# II. Algorithms and Automation

# Algorithm-friendly consumers – Consumer-friendly algorithms?

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## *A. Introduction and Overview*

In the digital era algorithms are ever increasingly integrated into our daily lives and structure almost every consumption decision and consumer choice. This contribution combines two distinct fields of research: i) Human-AI-Interaction (HAI), an interdisciplinary research field spanning disciplines from technology and innovation management, behavioural economics and marketing, to information systems research (all of which analyse barriers and enablers of algorithm adoption); and ii) consumer protection law and theory (which protects consumers from encroachments of their autonomy). While the premises of these two fields of research seem at odds with one another – HAI predominantly strives to bring the consumer closer to the algorithm, while consumer protection law wishes to protect the consumer from the black box – we argue that the ubiquitous use of algorithms creates a common perspective. Both HAI and consumer protection law should strive to enhance the understandability and transparency of algorithms, making their use not only more commonly accepted, but also a true expression of autonomous choice. In addition, a combination of the two fields provides unique insights into how consumers interact with algorithms and how choices are made by algorithmically-enhanced consumers. We suggest that some of these insights can be used to design more concise and effective consumer protection tools in the future.

This article thus does two things. It, first, describes novel ways in which humans are interacting with algorithms and how this changes the rational choice paradigm and may even give rise to a new type of consumer. It then suggests that consumer protection tools should be designed around this form of interaction and knowledge and shows ways how trust and transparency can be increased.

In order to do so we first describe how consumers encounter algorithms. We also describe and elaborate on normative notions of algorithmically-enhanced consumers. Here we suggest that consumers are not only assisted or nudged by algorithms, but that a new type of consumer is emerging: the *hybrid consumer*, whose choices are the combined result of human and machine rationality, agency and subjective inclination. Since such developments can lead to large information asymmetries, the loss of autonomy and also a reluctance of consumers to employ such tools and mechanisms, we look at how consumer acceptance is driven by understandability, trust and transparency in current literature evolving around human-AI research. Last, we look at how these findings can perhaps support the development of new consumer protection tools. While mandated disclosures are classical tools to reduce information asymmetries, we show that more nuanced and novel ways to create more intuitive forms of understandability and transparency are emerging. Before suggesting that these findings may speak in favour of personalised or dynamic and integrated disclosures, we reflect on the function of consumer protection law and the development of the notions of agency and autonomy.

## *B. Consumer interaction with algorithms*

In the digital world, consumers encounter algorithms (digital tools representing a fixed step-by-step decision-making process, making use of statistical calculations, mathematical tabulations, and/or computer programs) everywhere – regardless of whether they want to actively use them or not.[1]

This is primarily due to the fact that many current business models and products – e.g., streaming services, dating portals, or recommendation systems on online shopping platforms – are based on algorithms.[2] For example, in the case of a new product purchase, the digital purchasing process differs significantly from an offline purchase due to the algorithms used. In the latter case, the decision-making process and the decision-making criteria (e.g., product type, price) are known. When the buying process is shifted to the digital world, however, the process takes a different form. The input (product search) remains the same, but the output (suggestions of products) and the decision-making process differ, and while it is traceable and reproducible in the non-digital space, it resembles a 'black box' in the digital space. The algorithm decides which products appear in which place and thus implies a kind of popularity. This is often done by

1 *B. J. Dietvorst/D. M. Bartels*, Consumer Object to Algorithms Making Morally Relevant Tradeoffs Because of Algorithms' Consequentialist Decision Strategies, Journal of Consumer Psychology, 2021, 406.
2 Examples based on *Dietvorst/Bartels.*, Algorithms (n. 1).

so called 'neighbourhood-based collaborative algorithms', which suggest products that have the highest rating among a customer group which is similar to the user.[3] However, algorithms structure the decision-making process not only for product purchases, but also for other online services, such as algorithmic dating websites, online calculators for insurance and loans, or robo-advisors for investment decisions.[4] These examples show that the most typical form of interaction between humans and AI-based algorithms in a digital environment is the use of so-called search and recommendation systems. Yet, although similar, search and recommendations are different.[5] While search algorithms provide a system response toward an active search action (e.g., Google search or Amazon product search), recommendations will then rank the search results – implying a good fit for the search activity.[6] Pure recommender systems show recommendations without actively searching for information or products, e.g., landing pages of YouTube, Amazon or Google.[7]

In spite of this ubiquity and the feeling that one cannot avoid these systems, consumers generally show adverse behaviours with regard to the use of algorithms. This adversity may be troublesome for two reasons. Either consumers are not using and reaping the benefits of certain algorithms, or consumers are employing algorithms but do so begrudgingly and at the cost of their autonomy (and in many cases privacy). Safeguarding consumer autonomy and thus repairing this market failure is the classical function of consumer protection law. Before we turn to consumer protection law and questions of transparency, we look at new normative notions of the consumer that are emerging in the digital world.

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3 *F. Ricci/L. Rokach/B. Shapira.*, Introduction to recommender systems handbook, in: Recommender Systems Handbook, Boston, Springer, 2011, 1.

4 Examples based on *Dietvorst/Bartels,* Algorithms (n. 1).

5 *O. Budzinski/B. A. Kuchinke,* Industrial organization of media markets and competition policy, in: M. B. Rimscha/S. Kienzler (eds.), Handbooks of communication science [HoCS]: Bd. 30. Management and Economics of Communication, Berlin/Boston, 2020, p. 21.

6 *B. Edelman,* Bias in Search Results?: Diagnosis and Response, Indian Journal of Law and Technology, 2011, 16.

7 For a detailed discussion see *O. Budzinski/S. Gaenssle/N. Lindstädt*, Data (r)evolution: The economics of algorithmic search and recommender services, in: S. Baumann (ed.), Handbook of Digital Business Ecosystems, Cheltenham: Elgar, 2022, p. 349.

## C. Algorithmically enhanced consumers

Consumers' choice and actions interactions can be altered and enhanced by algorithms in a number of different ways. In the following section, we therefore describe and elaborate on normative notions of algorithmically-enhanced consumers and suggest that consumers are not only assisted or nudged by algorithms, but that a new type of consumer is emerging: the *hybrid consumer*.

### I. Consumers as products

It is trite fact that consumers are mined and targeted for their data.[8] While the notion of the 'consumer as a product' is not a new category of consumer and does not specifically describe changes in consumer choice, it has brought some underlying and fundamental features of digital capitalism and digital market mechanisms and their effects on consumers to our attention. In 2016/2018 *Tim Wu* and *Shoshana Zuboff* coined the related terms 'surveillance capitalism' and the 'attention economy',[9] to describe mechanisms and strategies to capture consumer attention and human experience – information about us, our interactions, habits and interconnections – in the form of data, as though they were a natural resource,[10] and in turn making platforms and products ever more targeted and personalised, thereby aiding further attention and extraction.[11] *Zuboff* shows how, in the platform economy,[12] consumers become supply chain interfaces as their personal information, experiences and interactions are harvested as

8 *S. Zuboff*, The Age of Surveillance Capitalism, New York, PublicAffairs, 2018; for a review of how this has been incorporated into contract law: *T. Bauermeister*, Die "Bezahlung" mit personenbezogenen Daten bei Verträgen mit digitalen Produkten, AcP 222, 2022, 372.

9 The attention economics itself is not a new phrase or field of study, but has been an essential part of media economics for decades. See *T. Davenport/J. Beck*, The Attention Economy: Understanding the New Currency of Business, Harvard Business School Press, 200.

10 *Zuboff*, The Age of Surveillance Capitalism (n. 8).

11 *Zuboff*, The Age of Surveillance Capitalism (n. 8); *T. Wu*, The Attention Merchants, New York 2016.

12 For the economic foundations of the platform economy see *O. Budzinski/J. Mendelsohn*, § 1 Hintergründe, Ziele und wettbewerbspolitische Einordnung des Digital Markets Act, *J. P. Smidt/D. Hübener*, Das neue Recht der digitalen Märkte, forthcoming, Nomos, 2022.

data.[13] They are thus distanced from their traditional role in the market and, in part, become the commodity,[14] *Wu* first used the phrase 'consumers as products' by pointing out that "*when an online service is free, you're not the customer – you're the product*".[15] While the addictive elements of several platform services, as well as the integration of consumers in the product test process have long been considered problematic, both *Zuboff's* and *Wu's* focus on the 'hidden' elements[16] and the pervasive expanse of these technologies (from online stores, to communication platforms, to games) offer insights into the more fundamental shifts taking place, which in turn inform consumer protection law.

The first shift is the effect on autonomy and the traditional idea that the act of autonomous choice is located with the individual. In fact, while the economy (its products and services) has become ever more targeted, 'customised' and 'personalised', *Wu* and *Zuboff* argue that the role of the autonomous individual – the person beyond their data – is fading.[17] Second, with the commodification of consumers, or rather their data, and „*unilaterally claims human experience as free raw material for translation into behavioural data*"[18], information (and power) asymmetries grow. In addition, information asymmetries become more pervasive as they now include not only market factors and transaction parameters, but information on the consu-

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13 *A. Jenkins*, Shoshana Zuboff on the age of surveillance capitalism, interview 16.09.2019, contagious, available at https://www.contagious.com/news-and-views/shoshana-zuboff-on-the-age-of-surveillance-capitalism (last access: 04.10.2022): „There is a complete misunderstanding of what all these things are. They are supply chain interfaces. The only thing that surveillance capitalists really have to worry about is supply chain. It's about expanding new flows of behavioural surplus. Every interface for the internet becomes a supply chain interface." also *Zuboff*, The Age of Surveillance Capitalism, (n. 8) p. 129 et seq.

14 *Zuboff*, The Age of Surveillance Capitalism (n. 8) p. 63 et seq.

15 *Wu*, The Attention Merchants (n. 8).

16 *Zuboff*, The Age of Surveillance Capitalism, (n. 8) p. 87 et seq.: Zuboff states that these business models, which are founded on predictive algorithms, mathematical calculations of human behaviour are designed to extract the maximum amount of information about any consumer or interaction and managed to shade or disguise such intention. See interview also *S. Naughton*, The goals is to automate us: welcome to the age of surveillance capitalism, The Gurdian online 20.01.2019, available at https://www.theguardian.com/technology/2019/jan/20/shoshana-zuboff-age-of-surveillance-capitalism-google-facebook (last access: 04.10.2022).

17 „Surveillance capitalists no longer rely on people as consumers. Instead, supply and demand orients the surveillance capitalist firm to businesses intention anticipating the behaviour of populations, groups and individuals." See *Naughton*, The goals is to automate us (n. 16).

18 *Naughton*, The goals is to automate us (n. 16).

mers themselves. Last, while the participation (and the lending of data) in such services or markets is seen as voluntary, and it is often stipulated that consumers simply don't care enough to opt out of sharing their data with large platforms (this is the logic underlying so-called 'privacy paradox'). *Zuboff*, however, points out that consumers barely have a choice at all: „*we are trapped in an involuntary merger of personal necessity and economic extraction, as the same channels that we rely upon for daily logistics, social interaction, work, education, healthcare, access to products and services, and much more, now double as supply chain operations for surveillance capitalism's surplus flows*".[19] This may not always be true, but is certainly worth reflecting upon when reviewing designing remedies to reclaim consumer autonomy.

## *II. Assisted consumers*

Several search and rank algorithms, as well as algorithms based on previously determined preferences, can help consumers make decisions.[20] If we could assume that consumers consciously and willingly use these algorithms, we could stipulate an enhancement, rather than an encroachment, of autonomy and consumer choice throughout.[21] Several factors, however, point to growing limitations on 'true' consumer choice. The more such algorithms are incorporated in large ecosystems, the more path dependencies and 'lock-in' effects become likely. In several platforms, consumers are already concerned with orchestrated choices, in much the same way as they are caught in 'filter bubbles' on media platforms.[22] In addition, even where algorithms make simple choices, the line between the human decision and that of the algorithm can easily become blurred. Studies find that consumers are likely to align their choice with that of the algorithm and, for instance, choose products or services marketed as the 'best deal'[23] (e.g., 'Amazon's Choice'[24]). In addition, rather than enabling the consu-

19 *Naughton*, The goals is to automate us (n. 16).
20 For examples see *M. Gal/N. Elkin-Koren*, Algorithmic Consumers, Harvard Journal of Law & Technology 2017, 309 (314).
21 *Gal/Elkin-Koren*, Algorithmic Consumers (n. 20) 309 (314).
22 *E. Pariser*, The Filter Bubble: How the Personlized Web is Changing What We Read and How We Think, New York 2011.
23 E.g., *D. DelVecchio*, Deal-prone consumers' response to promotion: The effects of relative and absolute promotion value, Psychology & Marketing 2005, 373
24 *L. Matsakis*, What Does It Mean When a Product is Amazon's Choice, Wired magazine 4.6.2019, available at https://www.wired.com/story/what-does-amazons

mer, the increased use of such algorithms may diminish the role of the (non-assisted) consumer in such choice processes and as a (fully) rational agent. It will increasingly be assumed that a choice made with the use of an algorithm is *per se* the better choice and that the choice suggested by the algorithms is already fully rational. The use of an investment app (e.g., 'eToro') is one blatant example. The amount of data fairly simple algorithms can process alone will increasingly make unassisted choices or those based on idiosyncrasies or a 'gut feeling' appear less rational and thus suboptimal.

### *III. Algorithmic consumers*

A new generation of algorithms takes such assistance one step further, making and executing decisions for the consumer by directly communicating with other systems through the internet. As per the analysis of *Michal Gal* and *Niva Elkin-Koren*, 'algorithmic consumers' are no longer people or human agents, but algorithms and devices that have taken over the function of making independent and autonomous decisions and purchasing choices: a refrigerator that stocks up on milk, a car that drives itself to the gas station or an investment tool that purchases a certain stock at a certain price.[25] While a range of benefits are driving this development – speed, analytical sophistication, the reduction of transaction and information costs,[26] and even the overcoming of language and information

-choice-mean/ (last access: 04.10.2022); *J. Luguri/L. Strahilevitz,* Shining a light on dark patterns, Journal of Legal Analysis 2021, 43.

25 *Gal/Elkin-Koren*, Algorithmic Consumers, (n. 20) 310: "The next generation of e-commerce, researchers say, will be conducted by digital agents based on algorithms that can handle entire transactions: using data to predict consumers' preferences, choosing the products or services to purchase, negotiating and executing the transaction, and even automatically forming coalitions of buyers to secure optimal terms and conditions. Human decision-making could be completely bypassed. Such algorithms might be written by consumers for their own use or supplied by external firms. We call these digital assistants 'algorithmic consumers'.

26 *Gal/Elkin-Koren*, Algorithmic Consumers (n. 20) 318–320.

constraints[27] – it will have large implications for consumer autonomy,[28] since the consumer will now always be at least "*one step removed from the consumption decision*".[29] Of course, the consumer chooses the tool, some of the primary factors, and may even be able to influence or deviate from the choices made, but, as stated by *Gal* and *Elkin-Koren*, these remaining instances of autonomous choice will largely be dependent on the design and transparency of the algorithm.[30] While the reduction of autonomy is a grave principle problem, as it detaches individuals ever more from the contractual conditions that form the legal architecture of their lives, there are potential welfare and equality harms as well. Individual welfare harms can result from an imperfect reflection of a consumer's preferences, i.e., personalized pricing according to luxury rather than standard preferences. In addition, welfare concerns go hand-in-hand with concerns about manipulation and coercion. As *Gal* and *Elkin-Koren* put it: "*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 the algorithms*." Equality concerns, on the other hand, arise from a group of individuals being cut off from these technologies and thus from the cost benefits.

## *IV. Hypernudged consumers*

Even where consumers have not intentionally outsourced their choice, algorithms increasingly influence consumer purchasing decisions, by preselecting offers and 'nudging' them in a certain direction.[31] In any digital consumer environment, be it a store website, a platform, a mobile applica-

27 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. See also *O. Bar-Gill*, Seduction by Contract: Law, Economics, And Psychology In Consumer Markets, Oxford 2012, 19; *O. Ben-Shaher/C. Schneider*, More than you wanted to now: the failure of the mandated disclosure, Princeton 2014, 7–9.

28 See also *Gal*, Technological Challenges to Choice 24 (Feb. 19, 2017) (unpublished manuscript) (on file with the Harvard Journal for Law & Technology).

29 *Gal/Elkin-Koren*, Algorithmic Consumers (n. 20) 322.

30 *Gal/Elkin-Koren*, Algorithmic Consumers (n. 20) 322, 323.

31 *J. Mendelsohn*, Die normative Macht der Plattformen, MMR 2021, 857 (859); *L. E. Willis*, When Nudges Fail: Slippery Defaults, University of Chicago Law Review 2013, 1155; *K. Yueng*, "Hypernudge": Big Data as a Mode of Regulation by Design, Information, Communication & Society 2016, 19; *N. Zingales*, Anti-

tion (app) or an IoT-interface, navigation takes place through algorithms and consumers are increasingly confronted with so-called 'dark patterns'.[32] In this context hypernudging – a term derived from *Sunstein* and *Thaler's* 2008 notion of nudging[33] – refers to "*algorithmic real-time personalization and reconfiguration of choice architectures based on large aggregates of personal data*."[34] A large amount of this nudging is both necessary to make large online platform manageable for the consumer and in the interest of the consumer, who would otherwise drown in an information and choice overload.[35] At the same time, the risk of manipulation and coercion is virulent and increases with lack of transparency and the inability of the consumer to comprehend the choice architecture. While choices in the real world have never been perfect (based on perfect information) and have always been (at times severely) limited, hypernudging can mean that autonomous consumers are removed from at least the first steps of the decision process, limiting their choice from the outset.

## *V. Hybrid consumers*

In all of the constellations of interactions between algorithms and consumers listed above, it is striking that the consumer is still considered a separate and distinguishable entity. The consumer is described as being either assisted or guided by, nudged towards, or replaced with, algorithms. Little attention, however, is payed to the more fundamental shift taking place: the merger of human and machine (or algorithmic) choice and agency. We notice that these lines are blurred. Not only is it becoming increasingly difficult to locate instances of isolated consumer choices; but consumers will be making choices together with algorithms in the future,

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trust Intent in an Age of Algorithmic Nudging, Journal of Antitrust Enforcement 2019, 3.

32 See *Luguri/Strahilevitz,* Shining a light on dark patterns (n. 24), 43.

33 *R. Thaler/S. Sunstein*, Nudge: *Improving decisions about health, wealth, and happiness*, New Haven 2008, p. 3: „any aspect of choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid."

34 *M. Lanzing,* "Strongly Recommended" Revisiting Decisional Privacy to Judge Hypernudging in Self-Tracking Technonologies, Philosophy and Technology 2019, 549; *K. Yeung*, Information Communication and Society 2017, 118 (126); see also *Mendelsohn*, Normative Macht (n. 31), 859.

35 *Budzinski/Gaenssle/Lindstädt*, Data (r)evolution (n. 7).

and that the point where the one begins and the other ends will barely be determinable. Where a choice is nudged, assisted and then partly executed by an algorithm, any such choice will be made simultaneously by a machine and a human. We thus suggest that a new generation of consumer algorithms and a new notion of the consumer is emerging. We call this the ***hybrid consumer***. The hybrid consumer is the choice agent that results from the combined and interacting rationality between an algorithm or machine and an autonomous human individual. A good example is the use of 'trial-and-error'-based algorithms that require a lot of interaction and 'learn' from an ongoing set of user choices, while, in turn, the user too adapts her choices, interaction, expectation, and in part even her rationality, as she gets used to the way the algorithm works.

For closer insights, imagine investment decisions in the digital space: Investment tool algorithms often employ machine learning techniques and thus learn from the users already on the platform to identify and allocate their wishes and needs. When a new customer registers with such a platform, the algorithm typically already knows her gender, age, education, marital status, income and race categorization. With the use of neighbor-based-algorithms, the algorithm first matches the new user with other similar user groups and offers her initial choices in line with preferences that are popular in this group. Afterwards, the new user can interact with the platform by scrolling through investment plans and – potentially -making first investment decisions. The algorithms are designed to learn about the customer and the customer learns about the algorithm while providing it with further data, filtering decision outcomes and describing preferences. The algorithm is thus designed to make ever better suggestions for investment plans. Vice versa, in an ideal setting, the customer learns ever more about the algorithm and its behavior. This interactive environment is said to provide the (hybrid) consumer with ever better and ever more tailored options. The emergence of the hybrid consumer, however, also raises a number of concerns and challenges. The stronger the lines between the machine and user are blurred, the more important it is to secure human autonomy. We assume that more transparency and understandability of algorithms can enhance trust, acceptance and thus autonomy. We thus look at algorithm acceptance and transparency in more detail.

## D. Acceptance of algorithms: current state of research

Research on factors that facilitate or impede technology adoption has a long tradition in marketing, technology, and innovation research. Well-known models such as the TAM (Technology-Acceptance-Model)[36] or the UTAUT (Unified Theory of Acceptance and Use of Technology)[37] model have long formed the starting point for research into acceptance factors of new technology. However, with the advent of algorithms, this type of research has taken on a new angle, as current models do not yet fully represent the far-reaching consequences that arise from the application of algorithms and artificial intelligences, e.g., in employee scenarios,[38] but also in consumer research.

The adoption of AI and algorithms is thus unique in the following four ways:[39] (1) AI tools are considered 'black boxes', i.e., the input and output is usually transparent, but not the process to produce the output; (2) underlying models and computations are never 100% error-free – although often superior to human capabilities – and often have an error rate that even increases in very dynamic environments or with little data access; (3) models need time to learn, and thus are more error-prone in early than in later applications; (4) algorithms are subject to biases that can vary in severity, at times with far-reaching consequences. These points create resistance among users who have to interact with algorithms. Negative reactions often occur even when users know that the algorithm provides better insights than human decision makers.[40] While this finding has been confirmed in numerous studies, some studies indicate that algorithms are, in some cases, preferred over human decision-makers.[41] Overall, four thematic areas can be listed that influence algorithm adoption: (1) higher-level factors (e.g., cultural, societal, or environmental factors); (2) individual factors (e.g., personality, demographics, psychological attributes); (3) task-related factors (e.g., complexity and moral classification of the task); and

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36 *F. D. Davis,* Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, MIS Quarterly 1989, 319.

37 *V. Venkatesh/M. G. Morris/G. B. Davis/F. D. Davis*, User acceptance of information technology: Toward a unified view, MIS Quarterly 2003, 425.

38 *V. Venkatesh,* Adoption and use of AI tools: a research agenda grounded in UTAUT, Annals of Operations Research, 2021, 641.

39 *Venkatesh,* Adoption and use of AI tools (n. 38).

40 *B. J. Dietvorst/J. P. Simmons/C. Massey*, Algorithm aversion: people erroneously avoid algorithms after seeing them err, Journal of experimental psychology, 2015, 114.

41 *Dietvorst/Bartels,* Algorithms (n. 10).

(4) algorithm-related factors (e.g., design, decision, delivery mode of the outcome)[42]. We argue, that algorithm-related factors in particular play a critical role in the acceptance of algorithms in the consumer sector and thus also in consumer protection, since they can be influenced by companies and also by consumer protection law.

Current research from the field of dedicated consumer research shows that consumers are not willing to employ algorithms in every purchase decision[43] and overwhelmingly reject them for very subjective tasks.[44] We know from HR research that human decision makers are more likely to be seen as having the ability to consider individual and moral circumstances, while algorithms are perceived as reductionist and limited to consider qualitative information as well as contexts.[45] Consumers are particularly prone to such conclusions, if the algorithms are not transparent. Current studies show that even experts are often unable to understand how an algorithm works in detail.[46] It is thus necessary to look at transparency in more detail.

## *I. Transparency*

The transparency of an algorithm is generally understood to be the degree to which the underlying rules of operation and internal logic of a technology are apparent to users, and is considered critical to the development of trust in new technologies.[47] Researchers therefore suggest creating more

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42 *H. Mahmud,* What influences algorithmic decision-making? A systematic literature review on algorithm aversion, Technological Forecasting and Social Change, 2021.

43 *B. J. Dietvorst/D. M. Bartels,* Consumers Object to Algorithms Making Morally Relevant Tradeoffs Because of Algorithms' Consequentialist Decision Strategies, Journal of Consumer Psychology 2021, 406.

44 *N. Castelo/M. W. Bos/D. R. Lehmann,* Task-Dependent Algorithm Aversion, Journal of Marketing Research 2019, 809.

45 *D. T. Newman/N. J. Fast/D. J. Harmon,* When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions, Organizational Behavior and Human Decision Processes 2020, 149.

46 *J. Burrell,* How the machine 'thinks': Understanding opacity in machine learning algorithms, Big Data & Society 2016; *J. Kroll/J. Huey/S. Barocs/E. W. Felten/J. R. Reidenberg/D. G. Robinson/H. Yu,* Accountable algorithms, University of Pennsylvania Law Review, 2016, 633.

47 *K. A. Hoff,* Trust in Automation: Integrating Empirical Evidence on Factors That Influence Trust, Human factors 2015, 407.

transparency on both sides of the human-algorithm interaction to form more trust and trust calibration.[48] A great driving force of acceptance is to open the 'black box' and disclose the decision-making process of an algorithm.[49] People arguably have an intrinsic interest in knowing the underlying principles of algorithmic decision making, that is, in understanding the algorithm and its rationale.[50] This means that transparency must be increased to gain acceptance. Increasing transparency can be influenced by five factors in particular: access to decision patterns; explanation of decision rationale; understanding of what is explained; interaction with the algorithm; and integration of personal opinions.[51]

1. **Accessibility** Current research shows that human decision makers are preferred to algorithmic decision makers because it is felt that there is more and better access to them and they can be asked for their rationale.[52] On the other side, algorithms cannot be consulted about their decision making[53] and thus the reasons for the decision-making cannot be understood, which ultimately leads to a loss of trust in algorithms.[54]
2. **Explainability** This can be countered by making algorithmic decisions more explainable.[55] For example, studies show that linking a decision

48 *J. W. Burton/M. Stein/T. B. Jensen,* A systematic review of algorithm aversion in augmented decision making, Journal of Behavioral Decision Making 2020, 220.

49 *R. Litterscheidt,* Financial education and digital asset management: What's in the black box?, Journal of Behavioral and Experimental Economics, 2020; *N. N. Sharan/D. M. Romano,* The effects of personality and locus of control on trust in humans versus artificial intelligence, Heliyon 2020.

50 *H. Mahmud/A. K. M. Najmul Islam/S. I. Ahmed/K.* Smolander, What influences algorithmic decision-making? A systematic literature review on algorithm aversion, Technological Forecasting and Social Change 2022, 1.

51 For an overview and a detailed review see *Mahmud/Najmul Islam/Ahmed/Smolander,* Decision-making (n. 50); Criteria by *A. Chander,* Working with Beliefs: AI Transparency in the Enterprise, IUI Workshops 2018.

52 *D. Önkal/P. Godwin/M. Thomson/M. S. Gönül/A. Pollock,* The relative influence of advice from human experts and statistical methods on forecast adjustments, Journal of Behavioral Decision Making 2009, 390.

53 *U. Kayande,* How Incorporating Feedback Mechanisms in a DSS Affects DSS Evaluations, Information Systems Research 2009, 527; *Önkal/Godwin/Thomson/Gönül/Pollock,* Influence (n. 52).

54 *P. Goodwin/M. S. Gönül/D. Önkal,* Antecedents and effects of trust in forecasting advice, International Journal of Forecasting 2013, 354; *Önkal/Godwin/Thomson/Gönül/Pollock,* Influence (n. 52).

55 *M. S. Gönül et al.* The effects of structural characteristics of explanations on use of a DSS. Decision Support Systems, 2006, 1481.

to a provided explanation of how the algorithm works increases the acceptance of algorithms.[56]

3. **Understandability** However, an explanation alone is not sufficient to fully increase acceptance. Another important factor is to understand the algorithm itself.[57] An increase in comprehensibility can be achieved by personalized language,[58] a friendly tone of voice,[59] descriptive illustrations[60] and a convincing style of speech.[61]
4. **Interactability** Furthermore, an interaction of consumers with the algorithm to find out which factors lead to which result, by a so-called trial-and-error procedure,[62] can have a positive effect on transparency. This calibration process increases confidence in the algorithmic decision maker,[63] feedback on the algorithm's performance alone, on the other hand, is not sufficient; there must be some kind of iterative learning process by the user.[64]
5. **Integratability** Finally, it is also crucial that algorithms are integrative, i.e., considers the input of users ('human-in-the-loop')[65]. Although this does not necessarily lead to better results, consideration in the sense of including points important to the individual is helpful in accepting the algorithm output.[66]

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56 *Goodwin/Gönül/Önkal*, Forecasting, (n. 54); *L. Zhang*, Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services, Journal of Services Marketing 2021, 634.

57 *M. Yeomans*, Making sense of recommendations, Journal of Behavioral Decision Making 2019, 403.

58 *J. H. Yun/E. Lee/ D. H. Kim*, Behavioral and neural evidence on consumer responses to human doctors and medical artificial intelligence, Psychology & Marketing 2021, 610.

59 *Yun/Lee/Kim*, Artificial Intelligence (n. 58).

60 *L. Zhang*, Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services, Journal of Services Marketing 2021, 634.

61 *Önkal/Godwin/Thomson/Gönül/Pollock*, Influence (n. 52).

62 *K. van Dongen*, A framework for explaining reliance on decision aids, International Journal of Human-Computer Studies 2013, 410.

63 *Van Dongen*, Framework (n. 62).

64 *Van Dongen*, Framework (n. 62).

65 *N. Köbis/L. D. Mossink*, Artificial intelligence versus Maya Angelou: Experimental evidence that people cannot differentiate AI-generated from human-written poetry, Computers in human behavior 2021, 1.

66 *B. J. Dietvorst/J. P. Simmons/C. Massey*, Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them., Management Science 2018, 1155.; *K. Kawaguchi*, When will workers follow an algorithm? A field experiment with a retail business., Management Science 2021, 1670.

### *II. Creating transparency*

While we often think about increasing transparency in very straight-forward terms, the sub-factors identified above as well as experimental studies with 'trial-and-error'-based learning and 'human-in-the-loop' mechanisms, show that both transparency and acceptance are more fluid notions and can be achieved in a number of ways. While opening the so-called black box is primarily determined by transparency, especially the subfactor familiarity with algorithms and algorithmic tasks has a major impact on the willingness to accept an algorithm. Studies have shown that a perceived general unfamiliarity with the algorithm leads to higher aversion.[67] Yet, familiarity can be a double-edged sword, as becoming familiar with an algorithm can also mean becoming familiar with algorithmic errors.[68] People lose trust in buggy algorithms faster, especially for supposedly simple tasks.[69] Similarly, *Andrew Prahl* and *Lyn Van Snowl* show in their experimental work that humans loose trust in bad algorithmic advice more quickly than in the bad human advice.[70] However, the experimental work of *Berkeley Dietvorst* and his co-authors shows that people might distrust algorithms, but that this aversion can be overcome by giving them the opportunity to slightly influence the outcome.[71] When users can personally experience that algorithms are capable of learning, acceptance increases.[72] In addition, studies have shown that users will accept algorithms more frequently if they feel that the results of the algorithms will be favourable to them.[73] Hence, not only the typical transparency aspects help to over-

67 *J. S. Lim/M. O'Connor*, Judgemental adjustment of initial forecasts: Its effectiveness and biases, Journal of Behavioral Decision Making 1996, 149; *S. M. Whitecotton*, The effects of experience and a decision aid on the slope, scatter, and bias of earnings forecasts, Organizational Behavior and Human Decision Processes 1996, 111.

68 *Mahmud/Najmul Islam/Ahmed/Smolander*, Decision-making (n. 50).

69 *P. Madhavan/D. A. Wiegmann/F. C. Lacson*, Automation Failures on Tasks Easily Performed by Operators Undermine Trust in Automated Aids, Human Factors 2006, 241.

70 *A. Prahl/L. Van Snowl*, Understanding algorithm aversion: When is advice from automation discounted? Journal of Forecasting, 2017, 691.

71 *Dietvorst/Simmons/Massey*, Overcoming aversion (n. 66).

72 *B. Berger/M. Adam/A. Rühr/A. Benlian*, Watch Me Improve—Algorithm Aversion and Demonstrating the Ability to Learn, Business & Information Systems Engineering 2021, 55.

73 *I. Toma/D. Delen/G. Moscato*, Impact of Loss and Gain Forecasting on the Behavior of Pricing Decision-making, International Journal of Data Science and Analysis 2020, 12.

come negative prejudices, but the interaction with the algorithm itself contributes immensely to a profound understanding of how the algorithm works, which errors it is prone to and if it is positive for one to use the algorithm.

We therefore argue that key to an informed and comfortable usage with algorithms is the interplay between an informed understanding of the algorithm's functionality and the ability to experiment with or to learn about the algorithm in a mock-up environment. We argue that trial-and-error-experience in a learning environment is just as important as being intellectually educated about how the algorithm works and was made. Through interaction, human-in-the-loop and trial-and-error, the black box can open up even further, and the user can begin to find its mechanisms and functionality transparent in ways that are more intuitive and also closer to the user's experience. Ultimately, consumers are able to make more informed decisions when interacting with algorithms in a digital environment.

In summary, we have suggested that a comfortable user interaction with algorithms depends on transparency and familiarity. Explanations for the algorithms would have to be available, describing how the algorithm works. In particular, clear, understandable language and illustrations should be used. It should also be possible to interact with the algorithm. One method would be to learn about the algorithm in a test environment and through trial-and-error. Ultimately, it is also crucial for an increase in acceptance that users feel that their voices are heard and their preferences are incorporated. One possible approach here would be to allow factors to be weighted or criteria to be included or excluded.

## *E. Consumer protection in the age of algorithms*

In light of current developments in digital spaces, large information asymmetries, the loss of autonomy and also a reluctance of consumers to employ such tools and mechanisms are likely to occur. We thus explore how to design new consumer protection tools to overcome these barriers by incorporating the findings and results of the research on consumer acceptance of algorithms into the design of these remedies.

### *I. The aims and rationale of consumer protection law*

According to classical law and economics dogma, the function of consumer protection is to remedy market failure resulting from information asymmetries that exist between consumers and businesses.[74] In contract theory and economics, information asymmetry deals with transactions where one party has more or better information than the other. This causes market failure and at times even moral hazards and a 'monopoly of knowledge'.[75] These imbalances affect the formal preconditions of private and contract law, that stipulate that contracting parties are 'equal' and also autonomous. Standard consumer protection tools such as mandated disclosures, 'notice and consent' (privacy), but also withdrawal rights, aim to boost autonomy and counteract asymmetry by lending ever more information to the consumer. The mandated disclosure (*Informationspflichten*) is a regulatory instrument and contract law tool that requires the discloser to give the disclosee information which she may use to make a more informed and hence better decision and to prevent the discloser from abusing his information power.[76] Notice and consent is a form of mandated disclosure most commonly used to protect privacy and requires that consumers/users are notified and give permission before any information may be stored or used about them.[77] Withdrawal rights grant consumers a period during which they can cancel and revoke their contract or purchase.

Both the normative assumptions and the effectiveness of these consumer protection tools have been debated for a long time.[78] Significantly, behavioural economics has shed light on several irrationalities and idiosyn-

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74 *R. Cooter,* Law and Economics, 6th ed., Boston 2016, 276; *O. Bar-Gill*, Seduction by Contract, Oxford 2012; *O. Williamson,* Legal Implications of Imperfect Information in Consumer Markets, The New Institutional Economics Market Organization and Market Behavior 1995, 49.

75 See *G. A. Akerlof*, The Market for „Lemons“: Quality Uncertainty and the Market Mechanism, The Quarterly Journal of Economics 1970, 488.

76 See *O. Ben-Shahar/C. E. Schneider*, The Failure of Mandated Disclosure, University of Pennsylvania Law Review 2010, 647.

77 See *D. Susser,* Notice after Notice and Consent: Why Privacy Disclosures Are Valuable Even If Consent Frameworks Aren't, Journal of Information Policy 2019, 37.

78 *Ibid;* A. Ferrell, Measuring the Effects of Mandated Disclosure, Berkeley Business Law Journal 2004; *Ben-Shahar/Schneider*, The Failure of Mandated Disclosure (n. 76).

crasies driving consumer choice.[79] While this has not changed consumer protection law, it has meant that its assumptions and foundational stipulations are increasingly 'formal' in function and say little about actual or material consumer choice.[80] We are thus forced to admit that simply giving consumers extensive additional information, may serve to empower them legally, but does little to change the rationality of their choices or to remedy related market failure.[81] Instead, tools such as mandated disclosures have found more nuanced and theoretical justifications.[82] The interactions with algorithms further blur the conditions for rational choice. On the one hand consumers use algorithms to guide and steer their choices, thereby in part assisting or outsourcing them. Here the algorithm may be considered the *agent* of the consumer and the consumers are assumed to be making autonomous and rational choice by choosing to integrate algorithms into the process.[83]

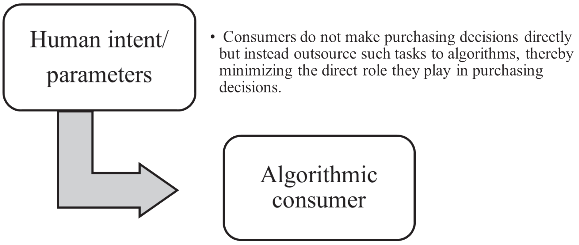
79 *Cooter*, Law and Economics, (n. 74), 50; In 2013 Richard Posner described it as follows: "What is called 'behavioral economics' […] has undermined the economic model of man as a rational maximizer of his self-interest and helped to expose the rampant exploitation by business of consumer psychology. Businesses know, and economists are learning, that consumers are easily manipulated by sellers into making bad choices—choices they would never make if they knew better." *R. Posner*, Why is there no Milton Friedman today?, Econ Journal Watch 2013, 210.

80 For the destinction between formal and material statements in contract law see: *W. Canaris*, Wandlungen des Schuldvertragsrechts – Tendenzen zu seiner "Materialisierung", 200 AcP 2000, 273.

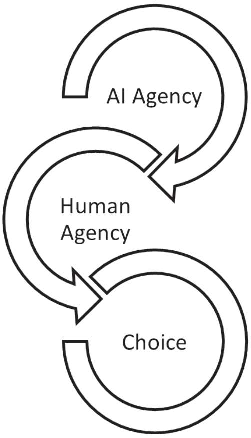
81 *A. N. Scholes*, Behavioural Economics and the Autonomous Consumer, 14. Cambridge Yearbook of European Legal Studies 2012, 297 (306–318); *S. Issacharoff*, Disclosure, Agents, and Consumer Protection, Journal of Institutional and Theoretical Economics 2011, 56: *E. M. Tscherner,* Can Behavioral Research Advance Mandatory Law, Information Duties, Standard Terms and Withdrawal Rights?, Austrian Law Journal, 2014, 144; *H.-W. Micklitz/L. A. Reisch/K. Hagen*, An Introduction to the Special Issue on "Behavioural Economics, Consumer Policy, and Consumer Law", Journal of Consumer Policy 2011, 271.

82 *P. McColgan*, Abschied vom Informationsmodell im Recht der Allgemeinen Geschäftsbedingungen, Tübingen 2020; *Susser,* Notice after Notice and Consent (n. 77).

83 *Gal/Elkin-Koren*, Algorithmic Consumers (n. 20), 309 (314).




On the other hand, only a limited number of algorithmically-enhanced consumer decisions are this straightforward. If we assume that choices are increasingly made not just with the help of algorithms, but *with* algorithms and in algorithmic environments, where choices themselves are technically predefined and determined, the interaction between algorithms and humans seems far less linear. In addition, algorithms inform different stages of a consumer decision.[84] Increasingly consumer decisions will thus become choices that are made cooperatively by algorithms and consumers: they will be (hybrid) choices made by a culmination of machine and human intelligence and agency, both of which will be difficult to differentiate or untangle.




84 *Gal/Elkin-Koren* describe the different steps and stages typically involved, when algorithms become the agent of the consumer and make certain choices for them, see *Gal/Elkin-Koren*, Algorithmic Consumers (n. 20), 309 (317).

Since the choice ultimately made by the consumer can no longer be isolated from that made in combination with the algorithm, the question arises of how best to integrate disclosures and counteract asymmetries. Consumers must be made aware of their rights and the workings of the algorithms, but, increasingly, no longer stand apart from them as a separate, rational entity. This means that mandated disclosures could become even less effective and foreign to the process.

### *II. A brief reflection on autonomy and agency*

Consumer protection tools have been a contentious issue for a long time.[85] While the practical ineffectiveness of disclosures and consent tools is overwhelmingly accepted and has been widely discussed,[86] these tools are still said to serve critical normative functions. Thus, before weighing in on any possible amendments to classical consumer protection tools and remedies, it seems prudent to reflect on some of the principles at stake. In economics, asymmetric information leads to consumer welfare losses. While this is certainly true for a range of different products and services, the legal mind may argue that something even larger is at stake: the principle of the equal autonomy of all contracting agents. This principle is the foundational assumption of both private law and economics in (modern) civil society.[87] For this reason, it helps to reflect on both the notion of 'agency' and 'autonomy' as the two principles that underlie several legal challenges with algorithmic transformation.

*Agency* is most fundamentally defined as legal capacity. It implies a capacity to act and to (normatively) shape reality.[88] We are currently accustomed to distinguish between the concept of an *agent*, as a static and

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85 *O. Bar-Gill,* Seduction by Contract: Law, Economics, and Psychology in Consumer Markets, Oxford 2012*; O. Ben-Shahar/C. E. Schneider*, More Than You Wanted to Know: The Failure of Mandated Disclosure, Princeton 2014; *Y. Bakos/F. Marotta-Wurgler/D. R. Trossen*, Does Anyone Read the Fine Print? Consumer Attention to Standard-Form Contracts, Journal of Legal Studies 2014, 1.

86 *W. Kerber/K. Zolna*, Konsumentensouveränität und Datensouveränität aus ökonomischer Sicht, S. Augsberg, Steffen/P. Gehring (eds.), Datensouveränität. Positionen zur Debatte, Frankfurt a. M./New York 2022, 45.

87 See *M. Auer*, Der privatrechtliche Diskurs der Moderne, Tübingen 2014.

88 *I. Kant,* AA V: Kritik der praktischen Vernunft. Kritik der Urteilskraft*,* 1788, available at: https://korpora.zim.uni-duisburg-essen.de/kant/aa05/ (last access: 03.10.2022); *H. Kelsen,* Théorie pure du droit, Paris 1962; *B. Smith,* Legal Personality, Yale Law Journal 1928, 283; *A. Bertolini/F. Episcopo,* Robots and Ai as Legal

statutory notion and that of *agency*, a dynamic notion.[89] While algorithmic or AI systems are not considered agents or granted personhood, it is possible to describe their rationality, and capacity to act, i.e., the choices they make, as expressions of agency. In this case, consumer protection laws don't safeguard agency, but rather the agent. The agent must thus have features beyond the simple capacity to act or formulate a 'choice' – features beyond *agency.* Such distinguishing features may be described as the ability to act freely and to act morally – "*the ability to decide freely and coordinate one's action towards a chosen end*".[90] This can be described as *autonomy*. It may thus be possible to distinguish agency (the capacity to act) from autonomy, as the 'free' and moral instance that makes us human and makes our choices our own.[91] Thus, while we suggest that algorithms increasingly have the capacity to act and thus possess the agency required to accept the hybrid consumer as a combination of human and machine agency, consumer protection law must still seek to guarantee the full autonomy of human agents. The ability to make both 'free' and moral choices only exists where the consumer has sufficient information to do so.

### *III. Towards personalised disclosures and dynamic disclosures?*

Much of the private law community has long been unhappy with disclosure tools.[92] While mandated disclosures serve the abstract function of delivering the consumers plentiful information on the products or services

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Subjects? Disentangling the Ontological and Functional Perspective, Frontiers in Robotics and AI 2022, 9.

89 This is the author's own thought, mainly grounded in the Kantian connection between agency, autonomy and morality, whereby an autonomous action is necessarily an expression of moral capacity. See also: *Bertolinin/Episcopo*, Robots and Ai as Legal Subjects (n. 88), 9: Ultimately, RAI applications do not share human's autonomy and moral awareness necessary according to an absolute—i.e., non-instrumental or sector-specific—definition of moral agency, as the latter "cannot abstract from the very determination of ultimate ends and values, that is, of what strikes our conscience as worthy of respect and concretization"- *F. Fossa,* Artificial Moral Agents: Moral Mentors or Sensible Tools?, Ethics and Information Technology 2018, 115.

90 *Bertolini/Episcopo,* Robots and Ai as Legal Subjects? (n. 88), 9.

91 *V. Dignum,* Responsibility and Artificial Intelligence, Berlin 2019; *M. D. Dubber/F. Pasquale/S. Das*, The Oxford Handbook of Ethics of AI, Oxford 2020, p. 215; *A. Bertolini,* Robots as Products: The Case for a Realistic Analysis of Robotic Applications and Liability Rules, Law, Innovation and Technology 2013, 214.

92 See all authors n. 85.

in question and their corresponding rights and obligations, it is broadly accepted that only a marginal number of consumers (or rather legal advisers)[93] read or take note of such disclosures at all.[94]

Many authors have suggested that as goods and services become more personalised and targeted, and so should disclosures.[95] Hereby "*personal information duties and standardised notices (w)ould be replaced by granular legal norms that provide personalized disclosures based on the personal preferences and informational needs of an individual*."[96] In addition to disclosures being tailored to the individual, we suggest that they could also be more tailored and integrated into the hybrid decision making process. The findings of algorithm aversion research indicate that users accept algorithms more when the functions of an algorithm are communicated in a clear, understandable language with accompanying illustrations, but that this also has to be accompanied by 'getting to know' the algorithm. Hence, interaction with the algorithm is crucial. These conclusions could be used to design such interactive and *dynamic disclosures.* Disclosures would thus not be static: the necessary information would not be provided all at once, but would be disclosed at every step and be precisely related to it – to each mechanism and the rights-sensitive relation in question. In this way, information asymmetries could be counteracted in a continued and interactive manner. Technically this could feature 'pop-up' functions and granular consent forms. Another method would be to learn about the algorithm in a test environment through trial-and-error, to understand how it works and reacts to different factors. Such a test environment should be similar to the real environment in which the customer will encounter algorithms, but broken down to the essential features that explain how an algorithm makes its decision. In addition, algorithms could be designed to incorporate mechanisms that explain the algorithm and its risks during the process of learning and adoption. Such methods could add another layer of interaction and of learning. We suggested above that learning (trail-and-error) and testing environments, as well as the continued development and

93 *C. Armbrüster*, McColgan, Peter: Abschied vom Informationsmodell im Recht allgemeiner Geschäftsbedigungen, Zeitschrift für die gesamte Versicherungswissenschaft 2020, 129.

94 *Bakos/Marotta-Wurgler/Trossen*. Does Anyone Read the Fine Print? (n. 85); *Bar-Gill*, Seduction by Contract (n. 85).

95 See in particular, *C. Busch*, Implementing Personalized Law: Personalized Disclosures in Consumer Law and Privacy Law, University of Chicago Law Review 2019, 309.

96 *Busch,* Implementing Personalized Law (n. 95).

incorporation of preferences and 'back-steps' are important ways in which consumers come to trust and understand algorithms.

### IV. *Withdrawal rights*

Many of these suggestions and developments rely on market-driven mechanisms and market actors, that intrinsically may not always have the consumer's best interest at heart. Far-reaching withdrawal rights are thus essential to safeguard autonomy and to give consumers a way out of choices that may very well have overwhelmed them or do not serve them.[97]

## F. *Conclusion*

We began this research endeavour with the assertion that algorithms and their integration into consumer decisions are treated differently in the (interdisciplinary) research field of HAI and the field of consumer protection law. However, this is only partially true. While the former focuses on bringing humans and algorithms together in an enlightened way, the latter focuses on the reduction of information asymmetries. Both areas of investigation attempt to find a way for a consumer to act in an informed and comfortable manner when faced with a decision in a consumer context. We first described how consumers act in a digital environment and how they encounter algorithms, before we elaborated on normative notions of algorithmically-enhanced consumers. We concluded that a new type of consumer is emerging: the *hybrid consumer*, whose choices are the combined result of human and machine rationality, agency and subjective inclination. This development surely leads to large information asymmetries, followed by a loss of autonomy and – potentially – a hesitation to make use of the algorithms. Before proposing measures, we elaborated on the current state of research on consumer acceptance and its driving forces. While mandated disclosures are classical tools to reduce information asymmetries, we showed that more nuanced and novel ways to create more intuitive forms of understandability and transparency are emerging.

97 See in particular *G. Wagner/H. Eidenmüller*, Down by Algorithms? Siphoning Rents, Exploiting Biases and Shaping Preferences – The Dark Side of Personalized Transactions, University of Chicago Law Review 2019, 582 (569 et seq.); *H. Eidenmüller*, Why Withdrawal Rights?, European Review of Contract Law 2011, 1.

Personalised and dynamic disclosures could allow users to get to know the algorithm in testing environment and through the learning ('trail-and-error') process. If done correctly and accepted by the consumers, this could reduce information asymmetries and enhance consumer autonomy in their interaction with algorithms.