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EDITORIAL

Electronic Markets on digital platforms and AI

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Artificial intelligence (AI) was mentioned in Electronic Markets' last editorial as a key enabling technology that is converging with other technologies such as distributed ledger or extended reality technologies (Alt, 2021). The notion of convergence implies the evolution of a technology and, in fact, AI has been on the table of academics and practitioners for some time. It meanwhile comprises a rather broad methodological and technological spectrum. An analysis of mentions in academic and newspaper sources revealed that AI has seen a steady growth since 1984 and experienced an even stronger rise since 2012 (Katz, 2017). The same source reported that "AI stands for a confused mix of terms—such as "big data", "machine learning" or "deep learning"—whose common denominator is the use of expensive computing power to analyze massive centralized data." (Katz, 2017, p. 2). Other attributes like "smart" could be added to this list leading to the legitimate concern as to when an information system qualifies as being "intelligent". It opens the stage for diverse discussions from various disciplines. To contain the debate at this point, intelligence shall be conceived as closely related to human skills and interactions. It follows the definition of a survey conducted by Lu (2019, p. 1), which defines AI as "any theory, method, and technique that helps machines (especially computers) to analyze, simulate, exploit, and explore human thinking process and behavior." Along the same lines and based on literature from cognition psychology, the functionalities of perception, processing, action and learning were found suitable to structure potential applications of AI in business (Dietzmann & Alt, 2020). Other attributes of AI were perceived anthropomorphism, perceived intelligence as well as perceived animacy (Balakrishnan & Dwivedi, 2021). In particular, the goal to match human intelligence is reflected in levels of AI systems, which range from smart information systems and reactive machines to weak and strong AI until the most "intelligent" form of self-aware AI (Abele & D'Onofrio, 2020). Since the properties of intelligence are key for decision-making across application domains, AI has been termed a "general purpose technology (GPT)" (Buxmann et al., 2021) with GPTs allegedly having a strong impact for digital transformation (or disruption). This also entails from the convergence with other GPTs, in particular, digital services and platform technologies such as cloud computing, social media and distributed ledgers. They indicate a close mutual link between AI and digital platforms, which shall be discussed with the triple relationship between AI and digital platforms in the following (see Table 1).

Digital platforms for AI

The first relationship recognizes digital platforms as vital data sources for AI and follows a prior editorial that introduced a special issue on big data services (Alt & Zimmermann, 2017). Centralized as well as decentralized platforms were described as service systems where data emerges from transactions and interactions on an individual as well as on an aggregated level. As illustrated in the upper third of Table 1, users leave a large variety of data when acting on digital platforms. First of all, they provide data on the technological performance of the platform itself, for example, the type of devices and operating systems being used. While these are rather application-agnostic and cross-domain in nature, data on content and actors will vary according to the purpose and the participants of the platforms. For example, data from transaction platforms will be more structured than data from innovation or social networking platforms, where content is likely to be unstructured. Since the early days of computer reservation systems and electronic stock exchanges, platform providers are known to leverage their access to this wealth of platform data. This priviledge explains why automotive companies such as Toyota or Volkswagen and banks like BBVA or Citibank are today striving to establish

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Table 1 Triple relationship between AI and digital platforms

Dimension	Examples
1. Platforms for AI	
• Data sources	• Data from single digital platforms: data from platform operation (e.g. uptime, API latency and usage), data from interactions (e.g. textual and multimedial content, metadata), data from transactions (e.g. order positions, shopping basket), data from profiles (e.g. personal data, network, preferences)
• Data spaces	• Data from multiple platforms: intermediate data repositories that hold partially preprocessed data, provide mechanisms for alerting, data quality management, and safeguarding principles like data sovereignty and data portability (e.g. for the exchange of data between many actors in diverse purposes/use cases)
2. AI for platforms	
• Platform processes	• AI support for digital platform processes: transaction processes (e.g. process automation systems), analytic processes (e.g. recommendation systems) and interaction processes (e.g. conversational systems)
• Platform services	• AI as a business model: domain-specific bundles of AI functionalities and provisioning as a service (AI-as-a-service)
3. AI as platforms	
• AI platforms	• AI as part of a platform stack (e.g. operating platforms, application and data platforms, analytics and AI platforms, assistant platforms)
• Platforms as ecosystems	• AI platforms as elements in an ecosystem of platforms (e.g. multiple interlinked digital platforms) and as coordination technology within these digital platform ecosystems

their own platforms. It allows platform providers to monitor the activites on the platform and to quickly adapt their offerings as well as their strategies. In addition, platform providers are also in a position to sell this data to create additional revenues. A past special issue of Electronic Markets on personal data markets has shown that dedicated electronic market platforms emerged for collecting and trading such data (Agogo, 2020; Spiekermann et al., 2015). However, from the fields of business intelligence (BI), big data (BD) and social media analytics (SMA), two key challenges should be considered.

First, the presence of vast amounts of data represents a potential that requires further processing to make it amenable to sense-making in business processes and for decision-making. Much is rooted in the fact that data emerges from various application systems and knowledge bases, which typically feature different conventions in terms of data syntax and semantics. To derive meaning from this heterogeneous "raw" data, existing technologies foresee tasks for data preprocessing:

- In BI, the task of data preparation is captured with the ETL process. It denotes the *e*xtraction of data via defined electronic interfaces, the *t*ransformation of data along a defined data model and finally, the *l*oading of this data in a consolidated database referred to as data warehouse.
- In BD, the approach is to collect native data in data lakes without anticipating the analytical purpose. However, the quality of this data determines analytical results and makes preprocessing with data cleansing, filtering and transformation an important element prior to the analysis and interpretation of data (Amatriain et al., 2011).
- In SMA, the three CUP steps distinguish the *c*apturing and preprocessing, *u*nderstanding and analysis as well as *p*resentation and evaluation (Fan & Gordon, 2014). Text mining techniques are applied to analyze, tag and label the unstructured content, which is then stored as preprocessed data in dedicated databases.

BI, BD and SMA are often associated with the notion of intelligence in terms of obtaining insight or in supporting decisions (i.e. perception, processing). They feed (human) decision makers as well as (automated) rule-based systems and pave the way towards AI technologies that also include adaptive skills, i.e. functionalities for learning. Since preprocessing influences data quality, it strongly determines the outcome of data science and AI models (Brous et al., 2020). Thus, data from single digital platforms or from intermediate data platforms with partly preprocessed data (Otto & Jarke, 2019) is essential for AI, but users should receive indications from platform providers that allow them to assess the quality of this data (e.g. regarding the source, credibility, timeliness, context). It should be mentioned that AI algorithms have been applied to the preprocessing task itself in an attempt to (at least partly) automate the preprocessing towards self-preprocessing (Osifeko et al., 2020) as well as to detect whether changes in the data (e.g. less available data) require changes in the predictive models (so-called concept or data drift, see Gama et al., 2014).

Second, data access depends on the gatekeeping role of platform providers. While in some cases they may decide to share or sell data with third parties, they might keep data for themselves in other cases. In fact, many big tech platforms feature behavioral patterns that raise questions about how they use their power position. In a recent opinion paper, a founder of multiple internet businesses assessed that "this quasi-oligopolistic market structure can be harmful for innovation and, user freedom" (Göldi, 2020, p. 50). This is visible in cases such as the recent investigation of the European Commission against Facebook, which is accused to illegally use advertising data from its online flea market and its online-dating platform to obtain competitive advantage for their own services (Schechner, 2021). To address the problem of trustful data access, three perspectives are conceivable (Alt et al., 2021, p. 192f):

- *Provider commitment*. In an act of self-regulation, platform providers could formulate credible guidelines that follow corporate social responsibility (CSR) approaches and propose rules not only for publishing, but also for using this data for further processing. Examples are oversight boards, which have the freedom to act independently from hierarchical structures, as well as functionalities that yield users more control on how their data is being used (e.g. Higgins, 2021).
- *Public regulation*. To contain the power of platform providers, public authorities have recently pushed regulatory measures that aim at enforcing individual data rights and ethical values like autonomy and sovereignty. A prominent example is Europe's Digital Markets Act that defines the role of gatekeepers and regulates data access (Krämer & Schnurr, 2021). Several other regulations are mentioned in a contribution on trustworthy AI by Thiebes et al. (2021) in this issue.
- *Decentralized solutions*. In particular, the advent of distributed ledger technologies (DLT) has provided an alternative to the centralized model of data storage that was characteristic for digital platforms (Abduljabbar et al., 2021). With DLT, data is distributed among many actors, but linked with high levels of privacy that are mainly a function of encryption technologies and the combination with identity management solutions (e.g. self-sovereign identities).

AI for digital platforms

The second relationship follows the architecture of corporate information systems or enterprise resource planning systems (ERP), where AI has been applied for decades to optimize operational decision-making (Goundar et al., 2021). Among the examples are routine tasks in production scheduling, compliance management or fraud detection. In addition, AI has spread in the field of BI, which comprises (besides ETL) functionalities for the multidimensional consolidation of transactional data and the presentation or management of this aggregated data in reports, ad-hoc analyses or simulations. An entire industry of software providers emerged in the BI field and many of these business analytics software solutions now also include AI functionalities. From an architectural perspective, they may either complement or substitute the functionalities in the ERP systems (Markus & Tanis, 2000) since, compared to the rather universal ERP systems, BI packages offer more advanced functionality in the areas of data preprocessing, algorithmic support and visualization. A similar picture may be found with digital platform businesses where the platform (or electronic market) management system corresponds to the ERP system and supports the platform's core business processes. From the early days of e-commerce and electronic markets, "market intelligence" has included the measurement of platform operations with defined metrics. For example, in electronic financial markets such metrics serve to detect insider trading and similar fraudulent behavior. The application of AI algorithms has been reported to date back to 2003 when Microsoft initiated automatic spam filtering on its platform and to 2006 when eBay started to improve product categorizations and product searches with AI (Mucha & Seppälä, 2020). Meanwhile Amazon, eBay and Google are known to apply machine learning for forecasting demand, detecting fraud, optimizing the selection and placement of search results and auction matches as well as to increase the reach of their platforms with automatic translating functionalities (Mucha & Seppälä, 2020, p. 4f). Following the GPT nature of AI, many of the existing use cases for AI (Dietzmann & Alt, 2020) also apply to digital platforms. Three shall be mentioned:

- *Transaction systems*. Despite the progress in digitalizing business processes, many routing tasks within and, in particular, between organizations are still handled manually. Contrary to the time-consuming setup of electronic data interchange (EDI) systems, more "lightweight" solutions have spread under the notion of robotic process automation (RPA). By mimicking human workflows, these software robots automate manual activities mainly in the presentation layer. Based on predefined rules, these solutions could support digital platforms in accessing external systems via defined interfaces (API) or in mapping between various data formats. Although most existing RPA implementations would not qualify as AI applications due to their static nature, it may be expected that RPA tools evolve towards cognitive automation where these robots are less rule-based and more self-(re)configuring (Hofmann et al., 2020). This could bear significant potential for inter-organizational integration since, for example, new business partners could be onboarded and transactions among multiple systems could be transferred more efficiently. The growing research on linking DLT with AI (e.g. Dietzmann et al., 2020; Pandl et al., 2020) illustrates that this perspective is also feasible for decentralized transaction infrastructures.

- *Analytics systems*. Deriving meaning from operational data has been the intent of intelligence in the sense of BI. Platform businesses have for long applied these technologies to support the tasks on their platforms. For example, a main challenge in multi-sided platforms is attracting a sufficient number of offerings on the platforms and matching these between the participants on both sides (e.g. buyers and sellers). For this purpose, a large body of knowledge has emerged in the field of recommendation systems, which may cover all three main functional clusters of business analytics (Lepeniotia et al., 2020): While descriptive analytics analyzes what has happened (e.g. it serves the classification and categorization of data on the platform by automatic filtering and tagging, as well as the uncovering of non-compliant behavioral patterns on the platform), predictive analytics analyzes what will happen (e.g. it estimates the success of campaigns or a customer's lifetime value), and prescriptive analytics identifies what should be done (e.g. it derives product recommendations and proposes nudges to customers). Research has shown that recommendation systems cover all three analytics clusters and may support actors on one or two sides of a digital platform (Malgonde et al., 2020). Clearly, the goal is not only to increase the platform's efficiency, but also to contribute to critical mass and revenue potentials.
- *Interaction systems*. Another GPT aspect of AI is visible when AI aims at supporting or even fully automating interactions with (human) users. AI technologies in the field of natural language processing have created a large field of applications known as virtual assistants or conversational systems. Since 2011, most big platform providers have embarked on such systems, in particular, Apple with Siri, Amazon with Alexa, Facebook with Messenger, Google with Assistant, Microsoft with Cortana, Tencent with Xiawei or Samsung with Sam. Similar solutions have also appeared with a stronger link to specific products, for example, chatbots like Ask Mercedes that answer questions about the vehicle. Using the spoken language as the human's most natural communication interface, such solutions aim at a high ease of use when interacting with digital services or smart products. Over the years, the functional scope and the presentation of these assistant technologies have grown towards understanding more vocabulary and phrases as well as towards stronger personalization in terms of visualization and vocal tone. These developments suggest that assistants may increasingly be applied for more complex interactions and that voice-based interfaces have the potential to substitute as well as to enhance many tasks of human workers. This includes the emerging segment of conversational commerce where platform purchases are initiated without human agents via assistant technologies (Balakrishnan & Dwivedi, 2021) as well as the field of hybrid intelligence where humans and machines complement each other (Ebel et al., 2021).

It should be added that these three applications of AI for digital platforms are not mutually exclusive. Platform companies will tailor them to their internal needs and – similar to the products of software providers in the BI or BD field – offer them as separate services on their platforms. In this vein, industry-specific cloud solutions were launched by platform providers, for example, Microsoft's Cloud for Healthcare or Amazon's initiatives for healthcare and life sciences (Healthlake), finance (Finspace) or manufacturing companies (Smart Factory) (Sawers, 2021). They point in the direction of AI-as-a-service offerings (Janiesch et al., 2021). Irrespective if these AI functionalities are applied internally or placed as services on the (external) market, a key question refers to traceability and the transparency of their behavior. The practice of influencing the service listings on electronic marketplaces has been denounced in many cases from the early days of computerized reservation systems in the tourism sector (Copeland & McKenney, 1988) to the most recent practices of Google, who agreed to adapt their matching algorithm, which biased results in ad auctions to the provider's favor (Rosemain, 2021). As embodied in the notion of trustworthy AI (see below), users of AI-based system need to trust the system's recommendation, in particular, if these decisions are implemented automatically, like in an autonomous AI-based trading system.

AI as digital platforms

The third relationship recognizes that AI technology has assumed the nature of a digital platform itself. This implies that AI embodies the properties of a digital platform and features platform characteristics. While various characteristics for digital platforms may be identified (e.g. Blaschke et al., 2019), functionalities for digitally mediating between actors that interact for various purposes (e.g. conversation, collaboration, consumption or acquisition) may be seen at the heart of digital platforms. Although most large platforms have broadened their scope, they emerged from a dedicated purpose, e.g. e-commerce platforms for consumption or social media platforms for conversation. To support these primary purposes, they provide or integrate platform functionalities for trust, payment or logistics that may be conceived as separate platforms. Like business application software, these platforms feature a certain domain focus while office tools as well as development and operating environments are rather agnostic to a specific application domain. One

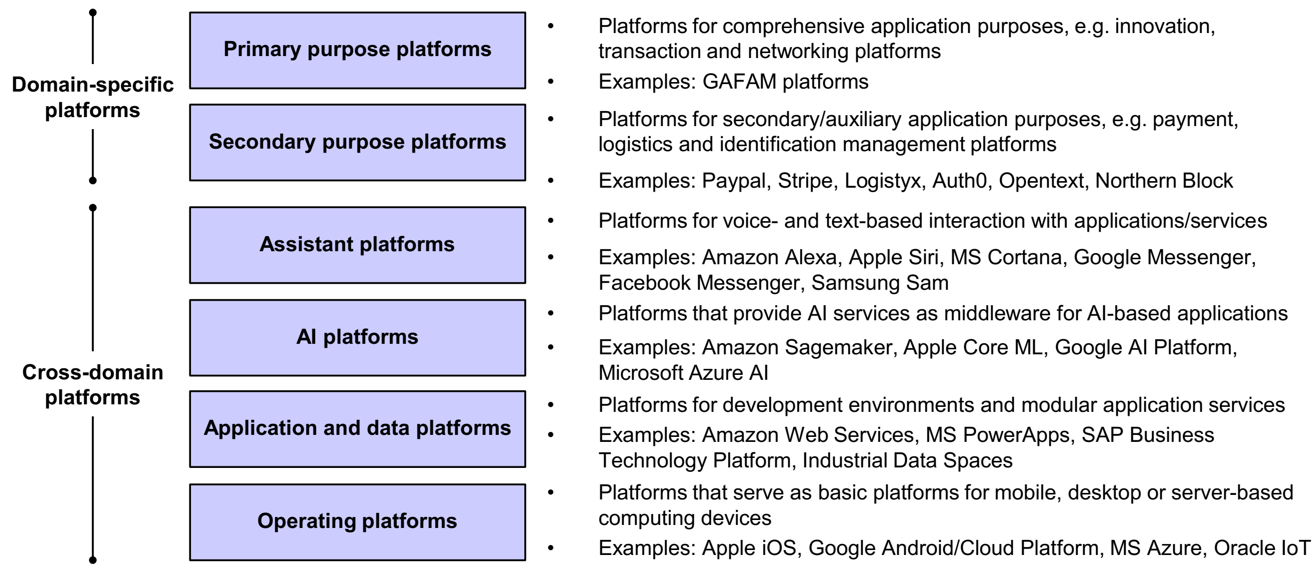

Fig. 1 Ecosystem of platforms

form of applications services are AI services that have assumed platform characteristics since they bring together a platform owner, users and AI application developers (Mucha & Seppälä, 2020). Very often, AI platforms have emerged from existing digital platform providers, who bundle existing algorithms and developer tools with their large databases and computing infrastructure. They allow (third-party) developers to craft new algorithms and to contribute to data collection and preprocessing. Finally, users benefit from offerings that bundle predefined algorithms with computing resources, which makes them "new middleware platforms" (Mucha & Seppälä, 2020, p. 5). For example, Ryanair is reported to use Amazon's Sagemaker machine learning service for their customer service chatbots (Carey, 2018).

An additional phenomenon occurs when services on AI platforms assume platform characteristics. This is the case with the virtual assistants mentioned in the paragraph on "interaction systems" above. The developer tools of Alexa allowed users like Ryanair not only to design their own voice-based capabilities (i.e. "skills", "actions", "intents"), but also to share them with other users. For this purpose, assistant platforms comprise a capability repository, where capabilities from various developers are retrieved and activated by users (Schmidt et al., 2021). These platforms impressively show the interlinked nature of platforms or the ecosystem of platforms: while the cognitive AI functionalities for the interpretation and matching of utterances stem from AI platforms, the capabilities may trigger activities on service platforms (e.g. as in-skill purchases on shopping platforms) or on IoT platforms (e.g. on smart home devices such as TV sets or air conditioning). This points at the existence of a (vertical) stack of cross-domain platform types as illustrated in Fig. 1, which converge in various constellations in domain-specific platforms. The differentiation of various interdependent types of digital platforms raises questions regarding structure and behavior.

From this background, the notion of an ecology of computation (Huberman, 1988) shall be suggested for the study of such ecosystems of platforms. This approach conceives computing as distributed ecosystems with complex dynamics and interdependencies that require specific coordination as well as reward mechanisms. Ecologies provide an interdisciplinary orientation and incorporate analogies from distributed systems in biology, computer science, economics and sociology, which deem appropriate to study AI for digital platforms as well as AI as digital platforms. In particular, they motivate a future where distributed AI systems coordinate actors in society. In particular, prior research on distributed AI (Bond & Gasser, 1988) and coordination research has recognized AI as an enabler for coordination technologies such as recommendation systems for communication, artifact and task management (Sarma et al., 2010). For electronic markets, this could mean an evolution of intelligent forms of coordination. Since coordination is information-based, the new wealth of (preprocessed) data could improve processes for planning, monitoring and allocation on a digital platform as well as between digital platforms (e.g. for linking and bundling platform services). This development could shed new light on concepts like smart business networks (van Heck & Vervest, 2007), where AI could improve the abilities for quick adaptation and reorganization.

Articles of present issue

The present issue of Electronic Markets comprises two special issues with three papers each and four articles in the general research section. All of them exhibit diverse links to the three relationships between platforms and AI mentioned above. Regarding the first relationship, it extends prior special issues (Otto et al., 2011) and publications in Electronic Markets on data quality and data spaces (e.g. Kleindienst, 2017; Otto & Jarke, 2019). In a general research paper of the present issue, Bernd Heinrich, Marcus Hopf, Daniel Lohninger, Alexander Schiller and Michael Szubartowicz focus on the data quality in recommender (or recommendation) systems and analyze how one data quality dimension impacts the prediction accuracy of these systems (Heinrich et al., 2021). In their empirical model, the authors elaborate on the completeness of data that is used by recommender systems. They find that the completeness of this data improves the accuracy of the recommender's predictions in most cases, but also that this accuracy declines if the data elements increasingly differ (or drift) from prior data. The authors conclude that understanding the importance of data for the users is key for attaining high quality results.

The two special issues may be assigned to the field "AI for platforms" with the first focusing on recommendation systems and the second on hybrid intelligence. Titled "Designing recommendation or suggestion systems: looking into the future", the former continues a legacy of past articles and special issues on recommendation systems in Electronic Markets (e.g. Zhang et al., 2019). The guest editors Ravi S. Sharma, Aijaz A. Shaikh and Eldon Li organized three papers, which elaborate on recommendations systems in electronic commerce and on digital platforms. In their introduction, they present these papers and define recommendation systems as "software agents which are widely utilized in online platforms to obtain users' preferences and interests, which in turn are used to generate product or service recommendations" (Sharma et al., 2021). In addition, they provide an overview on current (collaborative, content-based or social tagging-based) recommendation approaches and advocate for a collective intelligence social tagging as a promising hybrid solution.

Another association to hybridity is included in the second special issue, which comprises a collection of three papers on "Hybrid intelligence in business networks". In their elaborate preface, the guest editors Philipp Ebel, Matthias Söllner, Jan Marco Leimeister, Kevin Crowston and Gert-Jan de Vreede introduce these research articles, which discuss various aspects of how AI can create symbiotic partnerships between humans and machines (Ebel et al., 2021). Following the rationale for RPA, they see large potential for hybrid intelligence systems in the automation of repetitive tasks. They conceive hybrid intelligence systems as digital networks and "a special form of digital platforms", which need to consider various aspects of coordination such as the specification, allocation and aggregation of tasks as well as incentive and compensation mechanisms. In this respect, the special issue also connects to the third area in Table 1. The guest editors include these aspects in three research streams, which comprise the development, the design and the management of hybrid intelligence systems. They conclude that the combination of human and machine skills has the potential to redefine the future of work by combining the best of two worlds.

Closely linked to the hybrid intelligence special issue are two general research articles on virtual assistants. On the one hand, Frank Ebbers, Jan Zibuschka, Christian Zimmermann and Oliver Hinz investigate the design of privacy features in digital assistants, which typically require personal data to provide personalized support (Ebbers et al., 2021). The authors examine the influence of three privacy features on the willingness to pay, and contend that larger amounts of personal data shown to the user, more comprehensive explanations of the digital assistant's decisions, and the availability of (serious) gamification features are helpful in addressing privacy concerns and have the potential to positively influence the willingness to pay. On the other hand, Martin Adam, Michael Wessel and Alexander Benlian analyze the likelihood of how users comply with AI-based chatbots in requests for feedbacks in customer service (Adam et al., 2021). With an emphasis on online banking, the authors developed a chatbot for an online experiment that replicated existing text-based chat interfaces with the IBM Watson Assistant cloud service. Following the concept of anthropomorphism, they aimed at overcoming the limitations of existing assistants that lacked human characteristics such as identity, small talk and empathy. Using appropriate wording and a technique of small commitments, they present promising insights in how digital assistants may be used in customer service and electronic markets.

The general research section terminates with a contribution that is closely related to (decentralized) digital platforms and AI. Titled "Trustworthy artificial intelligence", it has been submitted by Scott Thiebes, Sebastian Lins and Ali Sunyaev (Thiebes et al., 2021) upon invitation, but underwent the same review scrutiny as other research papers in Electronic Markets. Besides the many potentials of AI that were discussed in other articles of the present issue, this research identifies the risks of AI-based systems as a main inhibiting factor for achieving the potentials of AI. The authors recognize trust in the development, deployment and use of AI as important for achieving trustworthy AI. Besides elaborating on these areas, they provide structure to the term and introduce

Table 2 Winners of Electronic Markets awards 2020

Outstanding Reviewers 2020
• Anastasia Constantelou, University of the Aegean, Greece
• Robert Harmon, Portland State University, USA
• Maria Madlberger, Webster Vienna Private University, Austria
Paper of the Year 2020
• Beverungen, D., Müller, O., Matzner, M., Mendling, J., & vom Brocke, J. (2019). Conceptualizing smart service systems. Electronic Markets, 29(1), 7–18. https://doi.org/10.1007/s12525-017-0270-5
• Hein, A., Weking, J., Schreieck, M., Wiesche, M., Böhm, M., & Krcmar, H. (2019). Value co-creation practices in business-to-business platform ecosystems. Electronic Markets, 29(3), 503–518. https://doi.org/10.1007/s12525-019-00337-y

five constituting principles that are used to derive a data-driven research framework. The elements emphasize the interdisciplinary nature of trustworthy AI and require the consideration of technological, economic, ethical, social and legal dimensions alike.

Despite the articles in this issue advance the body of knowledge, it is unlikely that AI as a GPT will exhaustively be covered in one issue and all articles emphasize the need for further research. Electronic Markets aims to take on these topics in several future special issues. In this vein, the next issue of Electronic Markets will include a special issue on AI and robotics in the domain of travel, tourism and leisure (Xiang et al., 2020), which are driving the digital transformation of customer-facing as well as of value chain processes in this industry. Another special issue that is to appear later aims to shed light on "the dark sides of AI" (Xiao et al., 2020), which are gaining attention with the rising diffusion of AI technologies. While these special issue calls are already closed, two others have been launched recently and are still open. They focus on "explainable and responsible AI" (Meske et al., 2021) as well as on the role of "trust in AI for electronic markets" (Maass et al., 2021) and will hopefully receive numerous high-quality submissions.

Electronic Markets awards

Finally, this issue reflects another convincing collaborative effort of many participating colleagues. Many thanks go to the guest editors of both special issues as well as to all authors and reviewers. The last paragraph of the editorial also provides an opportunity to honor the colleagues, who qualified for the 2020 awards of Electronic Markets. In both categories, quantitative as well as qualitative criteria were applied. In the category of the outstanding reviewers this referred to the number and the timeliness of reviews as well as to how elaborate and constructive the reviews were. In the paper of the year category, it comprised the citations and the downloads for papers published in Electronic Markets in 2019 as well as a voting on the quality and impact of the paper among associate and senior editors. Table 2 shows the winners of these awards, which Electronic Markets is proud to announce. Maybe the quality of these contributions is also a hint to the limitations of AI, which at least for the foreseeable future will be unlikely to live up to such convincing intellectual performance.

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