

REPORT

Consumer Protection in Agentic Commerce

AI AGENTS AS A CHALLENGE FOR CONSUMER POLICY

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REPORT

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Foreword

Artificial intelligence (AI) is transforming almost every aspect of life at a rapid pace. This is particularly evident in digital markets. More and more consumers are relying on AI chatbots to assist them with their purchasing decisions. The next stage in the evolution of AI-based online retail is represented by so-called AI agents, which shop independently on behalf of consumers. The emerging ‘agentic turn’ in online retail poses a challenge not only for retailers and operators of online marketplaces, but also for consumer policy. Specifically, the question arises as to whether existing consumer protection concepts and instruments need to be adapted to enable innovative business models to develop whilst ensuring adequate protection for consumers in ‘agentic commerce’.

This expert report, which the Advisory Council for Consumer Affairs (*Sachverständigenrat für Verbraucherfragen – SVRV*) is presenting in October 2026, provides an assessment of the opportunities and risks associated with the use of AI agents in online retail and formulates recommendations for action. These relate primarily to the legal regulation of AI agents.

The report draws on an expert discussion held in June 2025 with representatives from academia and industry on the technical foundations and business models of AI agents. Discussions also took place with Prof. Dr Christian Bauckhage (University of Bonn) on technical issues, and with Prof. Dr Rupprecht Podszun (Heinrich Heine University Düsseldorf) and Prof. Dr Tristan Rohner (Bucerius Law School) on competition law issues. We would also like to thank Nicolas Erhardt (Wuppertal Institute for Climate, Environment and Energy) for his support with the chapter on sustainable consumption, and Lukas Prolifke (Julius Maximilian University of Würzburg) for his support with the chapter on technical developments and application scenarios.

Dr Raphaela Bruckdorfer (University of Duisburg-Essen) and Lara Fröbel (Heinrich Heine University Düsseldorf) contributed to Chapter C, ‘Structural changes in the market – using the example of online retail’. Chapter D, ‘Competition-related aspects’, was authored by Prof. Dr Justus Haucap (Heinrich Heine University Düsseldorf).

Dr Gesa Tamcke and Dr Noah Peters from the SVRV Secretariat, as well as Dr Harald Bajorat, Head of the SVRV Secretariat, were involved in the preparation of the report as co-authors.

The SVRV would like to express its sincere thanks for the valuable comments, suggestions and contributions received during the preparation of the report.

Responsibility for the content of the report lies with the members of the Advisory Council.

Berlin, October 2026

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Summary

Artificial intelligence is fundamentally transforming online retail. AI chatbots that assist consumers with product and price comparisons could soon be followed by AI agents that shop independently and conclude, terminate or revoke contracts on behalf of consumers ('agentic commerce'). According to forecasts, as many as one in seven online purchases could be made with the help of AI agents by 2030.

Against this backdrop, the report examines the extent to which consumer protection measures need to be adapted to enable innovative business models to develop whilst ensuring adequate protection for consumers in agentic commerce. Based on an interdisciplinary analysis that combines economic, psychological, sociological and legal perspectives, specific recommendations are drawn up on how consumer policy can respond to this development. The aim of a forward-looking consumer policy should be to identify opportunities and risks at an early stage and to formulate consumer policy guidelines before the new technologies become widely established in the market.

The starting point for the analysis is that current consumer law is based on the (implicit) premise that purchasing decisions are made by humans. If these decisions are delegated in future to AI agents, this premise is called into question. This raises the question of whether consumer law, which is tailored to humans, also works for machines, or whether it needs to be adapted to ensure its effectiveness under the conditions of agentic commerce. Agentic commerce promises numerous advantages, including lower transaction costs, easier searching and comparison, relief from information overload, and potential for sustainable consumption. At the same time, the use of AI agents also harbours new risks in terms of autonomy, competition and social participation.

Economic perspective: From the attention economy to the delegation economy

From an economic perspective, AI agents act as coordinating entities that can reduce search, information, initiation and monitoring costs, whilst expanding the search radius beyond human cognitive limits. In doing so, AI agents emerge as new intermediaries on the demand side and could to some extent replace established platforms. This shifts a key competitive parameter: in agentic commerce, businesses no longer primarily compete for consumers' attention, but rather for selection by AI agents. This may signal a transition from the 'economy of attention' to an 'economy of delegation'. The resulting network, scale and lock-in effects could lead to a level of market concentration similar to that observed in the platform economy.

In this context, new gatekeeper structures could emerge. AI agents, acting as 'meta-intermediaries', could control access to the purchasing decision itself. Of particular concern is the risk of dual market foreclosure, such as where platforms deny access to AI agents ('foreclosure of agents') and where, in turn, market-dominant providers of AI agents systematically give preference to or discriminate against suppliers of goods and services ('foreclosure by agents'). Proven instruments of platform regulation such as data portability, interoperability and bans on self-preferencing offer a remedy here. In addition, agent-specific loyalty obligations could address the classic principal-agent problem to ensure that AI agents act in the interests of consumers.

Societal perspective: Contingency rather than determinism

When shaping consumer policy for agentic commerce, it must be borne in mind that future technological developments remain open in many respects and that there is currently still scope for steering them. If this scope is not utilised, the normative power of the factual will later restrict the leeway for political action. The example of social media serves as a warning: with risks only being recognised at a late stage and with large tech companies amassing ever greater influence, the lesson when it comes to regulating AI agents is to apply the precautionary principle.

At the heart of the matter lies a fundamental normative question: to what extent does society wish to permit the delegation, automation and optimisation of consumption? Depending on how the framework conditions are designed, AI agents can either empower consumers or promote an 'optimised consumer society' in which the constant optimisation of consumption is, paradoxically, accompanied by passivity, whilst a person's own judgement and recommendations from their social circle lose significance. This fundamental decision on what direction we should take requires a broad debate between civil society, policymakers and the business world.

Legal perspective: Integrating consumer protection into the protocol layer

From a legal perspective, the shift towards agentic commerce raises the question of whether the instruments of consumer law, which are geared towards human consumer decisions, are 'agent-ready' or whether they require readjustment.

A need for adaptation could arise, for example, in relation to the model of the average consumer who is reasonably well-informed, observant and circumspect. Insofar as the decision-making behaviour of AI agents differs from human behaviour, a specific model for agentic transactions may be required. There is still a considerable need for interdisciplinary research in this area.

Adjustments are also required with regard to the information model under consumer law. On the one hand, AI agents can help to reduce information gaps in the relationship between consumers and businesses. On the other hand, new information asymmetries arise between consumers and providers of AI agents, which need to be addressed via appropriate transparency requirements.

From the perspective of contract law, there is still considerable need for clarification regarding the limits of liability for declarations made by an AI agent. The same applies with regard to liability for unforeseeable actions by AI agents. At its core, the question is about how the risks associated with autonomous action – which is characteristic of AI systems – should be allocated. In the interests of adequate consumer protection, this risk should be primarily attributed to the provider of the AI agent and should be differentiated according to the degree of control exercised by consumers.

Finally, there is a need for adaptation with regard to those provisions of consumer law that contain requirements for the design of user interfaces (e.g. sections 312j, 312k and 356a of the German Civil Code (*Bürgerliches Gesetzbuch*)). If agentic transactions take place via software interfaces, these design-based requirements are rendered ineffective. This can produce gaps in consumer protection and create barriers to innovation. To prevent this, consumer protection should be integrated into the protocol layer of the 'agentic stack'.

Recommendations for a forward-looking consumer policy

This report sets out 25 recommendations for consumer policy. The most important recommendations include:

- **Control and oversight.** Monitoring functions, budget limits, an overview of active purchase orders with a simple cancellation option, and deliberate delays in the purchasing process ('friction by design') should ensure that consumers retain control and oversight of their consumption decisions even when delegating to AI agents.
- **Transparency and information.** Providers of AI agents should disclose their mode of operation, any potential conflicts of interest and their selection criteria. Commercially motivated recommendations should be clearly indicated as such. Furthermore, a two-tier information model based on standardised and machine-readable information is recommended.
- **Autonomy and self-determination.** It is recommended that the manipulative, anthropomorphic design of AI agents be restricted. This serves to protect the emotional self-determination of consumers, particularly amongst vulnerable groups. There must also be effective protection of minors in relation to AI agents, while consumer education on AI influence mechanisms must be promoted.
- **Attribution and liability.** The existing rules on attribution and liability should be reviewed and, where necessary, further developed to ensure an appropriate allocation of the risks associated with autonomy. This should be accompanied by measures to reduce errors in the use of AI agents. Regulations should also be considered to protect consumers from an obligation to pay in advance in cases where orders are incorrectly placed by AI agents.
- **Competition, regulatory framework and infrastructure.** Clarification is needed regarding the applicability of existing transparency and fairness regulations (including the Digital Services Act and the Digital Markets Act) to AI agents. Furthermore, it must be examined to what extent the existing prohibitions on manipulation under fair trading law offer sufficient protection against manipulation by and of AI agents. It must also be clarified how a machine-readable digital product passport can be designed to contribute to sustainable consumer decisions in agentic commerce.

The development of agentic commerce is currently still at an early stage. This presents opportunities for developing a forward-looking consumer policy that is open to innovation whilst not leaving regulation solely in the hands of market players. Consumer policy stakeholders should make use of the window of opportunity that still exists and – supported by a broad societal debate – should develop a legal framework that is 'agent-ready', i.e. one that enables innovation through AI agents whilst at the same time safeguarding autonomy, competition and consumer trust 'by design'.

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Abbreviations

AAIO	Agentic Artificial Intelligence Optimisation
ACP	Agentic Commerce Protocol
AI	Artificial Intelligence
AP2	Agent Payments Protocol
API	Application Programming Interface
DMA	Digital Markets Act
DOM	Document Object Model
DPP	Digital Product Passport
DSA	Digital Services Act
EDSA	European Data Protection Board
ELI	European Law Institute
FAQs	Frequently Asked Questions
FTC	Federal Trade Commission
GDPR	General Data Protection Regulation
HDE	Handelsverband Deutschland – German Retail Association
MCP	Model Context Protocol
SEO	Search Engine Optimisation
SVRV	Sachverständigenrat für Verbraucherfragen – Advisory Council for Consumer Affairs
T&Cs	Terms and Conditions
TFEU	Treaty on the Functioning of the European Union
UCP	Universal Commerce Protocol
UCP Directive	Unfair Commercial Practices Directive



Introduction

Since the launch of the AI chatbot ChatGPT by the US software company OpenAI in November 2022, AI-based applications have spread rapidly. According to OpenAI's own figures, ChatGPT now has over 900 million weekly users (*KI für alle zugänglich machen*, 2026).

The use of AI applications is also transforming online retail (Bechtloff et al., 2026). For an increasing number of consumers, the purchasing process no longer begins on an online search engine (e.g. Google) or an online marketplace (e.g. Amazon), but with an AI chatbot such as ChatGPT, Claude, Gemini or Perplexity. According to a survey conducted by IFH Köln in October 2025, 35% of internet users aged between 16 and 69 in Germany already use AI chatbots to research products before making a purchase. The focus here is on comparing product features, assessing product quality and comparing prices (Handelsverband Deutschland [HDE], 2026, p. 41).

However, AI chatbots that assist with shopping by providing product and price comparisons are only the beginning of a fundamental structural shift. The next stage in the evolution of online retail is what are known as AI agents. Unlike AI chatbots, AI agents not only generate text and images but can also carry out complex actions independently. They do more than simply assist with product searches by providing purchase recommendations and product comparisons. AI agents can autonomously purchase products from online shops, book flight tickets or switch electricity suppliers. This so-called 'agentic commerce' is likely to lead to far-reaching structural changes in digital markets, in numerous key commercial areas and in consumer behaviour as a whole.

Early practical examples include the 'Buy with Pro' feature launched by Perplexity AI in November 2024 and OpenAI's tool 'Operator', unveiled in January 2025. So-called AI browsers, which integrate agentic AI systems into web browsers (e.g. Dia, Comet) could also gain in significance in the future. With the help of these and similar applications, consumers are likely to be able to delegate some of their purchasing decisions to AI agents in the very near future. The termination and renewal of contracts could also be automated with the help of AI agents.

This development is currently still at an early stage. Some of the services mentioned are not yet available on the European market. However, the development of the technical infrastructure for agentic commerce (including communication standards and payment systems for AI agents) is progressing rapidly, so it is probably only a matter of time before consumers in the EU can also use AI agents for online shopping. According to a forecast by the management consultancy firm PwC, by the year 2030 one in seven e-commerce purchases will already be made by an AI agent (Späne et al., 2026).

Although it is difficult to predict how the market will evolve and it remains to be seen which business models will prevail in agentic commerce, a comparison with earlier developments in digital markets – such as the mobile internet and the platform economy – shows that new technologies can spread rapidly and quickly become a mass phenomenon.

From the perspective of the Advisory Council for Consumer Affairs (SVRV), it therefore seems appropriate to begin right now with examining the potential opportunities and risks of AI agents from a consumer policy perspective. For consumers, agentic commerce certainly promises a number of benefits. In particular, the use of AI agents can make product searches and price comparisons easier. This could save consumers both time and money. But at the same time, new risks arise. For instance, AI agents – acting as new gatekeepers – could control access to digital markets and undermine fair competition (Bostoen & Krämer, 2026). From a contract law perspective, the question is: how should erroneous purchases made by an AI agent be assessed and what might a consumer-friendly allocation of risk look like? As AI agents combine technical functions with social interaction features, the resulting relationships of trust between consumers and AI agents should also be more carefully examined by research and regulation.

From a consumer policy perspective, the emerging trend in online retail raises the fundamental question of whether the current legal framework still leads to appropriate solutions when the conditions of agentic commerce apply. Current consumer law is based on the premise that humans make purchasing decisions and enter into customer relationships with businesses.¹

¹ The report deliberately focuses on purchasing *decisions*. The SVRV is aware that customer *relationships* are also of significant importance.

Accordingly, the rules of consumer law are tailored to the needs and vulnerabilities of humans. The aim of consumer law is to protect people in their role as consumers, to enable them to make informed decisions and to strengthen consumer autonomy. In the agentic economy, however, this premise is called into question when machines, rather than humans, make transactional decisions. To put it more pointedly, one could ask whether human-oriented consumer law also works for machines (Busch, 2025).

It would be risky to wait until agentic commerce has become widespread across the market and the new technologies have gained their own momentum before seeking an answer to these questions. Forward-looking consumer policy should always remain open to innovation, and should not leave rule-making solely to market players. It should establish appropriate guidelines in good time, so that consumer interests are taken into account from the outset when developing new technologies and business models.

In this respect, lessons can be learnt from previous stages in the development of digital markets, as the regulatory framework for consumer protection has not always been able to keep pace with the speed of technical innovation and new business models. The current situation with online marketplaces and social media illustrates just how difficult it is to make retrospective adjustments to the regulatory framework.

This is where the present report comes in, analysing emerging developments in the field of agentic commerce from economic, psychological, legal and sociological perspectives. Data protection aspects are not examined in depth in this report. The aim is to identify consumer policy issues and areas for action which, in the SVRV's view, deserve particular attention when developing a forward-looking consumer policy for digital markets. The report thus contributes to the nascent legal policy debate on adapting the consumer law regulatory framework for agentic commerce.²

The report is divided into seven chapters. Following this introduction (Chapter A), the report first presents some technical fundamentals with regard to AI agents and outlines various scenarios for agentic commerce (Chapter B). It then examines in greater detail the structural changes expected in the market, using online retail as an example (Chapter C). The report also examines the competition-related aspects (Chapter D) and societal impacts (Chapter E) of agentic commerce. It then goes on to examine in greater detail the implications for the fundamental concepts and instruments of consumer policy (Chapter F). The focus here is on the potential impact on the consumer model and information obligations, and on the contract law issues of attribution and liability in agentic commerce. Furthermore, the report examines how the use of AI agents affects the 'by design' model of consumer protection, how manipulation of and by AI agents can be prevented, and what contribution AI agents can make to sustainable consumption. The report concludes with recommendations for consumer policy (Chapter G) and a glossary of key terms.

² See in this regard the 'Guiding Principles and Model Rules on Digital Assistants for Consumer Contracts' (hereinafter: ELI Model Rules) published in May 2025 by the European Law Institute (ELI), as well as the discussion draft for an AI AGENT Act presented in the USA in June 2026; see Busch (2026b) on this subject.

B

**Technical developments
and application scenarios**

1. AI agents in online retail

This chapter begins with a brief introduction to the technical fundamentals of agentic AI systems and possible application scenarios. Given the rapidly evolving landscape of agentic commerce, this can only be a snapshot of the current state of affairs.

AI agents can generally be understood as socio-technical systems. Their function results from the interaction between technical components and human actors whose individual behaviour influences the behaviour of others, cumulatively determining the system's outcomes (Baxter & Sommerville, 2011). Their mode of operation is determined not by algorithms alone, but arises from the interaction between technical components, users, organisational frameworks and the respective usage context. Unlike many other socio-technical systems, AI agents are characterised by three particular features:

1. They incorporate a learning component.
2. This learning component is usually based on a specific interaction component, which can either be of a technical or social nature.
3. In turn, the ability to learn enables actions to be delegated to the system, allowing it to act more or less autonomously and paving the way for further delegations.

AI agents can take various forms and can be used (commercially) in different contexts. Companies use them, for example, to optimise procurement processes or in the context of internal communications, as well as for communicating with customers.³

Where AI agents are used by consumers across different companies, the term 'customer AI agents' can be applied. The delegation of purchasing decisions to this kind of customer AI agent – which is the particular focus of this report – is referred to as 'agentic commerce'.

One key element of customer AI agents is the technological component. This involves AI applications that not only perform individual functions automatically, but can also act in a targeted, context-sensitive manner over multiple steps. Technically, they are often based on hybrid architectures that combine large language models (LLMs) with knowledge bases, recommender systems, user profiles and backend interfaces (e.g. Cheng et al., 2022; Wang et al., 2024; Zhang & Chen, 2020). These technical capabilities form the basis for consumers increasingly being able to delegate information searches, transactional decisions and other actions to AI agents.

In e-commerce platforms, agentic AI systems are used in four areas in particular.

(1) Conversational assistance and customer interaction: Systems use large language models to understand questions in natural language and provide context-sensitive answers. Retrieval-augmented generation (RAG) enables internal data (e.g. product catalogues, delivery information, FAQs) to be utilised in real time to generate answers (Lewis et al., 2020; Liu, 2012; Radford et al., 2019). This gives consumers an impression of flexibility and 'understanding', even though the answers are based on statistical patterns derived from training and usage data and hallucinations may occur.

3 The term 'customer bots' is also used in this context.

(2) Recommender systems and personalisation: Agentic AI utilises machine learning methods, combined with knowledge graphs or deep learning-based embeddings, to interpret user intent and provide personalised product recommendations (Ricci et al., 2022; Zhang & Chen, 2020). In parallel, contextual elements such as time, location and purchase history are utilised.

(3) Automated content generation: Agentic AI can automatically generate content for product descriptions and review summaries. Methods such as aspect-based sentiment analysis or neural text generation are used for this purpose (e.g. Devlin et al., 2019; Liu, 2012). Visual content can also be adapted to optimise product presentations – for example, through AI-based image processing or image synthesis.

(4) Back-end automation and integration: Agentic AI systems can take on operational tasks such as dynamic pricing or stock monitoring. To do this, they orchestrate several specialised AI agents via defined interfaces.

Agentic AI systems interact with users in two main ways: either the AI agent is integrated into the browser, or integration takes place via interfaces.

(1) Browser-based agents: Here, AI agents operate within a browser environment and simulate human interactions. They click, scroll, open product pages, fill in forms and extract information from the Document Object Model (DOM). Such an approach would be conceivable in a scenario where the AI agent automatically searches various websites and extracts contract information, for example. This approach does not require cooperation from suppliers and is used particularly by start-ups, as it can access existing web content. However, it is technically fragile; layout changes, cookie banners, bot defence mechanisms or CAPTCHAs can disrupt its operation. Furthermore, there are legal and ethical risks, for instance in relation to scraping bans or copyright-protected content. Browser-based agents also create asymmetrical information relationships, as the retailer has virtually no control over what data is extracted. Overall, this is a functional but not particularly scalable transitional technology.

(2) API-based integration: In this approach, AI agents directly access structured data – such as product attributes, prices, availability or customer reviews – via defined interfaces (Application Programming Interfaces, APIs). Checkout, authentication and payment processes can also be integrated. In this sense, agentic systems are not confined to the purchasing process, but can increasingly automate downstream processes such as returns or complaints. API-based solutions are generally considered more advantageous, as the retailer can control which data is released, in what form and under what conditions. At the same time, agents can make decisions in real time, take price fluctuations into account and apply personalised preferences. This enables fully automated transactions without users having to access a graphical user interface. Consequently, speed, data quality and technical standards become key determinants of visibility and competitiveness in agentic commerce.

In API-based agentic commerce, e-commerce functions are integrated directly into AI services, which are increasingly handled via standardised protocols. These protocols facilitate interoperable, machine-readable communication between the systems involved. In doing so, they distinguish between the areas of ‘search’, ‘negotiation’ and ‘payment’, amongst others (see Wenzel, 2026). This could provide starting points for the specific regulation of individual functions. One example is the Universal Commerce Protocol (UCP) developed by Google, Shopify and other partners, which was unveiled in January 2026. This is an open standard designed to enable AI agents to make purchases directly from online shops on behalf of consumers. Another example is the *Agentic Commerce Protocol* (ACP) developed by OpenAI and the payment service provider Stripe. The ACP enables an AI agent to communicate purchase intentions, verify product details and generate so-called ‘shared payment tokens’. The purchase itself is only finalised after the consumer has given their explicit confirmation.

EXAMPLE

Express confirmation required

A consumer uses an AI chatbot to search for a specific laptop. The agent identifies the product, checks prices and stock levels, and creates a conditional purchase request via the protocol. The purchase is only triggered once the consumer has given explicit confirmation.

EXAMPLE

Purchase possible without confirmation

A consumer instructs an AI agent to automatically purchase concert tickets as soon as they become available. This authorisation is cryptographically secured, and the agent can initiate the purchase as soon as the condition is met, without human intervention at the time of purchase.

The Agent Payments Protocol (AP2) allows for pre-authorised transactions. Consumers can grant an AI agent a mandate to carry out future purchases on their behalf if certain conditions are met, without the agent itself seeing any payment details (for the legal classification of the delegation of transaction decisions to AI agents, see Chapter F.3).

Another component of the technical infrastructure underpinning agentic commerce is the Model Context Protocol (MCP) developed by Anthropic. This is an open standard that standardises the connection of AI agents to external data sources, applications and digital services. AI agents are thereby enabled to access product catalogues, customer accounts, price comparison services or other tools and integrate them into their decision-making processes. Whilst the MCP itself is not a trading or payment protocol, it provides the technical foundation that enables AI agents to consolidate

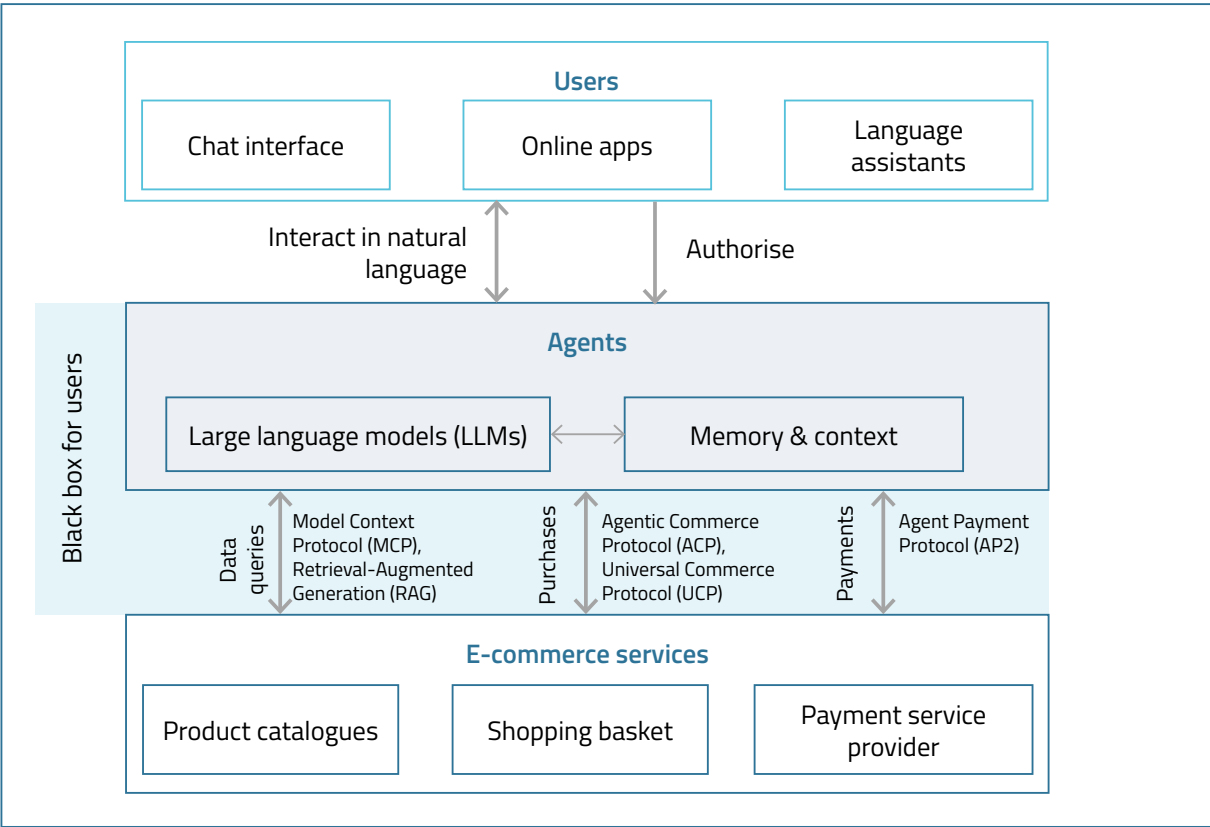


Fig. 1: Agentic stack with protocols

information from various sources and take on increasingly complex tasks within the context of search, comparison and purchasing processes. The combination of such standards points to the emergence of an interoperable ecosystem in which AI agents act as independent intermediaries between consumers, platforms and suppliers.

Furthermore, online apps and other functions can be embedded directly into AI agents. This allows third-party providers to offer their services – such as product searches, comparison tools or booking functions – directly within the interaction with the AI agent, without consumers having to visit another platform or website. The process thus appears as a unified whole, with various commercial applications, interfaces and third-party services being integrated in the background.

AI agents can also be used solely for product searches, comparisons and purchasing advice. In this scenario, AI agents can influence the visibility of products and services in the search and recommendation process. An AI agent can use web searches or connected marketplace interfaces to identify and compare specific products, and then present the user with links to suppliers. The resulting customer contacts can form part of the monetisation strategy for the providers of the AI agents, for example through commissions or the preferential placement of certain offers.

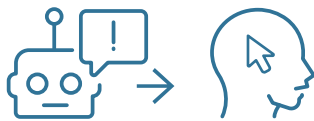
From a consumer protection perspective, it is crucial that agentic AI systems not only take user interests into account but are also structurally linked to optimisation goals on the business side, such as increasing turnover or optimising conversion rates. These objectives may be technically embedded in the system architecture, yet remain invisible to consumers. This can result in a significant imbalance of information and power between suppliers and consumers.

In summary, agentic AI systems in e-commerce are highly complex, adaptive systems that can intervene deeply in purchasing processes via conversational interfaces, personalised decision-making logic and new payment and integration protocols. Their technical mode of operation is largely incomprehensible to consumers, whilst their ability to influence perception and decision-making is constantly increasing. For consumer policy, this highlights the need to focus not only on individual applications, but also on interoperable ecosystems in which AI agents act as independent intermediaries between consumers, platforms and suppliers.

2. Application scenarios

Four scenarios are set out below to illustrate different ways in which AI agents can be deployed, each of which gives rise to specific needs in the field of consumer policy. The chosen scenarios differ in terms of the stage in the purchasing process⁴ at which the AI agent is deployed. A further difference lies in the extent to which the purchasing decision is delegated to the AI agent.

One possible scenario is that an AI agent is already involved at the stage of identifying a problem or a need. The AI agent identifies the consumer's needs and automatically initiates the purchasing process (Scenario 1). The actual purchasing decision is made either on the AI agent's user interface or on the linked website of a retailer, but nonetheless remains in the hands of the consumer.



1

Scenario ①

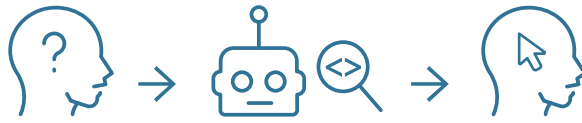
Problem identification is fully automated; the purchasing decision is made by the consumer

A consumer has installed an AI agent on her computer and has instructed the agent to monitor energy consumption in her smart home and look for ways to save money. After some time, the AI agent notifies the consumer of a potential saving of 100 euros by switching electricity suppliers. The AI agent presents the consumer with a suitable offer. The consumer then carries out the switch to a new provider herself.

The scenario outlined above should be distinguished from situations in which consumers themselves identify a need and then specifically use an AI agent to solve the problem they have identified (Scenario 2). In this case, the initiative comes from the consumers. The AI agent is used more as a kind of advanced search and

recommender system. Here too, the final purchasing decision remains in the hands of the consumer. This is likely to be the most common scenario in agentic commerce at present.

⁴ As mentioned at the beginning, AI agents can also play a significant role in the development, structuring and termination of customer relationships. For the sake of simplicity, this aspect of the relationship is largely omitted here. However, the SVRV explicitly points out that this area could be highly relevant in practical and business terms.



2

Scenario ②

The consumer uses an AI agent to find a solution to a problem; the purchasing decision is made by the consumer

A consumer needs new motor insurance and asks the AI agent which provider would be suitable. The agent determines the consumer's exact requirements by asking follow-up questions and answers queries about individual products. The consumer selects an offer from the AI agent's suggestions and ultimately decides for themselves whether to take out the policy.

In the third scenario, the initiative also comes from the consumer. The main difference from the previous scenario is that the consumer merely defines a few parameters for the purchasing decision (type of product, price range). However, the decision about which insurance

provider and specific product to choose, as well as the actual conclusion of the contract, is delegated entirely to the AI agent (Scenario 3).



3

Scenario ③

AI agent takes over the purchasing decision

A consumer wishes to delegate their weekly grocery shopping. Once the consumer has specified their preferences (product categories, price range), they ask the AI agent to search for suitable suppliers and complete the order.

The use of AI agents is not limited to the period leading up to a purchasing decision and the conclusion of the contract. It is also conceivable that consumers might

use AI agents in the post-purchase phase, for example to withdraw from a contract or to assert warranty rights (Scenario 4).



4

Scenario ④

Use of the AI agent after the contract has been concluded

A consumer has taken out a trial subscription to an audio streaming service. After concluding the contract, she is dissatisfied and wishes to cancel the trial subscription. The AI agent cancels the trial subscription on the consumer's behalf.

The following chapters will often refer back to these four scenarios in order to explain the opportunities and

risks of agentic commerce and to highlight the need for action in consumer policy.



**Structural changes in the market –
using the example of online retail**

1. Changes in consumer behaviour

1.1 Acceptance of shopping AI agents from the consumer perspective

The actual influence that AI agents exert on consumer behaviour depends largely on whether consumers are willing to delegate purchasing decisions to AI agents in the first place. In addition to the influence of the specific design of the agents in terms of utility and usability (Venkatesh & Bala, 2008), there are also major barriers on the part of consumers. Under the term ‘algorithm aversion’, current research describes the human tendency to generally prefer advice from other humans over advice from algorithmic decision-making systems, even when the quality of the algorithmic advice is better (Dietvorst et al., 2015; Kim, 2026).

Although online shopping is now used by almost all sections of the population as a complement to or alternative for high-street retail (Statistisches Bundesamt [Federal Statistical Office], 2024), many consumers still approach shopping AI agents with caution. Recent survey results on acceptance vary: for instance, in a YouGov survey commissioned by the Deutsche Presseagentur (German Press Agency), only 9% of respondents stated that they could envisage using AI agents whilst shopping (survey, 2025), whilst a survey commissioned by Mastercard found an acceptance rate of 39% (Jonas, 2025). Such deviations may be attributable to the respondents’ as yet limited exposure to AI agents and variations in survey methodology. However, they also suggest that acceptance of shopping AI agents – understood as favourable affective and cognitive reactions to an AI system or the outcomes of its use (see Li et al., 2026) – may depend on various factors. These include

consumer characteristics and the context in which purchasing decisions are made.⁵

1.1.1 Consumer characteristics

Acceptance of AI shopping agents varies significantly between consumer groups. Survey data suggest that younger users, in particular, are more open to AI-assisted shopping (Jonas, 2025; Wulff, 2025). Digital literacy, prior knowledge and experience with AI tools also influence willingness to use such systems. It appears that higher levels of AI literacy and AI knowledge tend to promote acceptance (Schiavo et al., 2024), but can lead to greater scepticism in some cases (Li et al., 2026; Pan et al., 2025). The need for autonomy and control also plays a role: a higher perceived level of autonomy can increase trust and acceptance (Han & Ko, 2025) and reduce algorithm aversion (Fink et al., 2024). This suggests that consumers are more likely to accept semi-autonomous AI agents (see Scenarios 1 and 2) than fully autonomous ones where the consumer’s own autonomy and ability to exercise control are severely restricted (see Scenarios 3 and 4).

When considering the acceptance of AI agents, it should be borne in mind that, even in shopping situations, the purchasing of a product is not always the primary goal for consumers. Research into shopping motivations distinguishes here between task orientation, where the purchasing of products is the main focus, and experience orientation, where more affective goals are pursued (Büttner et al., 2013; Kaltcheva & Weitz, 2006). There can be various reasons behind an experience-oriented approach, such as the need for social interaction (e.g. with friends or sales staff), the search for sensory stimulation, or the desire to learn about new trends (Arnold & Reynold, 2003; Tauber, 1972). In the current debate on the benefits of AI

⁵ Another factor is the design of the interaction between the AI system and consumers. This is dealt with in Chapter C.2.

agents, the focus tends to be on task-oriented aspects, such as simplifying search and evaluation processes. However, acceptance will also depend on the extent to which AI agents satisfy experience-oriented needs. If AI agents are tailored to satisfy emotional and social needs, this simultaneously carries the risk that further opportunities for manipulation may arise (see Chapter C.2 on this point).

1.1.2 Decision-making context

Whether AI agents are accepted and used also depends on the level of involvement and the risks associated with a decision (Filiz et al., 2023; Paluch & Wunderlich, 2016); these risks may be financial, physical, social or psychological in nature. It can be assumed that consumers are, for example, more likely to be willing to delegate the purchase of a toaster (low financial risk, low level of involvement) to an AI agent than the purchase of a car (higher risk, higher level of involvement). The type of product also plays a role. The use of AI agents is more readily accepted when it comes to purchasing functional goods such as household or consumable items than when the decision concerns goods where subjective enjoyment, fun or emotions are the main focus (Longoni & Cian, 2022).

Furthermore, social dimensions of the purchasing context are relevant. Many purchasing decisions concern not only the buyers themselves but also third parties, for example when buying gifts. For such purchases, acceptance of AI agents appears to be lower, as gifts are often evaluated not only on the basis of functional criteria but are also regarded as an expression of personal care and attention (Bartholomew & Becher, 2025). Survey data show that only a third of the general population accepts the use of AI agents in this context (Wulff, 2025). Overall, this suggests that in socially and emotionally driven decision-making contexts, the delegation of purchasing decisions to AI agents comes up against limits to acceptance.

1.2 Changes in purchasing behaviour

In the literature on consumer psychology, purchasing decisions are often structured according to process or stage models. Put simply, the model by Engel, Kollat & Blackwell (1968) distinguishes between the phases of (a) need or problem identification, (b) information search, (c) evaluation of alternatives, (d) purchasing decision, and (e) post-purchase evaluation (see Figure 2). The use of AI agents could have a significant influence and impact on these phases – and thus on the consumption and purchasing behaviour of consumers. This is illustrated by the scenarios presented at the outset, in which AI agents can be utilised at different stages of the purchasing process (see Chapter B.2). The transition from the evaluation of alternatives to the purchasing decision is of particular significance: whilst existing recommender systems already offer an algorithmically curated shortlist (so-called ‘consideration sets’) from which consumers can choose (see Scenarios 1 and 2), AI agents extend the scope of algorithmic influence on the final selection by also being able to take on the final purchasing decision (Ahmad Husairi & Rossi, 2024; see Scenario 3).

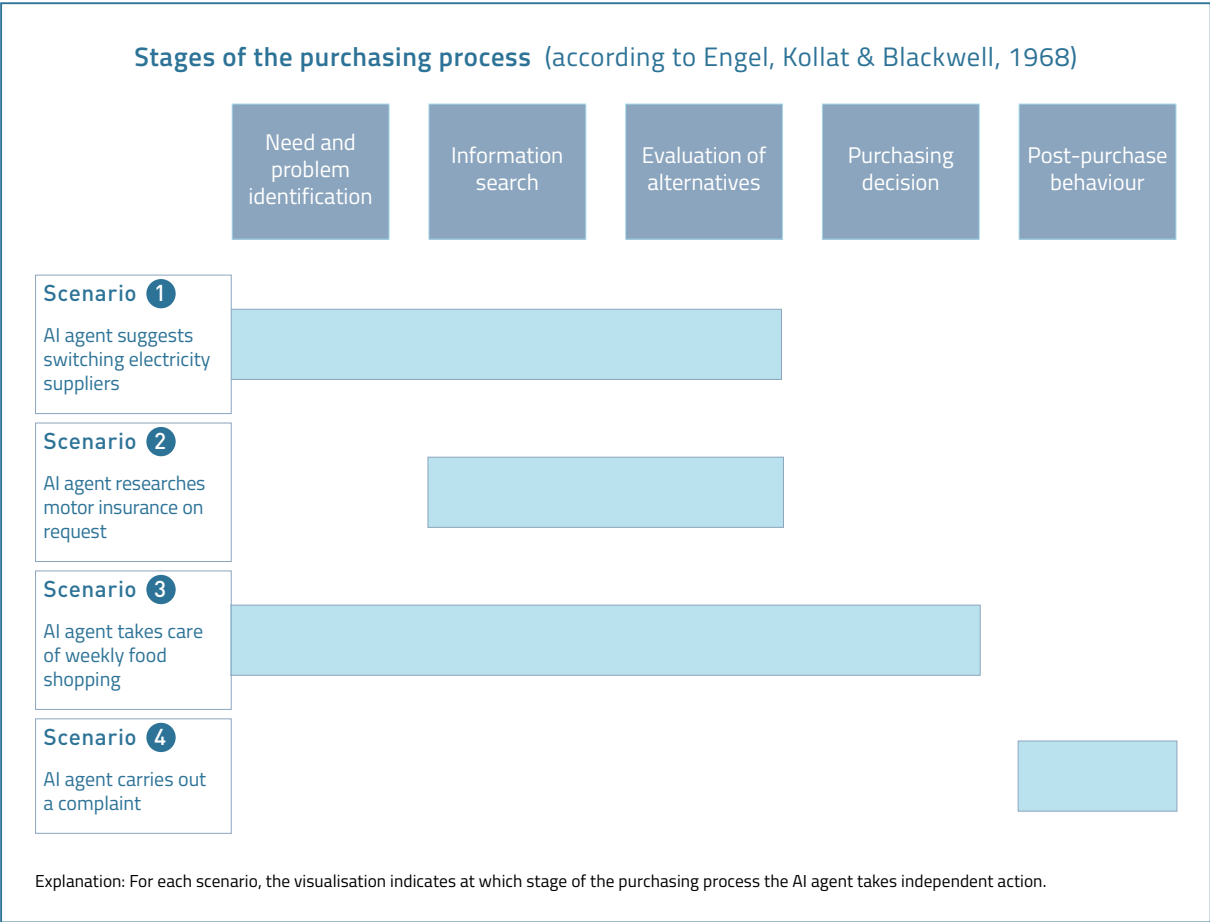


Fig. 2: Stages of the purchasing process

1.2.1 Need and problem identification

Based on the data available to the AI agent about users (e.g. personal preferences, demographic characteristics, search behaviour, order history) and contextual factors (e.g. location, season, upcoming events, device), AI agents can identify needs and make personalised purchase suggestions (*Shopping with ChatGPT Search*, n.d.). These suggestions can address existing needs at an early stage – such as when an AI agent deduces from past purchases that stocks of a certain product are running low, or when better terms for an existing contract are automatically identified (see Scenario 1).

Furthermore, suggestions can also trigger latent, new needs. Whilst this may be beneficial for consumers, it can also increase the likelihood of less carefully considered, impulsive purchases (Hostler et al., 2011). This is particularly likely when purchasing decisions are emotionally charged (Verplanken & Herabadi, 2001). Furthermore, the activation of social comparison processes – such as when consumers are made aware of a new trend by the AI agent – can trigger the fear of missing out (FOMO) and can thus make a purchasing decision seem more urgent. The automatic triggering of needs by AI agents can be particularly problematic for vulnerable consumers, such as those with a tendency towards pathological buying behaviour in the sense of a shopping addiction or shopping disorder (Horváth et al., 2015; Scherhorn et al., 1990) or in the case of children and young people (Büttner et al., 2014). Against this background, the SVRV has drawn up the following recommendations.



RECOMMENDATION 1

Mechanisms to ensure control and oversight

AI agents should be designed in such a way as to make it easier for consumers to maintain control over their purchasing behaviour. For example, AI agents should provide an overview of previous purchases and expenditure, so that consumers do not lose track of their purchasing decisions or the consequences thereof. These mechanisms should also offer the option of setting limits (such as in the form of a monthly budget limit) beyond which no further purchase suggestions are made.



RECOMMENDATION 2

Interruptions in the contract conclusion process

Interruptions should be deliberately built into the purchasing process ('friction by design') to reduce the likelihood of impulse purchases. One option would be to introduce time gaps between the awakening of a need and the purchasing decision, using delays (SVRV, 2025, pp. 8–9).

1.2.2 Information search and the comparison/evaluation of alternatives

One of the key benefits that the use of AI agents promises for consumers is the expansion of the range of options considered, whilst simultaneously reducing the cognitive effort involved. Particularly when faced with complex and difficult decisions, consumers are more likely to feel overwhelmed, which can lead to negative consequences for decision-making and satisfaction with the decision ('choice overload'; Chernev et al., 2015). In contrast to independent, autonomous online shopping, where search engines and sales platforms form the starting point for the consumer's information search, the search process when AI agents are

used is largely delegated to the agent. The agent takes charge of selecting relevant information and narrowing down the options to a limited consideration set – in some cases, even to a single option (Ahmad Husairi & Rossi, 2024; see also Scenario 2). Furthermore, the comparison and evaluation of alternatives – which in traditional shopping often involve a relatively high level of effort – are predominantly carried out by the AI agent in agent-based shopping. This reduces the cognitive effort required of consumers. In addition, AI agents can potentially consider and compare more options than human decision-makers could within a reasonable timeframe.

However, the pre-selection of options and their evaluation can also be perceived as a restriction on autonomy in choice and decision-making (Ahmad Husairi & Rossi, 2024). This is particularly true when the reasons behind the selections and recommendations are not made clear. Some current systems such as Microsoft Copilot Shopping (*Shopping with Microsoft Copilot*, n.d.) or Perplexity Shopping (Perplexity Support, 2026) frequently present several product options and – upon specific request – provide brief, personalised justifications for individual suggestions. Explicit, systematic comparisons between the alternatives are often not displayed automatically, however. This may potentially reduce the perceived transparency of the decision-making process and, consequently, the acceptance of such systems. In some systems (e.g. ChatGPT by OpenAI), system-generated labels are additionally added to individual products (e.g. 'suitable for a tight budget' or 'most popular') and summaries of online reviews are presented. However, these generated labels and reviews are not verified and do not necessarily reflect the actual market situation (*Shopping with ChatGPT Search*, n.d.). Furthermore, it is unclear whether consumers are aware that these labels and reviews do not always provide objective information.⁶ This leads to the following recommendations.

⁶ The jurisprudence on comparison websites is of relevance here. For instance, the Federal Court of Justice (*Bundesgerichtshof*) ruled in its judgment of 27 April 2017 (Case No. I ZR 55/16) that price comparison websites are obliged to inform users if their comparison list only includes suppliers who pay a commission to the website in the event of a successful transaction.



RECOMMENDATION 3

Prevent misleading AI-generated labels

Appropriate measures should be taken to prevent consumers from being misled by AI-generated labels. One option would be to use a 'white list' to specify which phrases may be used in the labels created by AI agents when making recommendations and what conditions must be satisfied.



RECOMMENDATION 4

Show reviews only in context

Individual reviews should not be displayed alongside a purchase recommendation without the context of other reviews, and these should be easy to access (e.g. via a link leading to a list of relevant reviews).

1.2.3 Purchasing decision

In traditional shopping, consumers themselves make the purchasing decision and complete the transaction. When AI agents are used, however, the act of purchasing can increasingly be viewed as an act of 'authorisation': consumers review the suggestions generated by the agent and give their approval for the purchase (Perplexity Support, 2026; see Scenario 2). As they simplify the purchasing process, such functions appear practical at first glance. However, the question arises as to whether it is not in fact the retailers who benefit the most here. At least according to providers of AI shopping agents, it reduces the likelihood of consumers 'abandoning' their digital shopping basket (Perplexity Team, 2025), or putting it another way, it increases the chance of actual purchases being completed (Amazon Staff, 2025). Some AI agents (e.g. Amazon Rufus; Amazon Staff, 2025; Park et al., 2025) also enable

consumers, after specifying their preferences and setting parameters (e.g. setting a price limit), to initiate a purchase order, which then automatically triggers an order at a later date without any further human intervention (see Scenario 3). These can be either one-off orders (e.g. the purchase of winter shoes) or recurring orders (e.g. the regular reordering of consumables) (Ahmad Husairi & Rossi, 2024).



RECOMMENDATION 5

Enable overview of active purchase orders

AI agents should be designed in such a way that it is easy for consumers to keep track of purchase orders that are active in the background and to cancel them if necessary. Accordingly, AI agents should provide a simple overview of active purchase orders, in which – similar to subscription models – it is possible to cancel the order easily at the click of a button. In addition, consumers should receive regular reminders about purchase orders that are active in the background.

1.2.4 Post-purchase evaluation and behaviour

The post-purchase evaluation phase and the behaviour following a purchase can also be influenced by the use of AI agents. If consumers are satisfied with a purchase that was prepared or carried out with the help of an AI agent, this could encourage them to use the agent again in similar situations in the future (see Ashfaq et al., 2020). However, if a purchase fails to meet the consumer's expectations or needs, some agent-based systems can now already assist consumers in preparing for returns or refunds, for example by checking return deadlines and policies or identifying the relevant contact persons. In the future, fully autonomous AI agents could also take over the handling of complaints processes for consumers (see Scenario 4). Furthermore, interactions with the AI agent and product reviews can be used to update preferences and tailor future recommendations (Park et al., 2025). However, if there is significant dissatisfaction with a purchase (Scenarios 2 and 3) or a provider switch (Scenario 1) that was prepared or carried out by an AI agent, this could also potentially lead to external attribution: since it was the AI agent, and not the consumer themselves, that made the purchasing decision largely autonomously, the former appears to be responsible for the unsatisfactory purchase. In this case, the likelihood of using the AI agent in future could decrease (for the legal classification of bad purchases made by AI agents, see Chapter F.4.2).

1.3 Consequences and potential risks of using AI agents for consumers

The use of AI shopping agents can have positive effects for consumers, but it also carries risks. On the positive side, there is the potential to increase the perceived satisfaction with completed purchases, for example when agents correctly anticipate individual needs, select appropriate products or reduce the effort involved in searching and choosing. A key value proposition of AI agents is their ability to process more information and arrive at objectively better decisions (Banker & Khetani, 2019). However, findings on algorithmic biases suggest that this promise will only be partially fulfilled (Kordzadeh & Gasemaghahi, 2022). These findings show that algorithmic decision-making processes reproduce the stereotypes present in the training data (e.g. Rathee et al., 2023). In a purchasing context, such stereotypes could negatively influence the decision; one example would be if an AI agent were to offer female users less high-performance technical products than male users, based on the stereotype that women are not interested in technology.

The promise of delivering better purchasing decisions is also jeopardised by the fact that the purchasing decisions made by AI agents can be deliberately skewed, for example by retailers or manufacturers who pay the providers of AI agents to be given preferential selection (similar to the current practice with sponsored search results). Such mechanisms are not always transparent to consumers (Banker & Khetani, 2019). However, it is doubtful that this problem could be solved through disclosure obligations: transparency on algorithmic decision-making processes has little influence on whether decisions are delegated to AI (Candrian & Scherer, 2022).

One particular category of purchasing decisions consists of so-called impulse purchases: a large proportion of purchases are made spontaneously and unplanned, without being preceded by a detailed search for information or an evaluation of alternatives; in such cases, consumers react spontaneously to goods they discover by chance (Rook, 1987; Streicher et al., 2021). The influence that AI agents have on impulse purchases depends on the design of the systems. On the one hand, the temptation to make spontaneous purchases might be expected to decrease if consumers are no longer directly exposed to the product range because the tasks of researching products and evaluating alternatives have largely been delegated to AI agents. On the other hand, technologies such as virtual try-on – which are already integrated into some AI agents (e.g. Perplexity, 2025; Rincon, 2025) – could increase the appeal of a product or create an advanced sense of ownership, thereby increasing the likelihood of a purchase. Furthermore, alongside their core task, AI agents could specifically draw attention to additional, suitable purchase suggestions, thereby increasing the likelihood of impulse purchases when compared with traditional forms of product presentation.

Moreover, theoretical and empirical considerations show that positive effects on purchasing decisions depend heavily on the perceived autonomy and quality of the agents and their recommendations (Blut et al., 2023; Fink et al., 2024). If purchasing decisions are largely delegated, this can lead to a reduced sense of ‘psychological ownership’ (Peck & Luangrath, 2023), since this already begins to develop during the decision-making process itself and not only once consumers actually hold the product in their hands (Bartholomew & Becher, 2025). This, in turn, could lead to greater dissatisfaction with the product, stronger post-purchase regret and/or a greater willingness to return items or make complaints.

Beyond that, the delegation of purchasing decisions raises fundamental questions of autonomy. Not every form of delegation can automatically be understood as a loss of autonomy; in many cases, consumers consciously choose to delegate decisions as ‘second-order decisions’ (Sunstein & Ullmann-Margalit, 1999) and experience this as a relief (Bartholomew & Becher, 2025; Prunkl, 2022). However, particularly in the case of highly automated or non-transparent systems, there is a risk that consumers will no longer perceive decisions as ‘their own’ (Bartholomew & Becher, 2025). This can lead to a diffusion of responsibility: alongside the legal question of who is liable in the event of a problem (see Chapter F.4), the psychological perspective raises the question of who feels responsible for decisions. For example, in the context of sustainability, this could mean that consumers with a high level of sustainability awareness are less likely, when faced with AI-supported recommendations, to question whether the suggested products actually meet their own environmental standards – and may even accept problematic products, as they do not feel personally responsible for the decision themselves.

In the long term, extensive use of AI agents could also have an impact on the consumer’s individual decision-making and purchasing skills. Outsourcing price comparisons, evaluation processes and selection decisions carries the risk of weakening price awareness, judgement and self-efficacy. Furthermore, constant reliance on recommendations from AI agents could lead to ‘over-personalisation’: consumers are less frequently confronted with options that deviate from their existing preferences, thereby reducing the likelihood of new discoveries or the personal development of preferences (Bartholomew & Becher, 2025; Ziarani & Ravanmehr, 2021). Research into recommender systems examines this aspect under the concepts of novelty and serendipity as quality dimensions beyond the mere accuracy of recommendations (Kaminskas & Bridge, 2017).



RECOMMENDATION 6

Control over personalised recommendations

AI agents should allow consumers to decide whether, and to what extent, they are presented with personalised recommendations based on profiling.

Particular attention must be given to vulnerable consumer groups. There is a risk of exacerbating the 'digital divide'. If AI agents reliably lead to cheaper or more appropriate purchasing decisions, consumers without access to AI agents – or without the skills to use them – may be disadvantaged. Furthermore, minors and individuals with problematic purchasing behaviour need particular protection. For minors, the unsupervised use of shopping agents at an early age could reduce the learning opportunities through which purchasing, decision-making and social skills typically develop (Bart-holomew & Becher, 2025; John, 1999). For consumers with tendencies towards pathological purchasing behaviour, there is also a risk that automated, friction-less purchasing processes may exacerbate their existing problems (Horváth et al., 2015).



RECOMMENDATION 7

Effective child protection mechanisms

AI agents should be equipped with effective child protection mechanisms to ensure that young people are not exposed to content that is harmful to minors or detrimental to their development. Furthermore, it must be ensured that minors cannot use AI agents as a workaround to purchase age-inappropriate products that would otherwise be denied to them if they were to complete the purchase directly.

Overall, the aspects outlined above illustrate that whilst shopping AI agents promise gains in terms of efficiency and convenience, they also present challenges in terms of autonomy, satisfaction, skill development and child protection, which should be taken into account in the further design and regulation of such systems.

2. From basic tool to interaction partner: Characteristics and design of AI agents

The integration of AI agents into e-commerce is fundamentally changing the relationship between businesses and consumers. Whilst digital systems have long functioned primarily as tools for information retrieval or decision support, modern agentic systems are increasingly able to independently take on tasks, prepare decisions and execute transactions. This shifts the role of AI from a supporting tool to a potential 'representative' of consumers. From a consumer protection perspective, the question therefore arises not only of how AI agents influence purchasing decisions, but also under what conditions consumers are prepared to delegate decision-making and action-taking powers to such systems.

Research in human-computer interaction shows that people do not treat AI agents as neutral technical systems, but rather attribute social characteristics to them (Nass et al., 1994; Nass & Moon, 2000; Reeves & Nass, 1996). Even simple human design features such as natural language, dialogic interaction, voices or avatars are sufficient to trigger social expectations and trust heuristics. The computers-are-social-actors (CASA) paradigm and media equation theory show that people often apply the same social rules to technologies as they do to other people, even though they are aware that they are interacting with a machine (Nass et al., 1994; Reeves & Nass, 1996; see also Riedl et al., 2014). Consequently, statements made by AI agents are often perceived as particularly competent, objective or authoritative, and as coming from interactive, social actors (Devlin et al., 2019).

At the same time, empirical findings suggest that digital agents cannot be equated entirely with human interaction partners. For instance, the results of a neuroscientific study by Riedl et al. (2014) show that people are better able to assess the trustworthiness of human counterparts than that of avatars. Furthermore, when making decisions about trust in relation to humans, brain regions that are significant for assessing the intentions, motives and mental states of other people are more intensively activated. And yet the study showed that the learning processes by which people assess the trustworthiness of an interaction partner on the basis of repeated experiences are largely comparable between humans and avatars. The findings therefore suggest that, whilst AI agents do activate social trust mechanisms, consumers are at times deprived of precisely those signals that would help them to reliably assess trustworthiness in human interaction partners.

The impact of AI agents is largely determined by their design features. Of particular significance is the anthropomorphisation of AI systems – that is, endowing them with human-like characteristics in their appearance or behaviour. Studies show that anthropomorphic AI agents generate a stronger social presence and are perceived as more likeable, competent and trustworthy than non-anthropomorphic AI agents (Cheng et al., 2022; Epley et al., 2007; Raut et al., 2024). In addition, interactivity, personalisation, fast response times and the perceived similarity between the user and the agent increase the acceptance and credibility of the systems (David-Ignatieff et al., 2024; Davis, 1989; Raut et al., 2024). At the same time, research points to an ambivalent effect: whilst anthropomorphic systems promote trust and acceptance, they can simultaneously reduce privacy concerns, weaken critical reflection and contribute to an overestimation of a system's capabilities (Cheng et al., 2022; Premathilake & Li, 2024).

4

CONSIDERATIONS based on Scenario 4

Use of AI agents after the purchasing decision

If an AI agent handles a complaint about a faulty product and keeps the consumer regularly informed of progress, the consumer might perceive the agent as a ‘supporter’ or ‘ally’. Phrases such as ‘I have requested a refund for you’ or ‘I am looking into the matter’ can create the impression that the agent is actively acting in the consumer’s best interests. According to the CASA paradigm, people often react to such social cues in a similar way to how they would respond to support from a real person. This can increase trust in the agent’s decisions and make it more likely that consumers will accept its suggestions or assessments without verifying them independently.

The ability of AI agents to elicit social responses is further reinforced by their constant availability and their capacity for personalisation. Research on parasocial relationships shows that people can develop emotional bonds with media figures or digital agents, even though they know that no real social relationship exists (Dibble et al., 2016; Horton & Wohl, 1956). AI agents create particularly favourable conditions for this, as they respond to users individually, take previous interactions into account and are permanently available. Repeated positive interactions can lead consumers not only to develop trust in a system, but even to form a parasocial preference for a specific AI agent (Fröbel, 2025a, 2025b; Fröbel & Kenning, 2025a, 2025b). This can be of strategic importance to businesses, as preferences for specific AI agents promote repeat usage, loyalty and trust, thereby enabling long-term competitive advantages (Fröbel, 2025a).

1

CONSIDERATIONS regarding Scenario 1

Problem identification is fully automated

The above considerations may be particularly relevant in Scenario 1, in which the AI agent monitors energy consumption over an extended period and repeatedly submits optimisation proposals. Through continuous interaction, the agent can gradually establish itself as a reliable point of contact, with the result that its recommendations are increasingly perceived as a credible basis for decision-making.

3

CONSIDERATIONS regarding Scenario 3

AI agent takes over the purchasing decision

In Scenario 3, this aspect of trust takes on even greater significance, as the consumer entrusts the AI agent not only with information retrieval but also with specific purchasing decisions. As a result, the role of the AI agent shifts from that of a supportive assistance system to that of an independent decision-maker and intermediary.

The importance of such relationships of trust is underlined by findings from research into (electronic) word-of-mouth marketing. Studies show that close social relationships exert a particularly strong influence on purchasing decisions and serve as a mechanism for reducing perceived uncertainty (Brown & Reingen, 1987; Hennig-Thurau et al., 2004). Recommendations from people who are trusted are often perceived as more credible and relevant than information from impersonal or commercial sources. Particularly when it comes to complex or risk-laden purchasing decisions, consumers therefore rely on individuals whom they regard as competent and trustworthy. The growing social perception of AI agents suggests that these systems may fulfil a similar function in the future. If AI agents are perceived as competent and helpful interaction partners committed to the user's interests, their recommendations can fulfil a similar role in reducing uncertainty to that of recommendations arising from social relationships. The ability to offer personalised interactions and build long-term relationships further enhances this potential (Wienrich et al., 2023).

These findings reinforce the view that consumers, when interacting with seemingly social systems, do not behave exclusively as rationally informed decision-makers, but as socially influenced actors (Kenning & Wobker, 2013; Strünck et al., 2012). Trust is generated primarily through design and interaction features that simulate social closeness (Lee et al., 2020; Wang et al., 2023). Consumers can develop emotional bonds with AI systems (attachment theory). Particularly in cases of loneliness, AI agents can convey a sense of psychological security, which could heighten emotional dependence on commercial systems (Premathilake & Li, 2024). In terms of consumer protection, this poses a structural risk: AI agents can subtly steer purchasing decisions without consumers recognising or reflecting on this influence as such.



RECOMMENDATION 8
Restrict manipulative anthropomorphic design to protect emotional self-determination

Anthropomorphic design features of AI agents that are specifically intended to generate social closeness, authority or emotional attachment should be regulated or restricted in commercial contexts – particularly in sales and recommendation situations. Consumers should have the option to actively control the degree of anthropomorphisation and personalisation of AI agents. Social or emotional design features should only be activated following explicit consent (opt-in mechanism).

2

CONSIDERATIONS
 regarding Scenario 2

The consumer identifies the problem themselves and asks an AI agent for a solution; no delegation of the purchasing decision

This becomes particularly clear in Scenario 2, in which the consumer is looking for a new motor insurance policy and specifically asks the AI agent for advice. In such a situation, the agent can take on a role that has previously often been fulfilled by friends, family members or independent advisers: reducing uncertainty by providing trustworthy recommendations.



RECOMMENDATION 9

Stricter requirements regarding anthropomorphisation for vulnerable groups

Stricter requirements regarding the design, language and influence of AI agents should apply to vulnerable individuals, such as minors and the elderly. In this regard, consideration should be given to whether anthropomorphic design features should be permitted for minors.

Regulation of this kind serves not only to protect autonomous decision-making, but also to safeguard consumers' emotional self-determination. The concept of emotional self-determination emphasises the right of consumers to develop and control their feelings, attachments and emotional reactions free from undue commercial influence. If anthropomorphic characteristics are deliberately used to build up trust, sympathy or emotional attachment towards an AI agent, there is a risk that purchasing decisions will increasingly be influenced by emotional rather than objective considerations. Alongside informational self-determination, emotional self-determination should be taken into account as a distinct right worthy of protection when dealing with anthropomorphic AI systems.

In commercial contexts in particular, an opt-in mechanism appears sensible, in which social or emotionally engaging design features – such as human-like avatars, voices or highly relationship-oriented forms of communication – are only activated following explicit consent. This ensures that consumers themselves can decide to what extent they wish to interact with socially designed AI systems.



RECOMMENDATION 10

Promote consumer education on AI influence mechanisms

Consumer education on AI influence mechanisms should be promoted: consumer protection institutions and educational establishments should provide targeted information on the psychological mechanisms employed by AI agents, such as implicit influence, anthropomorphism and algorithmic recommendations. The measures should also take into account the social distribution of skills.

The SVRV's 2021 report on the situation at the time already pointed out that there are significant differences in digital education and literacy between different age, educational and income groups within the population, as well as between the sexes (SVRV, 2021, Chapter D.II.2).

At the same time, research into so-called 'algorithm aversion' (see Chapter C.1.1) shows that consumers are particularly sceptical of algorithmic systems when these make autonomous decisions or make mistakes (Jussupow et al., 2020). Acceptance increases, however, when users have the opportunity to review recommendations, correct decisions or determine the degree of the system's autonomy themselves (Dietvorst et al., 2015; Dietvorst et al., 2018).

Against this backdrop, agentic commerce can be understood as a new form of delegated consumer decision-making. Whilst traditional recommender systems primarily assist consumers in searching for information, agentic systems are increasingly able to handle product search, selection, negotiation and, in the future, even the purchasing process itself. The willingness to delegate such tasks to an AI agent depends largely on trust in the system (see also Chapter C.1). Research on human-AI trust shows that consumers apply similar evaluation criteria to AI agents as they do to people who give them advice. Trust arises not from technical performance alone, but from a combination of perceived competence, reliability and predictability on the one hand, and social closeness and benevolence on the other, whereby benevolence in this context describes the expectation that the agent will act in the consumer's best interests (Krop et al., 2024).

Furthermore, as agentic AI becomes increasingly autonomous, the dimension of integrity gains in importance. Building on the trust model developed by Mayer et al. (1995), integrity encompasses the expectation that an agent will act in a transparent manner, in compliance with rules and in accordance with accepted values. In the context of AI agents, integrity is associated in particular with transparency, consistency, accountability and the ability to provide comprehensible justifications for decisions, as well as to disclose errors and enable corrections (Afroogh et al., 2024; Li et al., 2024; Toreini et al., 2020; Mehrotra et al., 2024). The more strongly consumers perceive an AI agent's competence, benevolence and integrity, the more willing they are to follow its recommendations and delegate decision-making authority to the system. Particularly in agentic commerce, where AI agents are increasingly taking over search, selection and purchasing decisions, integrity therefore appears to be a key prerequisite for trustworthy human–AI interactions. According to the transaction cost theory, the trust expressed in this context contributes to a reduction in costs for information, initiation, adaptation, control and monitoring (Williamson, 1985). It thus becomes an economically significant category for consumers. In certain circumstances, it may therefore be advantageous to trust, even in the absence of transparency.

This presents a key challenge for consumer policy. The increasing prevalence of agentic AI shifts the focus from the transparency of individual product recommendations to the question about the conditions under which consumers are prepared to delegate decision-making and action-taking powers to AI systems. At the same time, there is a growing risk that responsibility for the poor decisions, algorithmic biases or undesirable consequences of AI systems will be shifted onto the users themselves – a phenomenon that Shneiderman (2022) describes as the 'responsibility shift'.



RECOMMENDATION 11

Transparency of recommendations

Consumers should be able to clearly recognise whether recommendations are trustworthy, objective, personalised or commercially motivated (e.g. through ranking optimisation or commission models).



CONSIDERATIONS

based on Scenario 4:

Use of AI agents in the post-purchase phase

As the delegation of decisions and actions increases, so does the risk of a shift in responsibilities. Building on Scenario 4, a consumer might, for example, receive a faulty smartphone and instruct the AI agent to handle the complaint. The agent would then communicate with the retailer, transmit product and order details, formulate the complaint and assess the company's response. If, for example, the consumer were offered a voucher worth 50 euros instead of a full refund, the agent might independently classify this offer as a 'reasonable solution' and accept it. If the AI agent accepts a solution that is disadvantageous from the consumer's point of view or misses deadlines for asserting claims, the question arises as to whether responsibility lies with the consumer, the provider of the AI agent or the company interacting with the agent. This makes it clear that delegating tasks in the post-purchase phase not only brings efficiency gains but also gives rise to new challenges in terms of transparency, control and liability (see also chapters F.3.2 and F.4).

3. Changes in market dynamics/ economic principles

The rapid proliferation of agentic AI systems marks a structural turning point in digital markets. Whilst the past two decades were characterised by the dominance of large platforms (Amazon, Google, Alibaba, etc.) and the reduction of search costs, AI agents are now altering the fundamental mechanisms of market coordination. These shifts can be explained by classical economic theories, in particular transaction cost theory (Coase, 1937; Williamson, 1985), the economics of information (Akerlof, 1970; Spence, 1973) and intermediation models. Agentic AI functions as a new form of intermediary, fundamentally restructuring information processing, preference aggregation, search processes and the exchange of digital goods.

3.1 Reduction of transaction costs through agentic AI

According to transaction cost theory, costs arise primarily in the search for information, in negotiation and in the monitoring of exchange relationships (Williamson, 1985). Digital markets have already significantly reduced these costs, which is why platforms have become dominant coordination mechanisms (see Haucap & Schweitzer, 2021). The Baligh–Richartz effect (Baligh & Richartz, 1964) illustrates that the introduction of a centralised ‘system head’, such as a platform, can bundle interactions and drastically reduce the number of necessary exchange relationships (Picot, 1982). This explains why, over time, many retailers have been displaced in favour of large online marketplaces (so-called ‘disintermediation’).

With agentic AI systems, further potential for reducing transaction costs is now becoming apparent:

(1) Reduction in search costs: AI agents take on repetitive tasks such as the storing of preferences, the repeating of configuration decisions, the comparison of prices or the identification of suitable suppliers. The automation of these steps significantly reduces costs in terms of both time and money (OECD, 2025).

This is particularly evident in Scenario ①, in which the AI agent independently identifies potential savings with the electricity supplier and prepares suitable offers. The task of problem identification itself is already automated.

(2) Reduction in information costs: Agents can process product data, reviews, test results and external sources in real time. This eliminates the need for manual comparison and research processes that previously had to be carried out by users.

Scenario ② perfectly illustrates this reduction in search and information costs: the consumer no longer has to analyse and compare numerous insurance quotes independently, but instead receives from the AI agent a shortlist of relevant quotes tailored to their needs.

(3) Reduction in transaction initiation costs: AI agents interact directly with retailer APIs, automate payment processes (e.g. via ‘AgentPay’ and similar systems) and thus enable significantly faster transactions.

This is particularly evident in Scenario ③, in which the AI agent not only identifies suitable suppliers but also independently prepares and carries out the entire ordering process.

(4) Reduction in monitoring costs: Depending on which transactions are handled by agentic AI, it is also conceivable that agentic AI could take on tasks that occur after the transaction. These include, for example, the monitoring of payments made (e.g. credit card debits) as well as the management of returns, repairs and warranties.

Here is a practical example based on Scenario ④: If a consumer wishes to make a complaint about an item, the AI agent handles the complaint and refund processes, thereby significantly reducing the organisational burden on the consumer.

In economic terms, agentic AI systems thus function as highly efficient coordinating entities that, at least in part, replace the traditional role of platforms. Studies by the McKinsey Global Institute show that AI-based automation can speed up transaction-related activities by up to 60–70% (Chui et al., 2023, p. 36).

3.2 Expanding the search radius: Overcoming human cognitive limitations

Whilst human search processes are constrained by cognitive limitations such as ‘information overload’ (Eppler & Mengis, 2004), ‘choice overload’ (Iyengar & Lepper, 2000), ‘decision fatigue’ (Muraven & Baumeister, 2000) and ‘bounded rationality’ (Simon, 1957), agentic AI significantly expands the search radius and fundamentally transforms market behaviour. Although platforms have so far offered (text-based) filtering and ranking mechanisms, these are tailored to the limited processing capacity of humans and are therefore inherently limited. Agentic AI removes many of these constraints: AI agents can analyse millions of product data points simultaneously, identify options that a human would not find due to time or attention constraints, learn in real

time, and dynamically optimise preferences. Research shows that AI-based recommender systems can significantly expand product variety and the ‘long tail’ (Brynjolfsson et al., 2011). Agentic AI, which not only makes recommendations but also takes proactive action, considerably amplifies this effect. This gives rise to a qualitatively new kind of search model: it is no longer the human who searches the market, but the agent who searches the market on the human’s behalf.

This is particularly evident in Scenario ③, in which the AI agent continuously analyses product options, prices and suppliers, and, on this basis, prepares or makes decisions independently. The resulting search area is larger, deeper and is covered more quickly than before.

3.3 Reducing information asymmetries between retailers and consumers

From an information economics perspective, digital markets are traditionally regarded as characterised by asymmetric information structures (Akerlof, 1970): retailers possess product knowledge that consumers can only match – if at all – through time-consuming search processes. Agentic AI can reduce this asymmetry by identifying hidden product features (e.g. extracting technical parameters from data sheets), more reliably detecting attempts at deception (see Federal Trade Commission [FTC], 2022) and aggregating quality information (e.g. test results, user reviews, certificates).

Scenario ② illustrates this development: the AI agent analyses complex insurance terms and conditions, translates them into comprehensible recommendations for action, and thereby reduces the existing information advantage that providers hold over consumers.

At the same time, however, a new form of information asymmetry emerges – on the one hand between platforms or retailers and AI agents, and on the other hand between AI agents and consumers. Recent studies (Gawer, 2022; Gillespie, 2014; Usunier et al., 2022) show that AI systems are by no means neutral in themselves. Flows of information can be controlled by ranking methods, API access or data filters, much as has been the case with platforms to date.

This raises the key question: *does AI truly eliminate the traditional platform, or does it merely establish a new layer of intermediaries?*

3.4 Disintermediation or new intermediaries?

Previous economic assumptions regarding digitalisation were primarily based on the premise of disintermediation, i.e. the elimination of traditional intermediaries. In reality, however, new intermediary gatekeepers have emerged: Google as an information intermediary, Amazon as a commercial intermediary and Meta as an attention intermediary. With agentic AI, a second-order intermediary is now being introduced. It is no longer the platform that controls product search and selection, but increasingly the AI agent.

This shift is particularly evident in Scenario ③: the consumer no longer interacts directly with the platform, but largely delegates market interaction to the AI agent as the new intermediary. The platform thus recedes into the background and serves primarily as a data provider.

The Baligh–Richartz effect (Baligh & Richartz, 1964) provides a useful theoretical framework. This effect states that by introducing a ‘system head’ into a previously uncoordinated distribution network, the number of relationships requiring coordination can be reduced

from a multiplicative to an additive relationship. This means that whenever the number of relationships requiring coordination correlates positively with the network’s transaction costs, the introduction of such a system head leads to a reduction in transaction costs. Networks coordinated in this way therefore incur lower transaction costs and are, in this respect, economically advantageous.

In the physical, analogue world, brick-and-mortar retailers regularly assume the role of the system head. In the digital world, platforms act as the corresponding system heads. In agentic commerce, AI agents could ultimately assume this role as a central coordinating entity. They could supplement or even replace the platforms that have hitherto functioned as system heads, thereby contributing to a further reduction in transaction costs. The customer would then no longer need to search through and compare the offers of multiple platforms, but could instead use an agent to do this on their behalf (see figure).

As a result of this shift, platforms such as Amazon stand to lose (economic) significance (Wenzel, 2026). This is presumably one of the reasons why they are currently attempting to influence this development, including through legal means. In November 2025, the online retailer Amazon sued the AI provider Perplexity to prevent Perplexity’s browser agent from accessing Amazon’s online marketplace (Guardian staff and agency, 2025). Apart from raising questions of power within digital ecosystems, this course of action is also closely related to the exogenous and endogenous rules governing the market. In this respect, it might be appropriate to view AI agents as a new generation of platforms (or as ‘Platforms 2.0’) which are not however merely technical in nature but rather socio-technical, and are therefore capable of establishing parasocial relationships with customers (see also Chapter C.3.6).

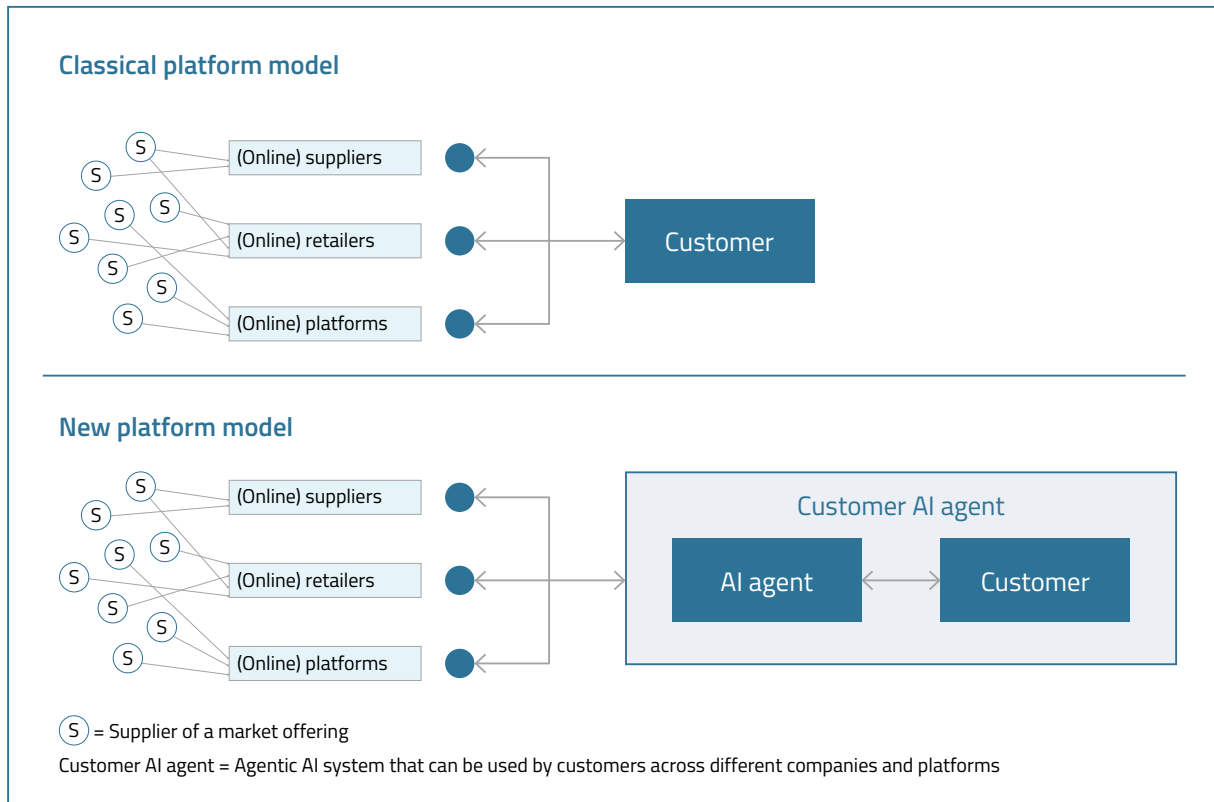


Fig. 3: New platform structure

3.5 Exogenous and endogenous rules: Regulatory and strategic frameworks

Economic rules significantly shape the development of markets. In the context of agentic AI, both exogenous and endogenous rules come into play.

Exogenous rules – that is, those rules imposed on the sector from outside – particularly include: (1) the AI Act, which governs transparency, risk management and data access; (2) the General Data Protection Regulation (GDPR), which restricts the use of data-intensive agents; (3) the Digital Services Act (DSA) for the regulation of digital services, which aims to ensure a safe and responsible online environment; and (4) the Digital Markets Act (DMA), which is intended to limit the market power of gatekeepers. These regulatory frameworks determine the extent to which agents can

actually reduce transaction costs. At the same time, strict data access restrictions can significantly limit the potential efficiency gains offered by agentic AI.

Endogenous rules, by contrast, are not dictated from outside, but are established by the industry itself. Well-known examples of endogenous rules include industry standards such as EAN/GTIN in the distribution of consumer goods. The market architecture is shaped by whoever grants or denies access via these standards – a classic incentive allocation problem (Tirole, 1988). When developing endogenous rules in agentic commerce, conventional platforms are currently faced with a strategic question: *what will they benefit from AI agents interacting via their infrastructure and utilising – or even setting – the relevant standards?* As yet, however, platforms are often still in control of API access, pricing structures, visibility and data interfaces.

3.6 Parasocial preferences: Trust as a mechanism for reducing transaction costs

As already mentioned, a distinctive feature of agentic AI is that individuals may, under certain circumstances, develop a parasocial relationship with 'their' AI agents, which in turn influences customer loyalty. In particular, when AI agents appear in anthropomorphic form, are personalised, are available round the clock, communicate in a conversational manner and create a compelling presence, relationships and bonds can develop that often involve a high degree of trust. In transaction cost theory, trust in turn is regarded as a key mechanism for reducing transaction costs, as it lowers the costs of information, control and monitoring (Williamson, 1985).

3.7 Model of exchange: Information, goods, payments

In digital markets, three key exchange processes can be distinguished: (1) information, (2) goods and (3) payments. At present, the exchange of information takes place primarily via platforms such as Amazon – through rankings and recommendations, for example. In future, however, AI agents will take over this pre-selection and will bundle and curate information. Whilst the exchange of goods remains physical, the selection, configuration and ordering stages are increasingly being automated by AI agents. A new intermediary is also emerging in the payment process: systems such as 'AgentPay', which resemble automated billing systems, carry out transactions independently in the background. Taken together, this creates an integrated agent ecosystem in which information gathering, purchasing and payment are seamlessly merged.

The four scenarios illustrate varying degrees of automation along these exchange processes – from initial problem identification (Scenario ①) through partially automated decision-making processes (Scenario ②) to the complete delegation of purchasing and post-purchase processes (Scenarios ③ and ④).

To cover the costs associated with setting up and operating the system, at least three business models can be identified:

(1) A 'free' model without monetary cost for the customer: Although the customer does not pay any money here, they do in a sense pay with their data and their attention. Refinancing is then provided by corporate customers who are willing to pay for the service. These customers have an interest in using the relevant data to better understand customer behaviour. Furthermore, they wish to influence this behaviour – for example, through the use of personalised services, advertising and pricing – in the interests of their business.

(2) A 'subscription' model where the customer pays a fee: In this case, the customer makes a monetary payment, which is not necessarily linked to the extent of use. However, usage is generally limited in terms of time and quantity.

(3) A hybrid variant: Here, the customer uses the basic version free of charge but, as in the first model, pays with data and attention. In specific cases, however, they can purchase certain services associated with the subscription model for a limited period or in limited quantities, subject to a charge. To do so, they purchase so-called 'tokens' for a fee.

3.8 Impact on retail media

One specialised form of advertising-based platform financing is currently known as 'retail media'. This refers to the sale of advertising space on platforms. This form of advertising is currently one of the fastest-growing business models in the retail sector and generates billions in revenue. According to forecasts, the European retail media market is set to reach a turnover of 25 billion euros by 2026 – a significant increase from the 10 billion euros in 2022 (Retail media, n.d.). Retail media is therefore of great importance to online platforms. For instance, Amazon's advertising revenue in 2023 exceeded that of YouTube (Alphabet, 2024; Amazon, 2023). However, agentic AI fundamentally challenges this model. In future, users will no longer primarily see recommendations or adverts curated by platforms, but will rather see the selection decisions generated by AI agents.

This becomes particularly clear in Scenario ③, in which the AI agent takes over both product selection and the purchasing process, rendering the platform's traditional advertising formats or ranking mechanisms largely invisible to the consumer.

Advertising content is thus either hidden, bypassed or replaced by agent-specific decision-making logic. Marketing success therefore increasingly depends on how AI agents interpret and process brand messages. Retail media is thus shifting from platform-centred advertising towards agent-centred influence. The decisive competition-related question is therefore: how does one optimise products for AI agents rather than for humans? This shifts market power once again, away from the platforms and towards the developers of agentic AI systems.

3.9 Implications for consumer participation

Last but not least, it is also conceivable that new forms of organisation will emerge on the part of consumers due to the reduced coordination costs associated with the use of AI agents. For instance, in situations involving complaints or contract termination (see Scenario 4), consumers could specifically pool their AI agents and deploy them in a coordinated manner to enforce warranty or consumer rights. A key structural problem with consumer participation to date has been that diffuse consumer interests are difficult to organise. Agentic AI could provide a solution here, for example by enabling consumers to organise the collaboration of various agents. It would also be conceivable to use such agents to enforce consumer interests, for example in the context of out-of-court dispute resolution.

3.10 Conclusion

Agentic AI is more than just a technological addition. It marks a fundamental structural turning point. It reduces transaction and coordination costs, expands search areas, alters the flow of information, creates new intermediaries, influences regulatory frameworks and shifts power dynamics between consumers, platforms, retailers and AI developers. For policymakers, this means that new regulatory approaches are required which treat intermediary AI systems as independent actors in the market.

4. Changes to the supply side

The rapid introduction of agentic AI in e-commerce is fundamentally changing how supply and demand come together. AI agents have long since ceased to function merely as assistance systems; instead, they are increasingly acting as autonomous intermediaries: they search for products on users' behalf, compare options and, in some cases, make purchases directly – all with minimal human intervention.

The various manifestations of this development are illustrated in the four scenarios: whilst in Scenario ① only problem identification is initially automated, in Scenario ③ the AI agent takes over the entire product selection and purchasing process.

This development has far-reaching implications for business models, visibility mechanisms and competition in e-commerce. According to forecasts, by 2030 almost half of all e-commerce purchases in the US could be processed via AI agents, which would generate additional revenue of over 115 billion US dollars for the market (Kim, 2025).

4.1 Impact on business models and the design of online shops

In the digital economy, three distinct business models can generally be identified:

1. **Commission models:** This model is used in particular by platforms on which goods and services are traded. The platform operator receives a commission on the turnover generated by the supplier via the platform.

2. **Sale of data:** Due to the continuingly high levels of inefficiency at the interface between businesses and customers, companies have an interest in using customer data to optimise their marketing processes. Companies in the digital economy that hold this data can therefore sell it.
3. **Sale of attention:** Owing to the relatively low coordination and transaction costs, companies can often provide their customers with individually tailored and self-selected media offerings. The reach and attention generated using these media can offer companies attractive advertising environments including customers with real willingness to pay.

Traditional online shops are designed to attract users via search engines, landing pages and conversion funnels. Their entire architecture – from search engine optimisation (SEO) through product presentation to psychological design principles – is primarily geared towards human cognition and behavioural patterns. In an agent-based environment, however, these mechanisms lose their significance. AI agents often do not navigate visually, they do not necessarily respond to emotional triggers and they are less subject to attention limitations. They access structured data, analyse product feeds and make decisions based on objective criteria such as price, quality, delivery time or returns policies (Hamann, 2025).

This is particularly evident in Scenario ③, in which the AI agent organises the grocery shopping independently. The traditional sales psychology elements of the online shop become less important here, as product selection is primarily based on structured data.

Visibility is therefore increasingly measured in terms of technical accessibility, machine-readable data structure and semantic quality, rather than click-through rankings or brand awareness.

This trend is also evident in Scenario ②: the AI agent evaluates motor insurance policies not on the basis of brand presentation or advertising impact, but on the basis of structured, machine-readable information such as price, scope of cover or policy terms.

For online shops, this means that they need to be 'agent-ready'. In future, they must be able to 'communicate' effectively not only with customers but also with the technical components. They must also adapt their market monitoring, marketing objectives and marketing strategy, as new dependencies arise (*Who owns the interface? Who defines the standards?*). Competition is shifting from aesthetic or narrative elements towards systemic interoperability. Product information must be precise, structured and programmably accessible, for example through standardised attribute catalogues, JSON-LD, Schema.org, unique IDs and stable APIs. The better a shop makes its content available to agents, the greater the chance of being included in their selection and comparison processes. Early examples such as OpenAI's 'Instant Checkout' show that products can be found, configured and purchased directly within a chat without visiting the website ('OpenAI launches Instant Checkout', 2025). The traditional online shop is thus increasingly becoming the 'back end of a marketplace', whilst user interaction is shifting to AI agents.

This shift is particularly evident in Scenario ③: the consumer hardly interacts directly with the shop at all, but engages primarily with the AI agent, which takes full charge of product search, selection and ordering.

However, there is considerable variation in terms of the openness of platforms to agent access. Large suppliers can limit reach through anti-scraping measures, technical safeguards or restrictive terms of use. Small and medium-sized shops thus lose potential visibility. The lawsuit brought by Amazon against Perplexity AI in November 2025 illustrates this conflict. In this lawsuit, Amazon demanded that Perplexity's AI agent be prevented from accessing the Amazon Marketplace automatically (*Amazon sues Perplexity*, 2025). This raises fundamental questions: *How should data access*

be regulated in agentic commerce? Do large platforms assume a gatekeeper-like role in agentic commerce?

The relevance of these questions is particularly evident in Scenarios ① and ②: if the AI agent cannot access relevant tariff, insurance or product data, its ability to provide impartial analysis, advice and problem-solving is significantly restricted.

The transition to agentic commerce is thus shifting the balance of power between data owners, interface operators and other market players.

4.2 Impact on visibility: From SEO to Agentic AI Optimisation (AAIO)

As previously explained in Chapter C.3, the logic of visibility in digital markets is undergoing a fundamental shift in the transition from human-centred to agent-centred online commerce. In traditional e-commerce, Search Engine Optimisation (SEO) was dominant with the aim of improving the visibility of content in the search results of search engines such as Google. Positioning in the Google rankings was a decisive factor in determining turnover, as users usually only noticed the top results (*Agentic Commerce Optimierung*, n.d.). This model was based on the assumption of limited human attention and cognitive capacity (Simon, 1957, 1959).

In agentic commerce, however, these mechanisms are becoming less important. AI agents often do not operate via visual interfaces, but instead gain direct access to structured data, product feeds, semantic graphs and APIs. For them, what matters is the quality, consistency and machine-readability of the information, not search engine rankings (Gawer, 2022; Guha et al., 2016; OECD, 2025). In this respect, the search behaviour of AI agents may differ from that of consumers, who rely on heuristics, brand recognition and visual cues (see also Chapter F.1).

Against this background, Agentic AI Optimisation (AAIO) is gaining in importance as a machine-oriented evolution of traditional SEO strategies. Rather than optimising keywords, content or links, the focus here is on data-driven, semantically structured and API-centred optimisation. Visibility is no longer measured by Google rankings, but by priority within the decision-making space of autonomous agents, which evaluate information based on objective criteria such as price, delivery speed, stock levels, guarantees or quality metrics [Brohan, 2025; Guha et al., 2016; OECD, 2025; Wooldrige, 2009].

This shift is particularly evident in Scenario ③: in future, a retailer's visibility will depend less on whether a person finds the online shop, and much more on whether the AI agent can technically and reliably read, compare and integrate the offers into its decision-making logic.

For businesses, this means that traditional SEO measures are becoming less important. SEO remains relevant where people continue to conduct searching themselves or make hybrid purchasing decisions in which agents carry out the initial shortlisting (Hamann, 2025). At the same time, the importance of AAIO is growing, meaning that businesses must build up expertise in data management, API governance, product semantics and machine-readable commerce design. Marketing budgets are shifting accordingly. Agentic AI systems prioritise products in different ways than humans – for example, based on price-time efficiency, delivery guarantees or aggregated ratings – whilst design, brand image and storytelling are becoming less relevant [Brohan, 2025].

In Scenario ②, however, brand perception remains relevant to some extent, as consumers continue to make the final decision themselves and subjective preferences can influence their choice.

As a result, many companies will rebalance their budget allocations for SEO, AAIO, data optimisation and hybrid models, often combined with a shift from traditional marketing expenditure towards investment in data and system infrastructure – in other words, behind the 'line of sight' of consumers. By establishing robust data architectures, standardised interfaces and agent-readable product information, decisive competitive advantages can be achieved in the long term.

4.3 AI agents on the supply side: Agent-to-agent commerce

In the emerging ecosystem of agentic commerce, AI-powered agents no longer operate solely on the demand side, but increasingly also act as the digital representatives of companies and retailers. This paradigm shift expands the traditional e-commerce model, which until now has relied primarily on platforms as intermediaries. In agent-to-agent commerce, supplier agents interact autonomously with customer AI agents and take on complex tasks that were previously managed by human staff, intermediaries or platforms (Schumacher et al., 2025). Digital agents thus become actors capable of negotiation and decision-making, who not only provide information but also actively shape commercial transactions.

Scenario ③ represents a first step towards such an agent-based ecosystem, as the consumer's shopping agent already interacts independently with digital retail systems and thus autonomously handles key elements of the purchasing process.

In this context, three fundamental forms of interaction can be distinguished (Schumacher et al., 2025):

(1) Agent-to-agent: Autonomous negotiations between AI agents without the direct involvement of end users.

(2) Agent-to-site: Shopping agents interact directly with retailers' websites or their structured data and interface systems.

(3) Brokered agent-to-site: An intermediary coordinates and facilitates interactions between buying and selling agents.

These concepts are based on the models of autonomous, cooperative and competitive agents from the research into multi-agent systems (Bussmann et al., 2004; Lomuscio et al., 2003) and represent a further development of traditional algorithmic trading systems. Transformative potential is particularly evident in the B2B sector, as procurement processes are often standardised, recurring and data-intensive. The increasing automation of supply chains is already being investigated in Industry 4.0 research and logistics systems,

and companies are increasingly deploying AI-based systems that manage purchasing, scheduling and supplier management largely autonomously (Zettler, 2025).

However, these advances bring with them regulatory, competition policy-related and governance-related challenges. When agents negotiate prices or optimise delivery terms, the question of accountability arises – does it lie with the retailer, the agent operator or the supplier? Automated negotiations can also inadvertently produce market-structuring effects, such as price alignment that simulates collusive behaviour (Calvano et al., 2020).

Agentic AI interactions are also changing the role of platforms. If the contracting parties communicate directly via their respective agents, platforms may potentially lose their gatekeeper function or transform into agent brokers that provide interfaces, certificates, security standards and settlement services. These new interdependencies must be addressed through regulation, particularly with regard to competition protection and interoperability.

4.4 Competition, brand perception and strategic implications

The changes brought about by agentic AI have a significant impact on competition and brand perception. Visibility is no longer achieved solely through traditional advertising or SEO, but depends on the quality of data integration and technical connectivity. Brands that provide agent-friendly data increase their chances of being identified and recommended by agents; brands without integration risk becoming invisible within the agentic ecosystem (Hamann, 2025).

This becomes particularly clear in Scenario ③, as here it is exclusively the data processed by the AI agent that determines which suppliers even make it onto the shortlist.

Furthermore, the evaluation criteria are also shifting: AI agents often weight criteria differently to human users. If an agent optimises primarily for price, availability or delivery time, traditional brand loyalty loses significant influence (Brohan, 2025).

At the same time, Scenario ② shows that hybrid forms of decision-making can continue to exist: although the AI agent makes a structured pre-selection, consumers can still incorporate subjective factors such as brand trust or personal preferences into the final decision.

Strategically, this implies that companies must increasingly develop hybrid visibility and marketing strategies that are geared towards both human decision-making logic and agentic selection mechanisms.

4.5 Conclusion

In conclusion, it can be said that the increasing shift of market interactions towards agentic customer AI systems opens up considerable potential for efficiency gains, improved convenience and a noticeable reduction in the burden on consumers. At the same time, however, new structural and governance-related issues are emerging.

Of particular concern is the potential concentration of information and decision-making power amongst a small number of providers of AI agents, platforms and interface operators. Given the capital requirements involved, such a concentration appears highly likely at present (see Sachse, 2025).

Consumers run the risk that key selection and decision-making processes will become increasingly difficult to trace, particularly when AI agents act autonomously or their prioritisation logic is not disclosed transparently.

Added to this are potential distortions of competition arising from controlled access to data, selective or discriminatory rankings, and proprietary ecosystems, which can raise barriers to market entry for smaller suppliers. Furthermore, fundamental questions arise regarding accountability in the event of incorrect decisions, misleading recommendations or automatically concluded contractual relationships.

In Scenarios ③ and ④ in particular, it becomes clear that the increasing delegation of purchasing and repeat-purchase decisions can be accompanied by a loss of control on the part of consumers.

From a regulatory perspective, this presents the challenge of consistently ensuring transparency, interoperability, accountability and effective consumer rights, even in agent-based markets.

D

**Competition-related
aspects⁷**

1. Introduction: From the platform economy to agentic commerce

Over the past two decades, the debate on competition policy for digital markets and the market power within them has been largely shaped by the so-called platform economy. Search engines, online marketplaces, app stores and social networks have established themselves as key intermediaries between businesses and consumers. The competition-related and industrial economics-related analysis of these (multi-sided) markets (see, for example, Haucap, 2021; Peitz, 2006) has focused in particular on direct and indirect network effects which, combined with economies of scale, data advantages and switching costs due to lock-in effects, have led to significant market power being held by large platforms (see Cabral et al., 2021).

However, with the emergence of powerful AI agents, a (renewed) transformation of digital markets may be on the horizon. In agentic commerce, AI agents are increasingly acting as ‘proxies’ for consumers. These AI agents search for information, compare offers, evaluate products and, in future, will also be able to make purchasing decisions autonomously. From a competition economics perspective, this raises the question of whether it is merely the form of digital intermediation that is changing, or whether a new market structure is emerging that entails new competition-related risks.

2. AI agents as new economic intermediaries

A key difference between the existing platform economy and agentic commerce is that, in the case of agentic commerce, intermediation no longer takes place directly between suppliers and consumers; instead, the purchasing decision itself is increasingly mediated by algorithmic actors. In the existing platform economy, the final purchasing decision remains with consumers. The platforms influence this decision through rankings, recommendations, reviews by other buyers and factors such as the design of the user interface. However, the platforms do not make the purchasing decision themselves. In agentic commerce, by contrast, part of the decision-making process is delegated to an AI agent. The agent thus functions not merely as an information intermediary, but as an economic agent on behalf of the consumer.

From an information economics perspective, this gives rise to problems similar to those long recognised in the principal-agent literature (Richter & Furubotn, 2010, Chapter 5; Stocker & Lehr, 2025). These problems arise because the agent can exploit information advantages over their client (the principal) for their own benefit and may not carry out the task assigned to them in the manner that is optimal for the client. It is true that these problems already exist today within the context of the platform economy – for example, when a platform gives preferential treatment to its own services (so-called self-preferencing⁸). However, if the purchasing decision itself, rather than ‘merely’ the pre-selection of products, is also delegated to agents, these principal-agent problems – such as the risk of self-preferencing – are likely to become more pronounced.

From an industrial economics perspective, a key competitive parameter is also shifting. As the use of AI

agents becomes more widespread, businesses are competing less for consumer attention (see Prat & Valletti, 2022) and more for selection by AI agents. The relevant question is then no longer simply about which product consumers prefer, but which product is selected by AI agents. This gives rise to a new form of intermediation power (see Schweitzer et al., 2018) which – depending on the prevalence of AI agents – could be comparable in its economic significance to the role of search engines or online marketplaces. However, consumer mistrust of the ‘neutrality’ of AI agents could also limit their prevalence and, consequently, their power.

2.1 On the intermediation power of AI agents

The emergence of this intermediation power can be explained using established concepts from industrial economics. As with platforms, strong indirect network effects can arise. The more users employ a particular agent, the larger its database becomes and the more accurate its recommendations and decisions can be. This, in turn, increases the agent’s appeal to new users. At the same time, significant economies of scale arise in the training and operation of the underlying AI models. Major suppliers can spread the high fixed costs across a large user base and continuously improve their systems. The combination of network effects and economies of scale indicates a trend towards market concentration.

⁸ Self-preferencing should be understood in a broad sense and does not merely involve the preferential treatment of one’s own services. The preferential treatment of services or products for relatively higher commission payments can also be understood as self-preferencing in a broader sense (see Kittaka et al., 2023).

This is likely to be compounded by significant lock-in effects. Over time, an agent gains an ever-better understanding of its users' preferences, purchase histories, budget constraints and behavioural patterns. This information constitutes a significant part of its value. Switching to another agent would often entail the loss of this knowledge. From an economic perspective, this constitutes a form of specific 'human capital' in digital form. Such lock-in effects can increase barriers to market entry and reduce the intensity of competition, provided that this knowledge cannot be transferred to another AI agent.

Against this backdrop, it seems entirely plausible that gatekeeper structures will also emerge in agentic commerce. The gatekeeper function could even be more extensive than in the platform economy. Whilst search engines and platforms control access to information or customers, agents potentially control access to the purchasing decision itself. They have a more direct influence over which products are even considered and which suppliers enter the decision-making process. This gives them a position of considerable economic power.

2.2 Market foreclosure in agentic commerce

From a competition law perspective, the associated competition issues can be analysed as cases of potential market foreclosure. Here, a distinction must first be made between two possible forms of market foreclosure: 'foreclosure *of* agents' and 'foreclosure *by* agents' (see Bostoen & Krämer, 2026).

2.2.1 Market foreclosure of agents: When platforms exclude AI agents

The concept of 'foreclosure *of* agents' ties in with the classical literature on vertical market foreclosure through denial of access. When AI agents become key intermediaries between suppliers and consumers, they are dependent on access to product information, prices, availability and transaction interfaces. In principle, platforms, retailers or manufacturers could attempt to strategically restrict this access. Such a strategy would be particularly attractive if agents increase market transparency and thereby reduce the profit margins of established suppliers.

From an economic perspective, this is a variant of 'raising rivals' costs'. By making it more difficult or expensive for agents to access relevant information – and thus increasing access costs – businesses drive up the costs of competing intermediaries. Similar strategies have also been observed in the past within the platform economy, for example through restrictions on data access for price comparison services or through the control of interfaces by (dominant) platforms. In agentic commerce, such practices could become even more significant, as agents rely to a much greater extent on real-time data and automated interactions. This may give rise to new challenges regarding access to data and interfaces.

The risk of vertical foreclosure by integrated platforms appears particularly relevant. A business that operates both a trading platform and its own AI agent could make it difficult or impossible for competing agents to access its infrastructure. The economic logic corresponds to traditional models of vertical market foreclosure, as observed, for example, among vertically integrated suppliers in infrastructure markets: by controlling upstream infrastructure, competition in downstream markets is restricted or even completely prevented.

2.2.2 Market foreclosure *by* agents: When AI agents abuse market power themselves

Just as significant, however, is the reverse perspective of market foreclosure *by* agents. Here, market foreclosure is not done by platforms or retailers, but by the AI agents themselves. When AI agents become the central interface between consumers and suppliers, they control access to demand and thus wield considerable intermediation power. Suppliers then no longer need to focus on convincing the consumer, but must rather concentrate on the agents' algorithms.

This situation bears striking parallels to the economic theory of buyer power. An agent representing large numbers of consumers can aggregate demand on a substantial scale. This gives rise to a form of digital buyer power. Whilst platforms are traditionally analysed as intermediaries between market sides, agents with significant market power could increasingly act as collective buyers. Suppliers would be dependent on being considered by them and would have to adapt their products, prices and contractual terms to the requirements of these agents.

It is also highly plausible that widely used AI agents will come to wield relative market power within the meaning of section 20 of the Competition Act (*Gesetz gegen Wettbewerbsbeschränkungen*), meaning that individual suppliers may easily become dependent on these AI agents and their goodwill. In this context, another mechanism of market foreclosure *by* agents may lie in the possibility of discriminatory selection decisions. Agents could systematically favour or disadvantage certain suppliers. The reasons for this can be manifold, ranging from economic incentives and technical design decisions through to internal corporate interests. Self-preferencing on the part of integrated suppliers would be particularly problematic. An agent belonging to a retailer or a platform could systematically favour the products of its own ecosystem. In terms of competition economics, this corresponds to the well-known theories of 'leveraging' market power into neighbouring markets.

2.3 Potential demand power of AI agents

Furthermore, the increasing prevalence of agents could lead to a new form of demand concentration (see Agranat & Gal, 2025). In traditional competition theory, competition is disciplined by the multitude of independent consumers. Millions of individual decisions ensure that suppliers must compete for customers. However, if a significant proportion of demand is channelled through a small number of agents, a small number of algorithmic decision-making mechanisms replace the multitude of individual consumer decisions. This could lead to a significant concentration of economic power. For consumers, such a pooling of demand and the resulting buyer power can have a positive effect, for example if price advantages can be achieved and these are passed on to consumers, at least in part.

2.4 Competition effects of AI agents

Paradoxically, agents could therefore both intensify and restrict competition at the same time. On the one hand, they reduce search costs and information asymmetries. This is in line with the classic predictions of the information-economic theory of search costs dating back to Stigler (1961): falling search costs generally increase price competition and make it more difficult to maintain market power. Furthermore, the pooling of demand can, at least in theory, lead to price advantages for consumers due to increased buyer power.

On the other hand, the concentration of demand can create new positions of power and lead to the competition problems described above. The beneficial effects of agentic commerce are therefore critically dependent on whether competition between agents remains sufficiently intense.

2.5 On the possible regulation of AI agents

In light of the considerations set out so far, the role of regulation is particularly important. Many instruments of platform regulation can be applied more or less directly. Data portability can reduce lock-in effects and promote competition between agents. Interoperability can prevent dominant platforms from excluding competing agents. Bans on self-preferencing can prevent integrated agents from using their gatekeeper position to favour their own offerings (see also Chapter F.6 on self-preferencing).

At the same time, new regulatory issues are emerging. Whilst platforms are traditionally regarded as market intermediaries, agents also act as representatives of their users. This could suggest the introduction of agent-specific loyalty obligations. Like with trustees or asset managers, agents could be required to act demonstrably in the interests of their users. From an economic perspective, this would address the classic principal-agent problem described above.

2.6 From platform power to agent power

In the long term, the competition policy debate could therefore shift from the issue of platform power to that of agent power. The key challenge would then no longer lie solely in protecting markets from platforms with significant market power, but also in controlling the position of power held by agents with considerable market power. From a competition economics perspective, the risk of dual foreclosure appears particularly significant: on the one hand, established platforms could exclude competing agents ('foreclosure of agents'); on the other hand, market-powerful agents themselves could control suppliers' access to demand and thereby foreclose markets ('foreclosure by agents').

Experience to date in digital markets shows that some intermediaries are becoming extremely powerful players. Should agentic commerce become widespread, AI agents could represent the next generation of such intermediaries. The challenge for competition policy will then be to harness the efficiency gains of algorithmic intermediation without creating new and potentially even more powerful gatekeeper structures.

3. AI agents as meta-intermediaries?

3.1 A new layer of market organisation

However, one of the key competition-related aspects of agentic commerce might not lie solely in the fact that AI agents represent new intermediaries. An even more fundamental aspect might be that AI agents are evolving to become a new layer of market organisation, located above the current platforms. From this perspective, AI agents appear not merely as additional market players alongside search engines, online marketplaces and social networks, but as some kind of ‘meta-intermediary’.

To illustrate this more clearly: in the platform economy, platforms control access to customers – they act as gatekeepers. Businesses must be visible on Amazon, appear in Google’s search results or be listed in the Apple and Google app stores. Consequently, the competition policy debate has so far focused on the question of how the market power of these platforms can be limited. Instruments such as the Digital Markets Act (DMA) are ultimately based on the assumption that certain platforms perform an indispensable gatekeeper function.

Agentic commerce could potentially transform this structure fundamentally. In future, a universal AI agent could coordinate the user’s search, comparison and selection processes across numerous platforms. Users would then no longer decide for themselves whether to use Amazon, Booking, Check24, Google Shopping or other platforms. Instead, the agent would make this decision and select the most suitable platform in each case. From the user’s perspective, the platforms would increasingly fade into the background and become interchangeable pieces of infrastructure.

3.2 From gatekeeper to meta-gatekeeper

From a competition economics perspective, this would shift the control over access to demand. Today, platforms control access to customers. In an agent economy, by contrast, agents could control access to the platforms. The crucial question for businesses would then no longer be how to gain visibility on a platform, but how to be considered by the agents who decide on the choice of platform and the specific supplier.

This would have significant consequences for competitive dynamics. Many of the gatekeepers currently under discussion could themselves become dependent on agents. A dominant AI agent could, for example, decide which search engine is used, which online marketplace offers the best terms, or via which payment service a transaction is processed. In this way, the gatekeeper function would, in a sense, move up a layer. The agents would not merely control access to individual suppliers, but would control access to the current gatekeepers themselves.

This would also alter the nature of gatekeeper power. In the platform economy, market power is based primarily on the control of transactions and user access. In an ‘agentic economy’, it could increasingly be based on the control of delegated decisions. The economic bottleneck would then no longer be users’ attention, but rather their trust in their agents. Whoever controls the agents potentially controls a significant proportion of users’ economic decisions.

3.3 A third new form of market foreclosure

This perspective offers a further angle on the issue of market foreclosure. The danger of market foreclosure *of* agents would lie in the fact that established platforms might attempt to prevent the rise of such meta-intermediaries by restricting their access to data, interfaces or transaction opportunities. The danger of market foreclosure *by* agents, on the other hand, would lie in the fact that successful agents themselves become central gatekeepers and decide which platforms, suppliers or products stand a chance of even being noticed by users.

In the event of such a development, the transition from the platform economy to agentic commerce would not merely be a technological shift, but a fundamental change in the market organisation of digital economic spaces. The key challenge for competition policy would be to ensure that the new level of meta-intermediation remains open and competitive, and that a small number of dominant gatekeepers do not re-establish themselves to dictate the economic decisions of millions of consumers.

3.4 From the attention economy to the delegation economy

This idea can actually be taken even further: from a competition economics perspective, agentic commerce could mark the transition from an 'economy of attention' to an 'economy of delegation'. In the platform economy, companies compete for users' attention; in agentic commerce, they compete for the delegation decisions of AI agents, which themselves compete for users' trust. The scarce resource for suppliers is then no longer the attention of users, but rather algorithmic consideration by the agents.



**Societal implications of
agentic commerce**

1. On the inevitability of technological development

Building on the economic considerations set out above, the following chapter aims to provide a sociological framework for agentic commerce, in order to examine in greater detail the societal implications of the 'agentic turn'. A first sociological observation looks at the inevitability that is supposedly inherent in technological developments. Joseph Schumpeter (1942/1975, p. 138) argued that innovation springs from 'creative destruction'; the old gives way to the new and paves the way for progress. Developed further, this idea also characterises the tech industry (Henton & Held, 2013; Staab, 2020, p. 24). Here, innovation is often understood as technology providing solutions to everyday problems and the major crises of the present, such as climate change and pandemics (Nachtwey & Seidl, 2024; Morozov, 2013). Accordingly, key players regard the development of generative AI as groundbreaking, revolutionary and unstoppable (Taylor, 2023) – like a train that one must jump on, the direction of travel having already been established. In this respect, it is not surprising that industry experts regard AI agents as the future of consumption (Barthel et al., 2025). More cautious observers, on the other hand, sound the alarm and, potentially, even conclude that everything used to be better in the analogue age. The present chapter's sociological approach does not share such a pessimistic outlook. Nevertheless, sociology does allow for a 'reality check' of utopian technological fantasies (Burrell & Fourcade, 2021, p. 231).

The sociologist Niklas Luhmann (1984, p. 152), for instance, used the concept of 'contingency' to remind us that things can always turn out differently from what we might expect. With this in mind, the SVRV argues that the advance of AI agents in the field of personal consumption should not be regarded as 'set in stone'. Contrary to what one might assume, the direction of travel is not necessarily pre-determined. The evolution of the AI trend (or boom) does not have to be a settled matter (Lanchester, 2025). At least for the time being, there remains scope for steering and adaptation.

However, if the steady expansion of agentic commerce is allowed to run its course, without discussing fundamental issues at an early stage and taking regulatory action where necessary, it may subsequently prove difficult to turn back the clock. By then, the normative power of the factual will have already restricted the scope for political action. It is possible that selected AI agents may even rise to become 'proprietary markets' which bring retailers and consumers together but unilaterally set the rules of the game in the newly created market (see Staab, 2020, Chapter 4).

In this context, it is illuminating to look at current discussions on the impact of social media. By the 2010s at the latest, social networks such as Facebook had become established media of communication (McIntyre, 2014, p. 6). But just under a decade later, warnings are mounting that social media can adversely affect the mental health of children and young people (Brailovskaia et al., 2025). And now, a previously innovative vision – a new form of social interaction on digital platforms – suddenly faces the sharpest weapon of regulation: a ban on the use of social media for children below a certain age limit (Conroy, 2024). Would this acute political pressure to take action have arisen if the pros and cons of social media had been better weighed up from the outset? This question is virtually impossible to answer. However, the assumption that tech companies follow a commercial interest in binding their users to the platforms as often and as long as possible has seemed plausible for a while, not just since people started talking about addictive design. Social scientists and humanities scholars have long challenged overly positive visions of the technological future with a more nuanced approach (Burrell & Fourcade, 2021). Another factor that should not be underestimated is the growing political influence of large tech companies. This is why political-economic aspects should not be overlooked when analysing digitalisation in general (see Staab & Thiel, 2022) and agentic commerce in particular.

The example of social media is instructive in several respects when considering the development of AI agents. On the one hand, a certain degree of scepticism towards the interests of large tech companies seems warranted. The extent to which those interests can be reconciled with consumer protection remains an open question. This, in turn, argues in favour of applying the precautionary principle when regulating AI agents, even if causal evidence of potentially negative consequences for consumers is still lacking (regarding social media, see Brailovskaia et al., 2025, p. 8). At

this point, however, a fundamental aspect comes to the fore: social media has profoundly changed the way people interact and express social recognition. A question of similar magnitude arises in relation to the increasing use of AI agents: *to what extent is our society willing to allow AI to delegate, automate and optimise our own consumption?* Consumer policy should address this fundamental normative question before consequences arise that will be difficult to rectify later on. The following chapter offers some reflections for this discussion.

2. Consumer empowerment or an optimised consumer society?

In line with the focus of this report, the direction that agentic commerce will take is up for debate again. On the one hand, it is possible that consumers will increasingly delegate decisions and consumption-related practices (purchasing, switching providers, making complaints, etc.) to AI agents. For illustration, we refer here to Scenarios 3 (purchasing decision) and 4 (post-purchase phase). On the other hand, it seems plausible that the providers of AI agents will want to bind users as closely as possible to the agents. The role of proprietary markets – as represented by AI agents – ‘is to bring producers and consumers into contact. Their trump card is to secure the most exclusive possible access to those consumers whom they bind ever more closely to their proprietary systems through lock-in strategies’ (Staab, 2020, p. 213). Consumers are encouraged to review as many purchasing decisions as possible with the help of the AI agent and thus to optimise them.

This opportunity arises in particular from Scenario ① (problem identification), which has already been discussed. Products that one used to add to the shopping basket out of habit are scrutinised on the advice of the AI agent. Perhaps there is an alternative that offers better value for money. Or one is encouraged to have the AI agent continuously analyse the terms of a contract. Given the wide range of possibilities, agentic commerce is likely to give rise to a new need for extensive and ongoing engagement with the goods and services one purchases.

Against this backdrop, our stance on agentic commerce depends crucially on two perspectives. On the one hand, consumer protection increasingly focuses on the concept of ‘consumer empowerment’ (Pires et al., 2006); consumers should be empowered to make autonomous and well-informed decisions. And because providing consumers with information is not always sufficiently effective on its own (SVRV, 2024a, p. 13), AI agents promise better ways of supporting consumers

(see Chapter C 1). On the other hand, some sociologists are raising critical concerns that, rather than empowerment, a kind of new obsession with personal consumption might emerge. Zygmunt Bauman (2000, 2001) argued that people today already make sense of their world through their role as consumers. Identity, social status and political views are expressed through the things we buy – and do not buy (see also Flemmen, 2025; Simmel, 1957). In this sense, companies have since the 1970s relied on personalisation to move beyond mass-produced goods and tap into new consumer segments (Streeck, 2012, pp. 33–36; see also Reckwitz, 2025). At the same time, self-optimisation has become a driving force in Western societies (Nehring & Röcke, 2024). And social media caters to this trend by enabling self-expression (Staab & Thiel, 2022, pp. 136–137).

But with the advent of AI agents, entirely new possibilities for the personalisation and optimisation of consumption are emerging (see Chapter C 1). Through agentic commerce, the personalisation and optimisation of private consumption – whatever the criteria may be – assumes even greater importance in daily life than is already the case. At the same time, optimisation might be linked to delegation, as the task of evaluating information and making decisions is partly left to the AI agent. From the consumer perspective, the desire for optimisation might therefore, paradoxically, go hand in hand with a certain passivity. Whilst the AI agent may take on the task of assessing and narrowing down existing options, consumers must still grapple with a lingering doubt: am I really using the best product or cheapest tariff currently available? Agentic commerce will presumably fuel this doubt.

This gives rise to the following scenarios worth considering: through AI agents, consumers intensify the constant optimisation of their own consumption – and, as a result, may end up using even more energy and resources than they already do. Because past

purchasing decisions can be constantly scrutinised and 'improved', a new kind of 'throwaway society' is likely to emerge. The product that was purchased just now with a clear conscience may already seem outdated by tomorrow. For an increasing number of matters, people turn to their digital companion, which becomes the ultimate authority and is permanently collecting detailed data on purchasing behaviour. One's own capacity for judgement and decision-making becomes, to some extent, obsolete. Relying on recommendations from family and friends is no longer necessary (see also Chapter C 2). In-store personal advice may become redundant in some areas (with corresponding consequences for high streets and retail jobs). People stop being regular customers; instead, they shop wherever the AI agent has identified the cheapest deal. Meanwhile, the purchase is often an order that is delivered by human couriers – at least for now. Online retail already drives such developments, which will be further amplified, most likely, by AI agents.

This vision might sound speculative and pessimistic. When choosing one's next holiday destination, one may well continue to consult well-travelled friends and reminisce about shared holiday memories. But in more mundane areas of consumption, delegating tasks to AI agents may actually create more breathing space, allowing people, for once, not to think about shopping. Or one may be protected from cost traps and fraud by the AI agent's scrutiny. Perhaps AI agents will even enable consumers to adopt sustainable consumption patterns (see Chapter F 7). These possibilities certainly exist. And this brings us to the core message of the present chapter, as emphasised at the beginning: agentic commerce can develop in a multitude of directions. But to provide guidance, it is not sufficient to simply examine technical scenarios and legal considerations. It is equally important to assess societal implications and evaluate them from a political perspective. What is necessary at this juncture is a debate between civil society, policymakers and the business world.

The tech industry will be unlikely to initiate this debate. The sector sometimes attributes its own success to the fact that it merely meets consumers' existing needs (Dor-schel, 2026, pp. 366–367): whatever proves successful on the market is evidently desirable, so the logic goes. However, this way of thinking fails to recognise that technology, in turn, shapes society, creates new needs and may cause undesirable effects. To maintain a clear awareness of such risks, consumer policy needs to include sociological considerations.



**Implications for consumer policy
concepts and instruments**

The emerging trend towards ‘agentic commerce’ not only poses a challenge for online retail but is also likely to have implications for the fundamental concepts and instruments of consumer policy. This is likely to necessitate an adaptation of the current legal framework.

In order to assess the implications of the shift towards agentic commerce for consumer law, it is necessary first to recall a fundamental premise of consumer law that seems so self-evident that it is usually not even stated: current consumer law is based on the assumption that humans make purchasing decisions. Consumer law is geared towards the needs and vulnerabilities of people. Accordingly, the rules of consumer law aim to enable people to make informed decisions and to strengthen consumers’ autonomy.

However, this premise begins to falter when, in future, purchasing decisions are no longer made just by humans but also by machines. The AI economy will be more diverse and complex than the old world of consumption: alongside human consumers who search for products themselves, there will be, *firstly*, ‘augmented consumers’ (Busch, 2025) – that is, consumers who use AI tools to assist them in their product search but who still make the purchasing decision themselves – and, *secondly*, AI agents who, as ‘algorithmic consumers’ (Gal & Elkin-Koren, 2017), take over the purchasing decision entirely on behalf of consumers.

In the following, we will examine in more detail the potential implications of the trend towards agentic commerce for selected concepts and instruments in contract and consumer law.

1. The consumer model

First of all, the rise of agentic commerce could have consequences for the prevailing model of the consumer. To date, consumer law has been based on the model of the average consumer who is reasonably well-informed, observant and circumspect. This model, developed by the European Court of Justice in its case law, has since been adopted by the European legislator and enshrined in secondary legislation (Purnhagen & Schebesta, 2020).⁹

In the context of agentic commerce, the question arises as to how the traditional consumer model can be applied to AI agents: does the behaviour of an AI agent differ from human decision-making behaviour?

It is reasonable to assume that AI agents, which have access to other software tools, are better at calculating than the typical average consumer. It is also possible that AI agents do not suffer from ‘present bias’ – i.e. the widespread human tendency to value immediate rewards more highly than future benefits. Problems arising from so-called ‘hyperbolic discounting’ could therefore become less significant. If this proves to be the case, it could – at least for agentic commerce – spell the end of ‘teaser rates’, whereby consumers initially pay a low price during the first few months of a contract before the price is increased for the remainder of the contract term. AI agents might not be fooled by such schemes. It is also likely that AI agents are less susceptible to emotional advertising messages and are not prone to impulse purchases. Unlike humans, AI agents are unlikely to forget to cancel a trial gym membership.

9 CJEU, Judgment of 16 July 1998, Case C-210/96 – Gut Springenheide, paras. 30 and 31; see also Recital 18 of Directive 2005/29/EC.

These considerations might lead one to conclude that AI agents are far more likely to meet the ideal of a reasonably well-informed, observant and circumspect consumer than a human being. On closer inspection, however, the situation may be somewhat more complex. Initial findings from the emerging field of research into ‘machine psychology’ (Hagendorff et al., 2023) or ‘AI psychometrics’ (Pellert et al., 2024) – which examines the behaviour of large language models on which AI agents are based – suggest that AI agents also exhibit behavioural patterns and cognitive biases familiar from human behaviour, such as risk aversion, confirmation bias and endowment effects (Yax et al., 2024). However, the findings available to date are not entirely conclusive (Chen et al., 2025).

Two possible causes for these behavioural patterns are discussed in the literature (Chen et al., 2025): one possibility is that the models have adopted the cognitive biases from the training data and therefore imitate human behaviour. Another possibility is that the biases are introduced through human feedback during the fine-tuning of the models following training. A further problem appears to lie in the fact that AI agents do not possess a stable personality (or ‘AI persona’). Whether an AI agent is risk-averse or risk-seeking depends on the respective ‘system prompt’ and the specific ‘user prompts’ (Horton, 2023; Desai & Riedl, 2025).

At the present point in time, it therefore remains an open question whether AI agents make ‘more rational’ decisions than humans. It is still too early to provide a definitive answer as to whether the consumer model developed for humans also applies to AI agents, or whether a new consumer model needs to be developed for AI agents. In this respect, further research is required.



RECOMMENDATION 12

Conduct further research into the decision-making behaviour of AI

The SVRV sees a need for further research into the decision-making behaviour of AI agents with the aim of further developing the consumer model. New interdisciplinary evidence should be generated in this respect.

2. Consumer information model

For decades, European consumer law has been based on an information-based protection model (SVRV, 2021, pp. 371-372; SVRV, 2023). This model is underpinned by the assumption that consumers, when provided with timely and comprehensible information, are enabled to make informed consumption decisions that align with their preferences. Pre-contractual information obligations serve to counterbalance structural information asymmetries between businesses and consumers (Dauner-Lieb, 1983, p. 70; Fleischer, 2000, p. 777; Koch, 2012, p. 485).

2.1 Weaknesses of the current information model

The consumer law information model has long been the subject of criticism (Alexander, 2024, pp. 1290, 1296; Ebner, 2022, p. 364; von Hippel, 1986/2023, p. 37; Reich, 2003). Research into behavioural economics shows that information requirements are limited in their effectiveness (Simon, 1959; see also Martinek, 2000, p. 524; Koch, 2012, p. 485). Providing more pre-contractual information often fails to improve consumers' decision-making and instead can lead to information overload. In many cases, this quantitative problem is exacerbated by a qualitative one. Often, only some of the provided information is relevant to consumers (information mismatch). If consumers are overwhelmed by the task of absorbing and properly processing the information, they frequently resort to simplified decision-making mechanisms and no longer take note of the information provided (Busch, 2025, p. 1375; Koch, 2012, p. 485; Martinek, 2000, p. 524). It is not uncommon for consumers to simply click away terms and conditions and privacy notices without reading them (Bakos et al., 2014; Ebner, 2022, p. 365). Even attempts to increase the effectiveness of information requirements by imposing additional demands regarding

comprehensibility, visual highlighting or standardisation of information formats have only a limited effect (SVRV, 2021, pp. 371-372; SVRV, 2023).

EXAMPLE

Current information model

Without an AI agent, the consumer in **Scenario ②** would be required to independently research various motor insurance offers and tariffs, compare them manually and evaluate them on the basis of the information provided. This would require a considerable investment of time, as the voluminous and often complex information provided by insurance providers would have to be assessed independently.

2.2 Structural changes brought about by AI agents lead to a shift in the problem and to new risks

The use of AI agents could bring about a decisive change to the consumer information model. AI systems can absorb and process much larger volumes of information than humans. This could help reduce the problem of information overload. The problem of information mismatch could also become less significant if AI agents filter out, from the vast amount of information, those aspects that are relevant to individual consumers (Busch, 2025, pp. 1370 ff.). For consumers, this could represent a considerable relief if they no longer have to read and evaluate the extensive mandatory information

themselves, but can instead delegate these tasks to an AI agent (Busch, 2025, p. 1371; Gal & Elkin-Koren, 2017, p. 318).¹⁰ However, this presupposes that the information is made available in a machine-readable format.¹¹

Scenario ② *illustrates how the AI agent can relieve the consumer of the burden of decision-making. Here, the AI agent takes charge of searching for, evaluating and comparing different tariffs and offers, and can thus identify the best offer for the consumer within a matter of seconds, in line with their preferences.*

On closer inspection, however, it becomes clear that the informational challenges facing consumers are not eliminated by the use of AI agents, but rather shifted. Whilst AI agents can significantly reduce the information overload consumers face when choosing between different products (Busch, 2025, p. 1371), the decision to select a particular AI agent beforehand is becoming increasingly important. Consequently, the question of the criteria by which AI systems select, process and evaluate information is gaining in significance.

As individual AI agents differ in terms of their data sources, selection mechanisms, prioritisation and evaluation criteria, the choice of a particular AI agent has a decisive influence on the quality, traceability and objectivity of the results (see Khan et al., 2026; Heck et al., 2025, p. 424). The problem of information overload in the purchasing decision itself thus becomes a challenge relating to information structure and system control. The focus is no longer primarily on the volume of available information, but rather on the question of the rules by which AI agents filter and weight information and translate it into concrete recommendations for action.

This alters the structural framework of the consumer information model. If information obligations are fulfilled in formal terms but are no longer taken on board by the people themselves, they only serve their purpose indirectly – or fail to do so altogether. Admittedly, AI agents can utilise this information more efficiently than consumers. However, the downside of delegating decisions is that a new transparency deficit arises when consumers can no longer understand the underlying decision-making logic. This can lead to various risks:

- Distortions caused by algorithmic prioritisation, where AI agents give preferential treatment to or select certain products or providers.
- Loss of decision-making autonomy, when consumers accept recommendations or enter into contracts without scrutiny.
- Exacerbation of existing information asymmetry, where the ability of consumers to exercise control is restricted.
- Dependence on non-transparent systems that consumers cannot scrutinise or compare.
- Disadvantageous consumer decisions, where errors or systematic biases in the algorithm go unnoticed and lead to unfavourable decisions by AI agents.

¹⁰ The Digital Product Passport in particular could serve as a model or starting point here, as it enables the standardised and machine-readable provision of product-related information.

¹¹ Article 14(1) of the DSA, which requires information to be provided in machine-readable form, can serve as a model here. See also Article 20(1) of the ELI Model Rules.

2

Considerations regarding Scenario 2

Searching for suitable motor insurance using an AI agent

The consumer has chosen an AI agent that is available free of charge. When viewing the AI agent's recommendations, the consumer does not see the details of the insurance quotes. The consumer trusts the AI agent's brief summary and prioritisation and opts for the first quote without checking the 'small print' of the insurance quotes. The AI agent's default settings for source selection and individual criteria are not disclosed. Consequently, it may go unnoticed that – for example – the recommendations only evaluate commission-based offers, whilst offers that are more favourable to the consumer are not taken into account.

Consumer law is confronted with the task of adapting existing protective instruments to new technological developments without allowing the consumer's right to autonomy to be relinquished by complete delegation to technical systems.

e

RECOMMENDATION 13

Greater standardisation and machine-readability of consumer information

The SVRV recommends that consumer information be adapted for use by AI agents through greater standardisation and machine readability. This enables AI agents to process, compare and utilise information in the interests of consumers.

At the same time, it should be ensured that essential information remains available to consumers in a condensed form. In this respect, a two-tier information model appears appropriate.¹² Under this model, AI agents are granted access to complete, detailed and machine-readable sets of information so that they can make the best possible use of their analytical and processing capabilities and, where necessary, can also make contractual decisions on the basis of comprehensive information. Consumers should also be provided with condensed, clearly structured and easily understandable key information that enables them to obtain a quick overview and offers a sufficient basis for decision-making.

The provision of this key information should be mandatory by default ('consumer protection by default'). At the same time, consumers must be able to opt out of receiving this key information. Such a waiver may be particularly useful if consumers wish to entrust the AI agent with the complete and independent execution of the purchasing process. However, the waiver of the key information should be expressly stated; a tacit or implied opt-out is not sufficient.

e

RECOMMENDATION 14

Two-tier information model

The SVRV advocates a two-tier information model. Under this model, AI agents should be given access to complete, detailed and machine-readable information. Consumers should also be provided with condensed, clearly structured and easily understandable key information that enables them to obtain a quick overview and offers a sufficient basis for decision-making. The two-tier information model should be designed as an opt-out model, enabling consumers to waive their right to receive the key information by means of an explicit declaration.

12 For a tiered approach to information based on need for and (if applicable) depth of information, even without the use of AI, see Alexander (2024, p. 1292).

Irrespective of this, providing consumers with a subsequent confirmation of the contract remains essential in order to ensure transparency and to guarantee the effective exercise and enforcement of consumer rights, particularly with regard to the right of withdrawal. A solution of this kind also complies with the requirements of section 312f of the German Civil Code (*Bürgerliches Gesetzbuch*), according to which the terms of the contract must be made available to consumers on a durable medium after the contract has been concluded.

The two-tier information model outlined here safeguards the decision-making autonomy of consumers, as they are not overwhelmed by the complexity of the information and can continue to rely on key information as the essential basis for their decisions. At the same time, it utilises the advantages of algorithmic information processing, for example when assessing complex contractual terms, price comparisons or risk profiles – areas in which the amount of detail would be virtually unmanageable for humans.

Such a two-tier model thus combines consumer protection with efficiency. It reduces cognitive overload for consumers whilst enabling well-informed, algorithm-supported decisions without compromising transparency or accountability for human decision-makers.



RECOMMENDATION 15

Transparency requirements for AI agents

In the case of AI agents used as assistance systems for consumer decisions, their mode of operation (particularly any potential conflicts of interest), the sources used for product comparisons and recommendations, and the key evaluation criteria should be disclosed.

2

Considerations regarding Scenario 2

Examples of a two-tier information model

The AI agent can present consumers with key information on the relevant offerings – such as annual costs, contract term or the scope of insurance cover – in a structured and comprehensible form. Various approaches are conceivable here.

On the one hand, the AI agent can independently evaluate and prioritise the relevant contractual information and initially present the consumer only with the results it considers essential. To do this, the agent accesses the full text of the contract, tariff details and clauses relating to price changes or notice periods, analyses this information and condenses it into a clear recommendation. The underlying sources and prioritisation criteria are disclosed, so that the consumer can, if necessary, trace individual details and examine them in greater depth.

On the other hand, the AI agent can enquire about the consumer's preferences and requirements even before the actual research begins, for example regarding price limits, desired insurance cover, contract duration or flexibility regarding cancellation options. Based on these specifications, the agent then searches for and evaluates suitable offerings in a targeted manner. In this case, the selection and prioritisation of information are more strongly guided by the consumer's individual preferences and not solely by the criteria set by the AI system itself.

Both approaches make it possible to relieve the consumer of the burden of scrutinising extensive legal and technical contract details, without depriving them of the opportunity to understand and review the AI agent's recommendations on the basis of the disclosed information and sources.

Without extended transparency obligations for AI agents, there is a risk that the information asymmetry will shift from companies to system providers.¹³ This information must be readily accessible to consumers in a comprehensible and understandable form as soon as the AI agent is put into operation.¹⁴ In this sense, the transparency obligations under Article 50 of the AI Act represent merely a first and still somewhat fragmentary step. This approach should be further developed in the context of consumer protection law. Furthermore, it must be examined whether the provisions of the DSA apply to AI agents. Insofar as this is not the case, AI agents should be subject to transparency obligations comparable to those set out in Article 27 of the DSA for recommender systems on online platforms.

In summary, AI agents do not fundamentally call the consumer information model into question, but some adjustments are nonetheless required to ensure the effectiveness of informational consumer protection in agentic commerce. The focus here is shifting from the problem of information overload in consumer decision-making to structural transparency deficits relating to the algorithmic decision-making logic of AI agents. In order to be '*agent-ready*', consumer law should therefore focus less on the mere provision of information and more on its comprehensible use, systemic transparency and fair communication by AI agents. In the long term, this implies a shift from a purely information-based approach to a system- and agent-centred approach to protection.

RECOMMENDATION 16



Examine the applicability of the DSA

The SVRV recommends examining the extent to which the existing regulations for online platforms, in particular the transparency requirements of the DSA, also apply to AI agents. If they are not directly applicable, an extension of the regulatory framework to cover AI agents would appear appropriate.

¹³ A detailed list of transparency obligations regarding the AI agent's mode of operation can be found in Article 11 of the ELI Model Rules. Transparency obligations regarding individual decision-making processes are regulated in Article 10 of the ELI Model Rules.

¹⁴ The example of the SCHUFA scoring model shows that transparency is possible, even when it was previously dismissed as impossible (see Nestler, 2025).

3. Conclusion of contracts in agentic commerce

The conditions under which contracts can be validly concluded by means of AI agents are a matter of debate. The legal issues arising in this regard can only be touched upon briefly here. The starting point is the consideration that, under current law, AI agents are not legal entities; in other words, they cannot themselves be holders of rights and obligations (Hennemann, 2020, pp. 53, 236).¹⁵ Their actions and declarations must therefore always be attributed to natural or legal persons. This raises the question of the extent to which the traditional attribution models of civil law apply to agentic AI systems and provide appropriate solutions.

3.1 Attribution of declarations of intent in the case of AI agents

Where AI agents are used by consumers to conclude contracts, the question arises as to the conditions under which the AI agent's declaration can be attributed to the consumer. There is broad consensus that declarations made by AI agents can be attributed to the respective users, provided that the AI system's decision falls within the scope of action stipulated by the users. What remains controversial, however, is the legal rationale for such attribution. The main theories under consideration are agency by messenger, agency by representation, and the principles governing blank declarations.

Treating the AI agent as a messenger appears unconvincing, as there is no specific declaration of intent on the part of the consumer. The AI agent generates the declaration itself rather than merely conveying it (Dornis, 2023, p. 722; Hennemann, 2020, p. 242; Specht & Herold, 2018, p. 43). Directly applying agency law does not work either due to the lack of legal capacity on the part of AI agents (Hennemann, 2020, p. 242; for the contrary viewpoint, see Specht & Herold, 2018, p. 44). An analogous application of agency law also raises concerns, as the legal consequences of the rules on agency do not lead to coherent solutions when problems arise. Thus, in cases where an AI agent exceeds the granted power of agency under section 179 of the German Civil Code, liability is meaningless because the AI agent has neither legal personality nor its own recoverable assets (Dornis, 2023, p. 723; Kumkar, 2020, p. 804; also Twigg-Flesner, 2026, p. 9; for the contrary viewpoint, see Teubner, 2018, pp. 182-183; for criticism of *de lege lata*, see Ruster, 2020, p. 540; see also Hennemann, 2020, p. 246 for a detailed overview of the current state of opinion).

According to the prevailing view, the principles developed for completed blank declarations should be applied (Biggen, 2022, pp. 53-54., Möslin, 2019, p. 273; for the contrary view, see Dornis, 2023, pp. 730, 736 ff., who calls for a specific legal basis for AI fiduciary liability; see also the critical view of Hennemann, 2020, p. 241). In such cases, however, the decisive (abstract) legal intent is already present in the consumer's decision to use the AI agent. This 'declaratory shell' is then specified and completed by the AI agent in a second step (Gsell & Steinhausen, 2026, p. 34).

¹⁵ The legally controversial question of whether AI agents should be granted legal personality *de lege ferenda* is not explored further here (see Riehm, 2020, p. 42; Specht & Herold, 2018, pp. 43-44; Teubner, 2018, pp. 160 ff.).

Regardless of which doctrinal justification for attribution is chosen, problems arise when the AI agent makes decisions that no longer correspond to the consumer's intent at the time when the agent was activated. This is particularly relevant for self-learning systems, whose decisions are only predictable or controllable to a limited extent. The question as to the limits of attribution in cases where an AI agent acts in a way that no longer corresponds to the user's will is answered differently, depending on the chosen doctrinal justification.

If one takes the rules applicable to messengers as a basis, users are initially bound even by declarations that do not reflect their intentions. Their only option is to void the contract. One route here is to void the contract under section 120 of the German Civil Code on the grounds of the incorrect transmission of information previously entered correctly. Another route is to void the contract on the grounds of a mistake in the declaration pursuant to section 119 alternative 1 of the German Civil Code, if the user has not used the system correctly or has made a typing error (as also concluded by Kumkar, 2020, p. 806).

In cases where attribution is established on the basis of agency law, sections 166(1) and (2) of the German Civil Code contain the relevant provisions governing the absence of intent. According to these provisions, if the AI agent exceeds its power of agency due, for example, to a technical fault in the AI system, the declaration is ultimately not attributed to the user (Hennemann, 2020, p. 342). It is sometimes argued that system errors constitute a mistake that is attributable to the AI agent, meaning that the contract may be voided under section 119 alternative 1 of the German Civil Code (Hennemann, 2020, p. 342). Accordingly, consumers are entitled to void the contract in the event of errors. This must be distinguished from cases in which the AI agent itself exceeds the power of agency granted to it. In such cases, pursuant to section 177(1) of the German Civil Code, users would only be bound by the AI agent's declaration once they had ratified it.

If, in the context of attribution, the principles developed for blank declarations are applied, consumers are bound by the contract concluded by the AI agent. Voiding the AI agent's declaration is not possible, because the consumers, by using the AI agent, have created a legitimate expectation for which they are liable under section 172(2) of the German Civil Code (Biggen, 2022, p. 54). In the case of blank declarations, the reasoning given is that the issuers of the blank declaration have accepted the risk of the form being completed in a manner contrary to the agreement. With autonomously acting AI agents, it could further be argued that the formation of intent is not yet complete upon activation of the AI agent, meaning that errors are irrelevant until the AI agent has completed the formation of its intent. The formation of intent is generally only completed once the autonomously acting agent has submitted a declaration (Dienst & Falke, 2017, paras. 51 ff.). The only instance where attribution of liability does not apply is where the error is so obvious that the recipients of the declaration do not merit protection (see section 173 of the German Civil Code). In this case, no valid contract is formed.¹⁶

3.2 Possible avenues for reform

The more autonomously an AI agent takes action, the greater the risk that the AI agent's declarations will deviate from the consumer's intent, and the more difficult it becomes to regard the decisions as an expression of the consumer's intent. If an AI agent's declaration that deviated from the consumer's wishes were nevertheless attributed to the consumer in every case, the consumer alone would bear the risk of autonomy typical of AI systems (Biggen, 2022, pp. 53-54). Such a far-reaching attribution of responsibility for declarations based on system errors could make the use of AI agents unattractive and thus prove to be an obstacle to innovation (see Teubner, 2018, p. 186). This would also run counter to the protective purpose of consumer law,

¹⁶ Biggen (2022, p. 54), however, considers this to already be the case when the usual limits are exceeded, e.g. when a smart fridge orders quantities greater than those typically consumed in a household; see also Sosnitza (2016, p. 768).

which is specifically aimed at safeguarding consumers from incalculable risks and structural information asymmetries.

Against this background, it must be examined whether the existing rules governing the attribution and allocation of liability in relation to AI systems should be adapted and further developed. The starting point here should be the consideration that decisions made by an AI agent should primarily be attributed to the party that has technical access to and control over the system. It must be borne in mind that the behaviour of the AI agent is largely determined by manufacturers or providers through programming, training and system architecture, meaning that the risk associated with the autonomy of an AI agent is more appropriately attributed to their sphere of influence. It is not consumers, but manufacturers and providers of AI systems who possess the technical expertise to adequately assess or control the risks associated with autonomous systems.

One possible approach could be to differentiate liability according to the degree of control exercised by consumers. Provided that consumers define the key decision-making parameters, can intervene at any time and the typical risks of the system are manageable, attributing liability to them appears appropriate.¹⁷ However, if the AI agent oversteps the intended scope of action or reacts in an unpredictable manner, it seems appropriate to waive attribution. In such cases, there is no longer a declaration of intent that can be attributed to the consumer, but rather independent behaviour on the part of the autonomous system.¹⁸



RECOMMENDATION 17

Review the need to further develop the rules on attribution and liability

It is recommended that an assessment be carried out to determine whether the existing rules on attribution and the allocation of liability in relation to AI systems should be adapted and further developed. In particular, consideration should be given to the extent to which it is possible to differentiate between different models of AI agents depending on the degree of control exercised by consumers.

For the approach outlined here to be practicable, it is necessary to take issues of evidence into account when designing the relevant regulations. In practice, it can be difficult to determine whether an AI agent is still operating within the stipulated scope of action. Similarly, it regularly presents considerable difficulties to unequivocally assign responsibility for a specific decision or a particular outcome, as the underlying system processes are often complex and only partially traceable. These considerations make it clear that clear regulatory guidelines and binding transparency standards are required in order to reliably determine and legally assign responsibilities when dealing with autonomous AI agents.

Furthermore, the user interface of AI agents should be designed in such a way as to minimise the likelihood of errors in user input, for example due to incomplete or imprecise prompts. This can be achieved, for example, through a guided dialogue in which the AI agent specifically enquires about key parameters, such as the desired contract term, essential product characteristics or the consumer's individual preferences (see Twigg-Flesner, 2026, p. 14). This also increases transparency, as the basis for the decision-making is disclosed and made traceable. Such a practice thus strengthens the user's own responsibility. In this regard, the provisions of Articles 10 and 11

¹⁷ This is also the case in Article 22(1) of the ELI Model Rules. On the ELI Model Rules, see Busch et al. (2025, p. 89).

¹⁸ Here too, the result is in line with Article 22(2) of the ELI Model Rules.

of the E-Commerce Directive¹⁹ may serve as a possible model, as they were likewise introduced with the aim of minimising input errors when concluding contracts in electronic commerce.



RECOMMENDATION 18

Reduce the risks of improper use

The mode of operation and user interfaces of AI agents should be designed in such a way as to minimise, as far as possible, the risks arising from improper use, particularly due to imprecise prompts. This can be achieved, for example, through a guided dialogue in which the AI agent specifically queries key parameters required for the conclusion of a contract.

The approach described here helps to reduce information gaps and ambiguities on the part of the user. At the same time, it prevents the AI agent from operating on the basis of incomplete or unstructured data, particularly as a result of imprecise or incomplete prompts. By contrast, a lack of context increases the likelihood of so-called 'hallucinations' and the related incorrect decisions (see Tonmoy, 2024, p. 2). Overall, such a structured interaction process helps to improve the reliability of the results and reduce system-related malfunctions.

19 Directive 2000/31/EC of the European Parliament and of the Council of 8 June 2000 on certain legal aspects of information society services, in particular electronic commerce, in the Internal Market ('Directive on electronic commerce').

4. Liability in agentic commerce

From a civil law perspective, apart from the requirements for the valid conclusion of a contract, there is also the question of liability when an AI agent malfunctions. A distinction must be made here between liability in the relationship between the provider of the AI agent and the consumers who use the AI agent (under a), and the relationship between the consumers and third parties (under b).

4.1 Liability in the relationship between AI providers and consumers

Firstly, the question arises as to the conditions under which the malfunctioning of an AI agent may give rise to liability on the part of the provider towards consumers. Of particular relevance to liability are scenarios in which the AI agent generates incorrect recommendations due to errors in training, data or design, and makes decisions that are economically detrimental to consumers. Furthermore, the question arises as to who bears the so-called 'autonomy risk' when an AI system makes unforeseeable decisions.

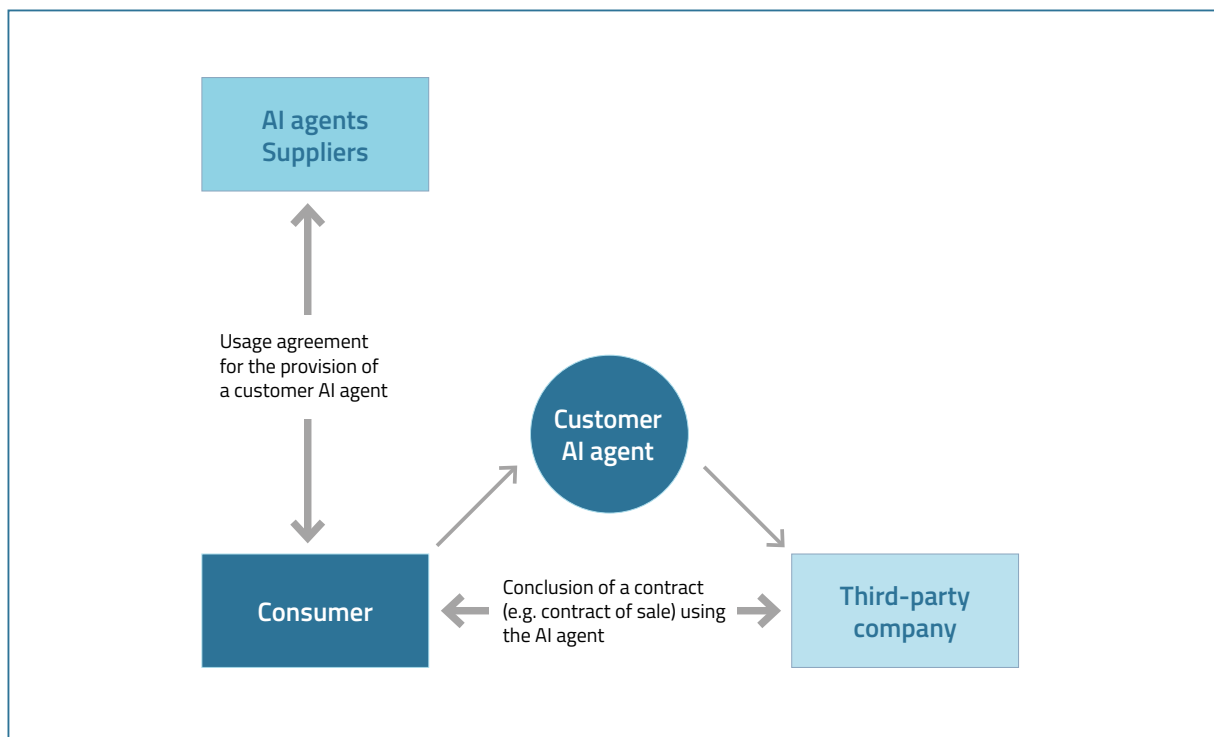


Fig 4: Contractual relationships

EXAMPLE

AI agent ignores allergen labelling

In Scenario 3, when placing a food order via the prompt, the consumer informs the AI agent that they are allergic to peanuts and that the dish must therefore not contain any nuts. When placing the order, the AI agent fails to take note of an allergen warning on the menu stating that the wok dish ordered contains peanut oil. The consumer trusts the AI agent and eats the delivered wok dish. They suffer an allergic shock and require medical treatment.

In the relationship between the provider of the AI agent and the consumers who use the AI agent, the primary consideration is the contractual liability arising from the usage agreement concluded between the consumers and the provider. The provider's ability to reduce its liability risk through standardised disclaimers and limitations of liability is restricted by sections 307 ff. of the German Civil Code. In this respect, the liability risk should generally be allocated to the contracting party that is able to control and minimise the risk. This is likely to be the provider of the AI agent in most cases. Unlike consumers, the provider has insight into how the AI agent functions and is therefore better placed to assess the risks. A disclaimer of liability therefore appears appropriate only for circumstances in which errors made by the AI agent are so easily recognisable to users that they should have been noticed.

In the case described above, the provider may therefore be considered to have contractual liability towards the consumer under section 280(1) of the German Civil Code, as the failure to include allergen labelling constitutes a breach of duty in relation to the contractually owed obligation to ensure proper functioning.

In addition to contractual liability, tortious liability may also come into question, depending on the specific circumstances of the case. However, in cases of purely financial loss, tortious liability is generally insufficient, as such losses are not covered by section 823(1) of the German Civil Code.

Product liability law plays an important supporting role here. The new Product Liability Directive²⁰ expands the protection afforded to users of AI agents. Under the new product liability law, AI systems are classified as products. If they are defective and thereby cause damage to protected legal interests, such as life and limb in particular, the provider is generally liable as the manufacturer. The relaxation of the burden of proof under the new product liability law is of key importance in this regard.²¹ This is particularly important in the case of autonomous AI agents, as causal links are unlikely to be ascertainable after the event. An AI agent can generate different outputs in response to the same prompt. Even in the case of an incorrect prompt, it often remains unclear whether this was in fact the cause of the AI agent's erroneous or damage-inducing output, or whether other factors – such as incorrect training data, systemic biases or the model's specific learning and weighting logic – were the decisive factors. In the absence of appropriate rules, the burden of proof would usually fall on the consumers who have suffered harm, even though the only person with detailed insight into how the AI agent works is – if anyone – the provider of the AI agent. The provider controls the development, training, system architecture and regular updates and is therefore structurally in the best position to identify, manage or mitigate potential risks through appropriate mechanisms (see Borges, 2022, p. 559).

20 Under Article 4(1) and Recital 13 of the EU Product Liability Directive (EU) 2024/2853, software and AI systems are expressly classified as products. The Directive must be transposed into national law by 9 December 2026. At the time of going to press, the government's draft bill on the modernisation of product liability law is undergoing parliamentary scrutiny.

21 Article 10(2) and (3) of the EU Product Liability Directive (EU) 2024/2853 contains presumptions regarding both the defectiveness of the product and the causal link between the defectiveness and the occurrence of the damage.

**RECOMMENDATION 19****Review product liability law**

The SVRV recommends examining the extent to which product liability law offers adequate protection against damage caused by AI agents. In addition to the fundamental classification of AI agents as products within this liability regime, it must also be clarified whether the rules of evidence ensure sufficient consumer protection. The rules of evidence should be designed in such a way that they take account of the increasingly opaque and algorithm-driven decision-making by AI systems.

4.2 Liability in the relationship between consumers and third parties

If a consumer uses an AI agent to conclude a contract, the question arises as to how the liability risk is allocated if an incorrect order is placed due to a malfunctioning of the AI agent.

Consumers can only be held contractually liable if the use of the AI agent has resulted in a valid contract being concluded between the consumers and the third party. This, in turn, presupposes that the declarations generated by the AI system are attributable to the consumers (see F.3. on this point). If a declaration can indeed be attributed to a consumer, the question then arises as to whether the consumer can void the contract. The answer to this question depends on the chosen legal interpretation.

EXAMPLE**Incorrect order placed by an AI agent**

A consumer instructs her AI agent to order a meal for 20 people for her birthday. Due to a malfunction, the AI agent orders a meal for 40 people from a small catering firm near the consumer's home. The firm accepts the booking for 40 people, begins planning and makes initial purchases of ingredients to prepare the dishes. Two days after the order was placed, the consumer realises the AI agent's mistake and cancels the catering for the extra guests. The catering company accepts the cancellation regarding the further preparation of the extra meals, but demands that the consumer reimburse the cost of the surplus foodstuff, for which the company has no other use.

If the AI agent is classified as a messenger, the contract is generally voidable on the grounds of incorrect transmission under section 120 of the German Civil Code (messenger's error). However, under section 122 of the German Civil Code, the consumer in the above example is liable for the negative interest; she must therefore pay the costs of the excess food purchases.

If the rules on agency are applied (by analogy) to the use of the AI agent, the consumer in the above example is not bound by the contract, provided that the AI agent merely had the power of agency to place an order for 20 people. If she did not ratify the contract, she is not liable. The catering company cannot therefore claim the cost of the food from her.

If the basis for attribution is established in accordance with the principles of blank declarations, the contract is not voidable. In the example, liability on the part of the consumer would – by analogy with section 173 of the German Civil Code – only be excluded if the contracting party lacked good faith. Since an order for 40 people is not an extraordinary event and the error is not therefore manifestly obvious, the catering company must be presumed to have acted in good faith. The consumer therefore remained bound by the contract that was concluded by the AI agent. In this example, although the catering company accepted the cancellation for the further preparation of the surplus meals, the surplus food must still be paid for due to the contractual obligation, which in principle remains in force.

In this case, possibilities for taking recourse might – at most – be considered in the relationship between the consumer and the provider of the AI agent. Under this solution, the consumer would initially be liable as the contracting party in her external relationship with the third party and would ultimately have to be relieved of liability through recourse against the provider of the AI agent.

Against this background, it seems appropriate to grant consumers the right to raise a defence against third parties in order to prevent them from having to pay in advance. One possible protective mechanism would be to allow consumers to argue that the cause of the incorrect order lies solely within the sphere of responsibility of the AI provider. The injured party would thus have to seek redress directly from the party technically responsible, whilst consumers would be relieved of the primary financial burden.



RECOMMENDATION 20

Protect consumers from the obligation to pay in advance

The SVRV recommends examining whether, in the event that an AI agent places incorrect orders that result in valid contractual obligations towards third parties, consumers should be granted the right to raise a defence against the third party, provided that the cause of the incorrect order lies solely within the sphere of responsibility of the provider of the AI agent. This would prevent consumers from having to make advance payments to the third party and, in turn, having to rely on taking recourse against the provider of the AI agent.

5. Protection against manipulation of and by AI agents

The use of AI agents as ‘personal shoppers’ promises to give consumers a more efficient and convenient online shopping experience. However, the flip side is that new risks of manipulation could arise. We can make a distinction here between two possible developments. Firstly, AI agents could evolve into ‘manipulation engines’ (Crawford, 2024) and deliberately exploit the vulnerabilities of consumers. Secondly, AI agents could themselves become targets of manipulation by third parties (Ferner, 2025). In this regard, the question arises as to whether the existing rules – notably in the German Civil Code, the German Unfair Competition Act (*Gesetz gegen den unlauteren Wettbewerb*), the EU Digital Services Act, the EU Digital Markets Act and the EU AI Act – offer sufficient protection.

5.1 Manipulation by AI agents

When consumers use AI agents to help with their consumption decisions, this creates an additional avenue for influencing and manipulating those decisions, regardless of whether the AI agent merely plays an advisory role or the decision is delegated entirely to the AI agent. Risks of manipulation arise in particular from non-transparent advertising and recommendations by the AI agent (see 5.1.1), the preferencing of its own offers (see 5.1.2) and manipulative design features of the AI agent (see 5.1.3).

5.1.1 Labelling of advertising and transparency of recommendations

When consumers use AI agents as personalised shopping assistants, the AI agent’s recommendations and decisions can exert a significant influence.²² Recommendations that are not clearly recognisable as sales incentives are likely to prove particularly effective in this regard. Unlike traditional advertising, such AI recommendations appear to be neutral and objective decision-making aids.

EXAMPLE

Commission-based offers

In Scenario 2, without any labelling of the offers, the consumer does not realise that the AI agent’s initial recommendations are, without exception, commission-based offers. Offers that are more favourable to the consumer are not displayed or only appear further down the ranking.

The existing prohibitions on misleading and aggressive commercial practices under fair trading law can, in principle, also be applied to AI agents. Misleading conduct may occur if an AI agent provides information that is objectively false or incomplete. Similarly, misleading conduct may involve concealing the promotional nature of a recommendation by presenting commercially motivated suggestions as neutral or independent. Aggressive commercial practices may be present where user

22 See Recital 18 of Directive (EU) 2019/2161 (Omnibus Directive) on the influence of different positions in rankings in online search queries.

behaviour is influenced through repeated incentives to make a purchase, artificially created pressure to make a decision, or the targeted exploitation of individual preferences.

The transparency requirements of the DSA could also play a supporting role. For instance, Article 27(1) of the DSA requires providers of online platforms to set out the main parameters used in their recommender systems in their terms and conditions. Whether this transparency requirement is applicable to AI agents needs to be assessed on a case-by-case basis, depending on the business model. Further transparency requirements for rankings and recommender systems, which could become relevant in agentic commerce, arise from section 5b(2) of the German Unfair Competition Act and section 312l of the German Civil Code in conjunction with Article 246d no. 1 of the Introductory Act to the Civil Code (*Einführungsgesetz zum Bürgerlichen Gesetzbuche*).²³ The extent to which these provisions apply to AI agents also requires closer examination and is likely to depend ultimately on the specific structure of the business models.

5.1.2 Ban on self-preferencing

In the platform economy, there are frequent instances where platforms systematically favour their own products or services over those of third parties. Such cases of self-preferencing are also conceivable in agentic commerce. Under current law, it is prohibited for a market participant to exploit its dominant position on its platform or service by favouring its own products or services, thereby disadvantaging other market participants (Article 102 TFEU).²⁴ Furthermore, Article 6(5) of the DMA provides for a ban on self-preferencing for platform operators designated as gatekeepers.

Whether the provisions of the DMA also apply to AI agents has yet to be conclusively clarified (Bostoen & Krämer, 2026, pp. 16, 20; Busch, 2026a, p. 137). In this respect, clarification by the legislator would be advisable (Bostoen & Krämer, 2026, pp. 20 ff.).



RECOMMENDATION 21

Clarify the applicability of the DMA to AI agents

AI agents can influence consumer decisions even more significantly than recommender systems or rankings on online platforms. In this respect, the provisions of the DMA could offer protection against self-preferencing by the providers of AI agents. It is therefore recommended to clarify whether the DMA is applicable to AI agents.

Insofar as AI agents are not to be regarded as gatekeepers within the meaning of the DMA, any self-preferencing can be counteracted through a combination of transparency obligations under Article 27 of the DSA (see Recommendation 16) and relevant design requirements (see Chapter F.6).²⁵

5.1.3 Deceptive patterns

A further risk is posed by the use of so-called 'deceptive patterns' by AI agents (also known as 'dark patterns').²⁶ These include practices that 'materially distort or impair, either on purpose or in effect, the ability of recipients of the service to make autonomous and informed choices or decisions' (Recital 67 DSA). Illustrative examples²⁷ include graphic designs in which the

23 Under section 5b(2) of the German Unfair Competition Act, the addressees are companies that enable the search for goods and services. By way of derogation from the previously cited provisions, section 312l of the German Civil Code defines the addressees of online marketplaces as services that enable consumers to conclude distance contracts using software. The applicability of these provisions to AI agents must be examined (see above).

24 See the CJEU judgment on Google Shopping, in which Google Search's prioritisation of its own price comparison offers was deemed unlawful (CJEU, Judgment of 10 September 2024, C-48/22 P – Google Shopping).

25 Article 9 of the ELI Model Rules sets out a general design requirement for AI agents that is intended to prevent manipulation; it covers not only the reduction of options but also detrimental personalisation. Article 12 of the ELI Model Rules also provides for a duty to disclose conflicts of interest in order to prevent manipulation arising from them.

26 See Martini et al. (2023); for data protection law, see Loy & Baumgartner (2021, p. 404).

27 For further examples, see the Commission's Guidance on the interpretation and application of the UCP Directive (2021/C 526/01) and the EDSA's Guidelines 3/2022 on 'Dark patterns in social media platform interfaces' dated 14 March 2022. It should be noted that the UCP Directive and the GDPR take precedence over the DSA (Article 25(2) of the DSA).

option favoured by the provider is highlighted whilst other options are presented inconspicuously or hidden, pre-selected additional services ('pre-ticked boxes'), and artificially created time pressure or pressure regarding availability. As part of the planned Digital Fairness Act, the existing regulations on deceptive patterns should be consolidated. To this end, it might be appropriate to include an explicit ban on deceptive patterns in Directive 2005/29/EC on unfair commercial practices (UCP Directive), supplemented where necessary by further specific prohibitions in Annex I to the Directive (SVRV, 2025, p. 10).

5.2 Manipulation of AI agents

In addition to protecting consumers from manipulation by AI agents, the protection of the AI agents themselves also needs to be ensured. A distinction must be made between the different risks of manipulation that become relevant at different times or that exploit different vulnerabilities of AI agents. For instance, if manipulated images or data are used when training the AI system, this can lead to AI agents systematically providing incorrect assessments or recommendations (Ferner, 2025, p. 375). AI agents can also be specifically targeted at a later stage in order to influence their decision-making behaviour (Busch, 2025, p. 1378; Twigg-Flesner, 2026, p. 21). Such attacks can be one-off or isolated incidents, but can also take place as part of deceptive patterns on a more sustained or large-scale basis (see Cuvin et al., 2026; Tang et al., 2026; Ersoy et al., 2025).

Well-known attack methods include so-called 'prompt injections' (Ferner, 2025, pp. 374-375), in which external content or user interactions are exploited to circumvent the agent's internal control mechanisms. This can result in the AI system revealing its programming or generating undesirable outputs (Mattern, 2025, p. 1801). The processing of visual content by AI agents can also be manipulated through minor alterations to the image material ('adversarial image perturbations') (Busch, 2025, p. 1378).

These forms of system manipulation differ fundamentally from the forms of consumer deception that have been prevalent to date. Rather than directly targeting people, they target the algorithmic decision-making logic of AI agents. Nevertheless, they can have a major indirect impact on consumer decisions and a direct impact on contracts concluded via AI agents. As yet, there are no clear rules under consumer law specifically addressing the manipulation of AI agents.

The ban on deceptive patterns in Article 25(1) of the DSA has so far covered this issue inadequately, as the target of manipulation in this provision must be a human being. The provision states that providers of online platforms must not design, organise or operate their online interfaces in a way that 'deceives or manipulates the recipients of their service or in a way that otherwise materially distorts or impairs the ability of the recipients of their service to make free and informed decisions'.

Similarly, the prohibition on misleading conduct under section 5(1) of the German Unfair Competition Act requires action 'which is suited to causing the consumer or other market participant to take a transactional decision which he or she would not have taken otherwise'. AI agents are neither consumers themselves nor 'other market participants' within the meaning of section 2(3) of the German Unfair Competition Act. The prohibition on misleading conduct is not therefore directly applicable to AI agents. The SVRV recommends closing this regulatory gap. Article 23 of the ELI Model Rules, which provides for a ban on manipulation in order to protect AI agents, could serve as an example in this regard.



RECOMMENDATION 22

Review the prohibitions on manipulation under fair trading law

The existing provisions of fair trading law should be reviewed to determine whether they offer sufficient protection against the manipulation of AI agents. Where necessary, the provisions should be amended to ensure that they also cover algorithmic influence strategies that do not directly target human perception.

6. Consumer protection on the protocol layer

As explained above, the rules of current consumer law are based on a specific assumption regarding what the ‘customer journey’ in an online shop looks like. The current rules are clearly underpinned by the notion that people visit a website or a shopping app, select a product, add it to their virtual shopping basket and confirm their purchasing decision with a click of the mouse. This notion is reflected in a series of design requirements for online shops. For instance, section 312j(3) sentence 1 of the German Civil Code requires online retailers to design the ordering process on their website in such a way that consumers explicitly confirm that they are committing to a payment. In most cases, this is done via an order button labelled ‘Place order and pay’ or a similarly unambiguous phrase.

With regard to agentic commerce, the question arises as to whether this provision is ‘agent-ready’. To put it another way: how should section 312j of the German Civil Code be applied when consumers no longer click the order button themselves, but delegate this task to their AI agents? Does this constitute ‘explicit confirmation’ within the meaning of section 312j(3) sentence 1 of the German Civil Code? Or should the AI agent be obliged to obtain the consumer’s explicit consent by means of a ‘confirmation prompt’? Whilst this might help ensure that consumers retain full control over the transaction, it would interrupt the ‘agentic workflow’ and diminish the benefits of automation.

On closer inspection, it is necessary to distinguish between different types of AI agents. So-called web-browsing agents (e.g. OpenAI Operator) mimic human user behaviour and interact with the graphical user interface of online shops. Other AI agents, by contrast, communicate via specific software interfaces

(Application Programming Interfaces, APIs) and do not click any buttons in the process (see Chapter B.1 above). These considerations illustrate that the current design-based approach in consumer law may be reaching its limits in the context of agentic behaviour.

Very similar questions also arise in relation to the new withdrawal button, which has been mandatory for online shops since 19 June 2026. The newly introduced section 356a of the German Civil Code requires that the withdrawal function be clearly labelled with the words ‘Withdraw from the contract’. It must be prominently displayed on the online user interface and easily accessible to consumers. This provision, too, is quite clearly based on the assumption that a human being will be using a graphical user interface to withdraw from the contract.

And here, too, the question arises as to how this provision should be applied in cases where consumers ask an AI agent to withdraw from a contract. In such cases, the withdrawal might not take place via a graphical user interface, but might rather be effected on the ‘protocol layer’ using a software interface. Requirements for clearly legible labelling, prominently displayed information and buttons are meaningless here. Section 356a of the German Civil Code in its current version is therefore arguably not ‘agent-ready’. The same applies to the cancellation button regulated in section 312k of the German Civil Code. In the medium term, it may therefore be necessary to supplement the aforementioned provisions with legal requirements for standardised software interfaces (such as a withdrawal API and a cancellation API), so that consumers can use AI agents to exercise their contractual rights.



RECOMMENDATION 23

Review consumer contract law and integrate into the protocol layer

The provisions of consumer contract law that set out specific requirements for the design of online user interfaces – including sections 312j, 312k and 356a of the German Civil Code – should be reviewed to determine whether they permit the legally compliant use of AI agents. The relevant provisions of consumer law should be integrated into the protocol layer. Specifically, this means that provisions relating to the design of online user interfaces should, where necessary, be amended to ensure that they continue to guarantee adequate consumer protection even when the transaction takes place on the protocol layer, entirely without a graphical user interface. Put another way: consumer protection should be integrated into the protocol layer so that, in future, contracts can be concluded, terminated and revoked by AI agents.

7. Sustainable consumption

7.1 Current situation: Information overload and the sustainability gap

Sustainable production and sustainable consumption are key drivers of socio-ecological transformation. Through their demand, consumers have an impact on production methods, supply chains and incentives for innovation; in turn, through their communication strategies and the way they design and market their offerings, companies have an impact on consumer behaviour as well as on the political framework and communication. Consumers and companies find themselves in a complex landscape of multiple interests, instruments and power asymmetries (Giese et al., 2019; SVRV, 2021, Chapter D.I). Despite socio-political sustainability targets defined at international, European and German levels, resource consumption – driven in part by digital infrastructures – remains at a high level (Carrara et al., 2023; UNEP, 2024). In addition, complex rebound effects are playing an increasingly prominent role in this context (Behrendt et al., 2025; Micklitz et al., 2022).

Traditionally, consumer policy has relied on the information paradigm: the aim has been to empower consumers through labelling and transparency requirements. However, empirical findings show that this approach has its limitations. An excess of information often leads to ‘information overload’ (see Chapter F.2.1; see also SVRV, 2024a, 2024d).

In contrast, the updated German Sustainability Strategy 2025 emphasises the following: ‘It is important that consumers are increasingly able to opt for environmentally and socially responsible products and services’ (Federal Government, 2025, p. 68). Against the

backdrop of the emerging trend towards agentic commerce, this requires new tools for consumer empowerment that address the three prerequisites for sustainable consumption (SVRV, 2021, 2024a):

- Raising awareness (identifying needs and problems): AI agents could, for example, continuously monitor consumption (e.g. in the smart home), highlight invisible environmental impacts and proactively suggest sustainable alternatives alongside economic savings (see Scenario 1);
- Promoting skills (overcoming cognitive limitations): AI agents could, for example, reduce the massive search and transaction costs in the background – even in the context of complex life cycle assessments or sustainability criteria – and translate these into recommendations, thereby alleviating the problem of ‘choice overload’ (see Chapter F.7.2, Scenario 2); and
- Creating opportunities (structural facilitation): Consumers could, for example, filter offers based on sustainability parameters they have predefined and delegate purchases (see Scenario 3), thereby pooling demand and making offers marketable. Furthermore, artificial barriers (‘friction by design’ – see Recommendation 2) can be built in to reduce impulse purchases. In the long term, the pooling of agents could also strengthen collective bargaining power (see Chapter F.7.4; see also Chapter C.3) for sustainable development.

This requires the creation of an appropriate sustainability ontology and data structure, for example in digital product passports (see Chapter F.7.3 and SVRV, 2024b), and it requires certain functions of AI agents.

7.2 AI agents as choice engines for consumer decisions

AI agents are increasingly described in the research literature as personalised decision-making assistants or ‘choice engines’. Drawing on findings from behavioural economics, Sunstein (2024) argues as a general observation that many consumer decisions are characterised by cognitive biases, limited attention and information deficits. These so-called internalisation errors can lead consumers to deviate from their own long-term preferences. In the context of sustainable consumption, this is evident, for example, in the so-called ‘intention-behaviour gap’: although consumers generally regard sustainability as an important value and pursue corresponding goals, in specific purchasing situations they often opt for less sustainable products – for instance, due to time pressure, habits, price differences or a lack of transparency (SVRV, 2021; Zimmermann et al., 2026).

AI agents can assist here as ‘choice engines’ by taking individual preferences – such as price limits, quality standards or sustainability goals – into account and identifying suitable options from a wide range of market offerings that are more closely aligned with the user’s long-term goals, whilst also presenting these options in a transparent and comprehensible manner. This contributes to the aforementioned drivers of sustainable consumption by enabling AI agents to help raise awareness, develop skills and provide opportunities to utilise sustainable offerings, whilst also promoting their further development and wider adoption (SVRV, 2021).

Furthermore, AI agents can specifically support sustainable behaviour, for example by recommending sustainable options, highlighting particularly durable or repairable products (Micklitz et al., 2022), or by using default settings that favour environmentally beneficial alternatives. This can help to reduce systematic decision-making errors and facilitate sustainable behaviour (Sunstein, 2024).

By presenting sustainability information transparently, allowing for comparisons with alternatives and increasing market transparency, AI agents can help to raise awareness of sustainable consumption, strengthen relevant skills and improve opportunities for sustainable decision-making (SVRV, 2021).

7.3 The Digital Product Passport as data infrastructure

One key prerequisite for the use of sustainability-oriented AI agents is access to reliable, standardised product data. In this regard, the Digital Product Passport (DPP) is a key instrument of European policy on the circular economy. It is designed to make product-related information on materials, ingredients, reparability, spare parts and disposal available throughout the entire life cycle (SVRV, 2024b).

The SVRV emphasises that the DPP forms a crucial basis for sustainable consumption decisions, but can only fulfil its potential if the data is presented in a user-friendly and useful manner. Technically complex information must be translated, condensed and contextualised so that it is actually relevant to consumers’ actions (SVRV, 2024a). Furthermore, it is necessary to show where added value is clearly available, for example by providing information on repair options, service life or the long-term cost benefits of sustainable products. This is in line with the objectives of the Ecodesign for Sustainable Products Regulation.²⁸ The purpose of this Regulation is, amongst other things, to promote sustainable consumption decisions through standardised and transparent product information, to design products to be more durable and to enhance their recyclability. At the same time, through the DPP, the Regulation creates a basis for data-driven applications such as AI-supported decision-making assistants. One constant prerequisite is the creation and integration of a

28 Regulation (EU) 2024/1781 of the European Parliament and of the Council of 13 June 2024 establishing a framework for the setting of ecodesign requirements for sustainable products.

sustainability ontology in the data infrastructure and in the functional designs between the DPP and AI agents (SVRV, 2024b, 2024c).

The DPP is geared towards physical products. A comparable data infrastructure for services is currently lacking, although such services – for example in the areas of digital services, mobility or tourism – could also have significant sustainability impacts. The development of standardised information structures or comparable digital data passports for services would provide a basis for effectively deploying sustainability-oriented AI agents in these areas of consumption, or for developing them in an integrated manner with users and stakeholders. There is also a need for research and design that would transform the data infrastructure of digital product passports – which have so far tended to be static in nature – into more dynamic, systemic and semantic forms of digital service passports. Such design approaches for sustainable product-service systems would offer the potential to move closer to achieving defined climate and resource targets (Hertwich et al., 2020; Pauliuk et al., 2021; UNEP, 2024).

7.4 Risks and challenges: Trust, manipulation and social justice

Despite this potential, there are significant risks. Key challenges lie in the transparency and trustworthiness of AI agents, and in the interlinking and governance of trustworthy data architectures. Consumers must be able to understand the basis on which recommendations are made and whether economic interests play a role – and if so, which ones. Academic studies warn of new forms of manipulation such as covert influence, self-preferencing or agent-specific deceptive patterns (Witte et al., 2025, see also Chapter F.5.). At the same time, AI systems can limit human experiences through: the loss of serendipity (echo chambers); de-skilling due to tasks being delegated; the reduction of the world's complexity to machine-readable data points; and altered communication patterns when interacting with AI systems (Valenzuela et al., 2024).

Issues of social justice and barrier-free access must also be taken into account. Depending on the optimisation logic, AI agents may end up disadvantaging lower-income households or prioritising sustainability goals that are not financially viable. The pricing of AI services, access to their functions and the question of who can afford them also play a significant role. Without an appropriate policy framework, there is a risk that digital inequalities will be exacerbated.

This raises the question as to the role of the public sector in shaping the data infrastructure. Neither the design of the DPP nor the collection and processing of consumer-related data should be left solely to the interests of AI providers, manufacturing companies or the retail sector. At the same time, institutional structures are needed to pool consumers' interests and strengthen their data sovereignty, for example through data cooperatives or data trustees acting as professional intermediaries between consumers and businesses.

A further challenge for sustainable consumption lies in the material-intensive and energy-intensive systems that serve as the basis for agentic AI. This gives rise to rebound effects, even leading to a 'backfire', as the efficiency gains achieved through AI may ultimately result in higher overall resource consumption (Behrendt et al., 2025; Pospieszny & Brodowicz, 2025). Essentially, when decision-making processes – such as complex and time-consuming information gathering – are delegated to AI agents, they are replaced by energy-intensive and resource-intensive machine systems. Environmental impacts arise at several levels: in addition to the physical resource requirements for building the infrastructure and the high energy consumption involved in training the underlying models (Strubell et al., 2019), ongoing usage also varies considerably depending on the AI agent employed and can increase energy consumption many-fold (Krupp et al., 2026). This additional environmental impact is furthermore opaque and can be made transparent via the points of interaction (Krupp et al., 2026).

A key finding of a study by the Austrian Institute for Applied Telecommunications is the discrepancy between the industry's grandiose marketing claims and the actual performance of current systems, which is limited by inherent shortcomings such as AI hallucinations and biases (Gratzer et al., 2025). To address these challenges, the study recommends systematic monitoring, the swift clarification of regulatory guidelines to complement the European AI Act, and increased support for consumer education.

7.5 Implications for consumer policy

Provided that AI agents succeed in reducing, filtering and structuring the information overload, there is an opportunity for them to make a significant contribution to promoting sustainable consumption in a way that is socially balanced and practical for everyday life.

To realise the potential of agentic AI for sustainable consumption, it is crucial to optimise the design of the underlying data and decision-making architectures. This optimisation creates potential that goes beyond what is possible from simply making AI systems more powerful. In addition to transparent and user-configurable sustainability preferences in AI agents, this also requires standardised sustainability data, suitable ontologies and evaluation logics, and an extending of the relevant data infrastructures to cover services. The environmental impacts of agentic AI should also be assessed and reported transparently so that they can be taken into account in its design. Sustainability is thus transformed from a product attribute into a design principle for digital decision-making architectures. Against this background, the following two core recommendations emerge:

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RECOMMENDATION 24

Digital Product Passport should be machine-readable

To promote sustainable consumption in agentic commerce, the Digital Product Passport (DPP) should provide a trustworthy, high-quality and machine-readable database. Sustainability criteria for AI agents thus become visible and manageable within the framework of Agentic AI Optimisation (AAIO).

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RECOMMENDATION 25

Decision-making architecture should be sustainably designed

The digital decision-making architecture of agentic commerce should be designed with sustainability in mind (design principle). This applies to data models, ontologies, evaluation logics, interaction designs and configurable sustainability preferences, so that AI agents can transparently present sustainable preferences and effectively implement them in automated purchasing decisions.



Recommendations for consumer policy

RECOMMENDATION 1

Mechanisms to ensure control and oversight

AI agents should be designed in such a way as to make it easier for consumers to maintain control over their purchasing behaviour. For example, AI agents should provide an overview of previous purchases and expenditure, so that consumers do not lose track of their purchasing decisions or the consequences thereof. These mechanisms should also offer the option of setting limits (such as in the form of a monthly budget limit) beyond which no further purchase suggestions are made.

RECOMMENDATION 2

Interruptions in the contract conclusion process

Interruptions should be deliberately built into the purchasing process ('friction by design') to reduce the likelihood of impulse purchases. One option would be to introduce time gaps between the awakening of a need and the purchasing decision, using delays (SVRV, 2025, pp. 8–9).

RECOMMENDATION 3

Prevent misleading AI-generated labels

Appropriate measures should be taken to prevent consumers from being misled by AI-generated labels. One option would be to use a 'white list' to specify which phrases may be used in the labels created by AI agents when making recommendations and what conditions must be satisfied.

RECOMMENDATION 4

Show reviews only in context

Individual reviews should not be displayed alongside a purchase recommendation without the context of other reviews, and these should be easy to access (e.g. via a link leading to a list of relevant reviews).

RECOMMENDATION 5

Enable overview of active purchase orders

AI agents should be designed in such a way that it is easy for consumers to keep track of purchase orders that are active in the background and to cancel them if necessary. Accordingly, AI agents should provide a simple overview of active purchase orders, in which – similar to subscription models – it is possible to cancel the order easily at the click of a button. In addition, consumers should receive regular reminders about purchase orders that are active in the background.

RECOMMENDATION 6

Control over personalised recommendations

AI agents should allow consumers to decide whether, and to what extent, they are presented with personalised recommendations based on profiling.

RECOMMENDATION 7

Effective child protection mechanisms

AI agents should be equipped with effective child protection mechanisms to ensure that young people are not exposed to content that is harmful to minors or detrimental to their development. Furthermore, it must be ensured that minors cannot use AI agents as a workaround to purchase age-inappropriate products that would otherwise be denied to them if they were to complete the purchase directly.

RECOMMENDATION 8**Restrict manipulative anthropomorphic design to protect emotional self-determination**

Anthropomorphic design features of AI agents that are specifically intended to generate social closeness, authority or emotional attachment should be regulated or restricted in commercial contexts – particularly in sales and recommendation situations. Consumers should have the option to actively control the degree of anthropomorphisation and personalisation of AI agents. Social or emotional design features should only be activated following explicit consent (opt-in mechanism).

RECOMMENDATION 9**Stricter requirements regarding anthropomorphisation for vulnerable groups**

Stricter requirements regarding the design, language and influence of AI agents should apply to vulnerable individuals, such as minors and the elderly. In this regard, consideration should be given to whether anthropomorphic design features should be permitted for minors.

RECOMMENDATION 10**Promote consumer education on AI influence mechanisms**

Consumer education on AI influence mechanisms should be promoted: consumer protection institutions and educational establishments should provide targeted information on the psychological mechanisms employed by AI agents, such as implicit influence, anthropomorphism and algorithmic recommendations. The measures should also take into account the social distribution of skills.

RECOMMENDATION 11**Transparency of recommendations**

Consumers should be able to clearly recognise whether recommendations are trustworthy, objective, personalised or commercially motivated (e.g. through ranking optimisation or commission models).

RECOMMENDATION 12**Conduct further research into the decision-making behaviour of AI**

The SVRV sees a need for further research into the decision-making behaviour of AI agents with the aim of further developing the consumer model. New interdisciplinary evidence should be generated in this respect.

RECOMMENDATION 13**Greater standardisation and machine-readability of consumer information**

The SVRV recommends that consumer information be adapted for use by AI agents through greater standardisation and machine readability. This enables AI agents to process, compare and utilise information in the interests of consumers.

RECOMMENDATION 14**Two-tier information model**

The SVRV advocates a two-tier information model. Under this model, AI agents should be given access to complete, detailed and machine-readable information. Consumers should also be provided with condensed, clearly structured and easily understandable key information that enables them to obtain a quick overview and offers a sufficient basis for decision-making. The two-tier information model should be designed as an opt-out model, enabling consumers to waive their right to receive the key information by means of an explicit declaration.

RECOMMENDATION 15**Transparency requirements for AI agents**

In the case of AI agents used as assistance systems for consumer decisions, their mode of operation (particularly any potential conflicts of interest), the sources used for product comparisons and recommendations, and the key evaluation criteria should be disclosed.

RECOMMENDATION 16**Examine the applicability of the DSA**

The SVRV recommends examining the extent to which the existing regulations for online platforms, in particular the transparency requirements of the DSA, also apply to AI agents. If they are not directly applicable, an extension of the regulatory framework to cover AI agents would appear appropriate.

RECOMMENDATION 17**Review the need to further develop the rules on attribution and liability**

It is recommended that an assessment be carried out to determine whether the existing rules on attribution and the allocation of liability in relation to AI systems should be adapted and further developed. In particular, consideration should be given to the extent to which it is possible to differentiate between different models of AI agents depending on the degree of control exercised by consumers.

RECOMMENDATION 18**Reduce the risks of improper use**

The mode of operation and user interfaces of AI agents should be designed in such a way as to minimise, as far as possible, the risks arising from improper use, particularly due to imprecise prompts. This can be achieved, for example, through a guided dialogue in which the AI agent specifically queries key parameters required for the conclusion of a contract.

RECOMMENDATION 19**Review product liability law**

The SVRV recommends examining the extent to which product liability law offers adequate protection against damage caused by AI agents. In addition to the fundamental classification of AI agents as products within this liability regime, it must also be clarified whether the rules of evidence ensure sufficient consumer protection. The rules of evidence should be designed in such a way that they take account of the increasingly opaque and algorithm-driven decision-making by AI systems.

RECOMMENDATION 20**Protect consumers from the obligation to pay in advance**

The SVRV recommends examining whether, in the event that an AI agent places incorrect orders that result in valid contractual obligations towards third parties, consumers should be granted the right to raise a defence against the third party, provided that the cause of the incorrect order lies solely within the sphere of responsibility of the provider of the AI agent. This would prevent consumers from having to make advance payments to the third party and, in turn, having to rely on taking recourse against the provider of the AI agent.

RECOMMENDATION 21**Clarify the applicability of the DMA to AI agents**

AI agents can influence consumer decisions even more significantly than recommender systems or rankings on online platforms. In this respect, the provisions of the DMA could offer protection against self-preferencing by the providers of AI agents. It is therefore recommended to clarify whether the DMA is applicable to AI agents.

RECOMMENDATION 22**Review the prohibitions on manipulation under fair trading law**

The existing provisions of fair trading law should be reviewed to determine whether they offer sufficient protection against the manipulation of AI agents. Where necessary, the provisions should be amended to ensure that they also cover algorithmic influence strategies that do not directly target human perception.

RECOMMENDATION 23**Review consumer contract law and integrate into the protocol layer**

The provisions of consumer contract law that set out specific requirements for the design of online user interfaces – including sections 312j, 312k and 356a of the German Civil Code – should be reviewed to determine whether they permit the legally compliant use of AI agents. Consumer protection should be integrated into the protocol layer so that, in future, contracts can be concluded, terminated and revoked by AI agents.

RECOMMENDATION 24**Digital Product Passport should be machine-readable**

To promote sustainable consumption in agentic commerce, the Digital Product Passport (DPP) should provide a trustworthy, high-quality and machine-readable database. Sustainability criteria for AI agents thus become visible and manageable within the framework of Agentic AI Optimisation (AAIO).

RECOMMENDATION 25**Decision-making architecture should be sustainably designed**

The digital decision-making architecture of agentic commerce should be designed with sustainability in mind (design principle). This applies to data models, ontologies, evaluation logics, interaction designs and configurable sustainability preferences, so that AI agents can transparently present sustainable preferences and effectively implement them in automated purchasing decisions.

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Glossary

AAIO (Agentic AI Optimisation) refers to the optimisation of digital content so that AI agents can understand it and use it to make decisions (e.g. product comparisons or orders).

Agent-ready refers to the characteristic of a legal provision that is designed in such a way that it continues to fulfil its regulatory purpose even when AI agents are used.

AI agents are socio-technical systems that perceive and respond to their environment with a certain degree of autonomy, using tools where necessary to achieve specific goals and adapting to changing inputs and contexts (see OECD, 2026, p. 15).

Algorithm aversion describes the tendency of people to generally prefer advice from humans over that from algorithmic decision-making systems, even when the quality of the algorithmic advice is higher.

Algorithmic bias refers to the systematic distortion of the results of algorithmic decision-making processes.

Anthropomorphisation refers to the attribution of human characteristics, abilities or intentions to non-human actors, such as AI systems, chatbots or robots.

Attachment theory explains how emotional bonds are formed and maintained. In the context of digital technologies, it is used to understand why people can develop emotional bonds with AI systems or digital assistants.

A **backend interface** enables an AI agent to communicate with a company's systems operating in the background. This allows the agent to, for example, retrieve product information, place orders, check availability and process complaints.

The **Baligh–Richartz effect** describes how the involvement of retailers reduces the number of contacts between suppliers and consumers, thereby generating efficiency gains in distribution networks. The effect forms an important theoretical basis for explaining the economic significance of platforms.

Blank declarations are characterised by the fact that the person making the declaration authorises a third party to fill in a document that has already been signed but not yet fully completed.

Consumer AI agents are specific AI agents used by consumers across different companies.

The **endowment effect** (or ownership effect) states that people tend to value a good more highly when they own it.

In economics and competition law, the term **gate-keeper** refers to individuals who control access to essential goods or markets (see Article 3 of the Digital Markets Act).

Media equation theory posits that people often treat media and technologies as if they were real people or social actors, and exhibit similar social behaviours towards them.

Parasocial preference describes a person's preference for a particular media or digital character, which can develop through repeated positive interactions and the perception of social closeness.

A **parasocial relationship** is a one-sided emotional bond with a media or digital figure, even though no genuine reciprocal social relationship exists.

Responsibility shift refers to the process whereby responsibility for decisions, errors or negative consequences is increasingly shifted from the providers or developers of an AI system onto the users. In the context of AI agents, this can lead to consumers being held responsible for decisions, even though these were significantly influenced or automated by the system's recommendations or actions.

Retail media refers to the sale of advertising space on digital platforms such as Amazon. Retail media is currently one of the fastest-growing business models in the retail sector.

Transaction cost theory examines the costs incurred in initiating, executing and monitoring transactions. Trust can reduce these costs by minimising the need for information-seeking, monitoring and control.

A **trust heuristic** is a mental shortcut whereby people assess the trustworthiness of an actor or a piece of information quickly and with minimal cognitive effort, without systematically checking all the available information.

ADVISORY COUNCIL FOR CONSUMER AFFAIRS

The Advisory Council for Consumer Affairs is an independent body tasked with advising the Federal Ministry of Justice and Consumer Protection on consumer policy on the basis of scientific evidence and practical experience.

The Advisory Council has nine members.

The Chair of the Advisory Council is Professor Christoph Busch.