The Rise of the Machines: Conceptualizing the Machine Economy

Completed Research Paper

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Abstract

Recently a novel phenomenon, the machine economy, experiences rapidly increasing recognition from both research and practice. However, we still lack a thorough conceptual understanding of its driving technologies and their interrelations. This hampers the incorporation of the machine economy in today's organizations to unleash its full potential. Therefore, we set out with a conceptual research approach. First, we investigate the characteristics of the central technologies, the Internet of Things (IoT), Artificial Intelligence (AI), and Blockchain (BC). Second, we examine the bilateral technology interrelations to explicate their synergistic interplay. Third, we shed light on their trilateral technology convergence and conflate our reasoning into a holistic conceptual model. Finally, we demonstrate the machine economy's real-world applicability with three exemplary instantiations. Throughout our research approach, we observe the machine economy concept through two theoretical lenses: the theory of self-adaptive systems and the actor-network theory.

Keywords: Machine economy, Internet of Things, artificial intelligence, blockchain, self-adaptive systems, actor-network theory

Introduction

Digital technologies enable and shape new ways of designing business models and processes. Ever shorter innovation cycles, pervasive and ubiquitous digital technologies, and the resulting enormous information flows induce a challenging paradigm shift for IT management. Instead of merely developing and deploying individual technologies, the focus changes towards the coordination and intelligent networking of technologies (Harwood and Eaves 2020). In practice, machines are considered to become more intelligent and interactive, leading to a novel understanding of machines and their interaction. Leaving the prevailing conceptual path of understanding machines as operands solely carrying out tasks on behalf of humans, the current transformation turns machines into operators carrying out tasks by themselves. Machines become capable of perceiving their environment, processing external information, and exchanging it with their surroundings. Consequently, machines are said to take over increasingly autonomous roles and participate directly in the value creation process. Both researchers and practitioners expect a transformation towards a machine economy (Schweizer et al. 2020).

We recognize the *machine economy* as the complete integration and participation of economically autonomous acting machines based on innovative technologies and their convergence. In this regard, we refer to machines as any material or digital artifact that creates or shapes the physical reality and the business activities therein (e.g., a production machine or a manufacturing execution system) (Baskerville et al. 2019). Considering the increasing coalescence of technologies, unleashing the machine economy's full potential requires an integrated understanding of its respective technologies and their interrelations. However, the incorporation and deployment of the machine economy in today's business activities lacks a thorough conceptual understanding. Companies are struggling to capture the machine economy concept's potential and challenges within their business models and processes. Further, research on the nature of the machine economy is scarce. Related work has primarily focused on the concept of machine-to-machine (M2M) communication initially neglecting the machine's intelligence and information processing capabilities (Leminen et al. 2020; Swain et al. 2017). Yet, related work increasingly addresses the role of artificial intelligence and distributed ledger technologies such as Blockchain due to the need for advanced information processing and data storage capabilities in the autonomous machine networks (Abraham et al. 2020; Schweizer et al. 2020; e.g., Sikorski et al. 2017).

A precise conceptual understanding of the machine economy may help practitioners in, among others, use case identification, technology assessment, and technology governance. Further, a clear machine economy concept may contribute to strategy building and long-term decision-making in technology management, including resource allocation and project planning. Following recent calls for research on the potential of IoT, AI, and BC to increase intelligent systems' autonomy (Beck et al. 2020), we ask:

RQ1: How can we conceptualize the machine economy?
RQ2: What are the roles and interrelations of its underlying technologies?

To answer our research questions, we set out with a conceptual research approach. First, we investigate the specific characteristics of the machine economy's central technologies, IoT, AI, and BC. Then, we examine the bilateral technology interrelations between the respective technologies before shedding light on their trilateral technology convergence and conflate our insights into a holistic conceptual model. Finally, we illustrate the machine economy's real-world applicability with three exemplary instantiations. Throughout our research approach, we observe the machine economy concept through two theoretical lenses: the self-adaptive systems (SAS) theory and the actor-network theory (ANT).

Conceptual Foundations and Theoretical Background

Recent Trends Towards the Machine Economy

Short IT innovation cycles (e.g., wireless transmission protocols, high-speed Internet, powerful CPUs, BC), advancements in robotics (e.g., small and powerful motors, intelligent sensors), and the latest achievements regarding data analytics are paving the way for increasingly autonomous machine-to-machine communication (Hammaert 2017). Communicating machines, which are equipped with computing power, sensors, and Internet connection, can interact with their surroundings and, thus, are regarded as smart machines. A network with multiple machines (or things) is also known as the IoT. To securely connect smart machines and establish a trust layer between unknown devices, BC technology proved its applicability (Schweizer et al. 2020). The data generated by these machines turn fruitful ground for the latest data analytics technologies like AI.

In this vein, the capabilities of smart machines can be enhanced over time – based on the learnings and insights of data analytics (Uckelmann et al. 2011). These developments lead to a novel economic paradigm where machines autonomously interact with, help, and share services with each other to create value within an optimized model: the machine economy. However, the advance of the machine economy is an emergent concept and debated controversially, for instance, owing to a potential risk of exacerbating global unemployment. This debate is important to guide the conceptualization and development towards the machine economy in line with our values and guidelines to utilize it best.

A crucial factor in shaping the machine economy is to understand its underlying technologies and paradigms thoroughly. The machine economy comprises the secure, transparent and decentralized communication (BC) of autonomous connected machines (IoT), which process transactions, act as self-determined market participants, and are able to make collaborative decisions without human intervention (AI) (Verma et al. 2016). Thus, IoT, AI, and BC technology can be seen as the machine economy's cornerstone technologies.

Only recently, research has started to analyze the combination of the technologies mentioned above. Huckle et al. (2016) investigated use cases of BC and IoT in the realm of the sharing economy. In 2018, Xiao et al. researched the utilization of machine learning as a security element of IoT. Further, Rabah (2018) underpins that the confluence of technologies like IoT, AI, and BC is inevitable when it comes to innovative economic models that shape the fourth industrial revolution. These publications represent important steps towards a detailed understanding of the focal technologies of the machine economy. However, none of the published articles has comprehensively investigated the convergence of IoT, AI and BC, and their economic implications. Thus, we focus on closing this research gap and want to better understand the combination of the three technologies and their contribution to the machine economy.

Theoretical Embedding

To better understand the underlying and enabling technologies, it is of vital importance to connect the machine economy to the scientific context. Thus, we draw on two established theoretical lenses to formally describe the machine economy: First, we define technologies' interplay in machine economy use cases as an advanced instantiation of a SAS with a high degree of economic system autonomy. Second, we use ANT to expose the machine economy's constitutive elements and their interplay. Thus, while SAS theory helps us to conceptually understand the fundamental workings of the machine economy as (mostly) autonomous systems, ANT provides a fruitful lens to demarcate the specifics of machine economy use cases compared to prior systems (Jaakkola 2020).

Research on SAS is well-established and comprises the quest for software that changes its behavior to achieve or improve its functionality (Macías-Escrivá et al. 2013). Thus, SAS shift design decisions from systems' development to systems' run-time to improve the system's behavior considering the unknown circumstances at run-time (Sabatucci et al. 2018). In essence, SAS rest upon the so-called MAPE-K loop; an iterative combination of monitoring, analyzing, planning, and executing activities that are complemented by activities to extend and lever the knowledge base around such a SAS (Garlan 2016). Monitoring activities foster situational awareness by gathering relevant information. Analyzing activities determine and assess potential needs for adaptive measures. Planning activities provide a strategy of appropriate adaptive measures. Finally, executing activities implement the adaptive measures. In their metamodel, Sabatucci et al. (2018) distinguish four types of SAS that exhibit increasing levels of self-adaptability. Further, Krupitzer et al. (2015) propose a taxonomy to structure the different aspects of SAS. Specifically, they present the time when a system adapts (reactive or proactive adaption), the reason why the system adapts (variations in the context, technical resources, or users), the level where the system implements change (e.g., changing application behavior or communication patterns), the technique the systems uses to implement change (changing parameters, structure, or context), and the adaption logic that determines how to adapt (comprising the approach, metrics, and degree of decentralization). In this paper, we address recent calls for research on the potential of IoT, AI, and BC to increase the (economic) autonomy of SAS (Beck et al. 2020).

Historically, ANT has emerged as an alternative theoretical frame that neglects any a priori distinction between human actors and technology to account for a world of ‘hybrid entities’ (Hanseth et al. 2004). Instead, ANT proposes that both can be studied using the same approaches by focusing on an abstract network of actors and their interactions. Thus, by following and describing the actors and their interaction, ANT provides an approach to analyze situations where human and non-human actors are becoming increasingly inseparable (Cordella and Shaikh 2003). Further, ANT serves as a conceptual tool to express complex networks and interactions between actors in a graphical format (Alexander and Silvis 2014). Prior research has already used ANT to explicate the socio-technical implications of the increasing interactions between non-human actors and those between human and non-human actors (Tatnall and Davey 2015). We follow this line of argumentation and draw on ANT to better understand technologies’ roles in forming a network of non-human actors that characterizes as a SAS with high levels of autonomy.

In sum, we posit the machine economy as a SAS network where focal technologies enable a shift of autonomous economic decisions from human actors to (mostly) technological actors (see Figure 1). Considering the increasing number of connected devices and the increasing number of M2M communication in the IoT (Bandyopadhyay and Sen 2011), more machines become actors in such a SAS network. While this trend entails higher levels of actors’ context-awareness and potential for adaptive measures (e.g., by gathering and levering sensor data), it also increases the level of interaction complexity between the actors (e.g., the amount of data available or interdependencies between machines or production processes). Thus, AI methods pledge to make use of the abundance of data to prepare and assist decision-making or even make autonomous decisions (Hofmann et al. 2020). Beyond existing rule-based automation approaches, AI promises higher levels of self-adaptive measures that can cope with the increasing task complexity (Brynjolfsson and Mcafee 2017). Thus, both the actors and their decisions are highly decentralized in the machine economy, i.e., there is no such thing as a “central decision-making computer” but a network of (more or less) autonomous actors. This poses challenges to the multilateral, real-time, and secure exchange of data and information. We see BC technology as a suitable architectural foundation to alleviate these concerns (Schweizer et al. 2020). Hereafter, we draw on this conceptualization of the machine economy to dive deeper and unveil technologies’ roles therein. Thereby, we seek to better understand how such a (mostly) autonomous SAS manifests.

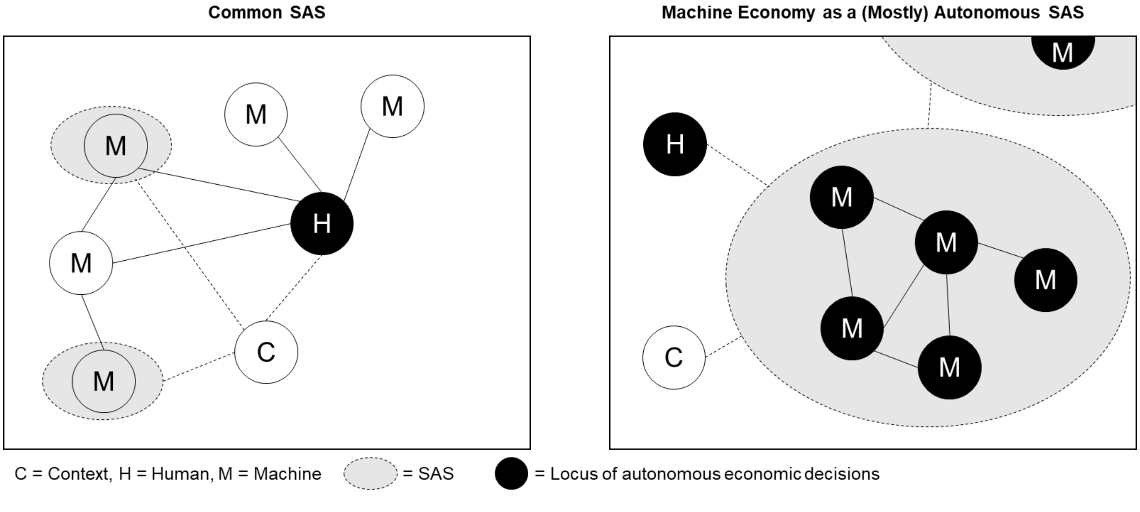

Figure 1. Machine Economy’s Fundamental Differences to Other (Self-Adaptive) Systems

Toward Conceptualizing the Machine Economy

We use a conceptual research approach to better understand the machine economy phenomenon by providing a framework for researchers and practitioners alike. Conceptual papers should integrate “theories in interesting ways, link work across disciplines, provide multi-level insights, and broaden the scope of our thinking” (Gilson and Goldberg 2015). Therefore, we combine theoretical insights and logical reasoning to derive a conceptual model of the machine economy (Meredith 1993). In particular, our conceptual model conflates the three focal technologies and describes their relationships that constitute the idea of the machine economy.

Conceptual models help to understand complex reality by decomposing it into its essential components (Burton-Jones and Meso 2006; Meredith 1993). For the resulting model to effectively represent the phenomenon, rigorous decomposition of a complex phenomenon is crucial (Nunamaker et al. 1990; Wand and Weber 2002). Accordingly, we first decompose the machine economy phenomenon into its underlying elements, i.e., the individual technologies, describe their respective bilateral interplay, and then put these into trilateral relationships. These relationships evolve as the technologies get increasingly interwoven into modern complex systems. In fact, the machine economy indicates that technologies seldom act independently but rather work synergetically in more complex systems. The arising technological convergence eventually opens the potential for new technology-based innovations and value creation paths (Coccia 2018). We draw on three exemplary instantiations of the machine economy to showcase its fundamental differences compared to existing SAS. Figure 2 summarizes our research approach, which we explain in more detail below.

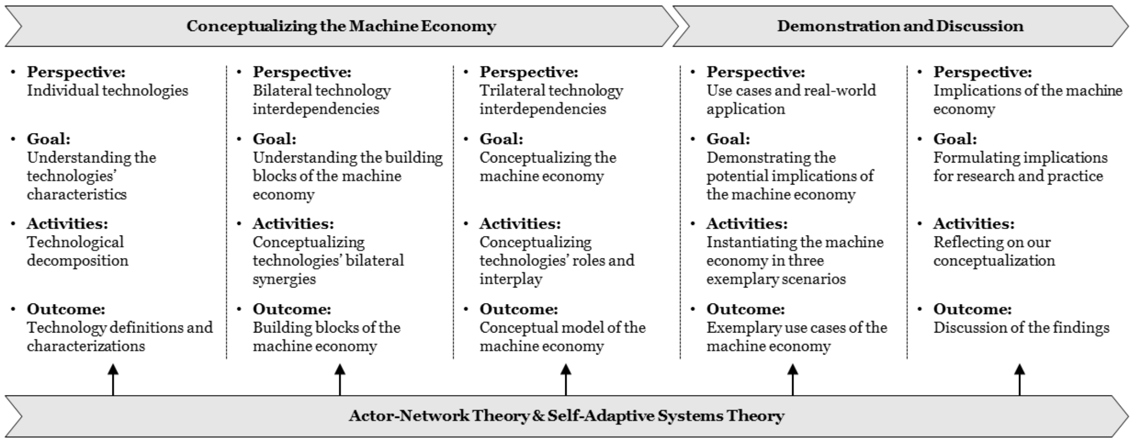

Figure 2: Overview of our Research Approach

First, we identify and describe IoT, AI, and BC as the focal technologies that form the machine economy. Thus, we conflate prior research to derive the technologies' specific characteristics as a prerequisite to understanding their interplay. Second, based on these insights, we identify how the technologies interact and define bilateral interrelations that form our conceptual model's connecting links. The identified technologies all have their particularities and pursue their respective tasks. However, the combinations of these technologies allow them to balance out their respective weakness and even facilitate the realization of new goals. Third, we combine these bilateral interrelations and aggregate them into a holistic conceptual model of the machine economy. By integrating IoT, AI, and BC, we are able to form trilateral interrelations that demonstrate the additional effect of the integrative nature of the machine economy. The holistic examination helps us to better understand the actors and their interplay so that, in the end, a (mostly) autonomous SAS emerges. Fourth, we demonstrate the applicability of this conceptual model by describing three exemplary real-world scenarios. In particular, we use the conceptual model as a blueprint to instantiate our claims about the technologies' roles in the machine economy and the fundamentally different economic decisions approach in a (mostly) autonomous SAS. Fifth, we discuss the impact and implications of the machine economy.

The Machine Economy and Its Technologies' Roles

Individual Technology Perspective

Internet of Things: As the first individual technological contribution to the machine economy's conceptual model, we consider IoT research's theoretical insights. The concept of IoT combines several technologies, communication standards, and application possibilities. Hence, IoT is regarded rather as a paradigm than a single technology and can be defined as the connectivity of physical objects equipped with sensors and actuators to the Internet via data communication technology (Oberländer et al. 2018). From a technological perspective, the implementation of IoT is based on a layered architecture that meets the requirements of various enterprises, industries, and societies (Atzori et al. 2010). It consists of two distinct divisions with an Internet layer in between to serve as a common medium for communication. The edge layer at the bottom, comprising the sensor-equipped hardware and the access gateway layer, contributes to data capturing, processing, and communication. The middleware and the applications layer at the top are responsible for device and information management as well as for data utilization in applications (Bandyopadhyay and Sen 2011). Enabled by its structural composition, the IoT represents a network of intelligent, interconnected objects that bridge the gap between the physical and the digital world. As such, IoT promises to create new perspectives for smart objects (e.g., innovative IoT-enabled products) to become largely autonomous actors in digital value-added networks, resulting in extensive business-to-thing (B2T) interactions (Oberländer et al. 2018; Xia et al. 2012).

Artificial Intelligence: We examine AI as a general-purpose technology comprehending machines that perform cognitive functions typically associated with human intelligence (Magistretti et al. 2019). Despite AI often being dismissed as a particular approach or method, it instead comprises a set of underlying techniques that enable agents to act intelligently. Depending on the role, scope, and value of AI integration in systems and processes, the literature identifies four types of AI solutions: rule-based solutions, AI-enabled solutions, AI-based solutions, and complete AI solutions (Hofmann et al. 2020). The former rely on predefined programming for the automation of standardized workflow integration (e.g., process automation by robotics). AI-enabled solutions use AI at the input and output interfaces (e.g., Natural Language Processing in chatbots). AI-based solutions rely on AI to facilitate the processing of core tasks and thus create new knowledge (e.g., budget estimation or risk management). Complete AI solutions implement AI for input and output processes as well as for task processing and can also consist of a grouping of individual solutions (e.g., chatbots for communicating AI-based budget estimates). From a functional perspective, AI solutions typically hold three components that first, assess input signals (e.g., detecting the traffic situation around an autonomously driving car in milliseconds), second, generate information from them (e.g., calculating the probability of a collision for the next three driving seconds), and third, convert this information into an output (e.g., initiating a necessary braking or evasive maneuver) (Vocke et al. 2019). Bringing together these capabilities with the ability to continuously improve performance and learn how to execute tasks independently (Brynjolfsson and Mcafee 2017), AI methods promise a purposeful use of the abundance of data by preparing, assisting, or even autonomously performing organizational decision-making (Albrecht et al. 2021). In this connection, AI will increasingly face challenges regarding data quality, data security, trust, and ethical concerns.

Blockchain Technology: Complementing the theoretical insights on focal technologies, we focus on distributed ledger technologies (DLT), such as BC as a decentralized transaction and data management technology (Yli-Huumo et al. 2016), which enables data exchange between numerous participants across a network of multiple participants (Xu et al. 2017). Transactions between users are grouped into blocks that are cryptographically chained to one another in chronological order – hence the name blockchain (Arnold et al. 2019). A consensus algorithm running on all network nodes of the participants guarantees the correctness and sequence of transactions. Existing algorithms pursue a variety of different purposes such as security, latency, energy consumption, or corporate environment use. Since BC's introduction by Satoshi Nakamoto in 2008, it has undergone a three-step evolution: BC 1.0, 2.0, and 3.0, which illustrates the progression of BC technology as a means of payment (1.0), the implementation of programs on the BC (2.0, e.g., smart contracts) and the addressing of problems of conventional BC implementations, most notably scalability, interoperability, and sustainability (3.0) (Arnold et al. 2019). In short, BC systems exhibit the following characteristics: data redundancy, to ensure persistence among the transactions and data; use of cryptography to ensure data security and integrity; use of a consensus algorithm to coordinate transactions among the network peers; decentralization, which enables trusted direct interaction among the network peers; as well as transparency regarding the traceability and verifiability of network activities. However, BC 1.0 and 2.0 do not meet the requirement to execute many microtransactions (e.g., in an IoT context) on time. While the traits of BC 3.0 are aspired to solve this issue, further development in terms of scalability and microtransactions for IoT applications is needed to build a sustainable infrastructure (Bashir 2017; Schweizer et al. 2020).

Bilateral Technology Interrelations

Based on the individual technology examinations, we assume IoT, AI, and BC's focal role in enabling the machine economy to arise from their synergetic interaction. Combining the technologies helps to overcome individual weak points and create entirely new use cases that individual technologies cannot realize. Building on these insights, in the next step, we identify how the technologies interact and define bilateral interrelations that form the connecting links of our conceptual model.

The first bilateral interplay we examine concerns **IoT and AI**. IoT provides sensor data that builds the basis for the training of AI models. To fully exploit the potential of new networks of products and services enabled by IoT, intelligent behavior in the form of informed decisions within these networks is required (González et al. 2019). By incorporating AI, digital ecosystems are created whose value far exceeds that of the individual technology strands. The central component in linking IoT and AI is data as the currency of the digital economy. Exponential growth in data volume is triggered and sustained by IoT. However, this data flood only offers added value if information can be generated by adding context and meaning (Osuwa et al. 2017). In doing so, AI enables interconnected intelligence. Smart networks are based on real-time exchange and providing information through analysis over a more extended period. In return, AI expands the scope of action of intelligent physical objects (Hansen and Bøgh 2020) as IoT applications by answering the questions "What will happen?" (predictive analytics), "What should we do? "(prescriptive analytics), and "What are the upcoming changes and what adjustments should we make? "(adaptive or continuous analytics). In this connection, AI also benefits from IoT. The ability of IoT to generate real-time feedback is of crucial importance for adaptive learning systems. Wherever sensors or devices for measuring, interacting, or analyzing are placed, an IoT device can be equipped with significant added value by combining it with AI systems (Xiao et al. 2018). This constellation promises early adopters and innovators enormous advantages in the form of lower costs, better customer experience, and a head start in developing new business opportunities.

Regarding **IoT and BC**'s interrelation, BC provides secure identities for IoT by employing a highly available, cryptographic public key infrastructure system. This avoids a single point of failure of a system or central decision-maker. In IoT, identities ensure that the correct device is addressed in shared communication. Here, the BC allows secure access control mechanisms via decentralized and highly available access rights (Mohanta et al. 2020). BC can also improve the general security of IoT applications (Singh et al. 2020b). To this end, device firmware hashing and subsequent comparison of the device's received firmware and the stored BC entry are executed. If the BC's value matches the received firmware, an update is performed. If the values are not equal, updates are refused, and thus the use of manipulated firmware is prevented (Minoli and Occhiogrosso 2018). The complementary combination of IoT and BC also manifests in the form of BC-based marketplaces (e.g., IOTA Marketplace). Here, microtransactions are processed to remunerate the provision of sensor data. During this process, Device A requests data, Device B releases data and, in consequence, receives a payment. As the number of devices increases and resources become scarce, this procedure allows economic calculation and optimal resource allocation (Huckle et al. 2016). In return, IoT provides sensor data that builds the basis for innovative BC solutions. Many BC-specific applications inevitably depend on the provision of sensor data referred to as oracles. These oracles have the task of providing real-world information for the BC. For instance, BC allows automatic payments based on weather events, which requires reliable temperature data. Sensor-equipped machines provide this information to the BC. To ensure a reliable representation of reality, a tamper-proof network of oracles is required (Moudoud et al. 2019). A large number of IoT devices can form these networks.

Focusing on the symbiotic combination of **AI and BC**, the former offers the potential of enabling intelligent consensus mechanisms for BC solutions. By analyzing ongoing transactions, misconduct and fraud can be detected more quickly. Moreover, an AI-based consensus mechanism can not only perform a formal check of transactions but also allow for validation of their content (Dillenberger et al. 2019). This capability can also help in the creation of new secure smart contracts. In return, BC enables trust-based training of AI models (Swan 2018). AI can benefit from BC by decentralized tracking of training processes. The training of AI algorithms is computationally complex and time-consuming. However, unused devices can provide computing power when they are not being used to capacity. In this case, BC can guarantee the secured coordination between entities, automatic remuneration, and traceable decision-making (Nassar et al. 2020). This enables a decentralized AI in a global network with theoretically unlimited computing power. Thus, different actors rent AI's capability as "AI-as-a-Service" on-demand and pay according to consumption via BC (Singh et al. 2020a). In conjunction with smart contracts, a high degree of automation and complexity management would thus be possible. BC also holds the potential of restoring data sovereignty and data protection in connection with AI (Vacca et al. 2021). Currently, AI is often trained in practice using data from private individuals that are neither aware of it nor rewarded. In this case, BC enables the control, selective release, remuneration, and traceability of data use. Thus, the data sovereignty remains with the private individuals. In this context, BC provides forgery-proof logging in case of anomalies involving AI.

Trilateral Technology Convergence

Building on the previously established understanding of the composing elements from an individual technology perspective and their bilateral interrelation, we examine their trilateral convergence to understand the concept of the machine economy and precisely describe its underlying components. To this end, we regard the interrelation of technologies in machine economy use cases as an advanced instantiation of a SAS with a high degree of economic system autonomy and draw on ANT as a structure-giving means to reveal the constitutive elements of the machine economy and their interplay.

The common angle on SAS is the quest for software that changes its behavior to achieve or improve its functionality. The key characteristics of such digital multi-agent systems are loose coupling, context-sensitivity, as well as robustness in response to failure and unexpected events. Goal orientation is provided through a certain degree of human involvement and supervision, while the loose coupling of agents provides the flexibility needed for self-adaptivity. In this case, agents are independent entities that can flexibly be combined with and segregated from other components in a system that iteratively monitors, analyzes, plans, and executes activities (Macías-Escrivá et al. 2013). Building upon this concept, the machine economy allows for a new perspective on cooperative strategies for multi-agent systems that implicates a higher level of autonomy as well as growth in complexity and size. The transformational concept of such (mostly) autonomous systems is enabled by the fundamental workings of the machine economy's underlying technologies. IoT establishes a more coherent connection of the digital and physical world, which minimizes the need for human input and maximizes context-sensitivity through extensive data collection. The close interplay with AI enables higher degrees of self-adaptivity through intelligent decisions and continuous system improvements. In the complex systems of interconnected agents without interposing human supervision, BC provides the required multilateral, real-time, and secure exchange of data and information. Only the rapid development at the individual technology level enables their purposeful interplay in new complex multi-agent systems that are primarily characterized by the further development and improvement of the key characteristics of common SAS. More thorough coupling of agents, greater context-sensitivity, higher adaptability, and robustness in

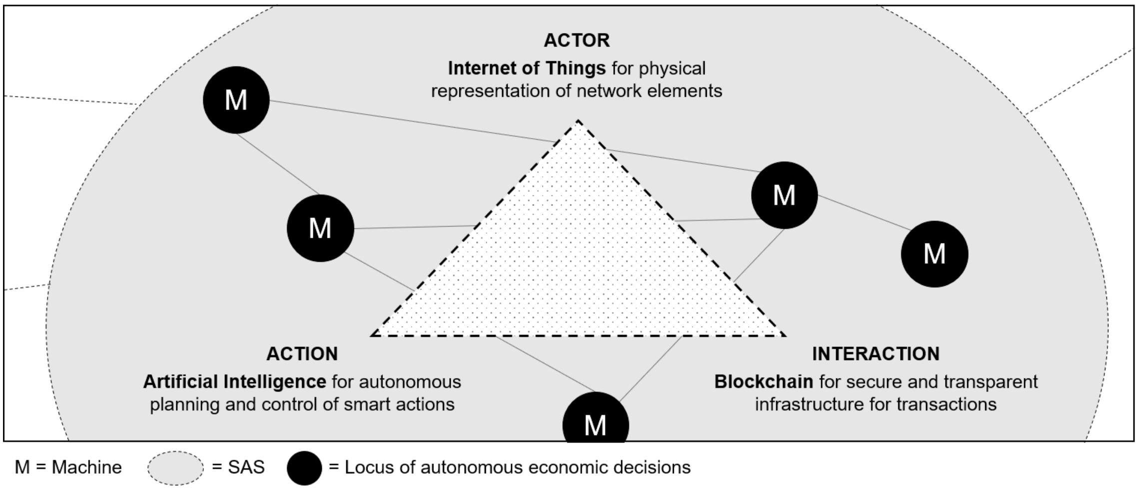

Figure 3: Constitutive Elements of the Machine Economy as a (mostly) Autonomous SAS

unexpected events in combination with less human involvement, and a previously unavailable secure platform for decentralized transactions and data management in the machine economy permit the employment of SAS in the economic decision space. To demarcate and further specify the distinct roles technologies take in forming a network of actors that characterizes as SAS with high levels of autonomy, we draw on ANT in the next step (see Figure 3).

Internet of Things – Representing ACTORS in the Machine Economy: Within the theoretical frame of ANT, IoT forms the physical representation and thus acts as the linking entity between the digital and physical world. In the form of interconnected devices and systems that collect data, exchange information, and carry out actions, IoT assumes the role of an actor actively participating in the economic market activities of the machine economy. By virtue of the interconnection of an ever-increasing number of devices, promoted by ever smaller, cheaper, and more flexible computing components, more sensor data are available. This opens a new range of possibilities to make the actions performed by the physical entities more intelligent and efficient through AI, thus enabling continuous improvement of products and services. Simultaneously, the combination of better and more powerful IoT devices creates a more stable structure of network nodes for BC as a secure, decentralized transaction platform. The facilitated gain and the more efficient and secure exchange of information, in turn, increase the application potential of smart devices in the IoT as actors in the machine economy.

Artificial Intelligence – Enhancing ACTIONS in the Machine Economy: AI accomplishes the autonomous planning and control of activities by providing relevant information based on collected data in the machine economy. By generating new knowledge, AI derives which actions, adaptations, and reactions in the digital ecosystem ensure optimal processes between technology components as well as in interaction with the environment. Thus, AI acts as an initiator for action in the machine economy. In the development of more and more powerful algorithms, a progression of AI applications along the complexity spectrum of tasks can be observed. The ability to gain insights from seemingly endless data streams of the physical world makes AI and its learning component an indispensable complement to IoT. Resulting from increased efficiency through intelligent monitoring, real-time forecasting, and smart decision management, both devices' connectivity and activity are improved. At the same time, the increase in efficiency is also relevant for BC-supported, decentralized data exchange. The implementation of decentralized learning systems offers the possibility to evaluate transactions regarding their relevance in the system and thus deal with the problem of high transaction frequency and the immense energy demand associated with it.

Blockchain Technology – Facilitating INTERACTIONS in the Machine Economy: As a decentralized transaction platform, BC ensures secure communication and multidirectional exchange between the machine economy players. By providing the economic framework, BC assumes the role of the provider of interaction in the machine economy. BC enables the unalterable mapping of all economic processes within the digital ecosystem by procuring a secure and transparent infrastructure. This guarantees a higher level of data security and integrity as well as the constant and comprehensive availability of data for all transactions. Within a network of IoT devices, the unique identification of devices through individual signatures or completely digital identities creates legally compliant traceability and thus trust among all market participants. Real-time transfers and the elimination of intermediaries also increase the efficiency of interactions in IoT. In turn, AI also benefits from more efficient and secure data exchange through the resulting increased data availability. In addition, boosted confidence in the data basis used and the recording of decision-making processes in the BC leads to better traceability of AI applications by market participants.

Demonstration of Machine Economy Instantiations

Having described the concept of the machine economy by aggregating the three technologies and respective interrelations, we now showcase how our conceptualization instantiates in three exemplary real-world scenarios.

Scenario 1 – Decentralized Energy Generation: In the course of the energy transition towards renewable energies, energy production is increasingly decentralized (Fridgen et al. 2021). Accordingly, the demands for flexibility in energy generation are also increasing to be able to integrate the share of renewable energies into the electricity markets without jeopardizing the security of supply. Increasingly, the role of (self-sufficient) peer-to-peer energy trading is also being discussed and evaluated. In this context, wind turbines or even larger wind farms may serve as decentralized, autonomous, and intelligent energy sources to adapt generation volumes in real-time to current and future market demand. They may act based on various parameters such as power exchange, consumption expectations, and weather forecasts. Gathering and exchanging this information, different sensors, information systems, or other kinds of smart machines are part of the actor-network in this context. Wind turbines regulate the output according to different maximization goals, such as profit or grid stability, thus, individually adapting to different situations. Using a variety of available historical and current data in real-time, this machine-centered system creates value (e.g., energy flexibility) that human-centered systems are struggling to provide (Fridgen et al. 2021). Further, customers – humans or machines (e.g., energy storage systems) – may purchase their electricity directly from the producer, which may lead to a reorganization of the whole energy market, as former electricity suppliers may simply provide a marketplace that is used for transaction processing and information exchange. Thus, this machine economy enables a paradigm shift from passive market participants to proactive energy trading by autonomous and intelligently acting wind turbines.

Scenario 2 – Autonomous Driving: An unprecedented proliferation of autonomous driving technologies such as the Tesla autopilot has been observed in the recent past. Autonomous driving represents a significant innovation for mobility and will have profound global impacts such as overall efficiency, convenience, and safety to roadways and transportation systems (Brenner and Herrmann 2017). In this context, autonomous vehicles are part of an actor-network, combining other (human-steered) vehicles, smart infrastructure such as traffic lights and signs, and smart charging stations, among others. By participating in this network, every actor constantly gathers information (through sensors, cameras, or other smart devices) while also producing further information which other participants then analyze. This self-reinforcing cycle of data processing and data producing leads to constant adaptation of every actor and ever smarter decision making. Autonomous vehicles may, for example, act to maximize different goals such as most economical driving to arrive at a destination by not only choosing the most efficient routing but also by considering the behavior and information of other actors (e.g., to optimize recharging times and strategies) (Baumgarte et al. 2021). This will lead to new business models such as platooning of multiple vehicles (Chen et al. 2020) while also reshaping existing business models (e.g., those of insurance companies). Further, car manufacturers are increasingly turning to mobility platforms, which will play a central in enabling so-called “seamless mobility”, i.e. the optimal connection of different means of transportation (Brenner and Herrmann 2017).

Scenario 3 – Intelligent Warehousing: Globally, the entire logistics industry faces major upheavals as a result of digitization. Though, the conditions for breakthroughs are better than ever before, considering the access to enormous amounts of data that can potentially be used for efficiency enhancements (Li et al. 2020). Utilizing industrial robots, warehouse management is prone to be improved by automation. Within this context, autonomous industrial robots form an actor-network that executes the orders of different enterprise systems. By combining and processing available data of different information systems within and beyond the organization (e.g., to predict supply and demand of products), intelligent real-time decision-making and thus more efficient warehousing is enabled. This includes not only the processing and execution of orders but also the prospective management of stocks, purchasing behavior, and supplier management, among others (Zhang et al. 2021).

By levering the different technologies’ convergence, the three scenarios showcase how the machine economy surfaces in real-world examples. An increasing amount of available data emerging through smart devices of the IoT, data analytics capabilities to utilize the data and generate meaningful results, and autonomy through a decentralized network of actors, provided by a BC infrastructure, enable new kinds of services and new values.

Discussion and Conclusion

This article provides a conceptual model of the machine economy and the interrelations between its underlying technologies. We followed a conceptual research approach to develop our understanding and present three key insights: First, IoT, AI, and BC are the core technologies of the machine economy. Second, the technologies' bilateral interrelations offer mutual synergies. Third, the convergence of the three technologies, depicted in a holistic conceptual model, constitutes the machine economy. Within our conceptual model, we show that the machine economy is more than just the sum of its parts, i.e., the technologies and their bilateral interrelations.

The convergence of IoT, AI, and BC technology is the main driver of the machine economy. It enables machines to become self-determined autonomous actors in innovative and value-adding processes. Based on their individual characteristics and potential, all three technologies make a specific contribution to the success of the machine economy. IoT connects physical objects with each other and with the Internet. Thus, additional information is made accessible in processes, such as sensor data, and new options for action are enabled through the objects' physical representation. With its diverse methods and applications, AI uses this additional information to dynamically design and adapt processes while also learning from them over time. This results in possibilities for self-regulation and -optimization of machines to achieve higher autonomy levels. Finally, interactions between machines are empowered and secured by BC technology in a decentralized, traceable way and without an intermediary. Thus, BC technology strengthens the confidence in autonomous process flows of the machine economy. We summarize the technologies' roles within the machine economy as “actor” (IoT), “action” (AI), and “interaction” (BC).

The three technologies' interaction offers great potential for practical application, as our three illustrative application scenarios indicate. However, the machine economy also implies significant changes for companies' approaches to value creation, which leads to a multitude of challenges. For organizational decision-makers, it is no longer sufficient to analyze digital technologies separately or their interaction with the existing IT infrastructure in isolated use cases. Instead, digital technologies' convergence in the machine economy creates entirely new application possibilities. Companies must think beyond existing innovation approaches, taking a holistic perspective to understand and manage technologies. Consequently, new ways of performing technology and knowledge management must be developed that provide a foundation for companies to shape the machine economy effectively. Thus, we encourage research to study the new required governance structures, processes, knowledge, and skills. We see various future research opportunities in application- and business-oriented research domains. In addition, design and engineering-oriented research should further extend our understanding of each underlying technology.

Considering our conceptual research approach, this paper is not without limitations. First, our conceptual model abstracts the machine economy as a single system. In manifestations of the machine economy, sub-systems will likely emerge that focus on specialized tasks. For example, a machine economy system could be solely responsible for harvesting crops in certain regions. Various of these autonomous SAS could work together and organize in a superordinate system. Thus, we see the incorporation of system networks, i.e., systems-of-systems, as a fruitful way to extend our model. Second, we provide three application examples of how the concept of the machine economy works. However, we base our examples in part on thought experiments. Thus, future research may follow design-oriented approaches to prove the feasibility of the examples or even capture empirical data of existing applications.

Summarizing, the machine economy is a highly promising concept providing a wide range of opportunities to add value to organizations. We think of our work as a foundation to better understand its constituting elements and their interrelations that may catalyze future research and theorizing in this field.

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