Artificial intelligence and entrepreneurial ecosystems: understanding the implications of algorithmic decision-making for startup communities

Received 19 July 2022
Revised 11 September 2022
Accepted 11 September 2022

Philip T. Roundy
Gary W. Rollins College of Business,
The University of Tennessee at Chattanooga, Chattanooga, Tennessee, USA

Abstract

Purpose – Entrepreneurs are increasingly relying on artificial intelligence (AI) to assist in creating and scaling new ventures. Research on entrepreneurs' use of AI algorithms (machine learning, natural language processing, artificial neural networks) has focused on the intra-organizational implications of AI. The purpose of this paper is to explore how entrepreneurs' adoption of AI influences their inter- and meta-organizational relationships.

Design/methodology/approach – To address the limited understanding of the consequences of AI for communities of entrepreneurs, this paper develops a theory to explain how AI algorithms influence the micro (entrepreneur) and macro (system) dynamics of entrepreneurial ecosystems.

Findings – The theory's main insight is that substituting AI for entrepreneurial ecosystem interactions influences not only entrepreneurs' pursuit of opportunities but also the coordination of their local entrepreneurial ecosystems.

Originality/value – The theory contributes by drawing attention to the inter-organizational implications of AI, explaining how the decision to substitute AI for human interactions is a micro-foundation of ecosystems, and motivating a research agenda at the intersection of AI and entrepreneurial ecosystems.

Keywords Entrepreneurial ecosystems, Artificial intelligence (AI), AI technologies, Algorithmic decision-making, Machine learning, Automation, Entrepreneurship communities

Paper type Conceptual paper

Introduction

Artificial intelligence (AI) algorithms are increasingly influential in organizational decision-making (Balasubramanian *et al.*, 2022; Lindebaum *et al.*, 2020; Raisch and Krakowski, 2021). A global survey of 3,000 managers across industries found that 57% are piloting or deploying AI programs (compared to 46% in 2017) and 59% have a dedicated AI strategy (compared to 39% in 2017) (Ransbotham *et al.*, 2020). The adoption of AI algorithms is not exclusive to the managers of mature organizations (Obschonka and Audretsch, 2020).

Journal of Ethics in Entrepreneurship and Technology
Vol. 2 No. 1, 2022
pp. 23-38
Emerald Publishing Limited
2633-7436
DOI 10.1108/JEET-07-2022-0011

Entrepreneurs are increasingly using branches of AI, such as machine learning, natural language processing and artificial neural networks, to automate tasks in their pursuit of opportunities and the creation of new ventures (Berger *et al.*, 2021; Lévesque *et al.*, 2022; Rojas and Tuomi, 2022; Townsend and Hunt, 2019). Entrepreneurs incorporate AI in prospecting and refining venture ideas (e.g. using AI to conduct rapid experiments and search for new technological solutions), designing organizations (e.g. automating routine tasks and roles), selling products (leveraging AI for advertising and the analysis of consumer data) and scaling ventures (e.g. growing salesforces through AI salesbots) (Chalmers *et al.*, 2021). Entrepreneurs also use AI algorithms to augment and automate their human resource systems to identify, screen and train new employees (e.g. in "people analytics") (Pereira *et al.*, 2021). Thus, the role AI plays in intra-organizational phenomena is receiving growing attention and is increasingly clear (Chalmers *et al.*, 2021). However, research has not explored how the adoption of AI influences entrepreneurs in inter-organizational relationships.

In addition to scholars' intra-organizational focus, much of the research on AI in organization studies and entrepreneurship has focused on the potential benefits of AI, such as increased speed and efficiency in processing large volumes of data, an improved ability to detect previously unidentified patterns and enhanced predictive power (Lévesque *et al.*, 2022; Townsend and Hunt, 2019). Research is beginning to explore the disadvantages and ethical implications of AI (Peckham, 2021), such as unique biases in prediction (Choudhury *et al.*, 2020), opacity in how algorithms function (Glikson and Woolley, 2020), reductions in human choice (Lindebaum *et al.*, 2020) and labour displacement from task automation (Tschang and Almirall, 2021). Yet the use of AI in entrepreneurial ventures is relatively unexamined (Chalmers *et al.*, 2021), and it is, therefore, unclear what the ramifications of AI algorithms are for entrepreneurs' inter-organizational relationships and meta-organizational communities.

The dominant stream of research focused on how entrepreneurs interact with local communities is work on entrepreneurial ecosystems – the interconnected actors and forces that support entrepreneurial activity within localized geographic areas (Acs *et al.*, 2017; Stam, 2015). Research studying entrepreneurial ecosystems in Silicon Valley, Bangalore, London and other regions finds that how entrepreneurs interact with entrepreneurial ecosystems, comprised of investors, mentors, support organizations (e.g. incubators, accelerators) and other actors who enable entrepreneurship, influence entrepreneurs' ability to acquire social, material and cultural resources which, in turn, influences the likelihood of venture growth and success (Goswami *et al.*, 2018; Spigel, 2017; Stam and Van de Ven, 2021). Although ecosystems research has begun to examine how entrepreneurs build businesses focused on AI technologies in ecosystems (Hannigan *et al.*, 2021; Cetindamar *et al.*, 2020), there is no theory to explain how entrepreneurs' use of AI influences their interactions with entrepreneurial ecosystems.

To address the lack of attention to the intersection of AI and entrepreneurs' local communities, this paper asks, *how does substituting AI algorithms for entrepreneurial ecosystem interactions influence entrepreneurship and ecosystem functioning*? To answer this question, theory is developed that builds on entrepreneurial ecosystems theory and organizational theories of AI to create a model explaining how the substitution of AI algorithms for local ecosystem interactions influences three facets of ecosystem functioning: social, knowledge and cultural coordination. The influence of AI on ecosystem coordination (i.e. the degree to which an ecosystem's elements are organized to enable entrepreneurs and promote ecosystem development; Roundy and Lyons, 2022; Spigel, 2016) has implications for entrepreneurial decision-making and the extent to which ecosystems can support entrepreneurship.

The theory of AI and entrepreneurial ecosystems makes multiple contributions to entrepreneurship and organizational AI research. First, the theory expands the boundaries of intra-organizational research on the ramifications of AI to the inter-organizational level by explaining the consequences of AI in entrepreneurial ecosystems, which are meta-organizations (i.e. networks of firms or individuals not bound by authority based on employment relationships, but characterized by system-level goals; Gulati *et al.*, 2012). Second, the proposed theory explains how entrepreneurs' decisions to substitute AI algorithms for ecosystem interactions are a micro-foundation (Felin *et al.*, 2015) of entrepreneurial ecosystem functioning. These decisions influence not only the behaviours involved in how entrepreneurs pursue opportunities but, collectively, the functioning and outcomes of entrepreneurial ecosystems. Third, the theory draws attention to how entrepreneurs' technology choices can influence entrepreneurship communities, which motivates additional research at the interface of entrepreneurial ecosystems, AI and technologies. Finally, the theory generates insights that can guide entrepreneurs in their decisions about incorporating AI in their ventures.

The remainder of the paper is structured as follows. In the next section, organizational research on the differences between AI and human intelligence and the role of AI in entrepreneurship is reviewed, with attention given to the most pressing questions in the two research streams addressed by a theory of AI and entrepreneurial ecosystems. A stylized example is then presented that illustrates how an entrepreneur can be faced with an organizational task – recruiting a new employee – that can be accomplished using either an AI algorithm or by leveraging human interactions in the entrepreneur's local ecosystem. Next, theoretical arguments and propositions are developed that explain the implications of substituting AI for ecosystem interactions. The paper concludes with a discussion of the theory's contributions, its boundary conditions, and a research agenda at the intersection of AI and entrepreneurial ecosystems.

Theoretical foundations

AI-based decision-making and human-informed decisions

AI is the capability of a computational system to imitate intelligent behaviour (Choudhury *et al.*, 2020). Algorithms are "computer programmed procedures for transforming input data into a desired output" based on automated, formalized and predefined rules, scripts and goals (Kellogg *et al.*, 2020, p. 370). AI algorithms (also: machine learning algorithms) are a subset of algorithms with the ability to learn from data and previous predictions and modify themselves without human intervention. AI algorithms are described as "intelligent" because they can adapt their responses to new data [1]. AI algorithms are used to replace (or augment; Leyer and Schneider, 2021) human decision-making in a broad array of contexts, including medical diagnoses, legal decisions, human resource decisions and corporate governance (Jussupow *et al.*, 2021; Meissner and Keding, 2021).

AI differs from human intelligence and decision-making in critical ways (Balasubramanian *et al.*, 2022). AI algorithms often use machine learning techniques, which are grounded on an ontology that prioritizes (and is constrained to) prediction rather than explanation or granular understanding (Lindebaum and Ashraf, 2021). The predictive and pattern detecting processes that comprise AI algorithms are "made possible by the availability of highly advanced correlational, clustering, and regression analyses and other techniques of pattern recognition" (Lindebaum *et al.*, 2020, p. 256). However, reliance on these computational methods has implications for the type of "intelligence" that AI exhibits.

Formal and substantive rationality in artificial and human intelligence

A key difference between AI algorithms and human intelligence is the rationalities on which outcomes are based. Lindebaum *et al.* (2020) build on Weber's work is the type of rationality (Weber, 1946/1915, 1978/1922) and explain that because machine learning algorithms are executed by computers and programmed according to the positivist paradigm (Lindebaum and Ashraf, 2021), AI is based on formal rationality. *Formal rationality* involves "following abstract and formal procedures, rules, and laws, which are taken as unproblematic and legitimate fixed ends" (Lindebaum *et al.*, 2020, p. 248). Because of their basis in formal rationality, AI algorithms prioritize mathematical means-end calculations that aim to optimize and maximize pattern recognition and other outcomes (Lindebaum *et al.*, 2020). An implication of relying on formal rationality is that AI algorithms produce outcomes that are the result of "brute calculation" (Lindebaum *et al.*, 2020, p. 253) and "without regard to [specific] persons" (Kalberg, 1980, p. 1158); that is, the algorithms produce outcomes that are not based on the complex qualities of human decision-makers or the idiosyncrasies of the subjects of the decisions. For example, AI based on natural language processing (i.e. computer-automated processing of large amounts of language data; Berger and Packard, 2021) does not incorporate the specific characteristics of speakers and their situations and, thus, struggles to account for "subtle changes in focal expressions, fluctuations in intonations, [and] speech processes [. . .]" (Lindebaum and Ashraf, 2021, p. 5).

The formal rationality of AI is contrasted with the *substantive* rationality that characterizes human intelligence, decision-making and learning. Substantive rationality is based on judgments, which are based on value-laden reflection involving imagination, morality, empathy and emotional attunement to the specifics of situations and contexts (Lindebaum and Ashraf, 2021; Lindebaum *et al.*, 2020, p. 248; Moser *et al.*, 2022). Because judgment incorporates imagination and values:

> Substantive rationality contains the possibility to normatively see "the world as it might be" (Suddaby, 2014, p. 408), involving "what is", "what can", and "what ought to be" in empirical, moral, and aesthetic terms. (Lindebaum *et al.*, 2020, p. 249)

In contrast, AI cannot engage in these higher-level reflective activities and, thus, is described as exhibiting "calculation" (i.e. decisions based on a mathematical calculus), not judgment (Moser *et al.*, 2022). In comparison to human intelligence, which is "varied, rich in social context, forward-looking and based on judgment and understanding", the formal rationality of AI is based on quantitative reasoning, which is used to select the best (statistical) model to fit historical data and make predictions (Balasubramanian *et al.*, 2022, p. 3; Broussard, 2018; Choudhury *et al.*, 2020).

The effects of AI go beyond being merely carriers of formal rationality. Indeed, AI algorithms are described as "supercarriers of formal rationality" because the rationality of algorithms can not only suppress substantive rationality but also can transform substantive rationality into formal rationality by formalizing learning, rules and decisions and eliminating values, emotions, imagination and other characteristics from the learning and decision-making process (Lindebaum and Ashraf, 2021; Lindebaum *et al.*, 2020, p. 248).

AI's reliance on – and promotion of – formal, rather than substantive, rationality has advantages and disadvantages. Formal rationality enables AI algorithms to process large volumes of data quickly and efficiently, which affords AI users greater computational power that can augment or conserve organizational resources. However, the formal rationality of AI algorithms also has disadvantages. For instance, machine learning algorithms can suffer from biases in predictions because of underlying biases in the data sets used to train the algorithms (Choudhury *et al.*, 2020; Osoba and Welser, 2017). Biases can result from data containing unintended (and unrecognized) preconceptions, errors and prejudices or because of deliberate attempts to mislead AI so that algorithms detect illusory patterns or produce poor predictions (cf. "adversarial machine learning"; Baracaldo *et al.*, 2018; Choudhury *et al.*, 2020). Furthermore, formal rationality enables AI to find patterns in data and predict outcomes rather than provide rich explanations of phenomena. Even proponents of AI acknowledge its explanatory limitations. For example, Leavitt *et al.* (2021, p. 4) state, "[. . .] algorithms generated by machine learning are optimized for detecting patterns, but generally fail to explain "why" such patterns occur". As described in the sections that follow, the adoption of AI has implications for entrepreneurs and their ecosystems.

Artificial intelligence and entrepreneurship

Entrepreneurs are increasingly embracing AI to bolster their resources and address needs (Obschonka and Audretsch, 2020). Practitioners and the popular press describe AI as an "entrepreneur's new best friend" (Morantz, 2021) and claim, "even small businesses can leverage the power of AI" (Fast Company, 2021). Yet, the main contention of entrepreneurial ecosystems researchers, as well as ecosystem practitioners (Feld, 2012), is that entrepreneurship is often place-based, context-specific and embedded in unique local communities. However, AI algorithms, based on formal (not substantive) rationality, struggle to capture unique and hard-to-quantify contextual differences. Despite these limitations, AI is appealing to entrepreneurs because of its potential as a cost-saving tool that can help entrepreneurs overcome resource scarcity and other constraints (Chalmers *et al.*, 2021). As described next, entrepreneurs' adoption of AI algorithms is not without consequences. The substitution of AI for human interactions in entrepreneurial decision-making and learning represents a shift from inter- to intra-organizational sources of information and also from formal to substantive rationality, which has implications for entrepreneurs and their local ecosystems.

Theory development

Before proceeding with theory development, a stylized example is presented that to illustrate how substituting intra-organizational, AI algorithms for entrepreneurial ecosystem interactions can have implications for entrepreneurship and ecosystem functioning.

Leveraging AI or entrepreneurial ecosystem interactions: an example

One of the primary activities in which organizations are substituting human decision-making for AI-based decisions is human resource management and, specifically, talent recruitment and selection (Pereira *et al.*, 2021). Consider, for instance, an entrepreneur faced with identifying and choosing a new employee. AI can be used to collect and process applications and screen job candidates (Upadhyay and Khandelwal, 2018), thereby saving entrepreneurs time and resources.

An alternative method for identifying new employees is for entrepreneurs to leverage their local entrepreneurial ecosystems as inter-organizational talent management systems, which connect entrepreneurs with talent (Roundy and Burke-Smalley, 2021). Specifically, entrepreneurs can consult their local network of ecosystem participants for new employee recommendations. In making these recommendations, entrepreneurial ecosystem participants can consider a broad array of job candidate characteristics, the specific requirements of entrepreneurs and idiosyncratic features of ventures that might influence a job candidate's success. In contrast, an AI selection algorithm is often constrained to considering a predefined set of quantifiable factors. For instance, an AI-based talent management system may be confined to processing the data represented in resumes and cover letters and its candidate recommendations will be based on the (narrow) constraints of formal rationality (e.g. identifying candidate characteristics that match current employees). In contrast, the recommendations of ecosystem participants are informed by substantive rationality, which incorporates a richer array of values, emotions and idiosyncratic experiences. Thus, the benefits in processing speed and efficiency that AI-based hiring algorithms provide come at the cost of foregoing more granular and nuanced data that can be obtained from human interactions in an entrepreneurial ecosystem.

Furthermore, even if entrepreneurs meet and interact with ecosystem participants who cannot be of assistance with entrepreneurs' hiring decisions, in communicating with these community members, the entrepreneurs may gain other information that is valuable to their businesses (e.g. advice about how to manage employees or improve their business models) (Chatterji *et al.*, 2019). Interacting with entrepreneurial ecosystem participants may also result in "collisions" with other members of the ecosystem who, in turn, represent new connections and resources. Substituting AI for entrepreneurial ecosystem interactions eliminates the opportunities for fortuitous and spontaneous interactions and exchanges of resources. The reduced interactions (i.e. lower "collision density"; Nylund and Cohen, 2017) has implications for ecosystem functioning. The quantity and variety of information exchanged in the entrepreneurial ecosystem will decrease and the strength and number of connections will decrease. Informal conversations and unplanned interactions also have the benefit of producing new and unforeseen information. Informal conversations help knowledge flow among ecosystem participants and can increase the variety of knowledge available to them. As explained later, informal interactions can also serve to transfer and reinforce entrepreneurial ecosystem culture, which supports and encourages entrepreneurship. In sum, as this example illustrates, substituting AI algorithms for entrepreneurial ecosystem interactions in entrepreneurial decision-making represents more than simply a shift from external to internal decision tools. As the theory developed in the next section explains, incorporating AI has wide-ranging effects on entrepreneurs and ecosystems.

AI, entrepreneurship and entrepreneurial ecosystem coordination

Beyond the presence of entrepreneurial ecosystem elements, such as a region's institutions and physical infrastructure (Stam and Van de Ven, 2021), how ecosystem elements are *coordinated* influences the extent to which an ecosystem can support entrepreneurship and develop as a fertile environment for entrepreneurs (Knox and Arshed, 2022; O'Connor *et al.*, 2018). Entrepreneurial ecosystem coordination is the degree to which an ecosystem's elements are organized to enable entrepreneurs and promote ecosystem development (Roundy and Lyons, 2022; Spigel, 2016). Ecosystem coordination depends on relational contracts (Fahn and Zanarone, 2021) and the strength of the linkages among ecosystem participants. However, substituting AI algorithms for entrepreneurial ecosystem interactions influences three aspects of ecosystem coordination: social, knowledge and cultural coordination.

AI and entrepreneurial ecosystem social coordination. Entrepreneurial ecosystems are comprised of the inter-connected social networks of ecosystem participants, including entrepreneurs, investors, mentors, support organization staff and university members (Neumeyer *et al.*, 2019; Wurth *et al.*, 2021). Social coordination represents the degree to which ecosystem networks are dense and connect ecosystem participants through strong relationships (Fang *et al.*, 2021). In socially coordinated entrepreneurial ecosystems, the communities' networks represent a "meta-expert directory" (Roundy and Burke-Smalley,

2021) that entrepreneurs can use to quickly identify "who knows what?" about entrepreneurship in the ecosystem. In this function, social networks benefit entrepreneurs and other ecosystem participants by acting as conduits for the location and transfer of information and best practices about the entrepreneurship process (Pittz *et al.*, 2021). Entrepreneurs can use ecosystem social networks and the connections in their local communities to identify and acquire knowledge about prospective customers, where to find investment, how to incorporate a business and refine a business model and other skills necessary to create and scale new ventures. In contrast, in ecosystems with weak social coordination, networks are sparse and entrepreneurs do not have a myriad of diverse connections to other members of their local startup communities, which means that entrepreneurs operate largely in isolation and are not able to rely on connections in their ecosystems for resources (Spigel and Harrison, 2018).

Substituting AI algorithms for ecosystem interactions influences an entrepreneurial ecosystem's social coordination because entrepreneurs making this decision rely less on other ecosystem participants and there are fewer ecosystem interactions. Fewer entrepreneurial ecosystem interactions mean there are fewer (and weaker) ecosystem connections, which makes system networks less dense (i.e. a reduced number of network ties) (Motoyama and Knowlton, 2017; Theodoraki *et al.*, 2018). Fewer ecosystem interactions also reduce the strength of network connections, as tie strength generally increases with the frequency of social interactions and with communication among ecosystem participants (Hannigan *et al.*, 2021). Fewer ecosystem interactions mean that entrepreneurs are less likely to interact with knowledge brokers and entrepreneurial dealmakers who act as matchmakers in entrepreneurial ecosystems and connect entrepreneurs with other ecosystem participants who have access to resources (Pittz *et al.*, 2021; Yuan *et al.*, 2010). Thus, relying on AI algorithms instead of human interactions in local ecosystems makes entrepreneurs less likely to seek and contribute resources to their entrepreneurial ecosystem (Roundy and Lyons, 2022), which are activities that strengthen relational bonds, improve the flow of resources, and, ultimately, improve social coordination:

P1. Substituting artificial intelligence algorithms for entrepreneurial ecosystem interactions reduces an ecosystem's social coordination.

AI and entrepreneurial ecosystem knowledge coordination. Substituting AI algorithms for entrepreneurial ecosystem interactions also influences an ecosystem's knowledge coordination, which is the degree to which an ecosystem is organized to provide the differentiated, shared and meta-knowledge needed for entrepreneurship and ecosystem development (Rashid and Ratten, 2022). Differentiated ecosystem knowledge is unique knowledge about the entrepreneurship process that is not held by most ecosystem participants (e.g. an entrepreneur having insight into how to pitch to a specific venture capital firm). In contrast, shared knowledge is knowledge about entrepreneurship that most ecosystem participants have in common based on their overlapping knowledge bases (e.g. most ecosystem participants will have a general understanding of what venture capital is) (Lewis and Herndon, 2011). Lastly, meta-knowledge is understanding about other ecosystem participants' knowledge; it is knowledge about "who knows what?" in an ecosystem (e.g. an entrepreneur knowing who in the ecosystem to consult for knowledge about venture capital) (Roundy, 2020, p. 239).

Fewer entrepreneurial ecosystem interactions as a result of entrepreneurs deciding to leverage AI means that entrepreneurs have fewer opportunities to exchange entrepreneurship-related knowledge. Reducing informal ecosystem interactions also decreases the meta-knowledge about who are the most valuable sources of knowledge in an ecosystem because such knowledge is often shared during informal interactions and conversations (Scheidgen, 2021). Decreasing interactions with other community members also prevents entrepreneurs from sharing their differentiated knowledge with other ecosystem participants, thus reducing shared knowledge. One form of differentiated knowledge is tacit knowledge, which "is not easily described or transcribed, and that must be contextually grounded to be understood and make sense" (Pérez-Luño *et al.*, 2016, p. 262). Tacit knowledge often cannot be encapsulated in technologies, like AI, that are based on formal rationality (Lindebaum *et al.*, 2020). Reducing the shared and meta-knowledge in an entrepreneurial ecosystem and decreasing the opportunities for participants to share their differentiated knowledge influences an ecosystem by reducing its functioning as a meta-organizational transactive memory system (Lewis and Herndon, 2011; Roundy, 2020) that collectively manages knowledge about the entrepreneurship process:

P2. Substituting artificial intelligence algorithms for entrepreneurial ecosystem interactions reduces an ecosystem's knowledge coordination.

AI and entrepreneurial ecosystem cultural coordination. Substituting AI algorithms for entrepreneurial ecosystem interactions also has implications for an ecosystem's cultural coordination – the degree to which an ecosystem's participants share a common culture that is supportive of entrepreneurship and ecosystem development (Spigel, 2016). In entrepreneurial ecosystems with high cultural coordination, during interactions, ecosystem participants share, re-enact and reinforce cultural characteristics such as values, norms and narratives about entrepreneurship (Colombo *et al.*, 2019). For instance, in high functioning and culturally coordinated ecosystems, participants share values about cooperating and collaborating with other ecosystem members, the legitimacy of entrepreneurship and the benefits of taking actions to build local communities (Muldoon *et al.*, 2018). Shared values and norms may also include simple rules that guide interactions, such as "be willing to help other ecosystem participants" and "give to the ecosystem, do not just take" (Feld, 2012). Cultural values in vibrant entrepreneurial ecosystems also encourage entrepreneurs to embrace experimentation, risk and autonomy, which are central to entrepreneurship, and encourage people to pursue innovation, opportunity pursuit despite resource scarcity, value creation and trial-and-error (Donaldson, 2021).

An ecosystem's shared culture is strengthened through repeated and frequent interactions among participants (Donaldson, 2021). By observing and taking part in these interactions community members learn an ecosystem's culture. Cultural coordination helps an ecosystem be comprised of participants who can effectively work together and collaborate in the pursuit of entrepreneurial opportunities. Ecosystem interactions also improve cultural coordination by allowing participants to share narratives and other forms of communication, such as vocabularies about entrepreneurship (e.g. the meaning of phrases like "minimum viable product", "lean startup" and "business model"), which helps ecosystem members assist one another and facilitates the spread of resources among the entrepreneurship community. In general, ecosystem interactions represent vicarious learning opportunities (Kim and Miner, 2007) and it is through interactions that entrepreneurs and other community members learn how to act in the ecosystem.

If entrepreneurs substitute AI for entrepreneurial ecosystem interactions in decision-making fewer ecosystem interactions means fewer opportunities for entrepreneurs to learn, exchange and reinforce an ecosystem's culture. Fewer interactions also result in entrepreneurs being less likely to share or be exposed to an ecosystem's narratives (e.g. through informal conversations). In the same way that AI algorithms are conceptualized as carriers of formal rationality (Lindebaum *et al.*, 2020), narratives are carriers of substantive rationality and, specifically, the values, norms, cultural histories and entrepreneurial successes of a local ecosystem (Mack and Mayer, 2016). Reducing ecosystem interactions in favour of intra-organizational AI algorithms means that entrepreneurs and other ecosystem participants will be less attuned to an ecosystem's culture, which, collectively, suggests:

P3. Substituting artificial intelligence algorithms for entrepreneurial ecosystem interactions reduces an ecosystem's cultural coordination.

Figure 1 summarizes the theoretical arguments and illustrates how substituting AI algorithms for entrepreneurial ecosystem interactions reduces the number, frequency and strength of ecosystem interactions and reduces overall ecosystem coordination.

Discussion

This paper responds to calls by Leavitt *et al.* (2021, p. 4) and others (Haveman *et al.*, 2021) who contend that "organizational scholars must significantly adapt their theory-building pursuits to the age of machine learning". Entrepreneurship-specific theory is needed to understand the unique ramifications of adopting AI technologies for opportunity pursuit and early-stage ventures. Despite AI's benefits, scholars are beginning to caution managers and other organizational decision-makers about the perils and pitfalls of AI (Lindebaum *et al.*, 2020). At the same time, scholars have only scratched the surface of the implications of the differences between AI and human intelligence for entrepreneurial ventures (Chalmers *et al.*, 2021). In the sections that follow, the implications of the proposed theory for entrepreneurship and organization theory are unpacked.

Contributions to entrepreneurship and organization theory

Prior research has focused on how adopting AI technologies influences roles, responsibilities and decisions within organizations (Balasubramanian *et al.*, 2022). In examining the intra-organizational consequences of adopting AI, the focus of most studies is the impact of AI on formal organizational relationships and interactions (e.g. how does the adoption of AI allow organizational leaders to reduce or augment a part of their workforce). However, the theory of AI and entrepreneurial ecosystem coordination offered in this paper explains how the

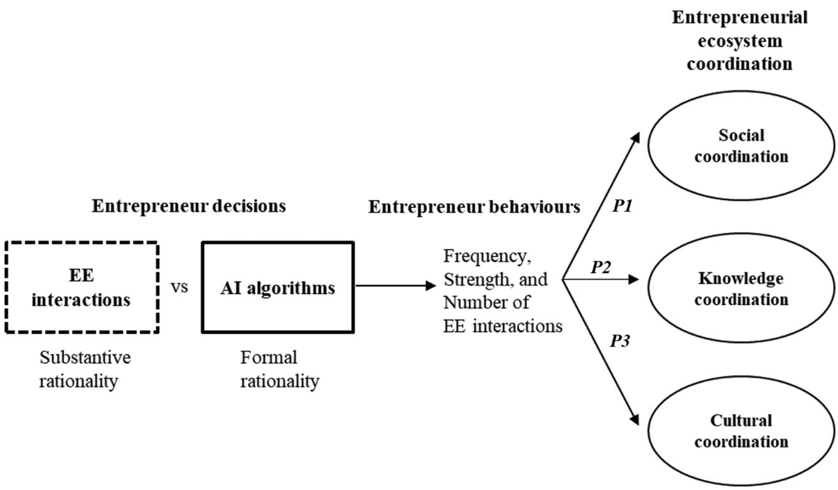

Figure 1.
A model of AI substitution and entrepreneurial ecosystem coordination

choice to adopt AI has implications that extend beyond organizational boundaries and influence the informal dynamics and unplanned interactions in inter-organizational relationships. As meta-organizations, the connections between entrepreneurial ecosystem participants are not based on formal mechanisms, such as employment contracts; instead, ecosystem relationships, and decisions to exchange resources, are based on the informal connections between entrepreneurs and other ecosystem participants. These connections are rooted in shared values and goals, friendship bonds, emotional connections to local communities and other relational factors. The theory argues that shifting from ecosystem interactions to AI reduces the frequency of informal interactions and reduces the strength of a community's informal relationships. Thus, the theory identifies a novel set of community-oriented, inter-organizational consequences of AI.

Entrepreneurial ecosystems research has been described as "under-theorized" (Cao and Shi, 2020, p. 1). The theory developed in this paper answers calls for more entrepreneurial ecosystems theory by identifying the processes by which AI algorithms influence ecosystem functioning and explaining the facilitating mechanisms linking AI to ecosystem outcomes, specifically system coordination. In doing so, the theory clarifies how the decision to substitute AI for ecosystem interactions is a micro-foundation (Felin *et al.*, 2015) of entrepreneurial ecosystem functioning that influences not only entrepreneurial performance (i.e. the performance of an early-stage venture) but, in the aggregate, ecosystem performance (i.e. the ability of a local community to support entrepreneurship). More specifically, the theory contributes to work on entrepreneurial ecosystem coordination by explaining how entrepreneurs' technology decisions can collectively influence coordination. Ecosystem coordination is increasingly recognized as a critical, system-level characteristic, which encapsulates how organized ecosystems are to encourage and enable entrepreneurship. Figure 2 illustrates the causal logic explaining how AI decisions are micro-foundations of entrepreneurial ecosystems.

The theory of AI-substitution and entrepreneurial ecosystems draws attention to the role played by specific technologies in ecosystems. Entrepreneurial ecosystems research has generally focused on the impact of non-technology ecosystem elements, such as support organizations (e.g. small business development centres) (Goswami *et al.*, 2018), culture (Donaldson, 2021) and networks (Neumeyer *et al.*, 2019). However, the technologies that entrepreneurs implement in their ventures can have community ramifications. For instance, as the theory explains, different types of rationalities are at play in entrepreneurial ecosystems and technology choice can inadvertently preference one type over another (e.g. formal rationality over substantive rationality). Thus, entrepreneurs' decisions about technology adoption and how technology is used in their decision-making influence more than just intra-organizational dynamics. More generally, the theory suggests that entrepreneurs' decisions can collectively influence the properties of their entrepreneurial ecosystems.

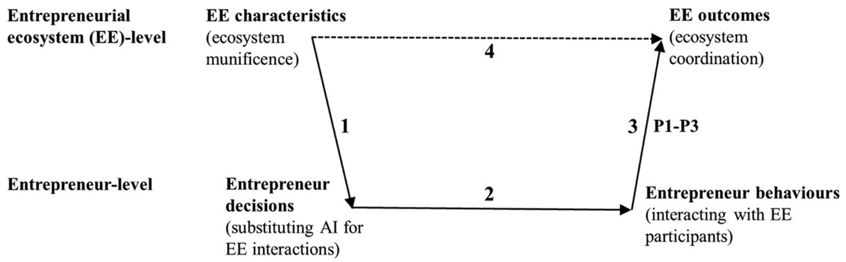

Figure 2. The micro-foundations of AI and entrepreneurial ecosystems

The theory of AI and entrepreneurial ecosystems also generates insights for entrepreneurs and ecosystem participants. Incorporating AI algorithms represents a new approach for addressing entrepreneurs' resource constraints. However, as the theory suggests, it is not without limitations. If AI is substituted for ecosystem interactions, the cost savings produced by AI may come at the expense of resources lost through reduced ecosystem interactions. Entrepreneurs should not blindly adopt AI without considering the potential "hidden costs" of AI, which may have implications for more than the direct organizational tasks that AI algorithms are being used to augment or automate. The decision to leverage AI may influence entrepreneurs' ability to gain subsequent resources from their local communities, which may be unrelated to an ecosystem interaction replaced by AI.

Boundary conditions and directions for future research

The micro-foundations framework (Figure 2) suggests an agenda of research opportunities at the intersection of AI adoption and entrepreneurial ecosystems. The theory presented in this paper focuses primarily on how entrepreneurs' behaviours and, specifically the frequency, strength and number of their entrepreneurial ecosystem interactions, influence entrepreneurial ecosystem functioning (Figure 2, Arrow 3). However, there are important questions involving other levels of analysis in the micro-foundations of entrepreneurial ecosystems, which are described next.

How do entrepreneurial ecosystem characteristics influence entrepreneurs' AI decisions? The characteristics of entrepreneurial ecosystems may influence entrepreneurs' decisions to adopt AI or substitute AI for ecosystem interactions (Figure 2, Arrow 1). For instance, an implicit assumption in this paper's theorizing is that entrepreneurs are located in entrepreneurial ecosystems with ample resources. That is, the theory assumes that entrepreneurs are in munificent ecosystems (Spigel and Harrison, 2018), which are rich in financial, social, cultural and human capital. Because of an ecosystem's munificence, there is a "cost" to the entrepreneur (and the ecosystem) associated with choosing to use an AI algorithm rather than interacting with participants in the entrepreneurial ecosystem. However, if an entrepreneur is located in an unmunificent ecosystem that lacks sufficient resources, he/she may not experience the trade-offs between AI and ecosystem interactions identified in this paper. Future research could identify important boundary conditions and constraints on the generalizability of the proposed theory related to the type of economy in which the ecosystem is located (e.g. developing, emerging or high-income) and the type of industry in which entrepreneurs are pursuing opportunities.

How do entrepreneurs' decisions regarding AI and ecosystems influence their behaviours? The theory developed in this paper focuses on the most obvious behavioural implications of entrepreneurs deciding to substitute AI for ecosystem interactions (Figure 2, Arrow 2). Yet, AI decisions may influence entrepreneurs' ecosystem-related behaviours in less intuitive ways. For instance, research is needed to determine if entrepreneurs who decide to adopt AI technologies may rely on their local ecosystem to obtain the knowledge and skills needed to incorporate AI in their ventures. Such skills may be obtained from AI training provided by support organizations, such as incubators that specialize in AI technologies. If entrepreneurial ecosystems function in this role, then ecosystems may actually assist, and determine the extent to which, entrepreneurs incorporate AI in their ventures.

Research is also needed to explore the specific types of entrepreneurship decisions that are best made using AI or ecosystem interactions. For instance, research could focus on different aspects of entrepreneurship and the venture development process, such as prospecting new venture ideas, designing new ventures, selling products and scaling ventures (Chalmers *et al.*, 2021) and examine the implications of entrepreneurs' decision to either incorporate AI or rely on ecosystem interactions in these specific processes. Related to this point, future research could also generate important insights by studying *how much* entrepreneurs substitute AI algorithms for human interactions (e.g. examining how entrepreneurs differ in replacing either a small or large number of community interactions with AI algorithms). Likewise, studies are needed that parse the effects of specific types of AI on entrepreneurial ecosystems. "Artificial intelligence" is not a monolithic set of activities but is comprised of different sub-types, such as natural language processing and artificial neural networks.

How does AI substitution influence other aspects of entrepreneurial ecosystem functioning? In examining how entrepreneurs' AI-related decisions and behaviours influence ecosystem functioning (Figure 2, Arrow 3), this paper focused on a single ecosystem-level outcome, coordination. Yet, the decision to substitute AI for ecosystem interactions may influence other system-level outcomes. For instance, future research is needed to understand the ramifications of AI adoption on ecosystem resilience – an ecosystem's ability to respond to disturbances and adjust to changing conditions (Ryan *et al.*, 2021). Resilience is a function of two factors, ecosystem diversity and coherence (Roundy *et al.*, 2017). Research is needed to understand if the impact of AI substitutions on the frequency, number and strength of ecosystem relationships also influences how diverse an ecosystem's participants are (e.g. in ideas, knowledge and business models) as well as the coherence of community members' entrepreneurial activities (i.e. if ecosystem participants are engaged in common activities).

Finally, this paper focused on the implications of entrepreneurs' AI decisions and behaviours on the outcomes of a specific type of geographically concentrated meta-organization – entrepreneurial ecosystems. However, the decision to adopt AI algorithms may have implications for the outcomes of other types of meta-organizations. Research is needed that considers the impact of AI on other loosely connected inter-organizational relationships that are tied to specific places, such as disaster response networks (Quarshie and Leuschner, 2020), cross-sector social partnership (Yin and Jamali, 2021) and cross-firm sustainability initiatives (Valente and Oliver, 2018). Such research could expand our understanding of how an individual's decision to substitute AI algorithms for human interactions has implications that extend far beyond organizational boundaries.

Note

1. Because AI cannot engage in activities such as "imagination, reflection, examination, valuation and empathy" the appropriateness of describing AI as having true "intelligence" has been questioned (Moser *et al.*, 2022, p. 3). To acknowledge these concerns, some have embraced Smith's (2019) convention of enclosing terms such as "learning" and "intelligence" in half brackets when referring to AI. For the simplicity of presentation, this paper does not adopt this practice; however, the importance of this distinction is noted.

References

Acs, Z.J., Stam, E., Audretsch, D.B. and O'Connor, A. (2017), "The lineages of the entrepreneurial ecosystem approach", *Small Business Economics*, Vol. 49 No. 1, pp. 1-10.

Balasubramanian, N., Ye, Y. and Xu, M. (2022), "Substituting human decision-making with machine learning: implications for organizational learning", *Academy of Management Review*, Vol. 47 No. 3, pp. 448-465.

Baracaldo, N., Chen, B., Ludwig, H., Safavi, A. and Zhang, R. (2018), "Detecting poisoning attacks on machine learning in IoT environments", *2018 IEEE International Congress on Internet of Things (ICIOT)*, IEEE, pp. 57-64.

Berger, J. and Packard, G. (2021), "Using natural language processing to understand people and culture", *American Psychologist*, Vol. 77 No. 4, p. 525.

Berger, E.S., von Briel, F., Davidsson, P. and Kuckertz, A. (2021), "Digital or not – the future of entrepreneurship and innovation: introduction to the special issue", *Journal of Business Research*, Vol. 125, pp. 436-442.

Broussard, M. (2018), *Artificial Unintelligence*, MIT Press, Cambridge, MA.

Cao, Z. and Shi, X. (2021), "A systematic literature review of entrepreneurial ecosystems in advanced and emerging economies", *Small Business Economics*, Vol. 57 No. 1, pp. 75-110.

Cetindamar, D., Lammers, T. and Zhang, Y. (2020), "Exploring the knowledge spillovers of a technology in an entrepreneurial ecosystem – the case of artificial intelligence in Sydney", *Thunderbird International Business Review*, Vol. 62 No. 5, pp. 457-474.

Chalmers, D., MacKenzie, N.G. and Carter, S. (2021), "Artificial intelligence and entrepreneurship: implications for venture creation in the fourth industrial revolution", *Entrepreneurship Theory and Practice*, Vol. 45 No. 5, pp. 1028-1053.

Chatterji, A., Delecourt, S., Hasan, S. and Koning, R. (2019), "When does advice impact startup performance?", *Strategic Management Journal*, Vol. 40 No. 3, pp. 331-356.

Choudhury, P., Starr, E. and Agarwal, R. (2020), "Machine learning and human capital complementarities: experimental evidence on bias mitigation", *Strategic Management Journal*, Vol. 41 No. 8, pp. 1381-1411.

Colombo, M.G., Dagnino, G.B., Lehmann, E.E. and Salmador, M. (2019), "The governance of entrepreneurial ecosystems", *Small Business Economics*, Vol. 52 No. 2, pp. 419-428.

Donaldson, C. (2021), "Culture in the entrepreneurial ecosystem: a conceptual framing", *International Entrepreneurship and Management Journal*, Vol. 17 No. 1, pp. 289-319.

Fahn, M. and Zanarone, G. (2021), "Transparency in relational contracts", *Strategic Management Journal*, Vol. 43 No. 5, pp. 1046-1071.

Fang, T.P., Wu, A. and Clough, D.R. (2021), "Platform diffusion at temporary gatherings: social coordination and ecosystem emergence", *Strategic Management Journal*, Vol. 42 No. 2, pp. 233-272.

Fast Company (2021), "7 smart ways even small businesses can leverage the power of AI", available at: www.fastcompany.com/90648920/7-smart-ways-even-small-businesses-can-leverage-the-power-of-ai

Feld, B. (2012), *Startup Communities: Building an Entrepreneurial Ecosystem in Your City*, John Wiley and Sons, Hoboken, NJ.

Felin, T., Foss, N.J. and Ployhart, R.E. (2015), "The microfoundations movement in strategy and organization theory", *Academy of Management Annals*, Vol. 9 No. 1, pp. 575-632.

Glikson, E. and Woolley, A.W. (2020), "Human trust in artificial intelligence: review of empirical research", *Academy of Management Annals*, Vol. 14 No. 2, pp. 627-660.

Goswami, K., Mitchell, J.R. and Bhagavatula, S. (2018), "Accelerator expertise: understanding the intermediary role of accelerators in the development of the Bangalore entrepreneurial ecosystem", *Strategic Entrepreneurship Journal*, Vol. 12 No. 1, pp. 117-150.

Gulati, R., Puranam, P. and Tushman, M. (2012), "Meta-organization design: rethinking design in interorganizational and community contexts", *Strategic Management Journal*, Vol. 33 No. 6, pp. 571-586.

Hannigan, T.R., Briggs, A.R., Valadao, R., Seidel, M.D.L. and Jennings, P.D. (2021), "A new tool for policymakers: mapping cultural possibilities in an emerging AI entrepreneurial ecosystem", *Research Policy*, in-press.

Haveman, H.A., Mahoney, J.T. and Mannix, E. (2021), "The evolving science of organization: theory matters", *Academy of Management Review*, Vol. 46 No. 4, pp. 660-666.

Jussupow, E., Spohrer, K., Heinzl, A. and Gawlitza, J. (2021), "Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence", *Information Systems Research*, Vol. 32 No. 3, pp. 713-735.

Kalberg, S. (1980), "Max weber's types of rationality: cornerstones for the analysis of rationalization processes in history", *American Journal of Sociology*, Vol. 85 No. 5, pp. 1145-1179.

Kellogg, K.C., Valentine, M.A. and Christin, A. (2020), "Algorithms at work: the new contested terrain of control", *Academy of Management Annals*, Vol. 14 No. 1, pp. 366-410.

Kim, J.Y. and Miner, A.S. (2007), "Vicarious learning from the failures and near-failures of others: evidence from the US commercial banking industry", *Academy of Management Journal*, Vol. 50 No. 3, pp. 687-714.

Knox, S. and Arshed, N. (2022), "Network governance and coordination of a regional entrepreneurial ecosystem", *Regional Studies*, Vol. 56 No. 7, pp. 1161-1175.

Leavitt, K., Schabram, K., Hariharan, P. and Barnes, C.M. (2021), "Ghost in the machine: on organizational theory in the age of machine learning", *Academy of Management Review*, Vol. 46 No. 4, pp. 750-777.

Lévesque, M., Obschonka, M. and Nambisan, S. (2022), "Pursuing impactful entrepreneurship research using artificial intelligence", *Entrepreneurship Theory and Practice*, Vol. 46 No. 4, pp. 803-832.

Lewis, K. and Herndon, B. (2011), "Transactive memory systems: current issues and future research directions", *Organization Science*, Vol. 22 No. 5, pp. 1254-1265.

Leyer, M. and Schneider, S. (2021), "Decision augmentation and automation with artificial intelligence: threat or opportunity for managers?", *Business Horizons*, Vol. 64 No. 5, pp. 711-724.

Lindebaum, D. and Ashraf, M. (2021), "The ghost in the machine, or the ghost in organizational theory? A complementary view on the use of machine learning", *Academy of Management Review*, in-press.

Lindebaum, D., Vesa, M. and Den Hond, F. (2020), "Insights from 'the machine stops' to better understand rational assumptions in algorithmic decision making and its implications for organizations", *Academy of Management Review*, Vol. 45 No. 1, pp. 247-263.

Mack, E. and Mayer, H. (2016), "The evolutionary dynamics of entrepreneurial ecosystems", *Urban Studies*, Vol. 53 No. 10, pp. 2118-2133.

Meissner, P. and Keding, C. (2021), "The human factor in AI-based decision-making", *MIT Sloan Management Review*, Vol. 63 No. 1, pp. 1-5.

Morantz, A. (2021), "Why AI is the entrepreneur's new best friend", Medium, available at: https://medium.com/geekculture/why-ai-is-the-entrepreneurs-new-best-friend-69bbdda47f6c

Moser, C., den Hond, F. and Lindebaum, D. (2022), "Morality in the age of artificially intelligent algorithms", *Academy of Management Learning and Education*, Vol. 21 No. 1, pp. 139-155.

Motoyama, Y. and Knowlton, K. (2017), "Examining the connections within the startup ecosystem: a case study of St. Louis", *Entrepreneurship Research Journal*, Vol. 7 No. 1.

Muldoon, J., Bauman, A. and Lucy, C. (2018), "Entrepreneurial ecosystem: do you trust or distrust?", *Journal of Enterprising Communities: People and Places in the Global Economy*, Vol. 12 No. 2, pp. 158-177.

Neumeyer, X., Santos, S.C. and Morris, M.H. (2019), "Who is left out: exploring social boundaries in entrepreneurial ecosystems", *The Journal of Technology Transfer*, Vol. 44 No. 2, pp. 462-484.

Nylund, P.A. and Cohen, B. (2017), "Collision density: driving growth in urban entrepreneurial ecosystems", *International Entrepreneurship and Management Journal*, Vol. 13 No. 3, pp. 757-776.

O'Connor, A., Stam, E., Sussan, F. and Audretsch, D. (2018), "Entrepreneurial ecosystems: the foundations of place-based renewal", in O'Connor, A., Stam, E., Sussan, F., Audretsch, D.B.

(Eds), *Entrepreneurial Ecosystems. Place-Based Transformations and Transitions*, Springer, New York, NY, pp. 1-22.

Obschonka, M. and Audretsch, D.B. (2020), "Artificial intelligence and big data in entrepreneurship: a new era has begun", *Small Business Economics*, Vol. 55 No. 3, pp. 529-539.

Osoba, O.A. and Welser, W. IV (2017), *An Intelligence in Our Image: The Risks of Bias and Errors in Artificial Intelligence*, Rand Corporation, Santa Monica, CA.

Peckham, J.B. (2021), "The ethical implications of 4IR", *Journal of Ethics in Entrepreneurship and Technology*, Vol. 1 No. 1, pp. 30-42.

Pereira, V., Hadjielias, E., Christofi, M. and Vrontis, D. (2021), "A systematic literature review on the impact of artificial intelligence on workplace outcomes: a multi-process perspective", *Human Resource Management Review*, in-press.

Pérez-Luño, A., Saparito, P. and Gopalakrishnan, S. (2016), "Small and medium-sized enterprise's entrepreneurial versus market orientation and the creation of tacit knowledge", *Journal of Small Business Management*, Vol. 54 No. 1, pp. 262-278.

Pittz, T.G., White, R. and Zoller, T. (2021), "Entrepreneurial ecosystems and social network centrality: the power of regional dealmakers", *Small Business Economics*, Vol. 56 No. 4, pp. 1273-1286.

Quarshie, A.M. and Leuschner, R. (2020), "Interorganizational interaction in disaster response networks: a government perspective", *Journal of Supply Chain Management*, Vol. 56 No. 3, pp. 3-25.

Raisch, S. and Krakowski, S. (2021), "Artificial intelligence and management: the automation–augmentation paradox", *Academy of Management Review*, Vol. 46 No. 1, pp. 192-210.

Ransbotham, S., Khodabandeh, S., Kiron, D., Candelon, F., Chu, M. and LaFountain, B. (2020), "Expanding AI's impact with organizational learning", MIT Sloan Management Review and Boston Consulting Group.

Rashid, S. and Ratten, V. (2022), "Subsistence small business entrepreneurs in Pakistan", *Small Enterprise Research*, Vol. 29 No. 2, pp. 109-137.

Rojas, A. and Tuomi, A. (2022), "Reimagining the sustainable social development of AI for the service sector: the role of startups", *Journal of Ethics in Entrepreneurship and Technology*.

Roundy, P.T. (2020), "The wisdom of ecosystems: a transactive memory theory of knowledge management in entrepreneurial ecosystems", *Knowledge and Process Management*, Vol. 27 No. 3, pp. 234-247.

Roundy, P.T. and Burke-Smalley, L. (2021), "Leveraging entrepreneurial ecosystems as human resource systems: a theory of meta-organizational human resource management", *Human Resource Management Review*, Vol. 32 No. 4, p. 100863.

Roundy, P.T. and Lyons, T.S. (2022), "Humility in social entrepreneurs and its implications for social impact entrepreneurial ecosystems", *Journal of Business Venturing Insights*, Vol. 17, p. e00296.

Roundy, P.T., Brockman, B.K. and Bradshaw, M. (2017), "The resilience of entrepreneurial ecosystems", *Journal of Business Venturing Insights*, Vol. 8, pp. 99-104.

Ryan, P., Giblin, M., Buciuni, G. and Kogler, D.F. (2021), "The role of MNEs in the genesis and growth of a resilient entrepreneurial ecosystem", *Entrepreneurship and Regional Development*, Vol. 33 Nos 1/2, pp. 36-53.

Scheidgen, K. (2021), "Degrees of integration: how a fragmented entrepreneurial ecosystem promotes different types of entrepreneurs", *Entrepreneurship and Regional Development*, Vol. 33 Nos 1/2, pp. 54-79.

Smith, B.C. (2019), *The Promise of Artificial Intelligence*, MIT Press, Cambridge, MA.

Spigel, B. (2016), "Developing and governing entrepreneurial ecosystems: the structure of entrepreneurial support programs in Edinburgh, Scotland", *International Journal of Innovation and Regional Development*, Vol. 7 No. 2, pp. 141-160.

Spigel, B. (2017), "The relational organization of entrepreneurial ecosystems", *Entrepreneurship Theory and Practice*, Vol. 41 No. 1, pp. 49-72.

Spigel, B. and Harrison, R. (2018), "Toward a process theory of entrepreneurial ecosystems", *Strategic Entrepreneurship Journal*, Vol. 12 No. 1, pp. 151-168.

Stam, E. (2015), "Entrepreneurial ecosystems and regional policy: a sympathetic critique", *European Planning Studies*, Vol. 23 No. 9, pp. 1759-1769.

Stam, E. and Van de Ven, A. (2021), "Entrepreneurial ecosystem elements", *Small Business Economics*, Vol. 2, pp. 809-832.

Suddaby, R. (2014), "Editor's comments: why theory?", *Academy of Management Review*, Vol. 39 No. 4, pp. 407-411.

Theodoraki, C., Messeghem, K. and Rice, M.P. (2018), "A social capital approach to the development of sustainable entrepreneurial ecosystems: an explorative study", *Small Business Economics*, Vol. 51 No. 1, pp. 153-170.

Townsend, D.M. and Hunt, R.A. (2019), "Entrepreneurial action, creativity, and judgment in the age of artificial intelligence", *Journal of Business Venturing Insights*, Vol. 11, p. e00126.

Tschang, F.T. and Almirall, E. (2021), "Artificial intelligence as augmenting automation: implications for employment", *Academy of Management Perspectives*, Vol. 35 No. 4, pp. 642-659.

Upadhyay, A.K. and Khandelwal, K. (2018), "Applying artificial intelligence: implications for recruitment", *Strategic HR Review*, Vol. 17 No. 5, pp. 255-258.

Valente, M. and Oliver, C. (2018), "Meta-organization formation and sustainability in sub-saharan Africa", *Organization Science*, Vol. 29 No. 4, pp. 678-701.

Weber, M. (1946/1915), "Religious rejections of the world and their directions", in Gerth, H.H. and Mills, C.W. (Eds), *From Max Weber: Essays in Sociology*, Oxford University Press, New York, NY, pp. 323-359.

Weber, M. (1978/1922), *Economy and Society: An Outline of Interpretative Sociology*, University of CA Press, Berkeley.

Wurth, B., Stam, E. and Spigel, B. (2021), "Toward an entrepreneurial ecosystem research program", *Entrepreneurship Theory and Practice*, Vol. 46 No. 3.

Yin, J. and Jamali, D. (2021), "Collide or collaborate: the interplay of competing logics and institutional work in cross-sector social partnerships", *Journal of Business Ethics*, Vol. 169 No. 4, pp. 673-694.

Yuan, Y.C., Fulk, J., Monge, P.R. and Contractor, N. (2010), "Expertise directory development, shared task interdependence, and strength of communication network ties as multilevel predictors of expertise exchange in transactive memory work groups", *Communication Research*, Vol. 37 No. 1, pp. 20-47.

Further reading

Allen, R. and Choudhury, P. (2022), "Algorithm-augmented work and domain experience: the countervailing forces of ability and aversion", *Organization Science*, Vol. 33 No. 1, pp. 149-169.

Shrestha, Y.R., Krishna, V. and von Krogh, G. (2021), "Augmenting organizational decision-making with deep learning algorithms: principles, promises, and challenges", *Journal of Business Research*, Vol. 123, pp. 588-603.

Tambe, P., Cappelli, P. and Yakubovich, V. (2019), "Artificial intelligence in human resources management: challenges and a path forward", *California Management Review*, Vol. 61 No. 4, pp. 15-42.

Corresponding author
Philip T. Roundy can be contacted at: philip-roundy@utc.edu