moreover, they

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107. *See* Yochai Benkler, *Degrees of Freedom, Dimensions of Power*, 145 DAEDALUS 18 (2016) (describing the forces that shape power in the information environment, including the law).

108. Alan Morrison, *Beyond IoT: How Blockchain Will Help Create the Collaboration of Things*, RECODE.NET (2016), http://www.recode.net/sponsored/12929410/beyond-iot-how-blockchain-will-help-create-the-collaboration-of-things [https://perma.cc/A2Tx-H3R7].

lower transaction costs for all involved, thereby further improving social welfare. Yet whether these benefits will be realized depends, inter alia, on the height of entry barriers into algorithmic consumer markets, which, in turn, affects the intensity of competition between algorithmic consumers. As shown, entry barriers can arise from many sources, including: input markets, via access to data on consumer preferences; output markets, via access to potential consumers), and exclusionary conduct by competing algorithms, via bundling, price parity, or exclusivity contracts. It is on these three challenges that we focus next.

IV. IMPLICATIONS FOR REGULATION

Having identified the potential effects of algorithmic consumers on market dynamics and social welfare, and the potential barriers to the realization of benefits by consumers, we focus now on the regulatory challenges that arise from this technological change.

The advent of algorithmic consumers raises a host of intriguing challenges to current regulatory tools in various legal areas. For instance, in contract law: Can an algorithm act in bad faith? When does an interaction between algorithms constitute a binding contract? In agency law: Does the algorithm act as an agent for the consumer? Does it have fiduciary duties towards the consumer? In tort law: Who is responsible for harm caused by an algorithm? Or in newer forms of regulation, such as privacy and cyber-security: Should algorithmic consumers be mandated to meet regulatory standards with regard to privacy or the level of security they employ?[109] Questions also arise regarding the interplay between laws regulating different aspects of the algorithmic world. Such challenges, as well as related ones, will surely arise in the brave new world of automated consumer decision-making. Each deserves a study of its own.

In this article, we focus on an important piece of the regulatory puzzle which arises from the analysis performed in Part III: Are existing regulatory tools sufficient to deal effectively with the three potential barriers to competition identified above, and are those tools therefore able to ensure that algorithmic consumers bring about the benefits they promise for consumers? Our goal is not to provide defin-

109. Additional questions arise. In corporate law: Under what circumstances does a corporate agent act negligently or in bad faith when the agent does not accept a decision made by an algorithm? In consumer law: When do manipulations by algorithmic consumers infringe consumer protection standards? What kinds of information must the algorithm's provider provide to the user? What types of actions should be regarded as negotiations? In criminal law: Who should be deemed responsible for purchasing an illegal artifact ordered by an algorithm if the consumer has given the algorithm carte blanche? What if the consumer is not even aware that such a purchase is possible?

itive answers for the myriad issues that arise, but rather to identify and map the main regulatory challenges.

A. Reducing Barriers to Consumer Access

Even if a firm creates the best of all competing algorithms, it could still find it difficult to reach consumers. Some barriers are natural, such as first-mover advantages, which may create a status-quo bias, and imperfect information on the part of consumers. Others are likely to be created by the new technological reality.

Some barriers in the first group can be at least partially removed by the market. For example, product-comparison firms might increase consumers' knowledge regarding the relative qualities of different algorithmic consumers. The law can also help lower such barriers, for example by prohibiting misleading information or by requiring transparency about some product qualities.[110] In this regard, algorithms are no different from other products, except that it might be more difficult to observe their relative qualities due to their "black box" features, especially if they make multiple interrelated decisions.

A more significant barrier involves access to consumers through intermediaries. As noted above, currently several large intermediaries control the platforms through which application providers and consumers interact, the most important being smart devices, operating systems, application stores, and browser entry points. Once such entry points are (partly) foreclosed to application designers, access to consumers is limited, and so is the ability to compete effectively. Moreover, intermediaries might use their market power over access points to promote their own algorithmic consumer, or to support one algorithm over another, thereby enjoying part of the profits to be had. As long as algorithmic consumers are an insignificant part of what the intermediary has to offer, such conduct might not create strong incentives for users to switch to another intermediary. Accordingly, in such instances market forces cannot be relied upon to solve this foreclosure problem, at least not in the short run.

Can existing law play a role in overcoming such barriers? The answer is a partial yes, depending on the conditions of the market and the type of conduct the intermediary is engaged in. The most relevant sphere of law is antitrust. Antitrust law is a foundational regulatory tool. It attempts to ensure that markets work for the benefit of society by preventing or limiting the erection of artificial barriers to competi-

110. Some existing consumer protection laws may already apply to algorithms, but others might need to be devised to especially apply to the unique characteristics of algorithms. For some ways to deal with algorithmic manipulations, see, e.g., Calo, *supra* note 44, at 1041–48.

tion by private firms.[111] It is grounded in the assumption that unobstructed competition, which creates a status quo based on the interaction of supply and demand in the market, will increase social welfare in the long run.[112] Furthermore, where increased competition, protected through antitrust law, can prevent or reduce market or regulatory failures, antitrust law may obviate the need to apply other, more interventionary regulatory tools. For example, where competition between providers of algorithms lowers their incentives to manipulate the algorithm's decisional parameters, consumer protection law might be less important. Finally, in the general absence of other, more specific regulatory tools that pertain to the furtherance of competition in algorithmic markets, antitrust law is the main tool which is currently relevant.

The antitrust prohibition against monopolization or attempted monopolization is designed to capture unilateral conduct by a firm with significant market power which uses this power to erect artificial entry barriers against its competitors.[113] For antitrust liability to arise, the following conditions must be proven: possession of or an attempt to possess monopoly power; an act of monopolization, which has been defined as "the willful acquisition or maintenance of that power as distinguished from growth or development as a consequence of a superior product, business acumen, or historic accident";[114] and a causal link between the conduct and market power.[115]

When these conditions are met, antitrust law can be used to mandate that the intermediary stop engaging in anti-competitive conduct. The monopolist might be required to stop discriminating in access terms, or to cease other exclusionary practices towards rival algorithmic consumer suppliers. One noteworthy doctrine is the essential facilities doctrine, under which a monopolist must grant access to a facility which it controls on fair and non-discriminatory terms, if (a) access to that facility is essential for other, similarly efficient firms to compete in a related market, and (b) granting access is feasible and not objectively unreasonable.[116] While much controversy has arisen

111. *See, e.g.*, 1 PHILLIP E. AREEDA & HERBERT HOVENKAMP, ANTITRUST LAW 3–4 (4th ed. 2013).

112. *See, e.g.*, Philippe Aghion & Mark Schankerman, *On the Welfare Effects and Political Economy of Competition-Enhancing Policies*, 114 ECON. J. 800, 818–19 (2004).

113. Sherman Antitrust Act §§ 1–2, 15 U.S.C. §§ 1–2 (2014). For an overview of antitrust, see generally 1 AREEDA & HOVENKAMP, *supra* note 111; HERBERT HOVENKAMP, FEDERAL ANTITRUST POLICY (4th ed. 2011).

114. United States v. Grinnell Corp., 384 U.S. 563, 570–71 (1966).

115. *Id*.

116. *See* MCI Commc'ns Corp. v. American Tel. & Tel. Co., 708 F.2d 1081, 1132–33 (7th Cir. 1983); Stephen M. Maurer & Suzanne Scotchmer, *The Essential Facilities Doctrine: The Lost Message of Terminal Railroad*, 5 CALIF. L. REV. CIR. 287, 301 (2014); Robert Pitofsky, Donna Patterson & Jonathan Hooks, *The Essential Facilities Doctrine Under US Antitrust Law*, 70 ANTITRUST L.J. 443, 448 (2002). Note that the essential facilities doctrine is also applicable in the EU. *See generally* Sébastian J. Evrard, *Essential Facilities in the European Union: Bronner and Beyond*, COLUMBIA J. EUR. L. (2004) (tracing the

with regard to the scope of this doctrine, it is still applicable in some cases.[117]

Antitrust law is, however, a very limited tool for mandating access to intermediaries for three main reasons. First, antitrust law is generally unable to limit the price that can be set by the monopolist in exchange for access. This, in turn, might limit the benefits to be had by consumers. Second and more fundamentally, it is difficult to prove the existence of a monopolistic position, especially in dynamic markets.[118] Third, antitrust does not deal effectively with situations in which market power arises from oligopolistic coordination — that is, parallel conduct by several large competitors which is not based on an illegal agreement among them. For example, suppose Google and Apple both limit access to their online application stores without prior agreement. Should it be established that neither enjoys a monopolistic position in the market for application stores, antitrust law could not be used to grant access.[119]

In the long run, other platforms may be created that will compete for users and may therefore grant better terms of access to algorithms. This is especially true if multiple types of intermediaries, including those competing in different markets, can grant such access (for example, access through Facebook rather than through Apple). Yet obtaining such access may not be easy due, inter alia, to the switching costs and inherent benefits created by scale economies, multi-tasking, first mover advantages and default options which characterize many digital markets.

B. Reducing Barriers to Relevant Data Access

Whenever data is essential for the successful operation of the algorithmic consumer, access to such data and to tools for analyzing it affect the level of competition. This becomes increasingly true as we move from stated preferences to predicted preferences based on data analysis and, especially, on machine learning. As such, all dimensions of big data — scale, scope, and speed — may contribute to the erection of entry barriers.[120] The scale or volume of data available influ-

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development of the essential facilities doctrine in the jurisprudence of the European Court of Justice since 1970).

117. *See, e.g.*, Aspen Skiing v. Aspen Highlands Skiing Corp. 472 U.S. 585, 600 (1985). For a list of EU cases in which the essential facility doctrine has been applied, see RICHARD WHISH & DAVID BAILEY, COMPETITION LAW 703–06 (7th ed. 2012).

118. *See, e.g.*, Brody Mullins, Rolfe Winkler & Brent Kendall, *Inside the US Probe of Google*, WALL STREET JOURNAL (March 19, 2015), https://www.wsj.com/articles/inside-the-u-s-antitrust-probe-of-google-1426793274 [https://perma.cc/9UFT-6US7].

119. *See, e.g.*, Scott Hemphill and Tim Wu, *Parallel Exclusion* 122 YALE L.J. 1182, 1198 (2013).

120. *See, e.g.*, Rubinfeld & Gal, *supra* note 66, at 535; STUCKE & GRUNES, *supra* note 78, at 162–63, 170, 186.

ences the presence of network effects, such as learning-by-doing and trial-and-error. Its scope or variety influences the ability of the algorithmic consumer to make optimal decisions by balancing the consumer's preferences between different products. For example, the algorithm could buy a desired book for the consumer and reduce the budget for clothes accordingly. The speed at which data are transmitted impacts the rate at which the algorithm can react to users' actions and needs. Where the scale, scope, and speed of data are high, those controlling the data might enjoy inherent advantages.

Here, again, antitrust law can reduce some barriers, but not all. Most importantly, benefits arising from data collection and analysis which are not the result of artificial entry barriers generally will not be caught by antitrust legislation.[121] Moreover, some remedies, such as granting access to data obtained anti-competitively, could harm other interests, like privacy, and require a delicate balance for which antitrust law is not necessarily well-suited.[122] Accordingly, should access to such data be deemed important for social welfare, other regulatory tools might need to be devised, such as rules on data portability.[123]

A related issue regards data interoperability. For new competitors to be able to use data collected by others, they must be able to recognize and interpret its patterns. Yet competing firms might not have incentives to create this interoperability. Whether the law should mandate interoperability is a difficult question. Both sides of the dilemma involve efficiency considerations. On the one hand, mandating standardization of data organization could limit the dynamic and productive efficiency of those collecting the data in accordance with their own needs. On the other hand, absent interoperability, synergies that could otherwise be created will not be realized. In any case, interoperability barriers generally cannot be removed by antitrust law as long as they are not the result of artificial entry barriers. Other regulatory tools might then need to be devised.

C. Exclusionary Conduct by Algorithms

The above analysis focused on barriers to competition resulting from third parties, namely access intermediaries and controllers of data. In this section, we analyze a third source of entry barriers: exclusionary conduct by algorithmic consumers. For instance, an algorithmic consumer might enter into exclusive dealings contracts with

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121. An important question focuses on what should be considered monopolization and what should be considered competition on the merits. *See, e.g.*, STUCKE & GRUNES, *supra* note 78, at 279.

122. For a similar conclusion see *id.*

123. For example, the European regulation includes a right to private data portability, thereby restoring at least some power to the consumer. Parliament & Council Regulation 2016/679, OJ L 119/1 27.4.2016, 68 (EU).

suppliers, thereby foreclosing access to other algorithmic consumers. Exclusionary conduct by algorithmic consumers can also raise artificial entry barriers to suppliers. For example, an algorithmic consumer may choose not to buy from a certain supplier even if the latter proposes the best terms. The analysis below generally applies to both cases. Here, in contrast to the two situations analyzed previously, antitrust law can play a major role.

A relatively simple case exists when an algorithmic consumer which enjoys significant market power engages in exclusionary anti-competitive conduct. Such conduct might then be captured under the monopolization prohibition. Yet even here, interesting challenges arise. For example, if a firm uses technology to link free services with algorithmic consumer functions in its algorithmic butler, is that firm engaging in anti-competitive tying?[124] The answer is not straightforward and will depend on the overall balance of harms and benefits to consumers.

The more interesting case arises when no one algorithm enjoys market power, but several existing algorithms engage in parallel conduct which might create anti-competitive effects. While the algorithm is applied separately and independently by each user on her own, the cumulative effects arising from parallel use of the algorithm(s) by many users can sometimes harm competition and welfare.

Nobel Prize winner George Stigler pointed to three conditions which must exist for the success of intentional parallel conduct: an ability to reach a status quo that benefits all those engaged in such conduct over the long run; an ability to monitor deviations from the status quo; and an ability to police such deviations.[125] Algorithms make meeting these conditions easier than ever.[126] First, algorithms can quickly and efficiently observe prices offered by suppliers to other consumers, or remember offers made by suppliers in the past, thereby simplifying the tasks of reaching a status quo and monitoring.[127] Second, they can automatically respond to price offers in accordance with predetermined decision parameters, thereby more easily reaching a status quo and policing the conduct of others.[128] Third, they may create a higher risk of policing deviations, especially if decisions are quick and changes to the algorithm's decision tree are

124. Tying is the economic practice of conditioning the sale of a first good or service on the purchase of a second good or service. Alden F. Abbott & Joshua D. Wright, *Antitrust Analysis of Tying Arrangements and Exclusive Dealing*, *in* ANTITRUST LAW AND ECONOMICS 183, 183 (Keith N. Hylton ed., 2010).

125. *See* George J. Stigler, *A Theory of Oligopoly*, 72 J. POL. ECON. 44, 45–46 (1964).

126. *See, e.g.*, Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 18–20; Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 MINN. L. REV. 1323, 1340 (2016).

127. *See* Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 18–20.

128. *See id.*

difficult, such as when the change requires going back to the coder.[129] Hence, algorithms may enable more durable parallel conduct. Furthermore, due to these more efficient ways of fulfilling Stigler's three conditions, parallel conduct can be reached even if the algorithmic market is comprised of many small algorithms, all coded to monitor and police deviations, rather than being highly concentrated.

For antitrust liability to arise from parallel conduct, an agreement must be found to exist among those engaged in the anti-competitive conduct.[130] Under established doctrines, parallel conduct emanating from the effect of similar external forces (for example, an increase in the price of a major input which affects all competitors alike) or from oligopolistic coordination does not constitute an "agreement."[131] Oligopolistic coordination is created when each market player unilaterally acts in a way that takes into account the reaction curves of other market players. The result is parallel conduct without prior agreement.[132]

Let us first explore which types of parallel conduct among algorithmic consumers satisfy this condition. In their seminal work, Ezrachi and Stucke identify four scenarios.[133] A relatively simple scenario involves the use of algorithms to implement, monitor, police or strengthen an anti-competitive agreement among users or providers of algorithms.[134] In such a situation a clear agreement exists.[135]

A more technologically complicated yet legally simple situation arises when the algorithms are purposely coded, by agreement among their users or providers, to enter in the future into an anti-competitive agreement (like boycotting a certain supplier), should such an agree-

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129. *See id.*

130. *See* Sherman Antitrust Act § 1, 15 U.S.C. § 1 (2014).

131. *See, e.g.*, William E. Kovacic, Robert C. Marshall, Leslie M. Marx & Halbert L. White, *Plus Factors and Agreement in Antitrust Law*, 110 MICH. L. REV. 393, 405 (2011).

132. *See, e.g.*, *id.* at 405 ("[T]he recognition of interdependence can lead firms to coordinate their conduct simply by observing and reacting to their competitors' moves. In some instances, such oligopolistic coordination yields parallel behavior . . . that one might associate with a traditional agreement to set prices, output levels, or other conditions of trade.").

133. *See* Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 7–9.

134. *Id.* at 10.

135. *See id.*; PRESS RELEASE, U.S. DEP'T OF JUSTICE, OFFICE OF PUB. AFFAIRS, FORMER E-COMMERCE EXECUTIVE CHARGED WITH PRICE FIXING IN THE ANTITRUST DIVISION'S FIRST ONLINE MARKETPLACE PROSECUTION (Apr. 6, 2015), https://www.justice.gov/opa/pr/former-e-commerce-executive-charged-price-fixing-antitrust-divisions-first-online-marketplace [https://perma.cc/QMT6-ZQMN]. It was alleged that the sellers "adopted specific pricing algorithms for the sale of certain posters with the goal of coordinating changes to their respective prices and wrote computer code that instructed algorithm-based software to set prices in conformity with this agreement." *Id.* Such agreements are illegal regardless of the market power of their parties. *See* United States v. Socony-Vacuum Oil Co., 310 U.S. 150, 221 (1940).

ment benefit them.[136] Once again, an agreement clearly exists and the algorithm simply acts as its facilitating device.[137]

A third scenario involves oligopolistic coordination among algorithms, reached without the need for a preliminary agreement among them. [138] Rather, a stable status quo is achieved when each algorithm is coded to make its decisions based on its predictions of the best responses and dominant strategies of other parties in the market.[139] This leads to parallel conduct without prior agreement, which could be facilitated automatically.[140]

In the fourth scenario, the algorithms are designed to achieve a given target, such as price reduction. [141] The algorithms determine independently the means to reach that target, through self-learning and feedback collected from the market.[142] Therefore, parallel conduct "is not the fruit of explicit human design but the outcome of evolution, self-learning and independent machine execution." [143]

Ezrachi and Stucke argue that the parallel conduct resulting from the last two scenarios does not constitute an agreement in antitrust law, because it constitutes oligopolistic coordination that is not captured under the law.[144] We would like to offer a different suggestion. "Plus factors" are exceptions to the rule that exempts oligopolistic coordination from antitrust liability.[145] These are positive actions, engaged in by market players, which depart from the market's natural conditions and allow firms to better achieve parallel conduct.[146] In both cases it can be argued that the algorithm, or rather its design, is such a plus factor. Consumer algorithms include in their decision trees elements that not only scan and compare the available options as a basis for consumption decisions, but also change consumers' decision parameters to include reactions to offers made by suppliers to other consumers, thereby also changing suppliers' incentives. The fact that algorithms facilitate coordination strengthens this suggestion. Arguably, therefore, the algorithm constitutes a plus factor to an agreement

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136. Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 14.

137. *See id.* at 14–16.

138. *See id.* at 16–17.

139. *See id.*

140. *See id.*

141. *See id.* at 22–25.

142. *See id.* at 23.

143. *See id.*

144. Ezrachi & Stucke briefly relate to this possibility. *See id.* at 21, n.41 ("The downsides of [an approach which treats algorithms as plus factors] are the cost, duration, and unpredictability of a rule of reason case, and the difficulty for the court in weighing the procompetitive benefits of product developments with the anticompetitive effects.")

145. *See, e.g.*, William E Kovacic, Robert C. Marshall, Leslie M. Marx, & Halbert L. White, *Plus Factors and Agreement in Antitrust Law*, 110 MICH. L. REV. 393, 395–96 (2011).

146. *See id.* at 393.

among the providers of such algorithms, and possibly also among their users.

Alternatively, legislators and courts might need to reevaluate the current policy of exempting oligopolistic coordination from the prohibition against anti-competitive agreements. This is because some of the factors underlying the decision not to regulate oligopolistic coordination[147] — principally that such coordination affects only a small number of markets — may no longer be true. Indeed, this justification was based on assumptions of limited human capacity that no longer hold.[148] Once we introduce algorithms, not only does oligopolistic coordination become more durable, but it may also actually be facilitated in non-oligopolistic markets, ones in which many competitors operate. The requirement that a prior agreement exist among market players therefore does not fit the algorithmic world. The major problem with this solution is similar to the one raised by Professor Donald Turner with regard to oligopolistic coordination more generally: How should the remedy be structured? Should the algorithm be mandated to ignore its competitors' potential moves?[149] Such a requirement may well undermine competition.[150] Therefore, the issue of remedy should be well thought through before the law is changed.

So far, we have focused on parallel conduct by different algorithmic consumers. We now turn to parallel conduct by different users of the same algorithmic consumer, which together might create anti-competitive effects. Once again, the question arises whether an agreement is created among such users, or between each user and the algorithm's designer or owner.[151]

One of the unique features of the digital world is the ability to create a group that can act in parallel for a joint cause on an ad hoc basis, without any formal organization. The negligible costs of communicating and processing information make coordination and integration cost-effective in a way that was not available before, enabling large-scale collaborations. As forcefully argued by Professor Yochai

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147. See the famous debate between Professor Donald Turner and Judge Richard Posner. Richard A. Posner, *Oligopoly and the Antitrust Laws: A Suggested Approach*, 21 STAN. L. REV. 1562, 1562 (1969); Donald F. Turner, *The Definition of Agreement Under the Sherman Act: Conscious Parallelism and Refusals to Deal*, 75 HARV. L. REV. 655, 671 (1962).

148. *See, e.g.*, Stigler, *supra* note 125, at 57 (giving as an example the fact that the number of competitors in the market affects the ability to coordinate).

149. *See* Turner, *supra* note 147, at 656.

150. *See* Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 22.

151. The question of whether such conduct creates anti-competitive effects is a separate issue. In most instances, the use of an exclusionary algorithm will create limited effects on competitive conditions in the market. Yet, when used to make consumption decisions by a significant portion of demand, whether due to the cumulative effect of consumption decisions by many users or a single consumption decision by one significant user, the algorithm can erect entry or expansion barriers for those excluded by it, and significantly affect competition.

Benkler, digital networks have facilitated a radically different mode of production, where goods and services can be generated by a large number of peers who are not formally organized by firms, governments, or any hierarchical institutional structure.[152] Wikipedia is a classic example of mass collaboration for producing creative works. Similarly, it has facilitated grassroots political action with no organizational or legal structures. The low costs of online coordination have facilitated a new, radically decentralized mode of ad hoc political action by unorganized crowds, individuals, and NGOs who use the Internet to raise awareness, disclose information, organize political pressure and engage in political action such as boycotts and protests.[153]

A similar type of conduct might arise among users of algorithmic consumers. One possibility is users' intentional decision to use a single algorithm to bargain for their trade conditions. Should a sufficiently large number of users make a similar choice, the algorithmic con-consumer may integrate the purchasing decisions of a large number of consumers and enjoy significant market power. This can be used to engage in anti-competitive conduct, the fruits of which consumers can then enjoy. In addition, users may have an incentive to purposely choose to use the same algorithm, even if it is not the most efficient, because of the parallel conduct it creates. An incentive to do so arises from using a similar algorithm that can contribute to the stabilization of parallel conduct, given that algorithms can more easily predict each other's reactions.[154]

To determine whether an agreement exists, several scenarios should be distinguished. In the first, consumers agree among themselves to use the same algorithm. Clearly, a horizontal agreement then exists.[155] Whether those consumers have thereby made an anti-competitive agreement under the law is a separate question, which partly depends on their awareness of the probable anti-competitive

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152. *See* YOCHAI BENKLER, THE WEALTH OF NETWORKS: HOW SOCIAL PRODUCTION TRANSFORMS MARKETS AND FREEDOM 2 (2006); *see also* JEFF HOWE, CROWDSOURCING: WHY THE POWER OF THE CROWD IS DRIVING THE FUTURE OF BUSINESS 14 (2008); CLAY SHIRKY, HERE COMES EVERYBODY: THE POWER OF ORGANIZING WITHOUT ORGANIZATIONS 143 (2008); DON TAPSCOTT & ANTHONY D. WILLIAMS, WIKINOMICS: HOW MASS COLLABORATION CHANGES EVERYTHING 1 (2006).

153. The Arab Spring, where repressive regimes were toppled by protesters organized via social media, is a classic example. This wave of online political activism did not bypass Western democracies, where the Internet was used to uncover knowledge (such as via Wikileaks), to raise awareness (for example, the campaign against the Stop Online Piracy and Protect Intellectual Property acts [SOPA/PIPA] in the US), and to coordinate street protests worldwide (for instance, the 2011 street protests against the Anti-Counterfeiting Trade Agreement [ACTA] in Europe). *See, e.g.*, Henry Farrell, *The Consequences of the Internet for Politics*, 15 ANN. REV. POL. SCI. 35, 39 (2012).

154. *See* Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 22.

155. *See* Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 8 (hub and spoke example).

effects of their parallel use of the algorithm.[156] Indeed, coordination of purchasing behavior might be based on benign considerations, such as enabling the algorithm to use the "wisdom of crowds" and big data analysis to make better choices. Furthermore, end consumers will generally not benefit from exclusionary conduct by an algorithm, but only from exploitative conduct.

A more likely scenario arises when many users independently decide to join the algorithm without prior agreement, based on recommendations by other users or each one's own analysis of the comparative advantages of different algorithms. While each user enters into a direct vertical agreement with the algorithm's provider, no horizontal agreement among users exists. In the simplest case, the user may not even be aware that she has contributed to the collective market power, which enables the algorithm to provide more advantageous trade terms. A more complicated case arises when the user is aware that the algorithm has significant market power and that the algorithm is monopolizing that power to obtain better trade terms. It seems to us that the focus should once again be on the user's awareness of the potential for anti-competitive harm.[157]

The fact that the user is one step removed from the decision, and hence perhaps even unaware of the relevant decision parameters set by the algorithm, also creates challenges regarding intent. For an anti-competitive agreement to arise, it is generally both necessary and sufficient that the parties to the agreement be aware of the factual elements of the offense.[158] When an agreement is regarded as per se illegal, an exception is made and no proof of intent is necessary.[159] In

156. For a recent case raising these questions in the context of Uber, see *Meyer v. Kalanick*, 174 F. Supp. 3d 817, 822–25 (S.D.N.Y. 2016) (denying Uber's motion to dismiss antitrust claims of horizontal conspiracy). *See also* Salil K. Mehra, US v. Topkins*: Can Price Fixing Be Based on Algorithms?* 7 J. EUR. COMPETITION L. & PRAC. 470, 473–74 (2016).

157. The above analysis, while relating to algorithmic consumers, can also relate to algorithmic suppliers, which may block access to the market for the former.

158. *See, e.g.*, U.S. DEP'T OF JUSTICE, ANTITRUST DIV., ANTITRUST DIVISION MANUAL III-12 (5th ed. April 2015) (stating that the Justice Department will not prosecute the offense criminally if "there is clear evidence that the subjects of the investigation were not aware of, or did not appreciate, the consequences of their action."). *See also* WILLIAM E. KOVACIC, AMERICAN BAR ASSOCIATION, THE ANTITRUST GOVERNMENT CONTRACTS HANDBOOK 23 n.107 ("[A]s a general matter, the Justice Department . . . will seek criminal sanctions when the following conditions are satisfied . . . (d) the conspirators generally are aware of the probably anticompetitive consequences of their conduct.").

159. *See, e.g.*, United States v. Gillen, 599 F.2d 541, 545 (3d Cir. 1979) ("[I]n price-fixing conspiracies, where the conduct is illegal per se, no inquiry has to be made on the issue of intent beyond proof that one joined or formed the conspiracy."). For an interesting analysis of awareness in a computerized system, see Case C-74/14 'Eturas' UAB and Others v. Lietuvos Respublikos Konkurencijos Taryba, EU:C:2016:42, *available at* http://curia.europa.eu/juris/document/document.jsf?text=&docid=173680&pageIndex=0&doclang=en&mode=lst&dir=&occ=first&part=1&cid=137883 [https://perma.cc/555D-YG72].

the discussion below, let us assume that the algorithm purposely excludes or discriminates against a certain supplier for anti-competitive reasons. In such a case, can we relate this anti-competitive intent to the user?

The answer is not simple. On the one hand, the user chose to use the algorithm, and could have checked with the algorithm's provider whether an anti-competitive result might arise. On the other hand, algorithms are generally black boxes for their users. Furthermore, once we demand that the user acquaint herself with the algorithm's decisional parameters, some of the benefits of using the algorithm in the first place, such as saving time and effort, might be lost. Moreover, as elaborated above, users who are not competitors will generally have no incentive to exclude either their suppliers or other algorithmic consumers. Finally, even if the user is aware of the exclusionary node in the algorithm, she might not be cognizant of the market power created when large numbers of people use the algorithm, which is what creates the harm to competition. Such an anti-competitive effect would depend on factors not necessarily under the individual user's control, and which could change over time. For example, more people start using the algorithm and thus its market power is increased. We therefore suggest that regulators should not assume the user is aware of the potential anti-competitive effect, at least in the absence of gross negligence on her part.[160] However, where the user is demonstrably aware of both the exclusionary node and its potential anti-competitive effects, the fact that a sophisticated system containing an autonomous algorithm performed the actual purchase operation should make no difference to the user's culpability.[161]

Most of these considerations are not relevant to the designers of algorithms. Rather, their intent could be based on designing the algorithm in a way which could predictably create anti-competitive effects. Yet another challenge arises when the algorithm has the capacity for machine learning, since even the algorithm's designer might not be aware of the anti-competitive effects of its decisions. In such situations, intent could be based on the designer's awareness of the possibility of harm. To avoid liability in such cases, the designer may need to code the algorithm to avoid anti-competitive conduct. For

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160. *See* Andreas Heinemann & Aleksandra Gebika, *Can Computers Form Cartels? About the Need for European Institutions to Revise the Concertation Doctrine in the Information Age*, 7 J. EUR. COMPETITION L. & PRAC. 431, 440 (2016) ("If pricing is completely delegated to software . . . with the object or effect of harmonising prices between competitors[,] . . . the 'Cartel of the Machines' amounts to a cartel between undertakings. In these cases, traditional meetings or forms of communication are replaced by an algorithm which renders direct concertation superfluous.").

161. Cheapest cost avoiders are, as their name indicates, are the actors who are in the best position to minimize the combined costs of accidents and their prevention going forward. *Cf.* Gabriel Hallevy, *Unmanned Vehicles — Subordination to Criminal Law Under the Modern Concept of Criminal Liability*, 21 J.L. INFO. & SCI. 1, 3–4 (2012).

instance, encoding the rule: "never exclude a specific supplier, even if it is in your economic interest to do so." Furthermore, designers of algorithms may well be the cheapest cost avoiders.[162] Yet to be socially welfare-enhancing, this solution must be technologically possible. Also, limiting the algorithm in such a manner should not reduce welfare, the concern being that the additional complexity added to the algorithm by designing it to avoid anticompetitive behavior would negate many of the algorithm's desired benefits. Otherwise, the test should be based on the probable consequence of one's conduct.[163] For instance, if a designer creates an algorithm to reduce costs, knowing that through self-learning this algorithm will find and choose a dominant strategy which is anti-competitive, intent may be established.[164]

An interesting issue relates to an exclusionary decision based on long-term considerations of competition. For instance, assume that an algorithmic consumer is designed to avoid buying products from a monopolistic firm (or more than a certain proportion of goods from such firms) in order to encourage competition in the market. Such considerations may even extend beyond the specific market, for instance if the algorithmic consumer attempts to level the playing field in related markets, such as the market for mega platforms. We suggest that such considerations be accepted as valid justifications in the right circumstances — that is, whenever there is a strong probability that the algorithm's decision tree will indeed further competition and welfare in the long run. However, the exclusion must be proportional to the harm to any given market players and effective in achieving the pro-competitive goal.

Finally, an interesting consideration that might burden enforcement efforts is the weight to be given to different decision parameters. Assume that an algorithmic consumer gives little weight to a certain parameter, thereby indirectly excluding a certain supplier. The allegations against Google may provide a glimpse of what could be expected in such cases. Google claimed that the weight given in its search algorithm to different parameters is protected under the First Amendment of the Constitution as free speech.[165] This raises the provocative question: Should we not expect such arguments also regarding our algorithmic consumer's choice of a detergent for our washing machine, or brand of pet food?

As we have shown, while existing regulation is generally sufficiently flexible to apply to the third challenge raised by algorithmic

162. *See* GUIDO CALABRESI, THE COSTS OF ACCIDENTS: A LEGAL AND ECONOMIC ANALYSIS 41 (1970).

163. Hallevy, *supra* note 161, at 7–8.

164. Ezrachi & Stucke, *When Computers Inhibit Competition*, *supra* note 11, at 27.

165. *See, e.g.*, Search King, Inc. v. Google Technology, Inc., No. Civ-02-1457-M, 2003 WL 21464568, at *1–2 (W.D. Okla. Jan. 13, 2003).

consumers, even if not solving all the problems that arise, it is more limited in its ability to deal with the first two challenges. Other regulatory tools might thus need to be devised in order to reduce entry barriers into the market for algorithmic consumers, to deal with issues such as control of access points and essential inputs, tying and bundling of services and goods, increased buyer power, and the increased ease of oligopolistic coordination.

V. CONCLUSIONS

We are standing on the verge of a brand-new world with respect to how we buy and sell. Roles that for centuries have been performed by humans will soon be transferred to algorithms. This change is inevitable, given technological developments that give algorithmic consumers strong comparative advantages over human consumers in some decision-making processes.[166] These trends are intensified by the rise of the Internet of Things.[167]

It is thus essential that we recognize the effects of such a change on market dynamics. How are the systematic deviation of consumer purchasing decisions from past assumptions and the changes in suppliers' conduct which will surely follow, likely to alter competition and welfare? This was the first goal of this article. As elaborated, algorithmic consumers have fundamental effects on consumer choice, market demand, product design, marketing techniques, and contractual terms, among other factors. They have the potential to significantly increase competition, and at the same time to significantly limit it.

Our second goal was to identify and analyze some of the regulatory challenges that arise from these changes, and in particular the ability of existing regulatory tools to ensure that consumers enjoy the benefits algorithmic consumers have in store. As shown, algorithmic consumers challenge the application of some of our regulatory tools, which were designed to cater to human transactions. When computer code determines important transactions, some of the assumptions on which current regulation is based must be revisited. For example, we explored how the antitrust notions of agreement and intent have to be rethought to ensure that competition is indeed protected.

We also identified some market failures and regulatory challenges which may require the creation of additional regulatory tools. One such regulatory challenge is the potentially significant increase in buyer power which does not result from or lead to exclusionary conduct. The social welfare effects of the exploitation of such power,

166. *See supra* Part II.

167. *See* Daniel Burrus, *The Internet of Things Is Far Bigger Than Anyone Realizes*, WIRED (Nov. 21, 2014), https://www.wired.com/insights/2014/11/the-internet-of-things-bigger/ [https://perma.cc/KRD2-NG77].

which generally do not fall under the rubric of antitrust law, should be carefully analyzed. Another is the need to reevaluate policies towards oligopolistic coordination, given that algorithms make such coordination much easier. A third challenge involves the erection of entry barriers that arise from the tying of free services with algorithmic con-consumer functions, which build upon economies of scale, scope, and speed.

Finally, our paper has also shown that new forms of regulation might also be necessary to deal with situations in which competition among providers of algorithms will not necessarily positively affect social welfare. For example, applying cyber-security measures to protect algorithms from cyber-attacks at a socially optimal level is costly.[168] One would expect competition to exclude unsecured systems by increasing demand for safer applications. Yet consumers often lack the information and skills needed to assess cyber-risk. [169] Moreover, security failures create externalities, by increasing vulnerabilities in other networks and products,[170] which each provider of algorithms does not take into account. Consequently, providers of algorithms will most probably not create protections at the socially optimal level.[171]

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168. *See, e.g.*, Nathan Alexander Sales, *Regulating Cyber-Security*, 107 NW. U.L. REV. 1503, 1545 (2013) (stating that in cyberspace defense is much more costly than offense).

169. *See, e.g.*, C.W. Johnson, *The Role of Cyber-Insurance, Market Forces, Tort and Regulation in the Cyber-Security of Safety-Critical Industries*, *in* 10th IET System Safety and Cyber-Security Conference 1–2 (2015), http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7792013 [https://perma.cc/7M4J-SVFW].

170. *See id.* at 3.

171. *See id.* at 1–2.