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AI meets Digital: A Critical Review on Artificial Intelligence in Digital Entrepreneurship

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AI MEETS DIGITAL: A CRITICAL REVIEW ON ARTIFICIAL INTELLIGENCE IN DIGITAL ENTREPRENEURSHIP

Research Paper

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Abstract

Driven by a reduction in the cost of data generation and computing power and simultaneous advancement of mathematical methods, algorithms are becoming increasingly capable of mimicking human learning, profound judgment, and decision-making, even outperforming humans in doing so. This recent emergence of artificial intelligence (AI) seems to not only change the way how entrepreneurial endeavors operate but also the way how they emerge. In general, digital technologies are prone to render the processes and outcomes behind entrepreneurial endeavors less bounded and the locus of an entrepreneurial agency less predefined. Addressing the role of AI in this is only nascent so far. We thus suggest it is time to perform a critical review of the literature at the intersection of AI and digital entrepreneurship. Our investigation adopts a socio-technical lens to capture the state of the AI entrepreneurship literature and identify promising research avenues to trigger further discussions.

Keywords: Artificial Intelligence, AI, Digital Entrepreneurship, Entrepreneurial Endeavors.

1 Introduction

Artificial intelligence (AI) is about to bring fundamental changes to our society and economy by influencing how ventures evaluate opportunities, make decisions, and deliver services (Buxmann et al., 2021). As digital technology, AI transforms the nature and scope of entrepreneurial activity (Nambisan, 2017). The changes triggered by AI are different from those elicited by other traditional information technologies, as it develops new ways to collect and process large amounts of information (Haefner et al., 2021). Recent advances in AI enable technical systems to process large unstructured data sets using complex, adaptive algorithms to perform tasks that usually require human intelligence (Choudhury et al., 2020). The new generation of intelligent systems can learn, adapt, act autonomously, and recognize the need for action without being prompted by users – and, increasingly, without their understanding remaining inscrutable to them (Baird & Maruping, 2021). Thus, AI turns out to be not only a method for achieving cost and productivity benefits but also into innovation for the tools we use to innovate (Chalmers et al., 2020).

Current AI technologies such as robots, autonomous vehicles, facial recognition, natural language processing, and virtual agents of all kinds are being used in a wide range of problem domains (Berente et al., 2021). Disruptive phenomena such as AI and related waves of technological change create a plethora of new opportunities (Kondratieff & Stolper, 1935; Steininger, 2019). AI applications are expected to be innovation drivers for at least five to ten years (Goasduff, 2021). These new technologies, however, do not necessarily generate economic value on their own; rather, they must be harnessed and exploited. “Entrepreneurs are at the forefront as change-agents” (Steininger, 2019, p. 364), working to discover, actualize, and exploit these new opportunities. Prior research highlights the individual-opportunity nexus, suggesting that the nature and characteristics of technology opportunities can be critical factors in triggering entrepreneurial endeavors (von Briel, Davidsson, et al., 2018). Entrepreneurship research has partially ignored the impact of digital technologies, as well as the role that users and agents play in digital entrepreneurship (Nambisan, 2017).

Digital entrepreneurship concerns the "creation of new economic activities embodied in or enabled by digital technologies" (von Briel et al., 2021, p. 51). Thereby, entrepreneurial endeavors regularly undergo radical reconfigurations afforded by digital technologies. Due to their editability, recombinability, and distributivity, digital technologies render the processes and outcomes of entrepreneurial endeavors less bounded and the locus of an entrepreneurial agency less predefined (Nambisan, 2017). Tesla, for example, is integrating fully-fledged features such as autopilot into the vehicle after it has been delivered (Verganti et al., 2020). As the next step of computational advancements, AI excels by autonomy, learning, and inscrutability (Berente et al., 2021). Since these are unique characteristics, AI is about to afford another wave of reconfigurations.

Research increasingly addresses the nexus of AI and digital entrepreneurship (e.g., May et al., 2020; Trocin et al., 2021). Given the momentum, research approaches this topic from various perspectives (e.g., Chalmers et al., 2020; Townsend & Hunt, 2019). Most articles, however, tend to take an arrow-like view on AI in digital entrepreneurship. It impedes structured subsumption of recent contributions in the intersection of AI and digital entrepreneurship. Further conceptual understanding is required to describe the nature and characteristics of entrepreneurial endeavors enabled by the new socio-technical paradigm. Entrepreneurial endeavors here encompass any entrepreneurial pursuit of opportunities (Shepherd et al., 2019), including forming entrepreneurial firms, intra-entrepreneurial ventures, and social movements (von Briel et al., 2021). As such, it requires further classification of what role specific aspects of AI play "in shaping entrepreneurial opportunities, decisions, actions, and outcomes" (Nambisan, 2017, p. 1030). As a first step towards addressing this issue, we aim to understand current research on AI in digital entrepreneurship. Hence, we pose the following research questions (RQs):

RQ1*: What is the current state of research on AI in digital entrepreneurship?*

RQ2*: What are potential future directions for studying AI in digital entrepreneurship research?*

To capture the current state of AI-related digital entrepreneurship research and guide future research in that area, we conduct a critical review of the literature at the intersection of AI and digital entrepreneurship. We seek to identify key themes that are useful to interpret AI-leveraging entrepreneurial endeavors as complex socio-technical systems (as defined by Nambisan et al., 2020) that reconcile technology-based opportunities and entrepreneurial agents' actions. Thereby, we open three research avenues. In doing so, our critical review integrates and extends recent reviews and commentaries on the AI-entrepreneurship intersection (e.g., Chalmers et al., 2020). The two review articles included in our sample have opposing perspectives, focusing on the social system (innovation management; Haefner et al., 2021) or the technical system (big data analytics; Mikalef et al., 2020). Finally, reviews on digital entrepreneurship (e.g., Kraus et al., 2018; Steininger, 2019; Zaheer et al., 2019) are only of limited help in understanding the intersection because they do not feature the particularities of AI.

In what follows, we briefly chart AI towards a digital entrepreneurship perspective and situate it within the context of socio-technical systems. Next, we explain our adoption of a critical literature review and acknowledge its limitations. After collecting studies in the AI-entrepreneurship intersection and assessing their relevance and quality, the remaining manuscripts are analyzed and synthesized based on three key themes identified – agency, processes, and outcomes. We develop a research plan based on the synthesis, identifying fruitful areas for future research.

2 Conceptual Background

2.1 Artificial Intelligence

Artificial intelligence (AI) has a history longer than is commonly recognized, dating back to ancient Greece (Collins et al., 2021). Our modern technical understanding can be traced back to the Analytical

Engine, developed in the 1830s by Ada Lovelace and Charles Babbage. Lovelace conceptualized what is regarded as the first operating program to compute Bernoulli numbers on Babbage's machine, creating a blueprint for modern AI and machine learning systems (Chalmers et al., 2020). The central iteration on this owes much to Alan Turing (1950) and the 1956 conference at Dartmouth College (McCorduck, 2004), where the term "artificial intelligence" was officially coined by John McCarthy at the time and defined as "the science and technology of making intelligent machines". In the 1950s, early advances in AI research coincided with advances in the fields of computer science and cognitive science. Pioneers such as Herbert Simon, Alan Newell, and Marvin Minsky pursued Turing’s goal to create a machine that could mimic intelligent behavior on par with humans. Turing's ambition is still maintained in the form of the Turing Test, in which programmers strive to develop an AI that passes this "imitation game" (von Krogh et al., 2021).

Although many promises were made regarding its practical usefulness, AI failed to deliver and the research field faded in the 1960s and 1970s. Starting in the 1980s, however, the public and private sectors began to invest significantly in research on expert systems, which renewed interest in AI. It was further stimulated by spectacular events such as IBM's computer software "Deep Blue" winning a chess game against grandmaster Garry Kasparov in 1997 (von Krogh, 2018). Finally, the current surge of contemporary AI is powered by three factors (von Krogh, 2018). First, the digitalization of everyday life and business has created ubiquitous data sets to feed AI algorithms. Second, the cost of the computation to perform AI has decreased significantly. Computer hardware and AI-specific chip designs are becoming more affordable and cloud-based services offer an increasing number of AI-specific functions and services. Third, significant advances in the science and technology underlying AI methods (e.g., recurrent and convolutional neural networks) complemented and fueled the previous two factors, leading to a rapidly emerging phenomenon of economic and societal significance.

Despite the long existence of the field, there is no universally accepted definition of AI. The reason for that may be twofold. First, given the breadth of discussion around AI, it may not be possible to expect AI to have a fixed definition yet (Collins et al., 2021). Second, AI may not be a technology or set of technologies but a continually evolving frontier of emerging computing capabilities (Berente et al., 2021) – “[o]nce in use, successful AI systems were simply considered valuable automatic helpers” (McCorduck, 2004, p. 453). AI that is indistinguishable from human behavior or capable of simulating human reasoning is sometimes referred to as “strong AI”. In contrast, computer-assisted systems performing simple tasks that were traditionally performed by humans, such as recognizing images, or processing natural language, are often termed “weak AI” (Iansiti & Lakhani, 2020). Building on that, we follow the notion of “narrow AI” which is the most common form of AI today. Narrow AI handles a singular task in a narrow context (Stone et al., 2016). Thus, we define AI as “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Haenlein & Kaplan, 2019, p. 17). As this, AI can be characterized as a collection of computational systems capable of performing non-trivial tasks traditionally reserved for human intelligence (von Krogh, 2018). AI systems comprise three components: (1) task processes (algorithms), (2) task input (data), and (3) task output (decisions or solutions). In the following, we refer to digital artifacts that contain AI as AI-enabled systems (Rzepka & Berger, 2018), which are the building blocks of digital ventures (von Briel, Recker, et al., 2018).

2.2 Digital Entrepreneurship

The entrepreneurship literature reveals that entrepreneurship consists of two phenomena: the emergence of an opportunity and the agency of an entrepreneurial actor (Shane & Venkataraman, 2000). The infusion of digital technologies into entrepreneurship alters both phenomena by making the processes and outcomes underlying entrepreneurial opportunities less bounded and the locus of an entrepreneurial agency less predefined (Nambisan, 2017).

First, in terms of processes, this implies that digital technologies change the way entrepreneurial endeavors innovate (e.g., develop new products and services). For example, by integrating heterogeneous knowledge sources and spawning a slew of digital tools and infrastructures (e.g., 3D printing or cloud computing; Yoo et al., 2012), digital technologies can initiate entirely new forms of innovation in terms of processes and organizational routines that would not be possible without digital technologies (e.g., eBook reader; Nambisan et al., 2017; von Briel et al., 2018).

Second, the inclusion of digital technologies necessitates a focus not only on processes but also on products and services (Yoo et al., 2010). Digital technologies fundamentally embody, enable, or reshape entrepreneurial outcomes (Nambisan, 2017; Yoo et al., 2010). For example, Andersen and Ingram Bogusz (2019), focusing on Bitcoin-based entrepreneurial endeavors, observe that entrepreneurs are forcing existing blockchain software code to create new market offerings such as Bitcoin XT and Ethereum. The novelty of these market offerings and their divergence from existing software code can range from simple customizations (i.e., development forking) to radical divergences and spin-offs into separate technologies (i.e., hard forking).

Third, until now, entrepreneurial processes and outcomes are largely treated as separate units of analysis, focusing on one or the other (process or outcome) while ignoring the interactions between the two (Nambisan et al., 2017). However, as digital technologies are incorporated into entrepreneurial processes and outcomes, these interdependencies become more complex and dynamic, potentially leading to unintended consequences. Digital technologies, for example, can cause a shift in innovation focus, which affects entrepreneurial outcomes (Nambisan et al., 2017). Dougherty and Dunne (2012) demonstrate how digital technologies can transform the drug discovery process by creating new forms of knowledge (e.g., bioinformatics or genomics) that enable product innovators to manage complex innovations more effectively. Thus, to explore the role of digital technologies, processes, and outcomes, as well as their blending, must be considered (Nambisan et al., 2017).

With the rise of digital technologies, the locus of entrepreneurial action disperses among a constantly evolving group of actors with varying goals and motivations (Aldrich, 2014; Nambisan, 2017). First, distributed entrepreneurial agency alters the way entrepreneurial activities are conducted and poses new challenges for coordination and decision making. For example, entrepreneurs use crowdsourcing to track their entrepreneurial efforts. Crowdsourcing as a type of digital technology-enabled phenomenon thus facilitates the distribution of entrepreneurial action among many actors while also posing new coordination, communication, and collaboration challenges. Second, research assumes relatively stable product and service boundaries underpinning entrepreneurial opportunities (Davidsson, 2015; Nambisan, 2017). However, most digital products and services today remain intentionally incomplete and can be extended or modified even after the product has been delivered (Lyytinen et al., 2016; Yoo et al., 2010). These products and services have fluid and extensible boundaries and are constantly evolving (Kallinikos et al., 2013). This, in turn, leads to a level of generativity (Yoo et al., 2010; Zittrain, 2005) which directs entrepreneurial activity toward the development of products and services that enable continuous evolution (Nambisan, 2017). Consider Tesla's cars once more, where new features are introduced even after the vehicles have been delivered (Verganti et al., 2020).

In conclusion, digital entrepreneurship is effectual in terms of both processes and outcomes (Lehmann & Rosenkranz, 2017): by introducing digital technologies into entrepreneurship, entrepreneurial processes become more fluid and porous, and entrepreneurial outcomes become increasingly malleable, extensible, and modifiable.

2.3 AI in Digital Entrepreneurship – A Socio-Technical Perspective

Digital artifacts are widely associated with traditional technical systems, separating technology and social actors (Boell & Cecez-Kecmanovic, 2015). In this view, digital artifacts are representations of an external domain or universe of discourse that reveal the state of the "real world" to the user (Recker et al., 2019). This understanding reaches its boundaries as we carry out activities online and digital technologies increasingly mediate our experiences. This new environment shapes the "digital first" era (Baskerville et al., 2020), with digital realms increasingly shaping the physical world rather than the other way around. Digital first requires an "ontological reversal" (Baskerville et al., 2020) and a reconsideration of the relationships between the digital, the material, and the social (Eriksson & Ågerfalk, 2022; Yoo et al., 2010; Zammuto et al., 2007).

The new generation of "machine learning technologies that are at the core of contemporary AI have greater autonomy, deeper learning capacity, and are more inscrutable than any of the 'intelligent' [digital] artifacts that have come before" (Berente et al., 2021, p. 1433). AI-enabled systems "are aware of the need to act without being prompted by users. [The agentic systems] can now assume tasks that involve a higher degree of uncertainty in unstructured and dynamic situations where interactions with the environment and other agents involve significant dependencies" (Baird & Maruping 2021, p. 316). Email clients offer writing suggestions (Buschek et al., 2021), navigation systems guide driving behavior (Harms et al., 2021), and algorithms propose potential drug candidates (Lou & Wu, 2021). This paradigm shift highlights the need to understand the new forms of a socio-technical system consisting of humans, entrepreneurial endeavors, and intelligent artifacts, where the primacy of the agent is unclear or fluid.

In the intersection of entrepreneurial endeavors and intelligent artifacts, the socio-technical system faces "three related, interdependent facets of AI – autonomy, learning, and inscrutability" (Berente et al., 2021, p. 1433). (1) Autonomy refers to the ability of contemporary AI to act increasingly without human intervention (Baird & Maruping, 2021). AI makes autonomous decisions and acts in the world in ways that have material consequences – often not only without human intervention but also without human knowledge (Berente et al., 2021; Murray et al., 2021). (2) Learning describes a system's ability to automatically improve based on data and experience. Based on the availability of large data sets, advances in deep or reinforced learning have enabled AI to proceed into more complex decision-making processes, including those involving audio and object recognition or natural language processing (Berente et al., 2021). (3) Inscrutability refers to AI being incomprehensible to certain audiences. With advances in autonomy and learning, modern AI increasingly can produce algorithmic models and results that are understandable only to a select audience while remaining opaque to others or, in some cases, not understandable at all to humans (Berente et al., 2021).

In summary, AI is not – unlike traditional digital artifacts – a mere representation of external reality, but a system that partakes in that very reality and exhibits (digital) agency (Baskerville et al., 2020). Appropriating AI, digital technologies are endowed with agency. As AI shifts from tool to agent, it alters the interaction between itself and its human counterparts (Schuetz & Venkatesh, 2020), ushering in a new generation of socio-technical systems. This situation calls for a closer look at the AI component in digital entrepreneurship, that is, the specific agency, processes, and outcomes enabled by AI. Our review, which adheres to established guidelines for conducting literature reviews

3 Methodology

Our literature review aims to develop an understanding of the current body of knowledge on the nature and characteristics of AI in digital entrepreneurship – the intersection of digital technologies and entrepreneurship. Our review is critical as we intend to "critically analyze the extant literature on a broad topic to reveal weaknesses, contradictions, controversies, or inconsistencies" (Paré et al., 2015, p. 189). We choose a critical review to identify thematic gaps and weaknesses in the discourse that require further research attention and provide future research directions. Unlike a systematic review, which seeks to integrate existing work, our review compares findings to a set of criteria – AI-induced agency, processes, and outcomes. Further, our sample does not cover all relevant literature but focuses on a representative set of articles (Paré et al., 2015). Our review, which adheres to established guidelines for conducting literature reviews (vom Brocke et al., 2009, 2015; Webster & Watson, 2002), covers relevant publications in peer-reviewed journals and conferences without claiming exhaustiveness.

Search Process

Our review topic is an area of interdisciplinary research (entrepreneurship and information systems). As a result, we chose the databases Scopus (SD), EBSCOhost (EB) AISeLibrary (AIS), Emerald (EM). We used the keywords "entre*" or "ventur*", which have been proven successful for reviews on digital entrepreneurship (Berger et al., 2019; Kraus et al., 2018). Likewise, for AI, we used the terms "AI", "artificial intelligence", "ML", and "machine learning" (applied by Collins et al., 2021; Enholm et al., 2021). We are aware that the keywords chosen do not cover the entire body of AI literature. Since the concept and methodologies of AI have been in constant flux in recent years, and there is still no unified definition for many areas, we have decided to start with search terms that indisputably yield research literature on AI. Combining these two terms yielded in search strings such as "artificial intelligence" OR "AI" AND "entrepr*" OR "ventur*". Search strings were entered into the databases to search within the title, abstract, and keywords. To ensure the quality of the articles, we only searched the databases for peer-reviewed articles.

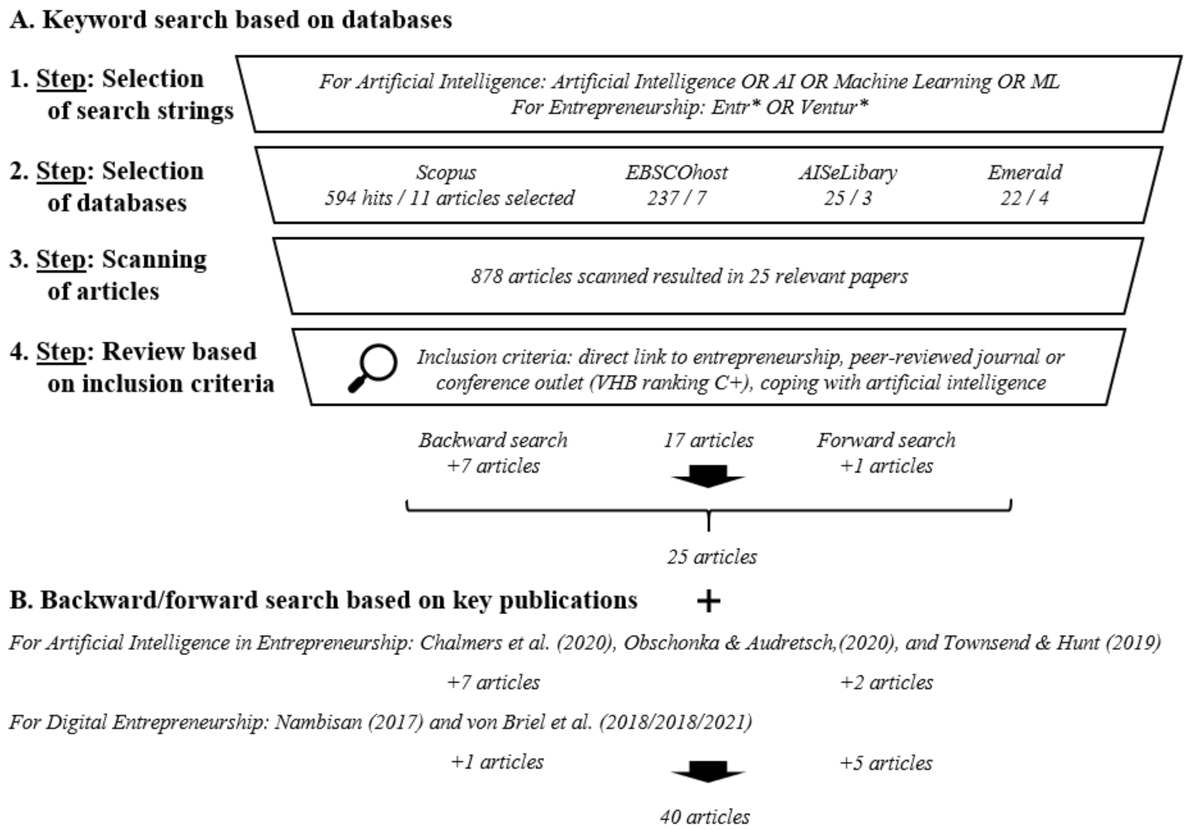

Figure 1. Overview of the literature review process.

Scopus yielded 594 results, which we reviewed based on screening the abstract. This resulted in the selection of 11 papers. In terms of the selection criteria at this stage, papers had to be in English, required a connection to both AI and entrepreneurship as well as passed the quality threshold established by Bouncken et al. (2015). Following the authors' recommendations to ensure article quality, we only used articles ranked "C" or higher in the German VHB Jourqual, with a JCR Impact Factor of greater than or equal to 0.7, or corresponding ABS ranking. Whenever we were unsure, we briefly reviewed the paper by reading the abstract and searching for the keywords within the paper. We then searched the databases EB (237 hits/7 articles selected), AIS (25/3), and EM (22/4). Based on 878 initial hits, this resulted in a total of 25 articles. From the 25 articles, we moved on to the second stage of screening, in which we assessed all articles. In terms of inclusion criteria, we checked if the paper had a clear connection to entrepreneurship and was explicitly discussing AI-related technologies. As part of the full-text assessment, we checked if the paper met the quality threshold outlined before. Regarding our exclusion criteria, we removed all articles that focused solely on entrepreneurship or AI, and that referred to our phenomenon in a non-socio-technical context. This resulted in 17 articles being retained. A forward and backward search of our sample added seven more articles, yielding a final set of 25 papers based on the keyword search.

In addition, we followed the recommendations of Webster and Watson (2002) by performing a backward/forward search based on the major contributions in the fields of AI and digital entrepreneurship. In the intersection of AI and entrepreneurship, the contributions of Chalmers et al. (2020), Obschonka and Audretsch (2020), and Townsend and Hunt (2019) were considered separately from the results by the keyword search, which also included them. Across the three articles, nine additional articles were included (7 backward / 2 forward). For digital entrepreneurship, the articles by Nambisan (2017) and von Briel et al. (2018; 2021; 2018) were considered key publications in the information systems domain. We came across six additional articles via these contributions (1 backward / 5 forward). Thus, we considered 40 articles in total in the following analysis. Figure 1 summarizes our process.

Analysis

We subjected the 40 articles to our analysis, creating a spreadsheet with key information about the articles (author, title, issue, year, and research design). As noted in section 2.3, we focused on AI-related agency, processes, and outcomes to clarify the current state of knowledge on AI in entrepreneurship. The coding process was inductive and iterative, yielding conclusive constructs for the categories. In contrast to deductive, a priori coding, the inductive approach focuses on a broader research question and draws codes from available data (Kuckartz, 2018). Two main coding steps were conducted: (i) we first coded along three perspectives (agency, processes, and outcomes) derived from a grouping of the digital entrepreneurship literature. Subsequently, (ii) we focused on the 27 articles from the above process perspective that we coded then along four new dimensions (activities in prospecting, developing, scaling, and exploiting). They form the basis of our subsequent analysis.

4 Results

Overall, our review followed three research perspectives to investigate the intersection of AI and digital entrepreneurship: agency, processes, and outcomes. We classify the majority of the articles to the process perspective (27), followed by the agency (22) and the outcome (19) perspectives. We also discover a subset of articles (4) on a meta-level that elaborate on AI to develop a more nuanced picture of AI in entrepreneurship and information systems research, as well as its theoretical foundations, supporting the rationale for conducting this review. As the articles we consider, take more than one research perspective on the role of AI in entrepreneurial endeavors, we visualize this overlap using a Venn diagram. Figure 2 depicts how many articles can be assigned to the distinct perspectives and their overlap. In the following subsections, we elaborate on the perspectives in further detail.

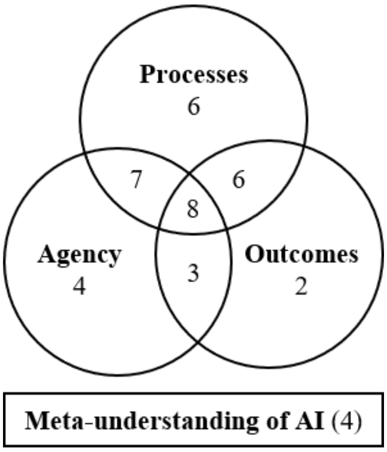

Figure 2. Overlap of digital entrepreneurship key themes in AI-related articles.

4.1 Artificial Intelligence and Entrepreneurial Agency

Reflecting on AI in terms of an entrepreneurial agency, we identify two facets of agency that we consider inside and outside the entrepreneurial endeavor. It is critical to keep in mind that agency refers to the locus of the ability to gather entrepreneurial ideas and the resources to develop them (Nambisan et al., 2017). In that vein, we go over how to generate and collect entrepreneurial ideas before moving on to where to find the resources to develop them.

First, a substream in literature focuses on the generativity of AI (e.g., Rai et al., 2019; Townsend & Hunt, 2019). The concept of generativity roots in psychology (Nambisan et al., 2019). Generativity represents combinatorial skills or the cognitive process of conceptual integration, where generativity results in consequences that are not always linear or predictable from inputs (Turner & Fauconnier, 1999). Following these ideas, Zittrain (2005) considers the inherent generativity of the internet (and related technologies) as technological generativity which he defines as "overall capacity to produce unprompted change driven by large, varied, and uncoordinated audiences" (p. 1980). The openness, editability, and re-combinability (Kallinikos et al., 2013) make digital technologies particularly suitable for generative processes (Nambisan et al., 2019). Technological generativity can spark creative or entrepreneurial endeavors as well as lead to security and privacy threats (Zittrain, 2005, 2008).

Building on the notion of cognitive generativity, Amabile (2019) reflects on the generativity of AI as "the production of highly novel, yet appropriate, ideas, problem solutions, or other outputs by autonomous machines" (p. 3). She assumes that the best results are to be achieved by computer-based human intelligence. However, the question of whether and under which conditions the creative process of entrepreneurs is inhibited or promoted by their affective and motivational reactions to innovative ideas from machines remains an open one. Continuing on from here, in a large-scale study of biopharma companies, Lou and Wu (2021) show how AI supports drug discovery, as the technology can facilitate recombination for certain types of drug candidates. In doing so, they note that the main impact of the AI agency comes from the interaction with collaborators who have a combination of AI skills and drug discovery expertise. The authors state that this combination is critical because developing and improving AI tools is an iterative process that requires input from both AI and subject matter experts to be synthesized. However, AI is less helpful in developing drugs for which no therapy yet exists. AI is also less helpful for drugs that are either completely new or incremental follow-on products.

In their conceptual work, Townshend and Hunt (2019) elaborate on AI's influence on creativity as the next step to generativity. Boden (1998) provides an early overview of the state of the art in AI creativity research, in which she identified three main types of creativity that are relevant in generating novel ideas: novelty through combinations of known ideas, exploratory creativity, which creates novelty by exploring structured conceptual spaces to find unexpected solutions, and transformational creativity, which produces novelty by changing specific structures or constraints of the decision environment. Consistent with this, Townshend and Hunt (2019) describe the case of Insilico Medicine, a startup company. Insilico's research estimates that there are 1030 potential drug-like therapeutic molecules, a vast possibility space of new drug candidates, only a tiny fraction of these is explored through established drug discovery processes. Insilico uses generative adverse networks that combine a set of generative algorithms to identify potential new therapeutics with various "adversarial" algorithmic filters to eliminate candidates that do not meet certain criteria. The startup evaluates these drug candidates with predictive algorithms to determine the likelihood that these drug candidates could successfully move through the clinical trial process. Further, Griebel et al. (2020) demonstrate with a design approach how different AI algorithms can contribute to divergent and convergent thinking in creative processes. For this purpose, they demonstrate how fashion designers can be supported in the divergent thinking of idea generation by developing a large number of possible designs and in the convergent thinking of idea selection by generative learning. This sequence is also classified as abduction reasoning (Garbuio & Lin, 2019).

The second substream in literature deals with the resources required to start an AI endeavor and how they are distributed (e.g., Paschen et al., 2020). There are three pillars of AI systems, including domain structure, data generation, and universal machine learning (Taddy, 2018). The first of these, domain structure, refers to the expertise required to develop tasks (i.e., an understanding of a problem and context such as the rules of the game of chess); the second is data generation which refers to the datasets required to train an AI system and the approach used to generate ongoing data to feed the learning algorithms; finally, machine learning, the "engine" of an AI system, works to recognize patterns and make predictions from the unstructured data (Chalmers et al., 2020). While most AI systems share the same overarching goals – learning and making predictions in a way that is appropriate for their environment – there are significant differences in how systems operate and the tools or combinations of tools used to provide machines with intelligence (Chalmers et al., 2020). However, AI's learning capability is based on data and the data used influences its agency. Consider Netflix a case in point. A key aspect of the platform is its capacity to make movie suggestions adapted to user preferences. By selecting a movie, users further optimize the algorithm according to their needs leading to a data-based problem-solving loop with its agency (Verganti et al., 2020). Moreover, AI combined with other digital technologies can reshape existing contexts or create new ones. It is done, for example, by opening up traditional industries to new economic activities from the outside (von Briel et al., 2021). Rothe et al. (2019) show that advances in genome sequencing technology have led to extensive open genome data, with the result that various biodata companies use this data in new ways to solve customer problems. In doing so, biodata companies contextualize, decontextualize, or recontextualize open genome data by using AI frameworks to capture value.

4.2 Artificial Intelligence and Entrepreneurial Processes

We now turn to the entrepreneurial endeavor activities as "new innovation playbook" (Cockburn et al., 2018) in terms of processes and explore prospecting, developing, scaling, and exploiting activities (Bakker & Shepherd, 2017; Chalmers et al., 2020) leveraged by AI.

First, literature that addresses the prospecting phase of entrepreneurial endeavors focuses on the activities of idea generation and evaluation. It is a materialization of entrepreneurial agency in terms of processes. Thus, there is a wide intersection with the agency infused by AI. Independently of new venture creation, idea exploration includes big data analytics (Lehrer et al., 2018; Mikalef et al., 2020). In a multi-case study, Kakatkar et al. (2020) show how different AI applications are used to explore the problem and solution space of entrepreneurial endeavors. They describe how a personal care product manufacturer uses a supervised neural network and unsupervised topic modeling with linear discriminant analysis (LDA) to identify and cluster consumer needs based on posts from online forums. Next, the authors illustrate how a semiconductor chip manufacturer detects problems in chip design by using unsupervised clustering and a combination of LDA and supervised learning to identify influencing factors and create a shortlist of problems. Another case shows how a team uses a web crawler and unsupervised learning to explore potential solutions to a problem that arose on crowdfunding platforms. Last, the authors show how a food campaign develops a new candy bar using LDA and supervised learning based on a random forest model to infer latent features in textual descriptions of the bars and relate them to ratings obtained through a crowdsourced evaluation project of different bars.

Second, once a promising AI-based business idea has been identified, it requires implementation. During the development phase, various AI-specific challenges arise. May et al. (2020), for example, report in a single in-depth case study how a medical imaging AI venture that develops a computer-aided detection application for diagnostic mammography copes with AI-caused tensions. Tensions arise from over-expectations of the AI solution's rapid benefits versus the actual development effort. The radiologists' workflow requires redesign so that they can reap the benefits of the AI features. Fountaine et al.'s (2019) survey, in which several thousand managers provide information about how their companies use and organize for AI, supports this stance. They find that only eight percent of firms implement AI in core practices, while tentative single business process application prevails. Besides, it requires creating acceptance and trust for the solution. Moreover, it calls for the integration of domain expertise. AI adds little value if the AI-creating endeavor lacks contextual knowledge. Further, Leone et al. (2021) emphasize the importance of co-creation for successful AI implementation in healthcare. This entails iterative collaboration with healthcare facilities as paying customers and iterative development with patients to improve operations and care through user knowledge.

Third, scaling AI endeavors is not trivial. Utilizing a quantitative framework, Schulte-Althoff et al. (2021) indicate based on Crunchbase data that the scaling behavior of AI ventures shares some features with service and some features with platform ventures. Uncertain business case implementation, a lack of leadership support, and limited technology capabilities are all barriers to creating value with AI technologies. There is a need for talent, data access, and the ability to leverage the value of AI applications. The cost of using cloud infrastructure rises dramatically as the user base expands. Further-more, due to a lack of data quality and specifications, the initial setup of AI models proves difficult. Current observations paint the picture that AI startups must invest a significant amount of time within the first two years to optimize their AI models and collect relevant data (Gregory et al., 2021), effectively making their growth rate more akin to that of a traditional service company rather than a platform or software company that can rely more heavily on existing ready-to-use frameworks. For example, many AI ventures in digital health focus on service business models before developing a more scalable approach (Witte et al., 2020); in e-commerce, they apply AI capabilities to steer network effects (Rai et al., 2019); and in manufacturing, they enable incumbent firms to improve value creation, delivery, and capture (Burström et al., 2021). Further, Sjödin et al. (2021) underline the importance of feedback loops for scaling in terms of the data pipeline, algorithm development, and AI democratization. To capitalize on the opportunities, ventures must be diligent about considering co-creation for adoption, building data-driven delivery processes, and envisioning scalable integration into the ecosystem. This goes hand in hand with an agile culture and a strong desire to learn, as well as efforts to build and improve sales capabilities (Griva et al., 2021).

Fourth, AI opens unique possibilities for opportunity exploitation but also challenges. Given the challenges that sales pose to as-yet-undiscovered entrepreneurial endeavors AI-assisted automation of sales activities is a promising area of research (Davenport et al., 2020). Applications range from offering tools that augment existing sales processes to free up time for higher-value customer-facing tasks (e.g., exceed.ai) to applications that completely replace human salespeople (e.g., Drift). In the fintech/proptech sector, for example, the startup Habito has developed a robo-advisor capable of capturing the complex information required to identify, match, and qualify a variety of mortgage products for customers. Other companies, such as Drift, are using AI techniques to analyze top salespeople to train machine learning systems that can replicate their performance on a larger scale within a company (Chalmers et al., 2020). As Power (2017) notes, these emerging conversational AI systems easily pass the Turing test, meaning that customers who interact with them are largely unaware that they are dealing with a machine.

Experiences with AI applications that have a specific scope encounter this. It can also be hard to communicate the value proposition to users in the medical field, which has a long history of decision support systems, particularly radiology (May et al., 2020). It is necessary to emphasize how AI systems differ from existing ones and address pre-existing reservations. It is critical for AI applications, in general, to consider how AI creates value, not only in terms of the value derived directly from the AI function itself but also in terms of how the function is communicated to the user. Does the presence of AI need to be pointed out at all? It implies that it is hard to build an off-the-shelf AI as a service suitable for every business sector application. Without significant customization, most of these solutions are inefficient. Customization, integration with the customer's alongside internal systems, and adaptation, however, are frequently required and demand dedicated effort. In many cases, retraining of the model is also needed to enrich the pre-built model and make it more relevant to the application at hand. It makes exhausting the possibilities much more difficult.

4.3 Artificial Intelligence and Entrepreneurial Outcomes

With the previous elaboration on entrepreneurial agency and activities, it is necessary to investigate what outcomes AI-enabled entrepreneurship may gain or how AI impacts entrepreneurial outcomes. In this regard, AI and outcomes can play different roles.

A first perspective considers the unique materiality of AI that entrepreneurial efforts create as the foundation of their value propositions (von Briel, Recker, et al., 2018). The introduction of AI into traditional products and services has opened extensive opportunities for entrepreneurs to create new value propositions. For example, AI enables digital products or services to adjust to the interests and needs of users. It promises a better user experience and greater market penetration because companies can adapt to different customer groups. Consider the cases of Netflix and Uber. Using stylized facts, Verganti et al. (2020) show how Netflix's movie suggestions are customized to the users' preferences. Each user sees individualized landing pages – that become even more customized to their preferences through user behavior by feeding their data to an AI. Kiron and Schrage (2019) describe how Uber runs a large variety of AI models to optimize its ride-sharing platform and food-delivery business and balance supply and demand. Countering this thesis, May et al. (2020) argue that narrow AI systems are highly specific. The intention to automate a certain task to achieve efficiency gains and to free resources results in high specificity. Increasing the capability of an AI requires, on the one hand, user trust and acceptance and, on the other hand, contextual knowledge about the data so that the algorithm achieves adequate performance, i.e., accuracy. Domain knowledge is crucial for both. Thus, AI – as a general-purpose technology with low specificity – triggers various new venture ideas and innovations (Ciriello et al., 2018). As the startup process matures and development activities take precedence, the need for specificity increases.

Second, another perspective addresses outcomes as enablers or contexts for other entrepreneurial endeavors. For example, in a multiple case study of Scandinavian organizations providing human resource services, Trocin et al. (2021) show how the materialization of AI-based digital process innovations provides the context for digital service innovation affordances. In terms of process, AI is used to collect and analyze information about the privacy-compliant suitability of job candidates. In the second step, this information, in turn, forms the basis for developing targeted recommendations for specific categories of online users. Companies can combine the patterns of online users' interests with potential online services such as job ads based on the previously collected information. Further, AI can reshape existing contexts or create new ones. Rothe et al. (2019) show that advances in genome sequencing technology led to extensive open genome data, which, in turn, encouraged the formation of biodata companies that use this data in new ways to solve customer problems.

Finally, one perspective focuses on the social, economic, and environmental outcomes of the entrepreneurial actions that are enabled by AI. Much noted is Zuboff's (2019) work on surveillance capitalism. Corporations are invading privacy with AI and other technologies to profit from the ever-growing body of data that each of us generates daily. This has resulted in significant profits for founders and venture capitalists who have successfully extracted value from data resources. But it has also resulted in numerous corporate scandals involving systematic misuse of personal data (Chalmers et al., 2020; Isaak & Hanna, 2018). Critics further claim that an oligopoly of centralized megacorporations currently dominates AI. In contrast, there is a general demand for AI services for enterprises and a lack of visibility for independent developers. Because of a fragmented development landscape, specific AI applications, and a lack of application interoperability, Montes and Goertzel (2019) advocate for a distributed, decentralized, and democratized market for AI-based on distributed ledger technology. Using SingularityNET as an example, the authors aim to show how the decentralization of AI can open the doors for the more equitable development of AI. “SingularityNET is a platform for an open AI marketplace in which buyers and sellers exchange AI services via distributed ledger technology (DLT) and AI agents transact with each other” (p. 355). Through open-source frameworks, the platform aims to help build a new socio-economic engine, connect advances in AI with goodwill, and become a common. This viewpoint includes social entrepreneurship projects such as OpenAI Inc., which is co-founded by Elon Musk and motivated not only by the possibilities of AI but also by the potentially existential risks it poses to humanity (Obschonka & Audretsch, 2020). How much social good is behind it, however, remains unclear.

5 Research Avenues: AI in Digital Entrepreneurship

As both digital entrepreneurship and AI research are emerging fields (Kraus et al., 2018, Obschonka & Audretsch, 2020), it is challenging to define clear-cut research pathways for AI in digital entrepreneurship. Here, we continue with our key themes agency, processes, and outcomes and consider their relationships to the AI facets of autonomy, learning, and inscrutability. We discuss the relations by highlighting aspects of these linkages. Moreover, we derive future research questions conceivable for each of the links. Table 1 provides an overview of the AI facets, their relations to the key themes, and selected aspects that result in possible future research questions. In what follows, we go over the relationships in greater depth.

Facets of AI	Description	Relation to key theme			Aspect									Selected future research questions
		Agency	*Processes*	*Outcomes*	Generativity	Data-based adaption	Over expectations	Domain expertise	Co-creation	Scaling barriers	Customization	Enabler	Social consequences	
Autonomy	Acting without human intervention	■	■	■	■							■	■	• Which affordances are provided by AI? • Which capabilities are required of entrepreneurial agents to activate these affordances? • How does AI change traditional benefits derived from spatial ecosystems?
Learning	Improving through data and experience	■	■	■	■	■		■	■	■	■	■		• How do entrepreneurial endeavors access and exploit meaningful volumes of data? • How do they cope with the paradox of providing functions that require data to operate, but these data are only generated by the operation?
Inscrutability	Being unintelligible to specific audience		■	■	■		■		■				■	• How does AI create new opportunity spaces for entrepreneurial action in other environments? • How do entrepreneurs create trustworthy AI applications? • How does AI influence entrepreneurial rewards?

Table 1. Relation of AI facets to digital entrepreneurship key themes and results

Understanding AI in Digital Entrepreneurship: Autonomy

A key takeaway of our review is that AI autonomy has many facets of effects in terms of work and entrepreneurship. While the previous focus of the automation literature has reflected the nature of more traditional forms of skilled and unskilled work, there is a need to understand how new technological affordances will influence entrepreneurs and myriad creative, cognitive, and physical processes enacted when initiating an entrepreneurial endeavor (Chalmers et al., 2020; Obschonka & Audretsch, 2020; Townsend & Hunt, 2019). Our review reveals how AI alters the nature of entrepreneurial endeavors, recasting the need to mitigate traditional limitations such as scale, scope, and learning (Iansiti & Lakhani, 2020). The self-learning nature of AI systems, in particular, enables entrepreneurs to find new solutions to previous challenges (Faraj et al., 2018). These include innovative ways to monitor, understand, and predict developments. Entrepreneurs may utilize these data-driven insights to create effective interventions that lead to new kinds of agency. More specifically, fintech entrepreneurs are employing AI to analyze key factors in capital markets without relying on hypotheses, to recognize their interdependence more clearly, and to generate more precise information from data noise, including the early recognition of market-relevant structural changes. The learning nature of AI renders it performative, as its use can shape and change reality. The rapid deployment requires that scholars and entrepreneurs alike devote attention to societal issues such as the extent to which AI should be empowered to make decisions, they need to incorporate morality into technology, and the potential of AI to create a digital iron cage.

Understanding AI in Digital Entrepreneurship: Learning

Another implication is that a data pipeline should be regarded as a critical learning capability. Because AI systems are "trained" (increasing performance through learning) rather than programmed, they typically require vast amounts of labeled data to perform complex tasks. Thus, the ability to creatively identify the data required from existing data catalogs and external data sources is key. This renders data a critical boundary resource that affects entrepreneurial behavior. Owning strategic data resources makes entrepreneurial endeavors leading developers of AI applications, further gives them a novel comparative advantage, and represents an asset that facilitates value appropriation (Hartmann & Henkel, 2020). On the one hand, this poses the question of how entrepreneurial endeavors build up these data resources and protect them as a new form of intellectual property. On the other hand, the need for data raises the question of how entrepreneurial endeavors deal with relying on external data in their endeavors. How do they guard against being subtitled by the data owner? And in addition, there is the question of how entrepreneurial endeavors cope with the paradox of providing functions that require a critical amount of process data to work, while the process itself services as necessary data source. These questions open a landscape for further research. They are also relevant in practical implementation. For example, in the development of autonomous vehicles, Tesla relies on an evolutionary approach that is strongly based on real-world training. Data catalogs are curated by many thousands of Tesla drivers who participate in everyday traffic, and the algorithms are trained by constantly monitoring driver behavior Companies like Waymo, on the other hand, take a rather brute force approach, whereby they rely on large quantities of deliberately gathered environmental data to create highly accurate maps. These maps provide the framework for training the driving system's algorithms through computationally intensive simulations. The maps also enable decision-making during operation.

Understanding AI in Digital Entrepreneurship: Inscrutability

Our findings imply that ventures need to overcome a trust gap, as they use systems affected by black-box problems, seeking to deliver hard-to-measure outcomes. While previous research has shown how distrust of AI is driven by a sense that machines may soon replace humans and lead to labor displacement (Frank et al., 2019), our review highlights a trust issue related to the design and functionality of AI. Although AI enables ventures to achieve impressive levels of human-centricity (Verganti et al., 2020), it does so without making the decision-making process itself transparent, making it seem like a black box. Since AI systems inherently know nothing about empathy, entrepreneurial endeavors must bridge the trust gap. The same, of course, applies to research that uses AI systems to interact with vulnerable groups or to make diagnoses and recommendations for medical treatments. In practice, an entrepreneurial ecosystem is forming around the development of a range of tools and frameworks towards "explainable AI". The goal here seems to be making the predictions of applied AI models more understandable and interpretable. Users admire the ability to identify and resolve biases and other gaps in data and models by providing the necessary information to improve datasets and model architectures to increase model performance. It also addresses the promotion of end-user confidence and improves transparency by providing understandable explanations for end-users. While explanations do not provide information about fundamental relationships in most data samples or populations, they do reveal patterns found by the respective model.

6 Conclusion and Limitations

Our review provides an up-to-date overview of the nature and scope of artificial intelligence (AI) in digital entrepreneurship research (see RQ1). Additionally, we present potential research avenues on the AI-entrepreneurship intersection (see RQ2). While AI is a general-purpose technology and core element of the fourth industrial revolution (Schwab, 2017), research has only begun to understand the phenomena of AI at the intersection of information systems and entrepreneurship. It is the "golden age for demonstrating the value of sociotechnical thinking" (Berente et al., 2021, p. 1445). We contribute to practice by pointing out the need to consider both the social and technical perspective when leveraging AI in entrepreneurship. Both sides are critical for developing a well-rounded understanding. We make the first effort in relating the agency, processes, and outcomes of digital entrepreneurship to the AI facets of autonomy, learning, and inscrutability. A savvy integration of AI technology and human needs aids in developing better entrepreneurial endeavors.

Our work must be viewed in the light of several limitations. First, the generalizability of our results should be further examined due to our sample's non-exhaustiveness. Second, we must acknowledge the low conceptual maturity of AI in entrepreneurship. Third, the ambiguous use of the term AI in current research presents challenges in capturing it. However, we see our findings and identified avenues for future research as a starting point for enhancing the understanding of AI in digital entrepreneurship. By presenting the avenues, we hope to inform future research to explore the AI-entrepreneurship intersection.

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