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# Pursuing Impactful Entrepreneurship Research Using Artificial Intelligence

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## Abstract

It is time for the entrepreneurship field to come to terms with leading-edge artificial intelligence (AI). AI holds great promise to transform entrepreneurship into a more relevant and impactful field, but it must overcome conflicts between the AI-driven research approach and that of the traditional, theory-based research process. We explore these opportunities and challenges and suggest concrete approaches that entrepreneurship researchers can use to harness the power of AI with rigor and enhance research relevance. We conclude that incorporating the power of AI in entrepreneurship research and managing the associated risks offer a new and "grand challenge" for the field.

## Keywords

entrepreneurship research, theory building, theory testing, research relevance, artificial intelligence

The success, impact, quality, and reputation of entrepreneurship research reflect its scientific rigor and real-world relevance. Consequently, entrepreneurship scholars pay close attention to scientific rigor and relevance when designing and conducting research (e.g., Maula & Stam, 2019). Concurrently, the management field is experiencing a misalignment between leading journals' demand for new theory and the actual research delivered by scholars. It appears that scholars feel compelled to produce an "illusion of theory development" lacking rigor, through incremental contributions with diminished real-world relevance (Tourish, 2019). This misalignment also plagues the entrepreneurship field struggling to achieve and secure relevance. Achieving such real-world relevance is deemed a "grand challenge" (Wiklund et al., 2019). It requires (i) research questions that inform practitioners and/or policymakers on current issues; (ii) hypotheses, assumptions, and rationale that directly apply to the work of practitioners and/or policymakers; and (iii) research findings and implications that directly and clearly inform these stakeholders (Toffel, 2016).

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Demand for impactful entrepreneurship research has been driven by the need for “true progress” in theory development (e.g., theory building and testing) and a closer connection between theory development and real-world relevance. Historically, evolving concepts and theories have driven entrepreneurship research, arguably beginning with Irish–French economist and banker, Richard Cantillon in 1755 (Bögenhold, 2019). Yet, Suddaby et al. (2015) criticize entrepreneurship scholars for having “largely failed to develop an indigenous theory” (p. 2), while Shepherd (2015) warns against a restricted focus on general principles and themes that value parsimony and consistency over richness and variety. This could foster a “crowding out” effect, where researchers opt for traditional methods and incremental theory contributions that could weaken the relevance of the field.

The promise of modern artificial intelligence[1] (AI) as an innovative approach to planning, conducting, and applying entrepreneurship research could help stimulate entrepreneurship theory development and help close the gap between theory and practice. AI can conceivably change not only the way entrepreneurial enterprises operate (The Economist, 2018), but also how entrepreneurship scholars conduct research. While entrepreneurs’ use of AI in their businesses has attracted considerable academic attention (e.g., Agrawal et al., 2019; Cockburn et al., 2018; Davenport, Guha et al., 2020; Nambisan et al., 2019; Ransbotham et al., 2018; Townsend & Hunt, 2019), entrepreneurship scholars’ use of AI to conduct research has not. While AI might not be a panacea per se for research rigor and relevance (based on its potential downsides, as discussed later), we contend that AI offers important, new opportunities to researchers to build and test theory, and to conduct rigorous, high-quality research that could greatly improve outcomes and real-world relevance. We therefore ask: *How can modern AI advance entrepreneurship research, and how can entrepreneurship researchers strategically employ AI to enhance research relevance while maintaining and/or increasing its integrity*?

AI comprises machine-based, intelligent learning and problem-solving techniques. What we view as “modern AI” encompasses the new, widely accessible, advanced research techniques facilitated by recent major advances in computer power, big data, and computer science. AI techniques can enable researchers to collect and analyze big data from, among others, crowdfunding campaigns, founders’ Tweets, and venture capitalists’ blogs, and could do so over time from whole populations, revealing real-time developments and concurrent mechanisms (Tonidandel et al., 2018). However, using AI could also *disrupt* how entrepreneurship scholars approach current research practices for theory development and validation. Can AI-generated big data address the *why* the same as theory does (Suddaby, 2014)? Can AI enable researchers to get rid of theory by learning “its own” unique lessons from data via machine communication processes applied to data? If theory helps us generalize observations and solve problems with “limited intelligence," does AI, which arguably exceeds certain aspects of human intelligence, require such theories to derive practical insights? Or, do machines need theory, and consequently, do we need theory to do research using AI?

We consider two extreme scenarios for the role of AI and its use of big data in entrepreneurship research: the abovementioned “disruption” scenario and its opposite, the “It’s all hype” scenario. The latter suggests that scholars will proceed with standard research methods and ways of testing and developing theories—a foreseeable scenario given that properly using AI techniques requires expertise to achieve rigorous analyses (Pollack et al., 2019). The entrepreneurship field has become “a big ship” over the last two decades, so changing its course could be difficult. Yet, we should not succumb to the resistance to change course, as witnessed in many human endeavors including fields of research. *Entrepreneurship* researchers should take their cue from entrepreneurs by welcoming change while embracing both opportunities and risks.

This editorial examines the competing views that AI could create hype or disruption in entrepreneurship research, as well as the middle ground between these two extremes. We build our case based on recent scholarly studies on how AI has been and could be used in information systems (IS), psychology, and neuroscience, while recognizing the unique aspects of entrepreneurship research. We consider five research dimensions that will be affected by AI and will influence *all business-related research fields*: relevance, rigor, application contexts, methodologies, and institutional forces. We further explore the opportunities and challenges associated with each dimension in the entrepreneurship field, in addition to offering a set of practical guidelines for entrepreneurship researchers and stakeholders. As entrepreneurially minded practitioners aspire to stay ahead of the curve, it has become imperative for entrepreneurship scholars to first examine the importance of AI for their research (Obschonka & Audretsch, 2019) as well as the downsides.

## Integrating AI with Entrepreneurship Theory Building and Testing

*Merriam-Webster*'s dictionary defines *artificial intelligence* as "a branch of computer science dealing with the simulation of intelligent behavior in computers" and "the capability of a machine to imitate intelligent human behavior".[2] The concept of AI—the programming of computers within a variety of areas including robotics, expert systems, neural networks, and natural languages[3]—dates back to the mid-1950s (Beal, 2019). However, in the last several years, AI has been applied within diverse industries (e.g., health care, banking, education, manufacturing, retail) and business realms (e.g., supply chains, customer relations, production processes). This, in turn, also poses critical challenges for researchers in fields such as entrepreneurship research that seek to inform industry practice and policy.

## The Importance and Downsides of AI for Entrepreneurship Research

AI can play a crucial role with several considerations that highlight its importance and downsides for entrepreneurship research. We offer a few here (more will emerge as we develop this editorial), starting with those speaking to the importance of AI for our field.

The first consideration is the *nature of data in entrepreneurship*. Many variables of interest do not follow a normal probability distribution function—a bell-shaped distribution—but instead follow highly skewed power distributions (Crawford et al., 2015) that require the use of nontraditional statistical methods (e.g., standard regression analysis). This is often the case with, for instance, latent constructs such as entrepreneurial motivation or skills (Murnieks et al., 2020). These variables require sophisticated methods for their measurement. AI, which can be used as a measurement method, can "detect" the "entrepreneurial potential" in individuals (or projects) better than human experts can owing to humans' limited intelligence to detect or assess such potential.

A second consideration is the *lack of available data on entrepreneurship*. AI can help to access and collect reliable and relevant data in the entrepreneurship field (Davidsson, 2016; Maula & Stam, 2019). For instance, nascent entrepreneurs and the emerging trends in new economic activity they generate are often difficult to study because founders might not yet have founded the firms that need to be tracked to speculate about these trends. AI can help to close this gap by, for instance, analyzing data that indicate nascent entrepreneurial activity from various sources, including social media. Maula and Stam (2019) also criticize the frequent mismatch between the research question and research design in entrepreneurship research. AI can help researchers to accurately align their research question and design, especially when they need to control variables often impossible to control, by instead simulating data since it is relatively easy to control the environment in a simulation. Likewise, AI could also supplement more traditional experimental designs where controlling the environment is easier.

A third consideration that highlights the importance of AI for entrepreneurship research is *processing and analyzing entrepreneurship data*. Various relatively big datasets on entrepreneurship exist, including data from the Global Entrepreneurship Monitor and the Kauffman Firm Survey[4]; AI techniques can be applied to mine and analyze these datasets. Maula and Stam (2019) argue that AI can help to triangulate different data sources by processing several large datasets combined (vs. one large dataset). They also contend that AI can help with very complex analyses (e.g., multilevel approaches, nonlinear relationships, Bayesian) and data visualization.

Several pointers speak to the downside of AI for entrepreneurship research. When AI-supported entrepreneurship research relies on big data, research rigor can suffer from well-established issues related to the acquisition and "wrangling" of big data (Braun et al., 2018; George et al., 2014). As highlighted by Pollack et al. (2019), crowdfunding research based on big data and AI is a concrete example where easy access to data (e.g., text data from crowdfunding campaigns and platforms) and the ease by which these large volumes of data can be analyzed (e.g., with AI techniques for computerized text analysis) could seduce researchers in this field to remain at a descriptive level, underestimate the importance of—and thus fail to perform—careful validity checks of data and analyses, and to make only minor conceptual and empirical contributions to the field. Similarly, an increasing number of studies analyze traditional and social media data but offer no concrete theoretical contributions (e.g., Suàrez et al., in press), which could be counterproductive if contributions to theory remain at the heart of entrepreneurship research.

With the growing availability of increasingly powerful AI techniques (some of which are highlighted below) and big data, the potential downside of AI for entrepreneurship research can be substantial, especially relating to rigor in the AI research process (but less so for AI itself). Entrepreneurship scholars therefore must invest more rigorous effort when using AI techniques and analyzing vast amounts of data. Instead of using AI to produce and analyze big data for the mere sake of "playing with new impressive data," AI can help to turn existing big data into smart data that can impact entrepreneurship theory and practice (George et al., 2014). However, this comes with new challenges for research rigor; therefore, researchers must carefully adopt high research standards (for concrete recommendations see Braun et al., 2018; Maula & Stam, 2019).

## Promises of AI for Entrepreneurship Research

Certainly, AI can be used to address basic big data challenges, such as harnessing large volumes of data, integrating data from various sources, and understanding their various formats (Chen et al., 2016). AI can also produce data, solve problems, and predict outcomes. By AI we mean fundamental techniques that include deep learning systems represented by diverse neural network models, multi-agent systems, natural language processing, as well as supervised (to forecast), unsupervised (to categorize), and reinforcement (to adapt) learning, among other machine learning techniques. Chen et al. (2008) offer a constructive review of applications for a variety of AI techniques along with ample references for details on these techniques, along with application examples for studying environmental systems. Next, we briefly highlight a few effective techniques and suggest when they should be considered.

As Chen et al. (2008) note, decision-making that requires solving a problem with case-based reasoning (using solved similar past problems), genetic algorithms (searching by mimicking natural selection), and artificial neural networks (finding relationships by mimicking the human brain) is most effective when the researcher focuses on the outcome (since these are "black-box" approaches) and does not seek information on the process itself. For instance, Kiani et al. (2017) use an artificial neural network to predict success in the context of corporate entrepreneurship.

What is having more traction among entrepreneurship scholars is agent-based modeling to simulate interactions in a system. For instance, Mauer et al. (2017) use Monte-Carlo simulation to compare the performance of effectuation as a control-based search (which is embedded in the logic of adaptive decision-making) to that of causation as a prediction-based search. A less well-known form of agent-based modeling is swarm intelligence, where the agents mimic colonies of social animals such as ants. In addition to agents interacting, interactions (or communication) in a swarm intelligent system can occur in the environment. Community-based systems such as makerspaces have attracted the attention of entrepreneurship and innovation scholars (e.g., Halbinger, 2018, 2020) and offer a setting where a swarm intelligence approach could provide fruitful research contributions.

However, not all agent-based models consider learning, which brings us to reinforcement learning, another AI technique to consider. Reinforcement learning enables learning through trial and error of individual agents interacting with each other and their environment. The potential of this approach is evidenced by entrepreneurship examined as a process where trial-and-error learning occurs as entrepreneurs make decisions; the study of serial entrepreneurs could be a good starting point for using this approach. Another approach relates to fuzzy systems, which are based on fuzzy sets from set theory that consider membership in a set based on vague, imprecise, and incomplete information/data. Most entrepreneurship scholars are likely familiar with fuzzy-set qualitative comparative analysis (fsQCA), which probes the causality of an outcome by not restricting its realization to be associated only with the same antecedent conditions. For instance, Muñoz and Kibler (2016) use fsQCA to identify configurations of local institutional elements that cause social entrepreneurship, while Lewellyn (2018) uses it to single out configurations of institutional factors and entrepreneurial activity types (e.g., high-growth vs. necessity) that result in significant income inequality levels.

Recently, big data, and AI to a lesser extent, have been the topics of editorials in various research fields (e.g., Johnson et al., 2019; Obschonka & Audretsch, 2019; Schwab & Zhang, 2019); however, big data alone is insufficient for theory building and testing. A more elaborate discussion is needed about AI applied specifically to our field, and in the context of existing challenges facing it (Shepherd, 2015; Wiklund et al., 2019). Though a substantial body of entrepreneurship research is based on data, algorithms can make "data sets valuable" (Martin, 2018, p. 2). Therefore, AI is integral to entrepreneurship research because it produces these algorithms. At a November 2019 presentation on Digital Transformation of Supply Chains, Remon Hanna, Canadian Tire Corporation Associate Vice President of ECommerce Fulfilment, noted that "a lake of data but no boat" does not help decision-making. Consequently, a focus on the "boat" (AI) is indeed warranted.

The easy accessibility of AI opens doors for scholarship in the fields of organization, management, and, more specifically, entrepreneurship. Over the past decade, scholars have welcomed AI into their research. However, judging from the paucity of studies published, this welcoming might meet with dashed hopes if researchers overlook the role of theory in research. As Haveman et al. (2019) state, "[w]ithout theory, empirical research can devolve into running numerous models and experiments and reporting any statistically significant results" (p. 241). The question then is: How will AI assist entrepreneurship research and under what circumstances will it help produce credible new theories? In addition to more general debates and concerns around the role of theory in research (e.g., Suddaby, 2014), we see considerable uncertainty associated with AI in the context of theory building and theory testing, which is the foundation of solid entrepreneurship research. Particularly, we see uncertainty about *how* researchers can integrate AI into the traditional research process. To address this uncertainty, we now turn our focus to relevance.

## The Role of Research Relevance

Specific to the current uncertainty of whether and how entrepreneurship research can be advanced with AI, we recommend that the connection between AI and theory be defined by research *relevance*. We see relevant research as studies that focus on issues that various stakeholders are highly likely to apply to what they do, want to do, and are interested in. Relevance is a key "building block" proposed almost 10 years ago by Wiklund et al. (2011) who see it as "the continued *raison d'être* of entrepreneurship as a distinct field of research" (p. 6). Relevance also brings into play social structure (e.g., trends in inequality) and context (e.g., entrepreneurial ecosystems). The importance of the latter has been heavily discussed in recent entrepreneurship literature (e.g., Baker & Welter, 2017; Welter et al., 2019). The significance of relevance herein is not mainly based on the recent call for more relevance in organization and management research (e.g., Kieser et al., 2015; Shapiro & Kirkman, 2018), but is grounded in what is at the core and the promise of the entrepreneurship field—"a young discipline rooted in practice" (Wiklund et al., 2019, p. 420). As a phenomenon-driven field focused on tackling problems relevant to entrepreneurship practices, the entrepreneurship field has been fighting for legitimacy since its inception, and has steadily moved toward the more solid, theory-driven field that it represents today.

With a focus on relevance, could AI bring the rigorous tools that enable the entrepreneurship research field to be both phenomenon- *and* theory-driven? The answer is, in our view, yes. But we must stress that this assumes that we will need to base future entrepreneurship research on theory, even if it may be disrupted by AI-based research. Interestingly, a fundamental debate is ongoing on the usefulness and importance of theory in business-related research that uses AI because of a potential "triumph" of mathematical, theory-free super predictions based on big data, versus theory-driven research shaped by human understanding and reasoning (Puranam, 2019). However, since human understanding and reasoning comprise the basis for theory building and testing—in contrast to AI using mathematics and prediction models that replace (and master) the critical researcher—we believe that theory will remain a central pillar in entrepreneurship research, particularly for a new generation of AI-supported research[5] that will produce findings with strong relevance and, as a result, will make a significant impact.

However, this will likely be a *collective* effort that calls on the whole field and its institutional actors to commit to a "system of knowledge production that is organized around keeping … individual biases and value propositions in check" (Suddaby, 2014, p. 410). When integrating AI in our research process, we see associations between three crucial components—theory building, theory testing, and AI—connected by bidirectional links driven by research relevance, as illustrated in Figure 1. AI (and its analytical techniques) can help "squeeze in" relevant information from relevant contexts populated by big data to facilitate relevant theory building (see, e.g., Berente et al., 2019). For instance, the data can come from entrepreneurs describing their products or services on their crowdfunding campaign (the context) to understand why some successfully reach their funding goal while others do not. In turn, the theory thus built can be tested by appropriate methods, including AI techniques, and revised accordingly. On the other hand, as exemplified in Schwab and Zhang (2019), theory can be used to program an AI system to create preliminary dictionaries for text mining, and machine learning algorithms (a branch of AI) can then be used iteratively to enhance these dictionaries. In other words, AI can play a vital role for both theory building *and* theory testing, albeit this may need to be tackled in steps. This in turn could improve or ensure relevance.

We should also emphasize that the increased relevance of future entrepreneurship research in the above scenario involves not only the *how*—robust research designs and methods supported by AI—but also the *what*—the research topic with its direct link to practice, including the *scope*

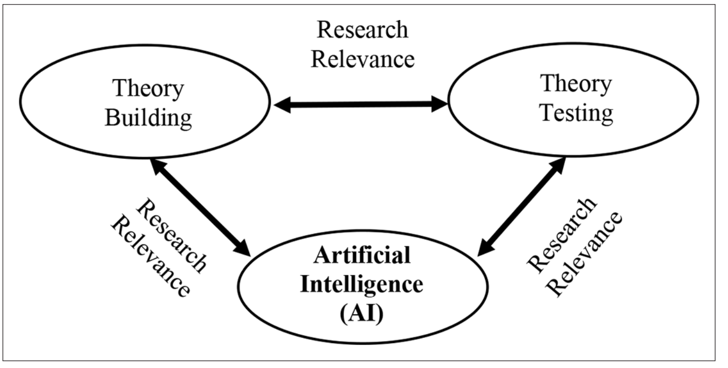


**Figure 1.** Associating Artificial Intelligence with Entrepreneurship Theory Building and Testing.

of the potential impact. For instance, researchers can increase the scope of their studies' impact (which appeals to top-tier journal editors, practitioners, and policymakers) by addressing the "grand challenges" in society (Colquitt & George, 2011; George et al., 2016). One of the most cited lists of grand challenges is the United Nations' Global Issues[6] (which includes poverty, inequality, climate change, environmental degradation, peace and justice, among others) and the accompanying Sustainable Development Goals,[7] which provide clear action items that can guide research (Ferraro et al., 2015). Consequently, if AI-integrated theory building and testing can help entrepreneurship researchers to (better) address these global issues and goals with scope and rigor, it will also help researchers address one of the current grand challenges facing entrepreneurship research itself—relevance.

## What Other Disciplines Say About AI

Some pieces of the puzzle on how AI can impact both theory building and testing can be found by looking at other disciplines. The IS field, which focuses on digital technologies and their applications, and considers both technical and human constituents (e.g., Sarker et al., 2019), offers some valuable insights. While the IS field has been studying AI quite intensively since the 1990s (e.g., as intelligent systems), recently, IS researchers have become engaged in a lively debate on the strategic integration of modern AI in the research process (e.g., Berente et al., 2019). For instance, Johnson et al. (2019) have contrasted three research approaches aimed to adapt research norms, practices, and traditions for the big data era. Among these approaches—the "classic hypothetico-deductive," "emerging big data empiricism," and "theory-informed big data research"—the third, a hybrid of the first two approaches, considers big data within the traditional approach to building and testing theory. Benbasat et al. (2020) warn IS scholars about the drawbacks of the growing body of research that focuses on large datasets analyzed by computationally intensive techniques, by predicting—based on preliminary evidence—that this trend is likely to produce IS research that will (i) address a specific firm's local issue (i.e., have a very narrow focus), (ii) expand research diversity as opposed to building on existing research, (iii) provide more subtle theoretical support, (iv) offer no strong theoretical generalization, and (v) focus on data-based and methodological contributions. While this editorial has been inspired by these debates, as we discuss later, the uniqueness of the entrepreneurship field brings research relevance and other current issues such as increasing data availability to the forefront.

Similarly, in the psychology literature, Yarkoni and Westfall (2017) acknowledge a crucial benefit of AI: *prediction* to complement *explanation*. They argue that psychologists can now afford to favor prediction over explanation owing to recent developments in

> machine learning theory and methodology—in which prediction of unobserved data is treated as the gold standard of success, and explanation is typically of little or no interest—as well as the increasing availability of large-scale datasets recording human behavior (p. 1101).

In the spirit of Johnson et al.'s (2019) work, Yarkoni and Westfall (2017) also encourage a hybrid approach for psychology researchers by using a mix of explanation-based (i.e., classic) and new, prediction-based approaches. However, their focus has been on discussing AI methods (i.e., machine-learning techniques) that can more accurately predict future behavior, rather than to build theory. Oswald et al. (2017) do highlight the challenge of integrating AI and big data within the theoretical psychology literature and traditional theory-driven methods.

In neuroscience, with its focus on understanding brain functioning, AI has had a major impact on theory building; in turn, advances in neuroscience have inspired important developments in AI itself (Hassabis et al., 2017; Ullman, 2019). The field of neuroscience provides rich examples of the usefulness of AI in aiding researchers to identify patterns and generate theory using big data (Churchland & Abbott, 2016). Scholars emphasize that when studying highly complex neural brain data, the main strength of AI "lies in recognizing patterns that might be too subtle or too buried in huge data sets for people to spot" (Savage, 2019, p. S16). Moreover, AI plays an important role in neuroscience by enabling more powerful theory testing, such as through functional magnetic resonance imaging (e.g., Cortese et al., 2012) and computational modeling (Sterratt et al., 2011). Neuroscience researchers using AI emphasize the essential role of theory development, stressing that "the overarching challenge is to build solid bridges" between theory and empirical evidence (Kriegeskorte & Douglas, 2018, p. 1150). Championing a closer link between neuroscience and entrepreneurship research, Nicolaou and Shane (2014) suggest how neuroscience methods (with their close link to AI) could be used to build and test entrepreneurship theories (see Shane et al., in press, for a concrete example).

From the computer science field, we see major developments not only in AI applications but also in machine power and capacity. For instance, researchers at Google recently announced that the computer science field had finally reached the milestone of "quantum supremacy," which enables faster calculations than any supercomputer to date (Arute et al., 2019). Nevertheless, the actual, direct implications for research and practice of this hard-to-understand and to some, indecipherable computational power are fiercely debated. What is certain, though, is that the increased computational and analytical power of the recent techniques from the computer science field have become quite accessible to a broader and growing group of business and management researchers. Indeed, some of these modern AI techniques (e.g., deep learning) are integrated with traditional techniques (decision trees) to make them more interpretable, as described in Rai (2019).

At a 2019 Academy of Management meeting's professional development workshop on "AI as Tools and Topics," Phanish Puranam discussed machine learning algorithms, which predict outcomes based on machine pattern recognition, by considering the algorithms as members of an organization. He proposed viewing these algorithms not only as tools for designing and analyzing, but as co-members of the organization and metaphors for organizing. At another 2019 Academy of Management workshop, "Entrepreneurial Action in the Age of Artificial Intelligence: Implications of the AI Revolution for Theory, Research, and Practice',[8] expert panelists represented AI practitioners and entrepreneurship scholars who pioneered the use of AI (albeit, its simpler forms) in their research through agent-based modeling and simulation. For instance, entrepreneurial processes have been a topic of interest among entrepreneurship scholars (e.g., Keyhani & Lévesque, 2016; Keyhani et al., 2015; Mauer et al., 2017) who have used simple agent-based modeling and simulation to identify the boundary conditions of current process theories, which can then be used to further refine theory.

We believe that AI's rigorous state-of-the-art technologies and methods can facilitate theory building and testing and bring more relevance. AI-based approaches promise to be *impactful* if used for both theory building *and* theory testing in entrepreneurship research. However, because published articles in this field are scarce, we can assume that few entrepreneurship researchers possess the expertise needed to use these state-of-the-art technologies and methods. This might encourage entrepreneurship researchers, in the near future, to embrace tradition and maintain the status quo—in other words, to lean toward the "It's all hype" scenario discussed earlier, and continue using standard methods for research and for building and testing theories. To inspire entrepreneurship scholars to move beyond the status quo, we next examine the opportunities and challenges for gradually moving toward two "middle ground" scenarios that are likely to be more accessible in the short term.

## Moving Beyond the Status Quo: Different "Moves" and Their Impacts on Entrepreneurship Research

We have so far established the need to consider the connection between theory building, theory testing, and AI, guided by a focus on relevance. This section offers a set of opportunities and challenges that entrepreneurship researchers are likely to encounter when integrating AI in theory testing or theory building or both, and the positive implications for real-world relevance in entrepreneurship research. We thus consider three possible "moves" that shift the relevance-focus on theory building and testing to more concrete action steps. We should stress that this is a simplified view—reality is always more complex and dynamic. For instance, a researcher could face different moves simultaneously while working on different research projects. But we hope this view can inform and guide future research that attempts to move beyond the Status Quo Zone—the zone where AI plays a minor role, as illustrated in Figure 2.

As detailed next, our central message is that, in principle, different moves to develop and/or test theory are possible but come with their own opportunities and challenges. This also concerns the risk level that researchers, and the entrepreneurship field in general, will need to assume, and cope with, in this process. Hence, it may also require certain, careful risk management strategies. Another reason for this variety of potential moves is the current uncertainty about the disruptive nature of AI. Since we cannot exactly predict if and how AI will disrupt the entrepreneurship research field, we identify different moves to prepare entrepreneurship researchers for, and help adapt to, *different* possible scenarios.

## Entrepreneurship Research Relevance and Rigor: Opportunities and Challenges

For the near future, we propose that merging or co-transforming classic theory building and testing with new AI techniques could be optimal for the entrepreneurship field. From this perspective, we see two broad sets of opportunities and associated challenges for AI to enhance research relevance. The first focuses on integrating AI and *theory testing*, creating what we call the Safe Zone shown in Figure 2. The second focuses on integrating AI and *theory building*, or what we call the Bold Zone (Figure 2). These two scenarios help build stronger and durable *linkages* between entrepreneurship theory and practice, thus addressing the issue of relevance, albeit in different ways than the traditional approach. While the Safe Zone focuses on research relevance

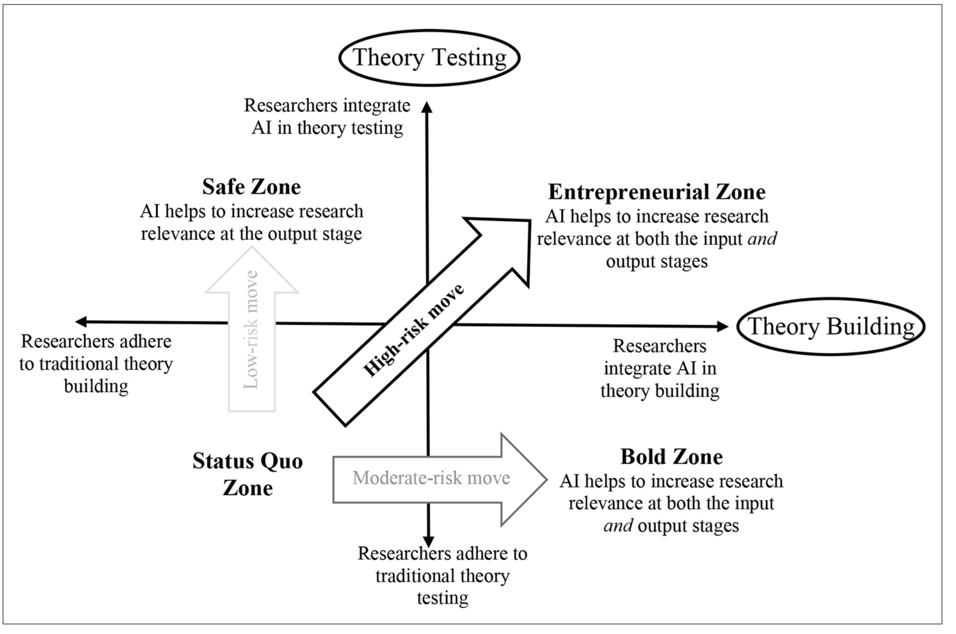


**Figure 2.** Zones of Artificial Intelligence Application in Entrepreneurship Research

at the *output* stage (e.g., enhancing the generalizability of study findings), the Bold Zone focuses on research relevance at both the *output* and *input* stages (e.g., enhancing the study findings' generalizability *and* ensuring real-world relevance of its focal phenomenon, constructs, and relationships). Both scenarios recognize (and embrace) entrepreneurship as an inherently *practice-oriented*, *interdisciplinary* research field. And, importantly, they *complement* existing entrepreneurship research methods—*they do not substitute for them*, as we discuss below.

### *Safe Zone*

Given that the Safe Zone is where researchers employ AI for theory *testing*, but not for theory *building*, we first focus on the role of AI in theory testing. Traditional theory-testing approaches (i.e., formulate hypothesis → test → support/reject hypothesis) are primarily concerned with ensuring a sufficient level of construct validity (related to the operationalization of the study constructs), statistical validity (related to the statistical power of the test), internal validity (related to the supremacy of the theoretically derived causal explanation), and external validity (related to the generalization of the findings). The techniques employed to enhance different types of validity can sometimes work at cross purposes, requiring researchers to make tradeoffs in selecting a testing approach (Smith et al., 1989), which affects rigor and relevance. For instance, entrepreneurship researchers often employ students and outsource services to recruit participants (e.g., MTurk) to ensure sufficient sample size and statistical power, while compromising (to a degree) the external validity of the results (Hsu et al., 2017; Maula & Stam, 2019) because these outsourced subjects might not perfectly fit the study's context or the research question. While no magic solutions can address these issues, we foresee two specific opportunities for AI to complement traditional methods in this regard.

Specifically, efforts to enhance construct validity can lead to operationalizing the theoretical concept in ways that make it harder for researchers to collect enough data from broad enough populations, or to readily interpret the data. While collecting the necessary amount or type of data reflects the potential tension between construct validity and statistical power (with implications for rigor), the ability to readily interpret the data reflects the tension between construct validity and external validity, which can compromise relevance. AI, when appropriately employed, can complement traditional research methods and address these tensions that typically arise in theory testing. First, the obtainability of big data that relate closely to the phenomenon of interest can present opportunities to apply AI to test relationships prescribed by the conceptual (theoretically derived) model. This requires identifying subsets of the big data that include variables that are sufficiently close to the study constructs to allay construct validity concerns, and yet provide large enough samples. As Johnson et al. (2019) suggest, this would, however, require the researcher to gain enough understanding of the metadata that underlie the big data so as to judiciously select variables. Thus, the researcher could employ AI and big data to test part of the conceptual model rather than all of it—in effect, to test different *sets* of theoretically derived relationships.

As an example, we now consider evaluating the effectiveness of entrepreneurial ecosystems. Recent scholarship on this topic (Acs et al., 2017; Audretsch et al., 2019; Autio et al., 2018) has clarified that any effort in this regard requires variables operating at multiple levels (individual, organizational, and regional) with outcomes also at different levels and in different areas (economic, technological, social). Relying exclusively on traditional methods could pose considerable challenges related to both the ease of data collection and the real-world relevance of such data and its derived outcomes. On the other hand, breaking down the complex model into multiple parts could enable researchers to use subsets of big data to validate the parts. For instance, a key premise of an entrepreneurial ecosystem is that sustained and intense interactions among members will enhance knowledge sharing and learning, and eventually increase opportunity exploration and startup activity. Research has largely relied on proxies such as the number and density of ecosystem members in a region to incorporate such a focus into member interactions. However, the last few years have brought a definitive movement away from traditional "offline" models to support local entrepreneurs and startups, and toward digitizing many entrepreneurial ecosystem activities (World Economic Forum, 2019). Initiatives such as the Startup Commons[9] have helped many regional and local entrepreneurial ecosystems and entrepreneurs build dedicated digital forums and other digital facilities to host interactions among members. Big data on member interactions available from these digital forums could be analyzed (in conjunction with more traditional variables such as the regional supply of skilled employees) using AI techniques to predict the intensity of regional/local startup activity. This approach to using appropriate AI and big data subsets could enhance studies' overall rigor, since it enables larger samples to be tested.

The above approach could enhance research relevance in various ways. Analyzing big data using AI could help enhance the generalizability of findings from traditional research. For instance, if traditional methods were used to validate the relationship between two variables in population A, the availability of big data on closely related variables among a larger or a different population B, could, when combined with AI, help to determine the generalizability of the original findings. Arguably, big data on entrepreneurial ecosystem-related variables are easier to obtain from some European Union countries than the United States. As such, findings from AI techniques on EU big data might complement those from traditional methods in the US context. Further, given that the variables drawn from big data are situated in the real world and thus close to the phenomenon of interest, the findings from AI-based analysis are likely to be more amenable to practice- and policy-guiding interpretations. Similarly, AI techniques could also enable more effective testing of the boundary conditions for a given theory. For instance, machine learning algorithms, when combined with simple simulation methods, would much better incorporate the learning of agents—entrepreneurs or other relevant stakeholders—by capturing their "intelligent" behaviors. Thus, all of these approaches would help enhance research relevance on the *output* stage by rendering the study findings more informative to practitioners.

While these suggestions provide promising opportunities to enhance the rigor and relevance of entrepreneurship research, their related challenges also must be carefully examined. A major concern, as noted previously, is that big data can originate from contexts unfamiliar to the researcher, which could impair the researcher's selection of variables. To a certain extent, this could be addressed if the researcher had developed a deeper real-world understanding of the focal phenomenon, which would, at the very least, help inform the researcher about the relevance of the different variables in the big data (Johnson et al., 2019).

Second and importantly, recent reports in the mainstream media (Smith, 2019) and elsewhere (Manyika et al., 2019) have shown that AI techniques that use biased data lead to biased findings. Although the problems associated with the use of biased data are relevant to scholars across fields, it is of particular significance for entrepreneurship researchers because their findings can also have policy implications. Take the earlier example of predicting startup activity based on entrepreneurs' interaction data from digital forums supported by regional entrepreneurial ecosystems. While such data may be readily available, they may also be biased due to a variety of reasons (e.g., spurious events and discussions); thus, identifying such potential biases may not be an easy task. Without a careful evaluation of the data for potential biases, algorithms developed to predict startup activity could lead us to misinformed policies. More broadly, the wide availability of big data and the alure of powerful AI techniques, combined with the high technical knowledge bar for evaluating data quality and content with AI, could result in misinformed or biased results and faulty cumulative knowledge creation in the entrepreneurship domain.

Third, breaking down a complex model into its parts (as discussed above) would enable rigorous AI testing, which can sometimes be challenging due to the nature of theoretical relationships and/or the interdependencies between the different parts. And even with such breakdown, integrating the findings from a faulty model and analyzing potentially different subsets of the big data with subsets from traditional analysis may be difficult because different assumptions are likely to underlie the faulty model and the corresponding data (e.g., from the different data sources). In our earlier example, findings from an AI-based analysis of data on member interactions and startup activity could be complemented by traditional analysis of survey-based data on members' (i.e., entrepreneurs') openness to share knowledge and their perceptions of the adequacy of the forums that facilitate this. Here again, the researcher's ability to bring together the knowledge—and assumptions that underlie the theoretical model—with that of big data may prove to be beneficial.

As should be evident from the discussion so far, in the Safe Zone, the objective should not be to *substitute* traditional testing techniques with AI. Rather, it is to best *complement* traditional methods with AI techniques so as to minimize the need for adverse tradeoffs that researchers sometimes must make. We now move our attention to the Bold Zone in Figure 2. Table 1 summarizes the opportunities and challenges with respect to research relevance and rigor by moving beyond the Status Quo Zone toward the Safe and Bold zones.

### *Bold Zone*

In this zone, researchers would employ AI for theory building, but not for theory testing. AI can help enhance research relevance at the *input* stage, specifically, by ensuring that the theoretical tools chosen for a study reflect (or are close to) the real-world phenomenon at hand. However, since AI not only assists in identifying patterns but also helps make sense of patterns (called "pragmatic empirical theorizing"; Shepherd & Suddaby, 2017), whereby empirical findings based on quantitative data are used to invigorate theorizing, AI can also help enhance research relevance at the *output* stage. As Shepherd and Suddaby (2017) put it, "[f]uture contributions will

**Table 1.** Opportunities and Challenges for Entrepreneurship Research Relevance and Rigor by Moving Beyond the Status Quo to the Safe and/or Bold Zones

| | Move to Safe Zone<br>Entrepreneurship researcher integrates AI only in theory **testing** | | Move to Bold Zone<br>Entrepreneurship researcher integrates AI only in theory **building** | |
|---|---|---|---|---|
| | **Opportunities** | **Challenges** | **Opportunities** | **Challenges** |
| **Relevance** | Address tension between construct validity and external validity by using big data closely related to the phenomenon<br>Enhance generalizability of findings using variables drawn from big data | Select variables when the entrepreneurship researcher is unfamiliar with the context from which big data are harvested<br>Break down a complex model to enable theory testing when the nature of theoretical relationships or the interdependencies between the different parts of the complex model makes it impossible | Enhance imaginative capabilities by reducing emphasis on theoretical contributions divorced from practice, and by reducing emphasis on the ideation process in existing literature<br>Reveal unexpected patterns in the dataset and potential connections between seemingly unrelated issues (those that researchers a priori could not imagine or conceptualize) that become the basis for developing new theories | Pursue spurious correlations and patterns while sacrificing the ability to generate cumulative knowledge on phenomena<br>Researchers and AI specialists must work together creatively to identify and explore new areas of theoretical inquiry |
| **Rigor** | Address tension between construct validity and statistical power by collecting data from broader populations<br>Analyze complex multilevel phenomena (over time) by deconstructing the complex model into parts that can be validated using large subsets of big data<br>Enable more effective testing of boundary conditions for a given theory by combining machine learning algorithms with traditional simulation to better capture the learning of “intelligent” agents | Integrate the findings from the analysis of various subsets of big data with the findings from a traditional analysis; this can be difficult due to the different assumptions that underlie the various data sources<br>Develop capabilities to critically evaluate data quality and bias potential (otherwise the findings will be biased too); this requires the critical evaluation of a (human) researcher | Reduce HARKing because researchers need not “pretend” to base empirical research findings on a priori hypothesizing and instead reveal that the theory was developed by an inductive approach | Reduce imaginative effort to connect the focal phenomenon to “received wisdom” from the literature; this lowers the findings’ long-term value<br>Perform a critical cross-check by (human) researchers on the connections between the causal explanation and their rigorous, real-world-oriented theory focus |

likely come from scholars' transparently offering interesting findings and then theorizing on possible explanations for them" with articles likely to be organized as follows: "Introduction, Research Method, Multiple Tests, Multiple Results, Initial Theoretical Model and Propositions, Discussion, and Conclusion" (p. 80).

The primary purpose of theory building is to develop a causal, generalizable explanation for a phenomenon evident in the real world. As a recent editorial in the *Academy of Management Review* notes, "theory forces us to dig into the explanation and to use logical reasoning" (Haveman et al., 2019), without which empirical results lose their "meaning" (Cortina, 2016). Traditional methods of theory building involve iterating between a deep knowledge of the focal phenomenon and knowledge of the underlying domain (i.e., the literature). Such iterations help researchers to formulate the problem and explore its underlying structure—steps that then help them identify the theoretical constructs, their relationships, and the plausible explanations (mechanisms).

While this iterative approach has enabled scholars to build cumulative knowledge about entrepreneurship, it has also raised important concerns regarding research relevance. Researchers have been accused of overly emphasizing theoretical contributions divorced from practice. To a certain extent, this suggests that the ideation process centers on (or is restricted by) existing entrepreneurship literature and traditional understanding and reasoning processes associated with theory building and testing. For instance, when investigating a new phenomenon, researchers may start their ideation process based on the literature that they are most conversant with, even if it only weakly relates to the focal phenomenon.

Returning to our earlier example of research on entrepreneurial ecosystems, much of the studies in this area are anchored in, and have merely refashioned, existing concepts such as clusters, regional systems of innovation, and the "triple-helix," without adhering to the "ecosystem" analogy and the complex web of interrelationships that exist in the real world (Audretsch et al., 2019; Autio et al., 2018). The ongoing gradual digitization of regional/local entrepreneurial ecosystems may, on the other hand, offer researchers a window to develop a more realistic interpretation of these interrelationships. For instance, big data on the nature and extent of user engagement on digital forums and platforms provided by local and regional entrepreneurial ecosystems (World Economic Forum, 2019) may reveal the nuances of the interrelationships and dependencies that exist among members, which in turn may point toward promising theoretical concepts that could be incorporated in future research. Similarly, content analysis of member interactions on these digital forums may offer additional insights not only on how cumulative knowledge on entrepreneurship practices are created and shared locally/regionally, but also on how this sharing shapes the underlying relationships among members, thereby indicating newer avenues to theorize such phenomena.

More broadly, theory building inherently requires *imagination*—the creative ability to make connections between the focal phenomenon and relevant parts of the existing knowledge domain (i.e., to connect the dots between theory and practice) and to form a mental image of the problem and its underlying structure. An extensive reliance on existing literature for focal phenomena suggests a lack of such imaginative effort; this in turn could distance research from real-world phenomena. At the same time, overly relying on the focal phenomenon suggests a lack of imaginative effort to connect it to received wisdom from the literature, which in turn could lower the rigor of the findings and their long-term value. We suggest that AI could help enhance the imaginative capabilities of the researcher in theory building in specific ways, described next, and thereby contribute to research relevance.

AI can help researchers focus attention on more relevant but less obvious aspects (or areas) of the focal phenomenon, thereby inspiring better articulation of the problem and its underlying structure. As noted previously, researchers' limited fields of interest or theoretical biases may limit their scope of focal phenomena to explore and lead to incomplete or inaccurate problem articulation. AI can help reveal unexpected patterns in a dataset and potential connections between otherwise unrelated issues, which in turn could point to more promising foundations for researchers' problem ideation processes. In short, the patterns discovered through AI may well become the basis for developing new theories (Goldberg, 2015). In the context of entrepreneurial ecosystems, arguably, scant scholarly effort has been exerted on theorizing potential connections between variables at multiple levels of analysis and in different domains (e.g., social, technological, economic, psychological). Perhaps the readily available access to appropriate big data and AI techniques could help uncover promising lines of inquiry in this regard. In effect, AI's role here will be to mine the rich and complex data landscape and point to patterns that could become potential candidates for developing new theoretical insights.

The availability of big data for such exploratory analysis might also inspire the researcher to make connections between the focal phenomenon and other existing phenomena in ways that could uncover novel connections with existing theories not readily apparent. In short, big data analysis could help identify potential sources for causal explanations for the focal phenomenon—that is, from other domains or fields. More broadly, we suggest that AI could help trigger novel theories that run counter to existing ones, or enrich existing ones, or broaden the scope of existing ones such as variables and relationships from other areas/domains that the researcher had never thought of. For instance, Levitt and Dubner's (2014) explanation for the sharply declining crime rates in US cities was not the zero-tolerance policy, but that the pool of potential crime perpetrators had been reduced due to strong abortion rights policies initiated in the 1970s. As illustrated in Figure 2, the move to the Bold Zone could help enhance research relevance at the *input* stage by bridging the gap between the focal phenomenon and the theoretical model envisioned by the researcher.

Moreover, using AI for theory building could also help address the costs (e.g., threats to research credibility) associated with problematic research practices such as HARKing (i.e., a priori hypothesizing; e.g., Bedeian et al. (2010); Murphy & Aguinis, 2019), which could severely harm the field if theory development—informed and guided by research findings—is misinformed. Researchers employing AI to build theory do not need to "pretend" to base their empirical research findings on a priori hypothesizing, nor do they need to practice "Sharking" (i.e., secretly HARKing; Hollenbeck & Wright, 2017). Instead, they should openly state that they developed their theories using AI and thus used a less deductive approach (e.g., "pragmatic empirical theorizing" as proposed by Shepherd & Suddaby, 2017). This, nevertheless, could follow what Johnson et al. (2019) describe as "theory-informed big data research," which considers the existing literature (i.e., the body of theories and prior research findings) when employing AI methods.

Importantly, we must recognize that AI can serve only a complementary role here and is not a substitute for the human researcher. While AI can inspire or point to new avenues for theory building, researchers still carry the burden of ensuring that their understanding of the extant theory and the phenomenon are linked so as to anchor the theory-building process. For instance, one danger of pursuing lines of inquiry based on patterns identified by AI is that issues are brought to light solely because the data exist. In other words, the *availability* of data rather than the *relevance* of the underlying issues drives our choices. Further, AI is unlikely (at least into the near future) to provide causal explanations that underlie the relationships; this remains the researchers' responsibility. Otherwise, we might pursue spurious correlations and patterns suggested by AI aimed to increase relevance, and thus sacrifice our ability to generate cumulative knowledge regarding the phenomenon. Specifically, devoid of human theorizing about the causal explanation, AI-generated predictions will remain a "black box" and cannot be acted upon by future researchers, thus impeding our ability to develop a deeper understanding of the focal phenomenon. In other words, we face considerable risk of sacrificing transparency and the human ability to interpret data for mere prediction accuracy (Rai, 2019). More broadly, our challenge is to use AI creatively in identifying and pursuing new areas of theoretical inquiry—a task that, as Amabile (2019) recently pointed out, calls for a deeper understanding of "AI creativity." Therefore, for AI-supported theory building, it is absolutely crucial for researchers to critically cross-check what AI delivers and focus on rigorous, real-world-oriented theory.

Raisch and Krakowski (in press) also bring to the forefront the important role of humans in providing the necessary quality and nonbiased inputs to be analyzed using Davenport and Kirby's (2016) key point on the importance for us as researchers to use our creativity, common sense, advanced communication, and integration skills, while debating *automation*—a machine taking over a human's job—versus *augmentation*—where humans and machines collaborate to complete the job. Raisch and Krakowski (in press) citing Calabretta et al. (2017) likewise argue that "automation and augmentation become mutually enabling" because their "juxtaposition stimulates learning and fosters adaptability, allowing the combination of (machine) rationality and (human) intuition, which enables more comprehensive information processing and better decisions." This juxtaposition pertains not only to using AI management practices, but for researchers considering using AI with theory building and theory testing.

### *Entrepreneurial Zone*

For the near future, we see this extreme "disruptive" move as less likely to occur in entrepreneurship research than moves toward the Safe and Bold zones. If researchers move toward the Entrepreneurial Zone, we can expect radical transformation of the research process. Specifically, in integrating AI in *both* theory building and testing, we see a more intricate involvement of AI in the research process—one that involves an iterative research loop wherein theory built through AI is tested by AI, and is then further revised by AI, with each iteration aimed to develop more nuanced practical insights on the focal phenomenon. Consequently, a key challenge we envision is an added responsibility for the researcher in ensuring that these AI-infused research processes are informed by existing theories and adhere to societal norms and values. In other words, the success of future entrepreneurship scholarship in the Entrepreneurial Zone might depend less on AI's overarching support of the research process and more on the researcher's interest in and ability to "manage" the AI-supported theory-building and -testing process by initiating, monitoring, and critically evaluating and fine-tuning that process.

Moreover, as moving toward the Entrepreneurial Zone can help researchers address the challenges in the Safe and Bold zones, it can also create a central opportunity unique to that move. For instance, if in the Bold Zone, the questionable real-world validity of AI-supported theory building represents a challenge, then AI-supported testing of this new theory (e.g., in other populations, later in time, or by using longitudinal data) could help address this challenge. Naturally, the entire process would be researcher-led and require different datasets. We should recognize the essential part of this human-led process: a strong focus on relevance and rigor. This focus could be best achieved by a collective effort in the field rather than by a single researcher or research team. As long as the concepts of relevance and rigor are defined by human understanding and reasoning, and not by data-driven AI, humans must always plan, guide, and oversee the process. In a future of disruptive "super machines," researchers (along with human-made theory) will lead the way (Puranam, 2019).

We conclude this section by highlighting two additional issues. First, although qualitative research may be underappreciated and underutilized (Suddaby et al., 2015), it can play a central role in contemporary AI-integrated entrepreneurship research. Qualitative studies (e.g., based on diary accounts, open-ended questionnaires, firm documents, participant observations, and ethnography) can improve research rigor and relevance by helping to cross-check theories built and tested via AI and big data. Qualitative research can be used to ensure the "meaning" and human understanding behind data-driven AI results that are prone to various biases (e.g., biased data or when the AI technique suggests an unrealistic model; Lapuschkin et al., 2019). This also suggests that qualitative research might, in some cases, prompt the rejection of AI findings. We believe we can trust AI (Belk, 2019), but only if consistent qualitative evidence continues to support AI findings.

Second, trust also plays a major role in terms of the comprehensibility of AI technique results. Rai (2019) considers this issue for practical applications of AI in marketing so as to highlight the distinction between abstract, nontransparent, ambiguous AI (e.g., based on deep learning and neural network algorithms) versus visible, explainable AI (e.g., based on decision trees or Bayesian classifier algorithms). We must also caution entrepreneurship scholars to carefully choose AI techniques for their AI-integrated research because each technique brings tradeoffs associated with trust in the approach, rigor, and comprehensibility. Also, deep-learning algorithms, considered rigorous and thus useful, might not achieve the research objectives. Conversely, "explainable AI" (Rai, 2019) might not be as rigorous or the most advanced AI technique in some cases, but the researcher can better control this tool (e.g., controlling a decision tree compared to a deep learning algorithm) and more fully comprehend what the AI "black box" contains; that is, understand and interpret an AI-generated result. Complementing a nontransparent AI technique with an explainable AI one could increase trust in and understandability of the research findings.

## Contextual Characteristics and Pursuing Societal Grand Challenges

Our discussion so far highlights the potential of employing AI techniques to enhance relevance in entrepreneurship research, both at the input and output stages. However, a critical issue is selecting the research contexts that are most suitable for these AI-based approaches (Haveman et al., 2019). In this section, we first briefly discuss some contextual characteristics that could guide researchers in identifying appropriate AI applications and then consider some of the methodological issues that entrepreneurship researchers might face when moving to the Safe and Bold zones. We use the earlier example of entrepreneurial ecosystems to illustrate the significance of these characteristics and issues. The Entrepreneurial Zone represents the culmination of opportunities and challenges associated with the moves toward the Safe and Bold zones.

We suggest that researchers consider three contextual characteristics when evaluating whether to complement traditional methods with AI techniques: (i) complexity of the focal phenomenon, (ii) availability and accessibility of big data in the related context, and (iii) novelty of the theoretical domain. In general, the more complex a focal phenomenon is, the greater the opportunity for AI techniques to inform theory building and its testing. More complex phenomena typically involve a greater number of variables that operate at different levels and relate to one another in more intricate ways. As such, more avenues for AI techniques to inform both theory building and testing likely exist. Similarly, the greater the availability and accessibility of big data that includes variables close to the theoretical concepts under consideration, the lower the cost of AI techniques (and bigger the payoffs). Recently, entrepreneurship scholars have cleverly mined big data from new, "rich" sources, including crowdfunding campaigns, company founders' Tweets, venture capitalists' blogs, and podcasts of various stakeholder, and recorded interviews with entrepreneurs (see the review in Prüfer & Prüfer, 2019). Finally, the insights drawn from AI-based analysis are likely to be more meaningful when the existing theoretical base is "young"—when the researcher is aiming to study a novel phenomenon, and not merely to identify or test a minor missing link in a well-established theoretical domain.

Looking to the broader world and ways to improve it through entrepreneurship scholarship, the number of recent calls from scholars to address some of the "grand challenges" facing our society (e.g., Shepherd, 2015; Wiklund et al., 2011) has increased. These challenges "relate to persistent and often perplexing societal needs that could determine the quality of life, affecting people's longevity, productivity, and well-being" (Wiklund et al., 2019, p. 422). Two such grand challenges from the United Nations' Global Issues are to end poverty and income inequality by generating more equitable economic growth (McMullen, 2011). From this perspective, research in entrepreneurial ecosystems can be re-envisioned to examine how these ecosystems may facilitate more equitable economic growth and help increase income equality across the globe. This area is ripe for employing AI techniques to complement traditional research methods for several reasons. The connections between entrepreneurial ecosystems and inclusive economic growth are multifaceted, and suitable for employing big data and AI-based analysis for building and testing theories. Also, several potential sources of big data related to regional economic performance and income disparities across different demographics exist. In addition, social media forums (e.g., for minority and women entrepreneurs) could offer textual big data on the challenges faced by entrepreneurs from various socioeconomic and cultural segments of society. Further, our current theoretical understanding of the underlying issues is very limited, suggesting that potential insights from AI-based analysis could illuminate fertile areas for theory development and enable us to test different aspects of the complex conceptual model.

However, pursuing the "grand challenges" in entrepreneurship research using AI also brings several methodological challenges, some of which we have already discussed. For instance, we noted the need for entrepreneurship researchers to be sufficiently well versed in the human–AI connection to ensure that human understanding (vs. algorithms) guides AI analysis. Entrepreneurship scholars will likely also need to partner with researchers in other computer analytics fields (e.g., computer science, data science, machine learning, data mining, predictive modeling) who better understand the emerging AI techniques and methods, along with the requisite technological infrastructure (e.g., access to computing power, bandwidth, data storage). Moreover, entrepreneurship scholars will be responsible for steering multidisciplinary teams to areas where the findings from traditional and AI-based studies could be integrated, interpreted, and disseminated in useful ways (Wilczek, 2019). Further, by incorporating real-world big data in theory building, researchers can shorten the timeframe between the appearance of a new phenomenon and its associated theorizing. This could enhance the relevance of the research question under investigation, but it could also eliminate the luxury of studying a phenomenon longitudinally, which researchers in traditional research settings have enjoyed. Thus, entrepreneurship researchers would need to theorize more cautiously about novel phenomena since "easy and fast" access to big data on an evolving phenomenon could lead researchers astray. In short, entrepreneurship researchers will need to adapt and sync their research design to employ AI on real-world phenomena without losing their theoretical anchor.

## What This Means for the Entrepreneurship Research Field

We have reflected on various avenues for advancing theory building and testing while integrating AI into entrepreneurship research. We have also explored avenues to do so while holding research relevance as a key goal. For the near future, we foresee that the field will take a middle road to avoid high levels of risk, but also stagnation, and will thus take careful steps toward AI most likely in the Bold and Safe zones (Figure 2). Nevertheless, in some instances, entrepreneurship researchers will move toward the Entrepreneurial Zone, but will require a careful risk management approach. For these three potential moves, we provide some practical guidelines—research opportunities and challenges—for entrepreneurship researchers with a focus on relevance. We also offer guidelines associated with three additional dimensions: rigor, application contexts, and methodologies. A key opportunity associated with application contexts that we highlight is the ability to study *truly* global issues, which are dynamic and complex by nature, but bring relevance to our field.

Finally, we ask, What does integrating AI to build and test theory mean for the *entrepreneurship field?* (See Figure 2, the three moves.) To answer this, we first note that this question shines a light not only on entrepreneurship researchers, but also on a diverse set of institutional actors (essential forces in the field)—journal editors and editorial review board members, university tenure and promotion committees, research funding organizations, practitioners (e.g., entrepreneurs, venture capitalists), and policymakers (representing governments)—since alignment among all stakeholders is essential for effectively integrating AI into entrepreneurship research. Without alignment among key stakeholders, the entrepreneurship field will face *resistance* from stakeholders who *elect to maintain the status quo* by looking upon AI techniques unfavorably for theory testing and theory building (e.g., because AI-integrated research might reduce academic reputations and public recognition, or because an AI-integrated research process does not evolve from traditional theoretical paradigms and thus is "suspect"). A failed alignment will result in costs for individual researchers who assume the risk of integrating AI into their research process. Nevertheless, to show their entrepreneurial spirit as innovators, rule-breakers, risk-takers, and failure embracers, entrepreneurship researchers should fearlessly lead the way and *resist the resistance to change*—their own and others'.

## Research Replication: An Opportunity for AI-Integrated Theory Testing

We now present scenarios for change. We begin with a major opportunity for entrepreneurship researchers choosing to exit the Status Quo Zone and move to the Safe Zone: research replication. Research replication is a prominent topic in social science research (e.g., for marketing research, see Evanschitzky et al., 2007; for economics, see Mueller-Langer et al., 2019; for strategic management, see Ethiraj et al., 2016), with debates regarding what types of research replication are acceptable and what types are not. Integrating AI in theory testing can assist replication studies to provide a stronger test of existing theories, since AI can be used to test the same theories with new methods and in more diverse contexts (Tourish, 2019). However, Mueller-Langer et al. (2019) recommend properly selecting the original studies to replicate to ensure relevance (and rigor), which illustrates how the strategic approach and researchers' skills still matter in this AI-integrated research process: human understanding and reasoning are at the core of AI-based theory building and testing.

We can consider, for instance, seminal entrepreneurial culture theories (e.g., Chinitz, 1961; Saxenian, 1996) that were, at the time, difficult to test owing to the high cost of collecting pertinent data. Today, large psychological datasets from millions of people have become available (Obschonka, 2017) to help researchers revisit and revise these theories. Another example is the "biology assumption" (e.g., Nicolaou & Shane, 2014; Nicolaou, Patel et al., 2018; Nofal et al., 2018), whereby scholars theorized that entrepreneurs have a genetic predisposition for the field (e.g., to think creatively, outside the box), where today's AI-supported genetic technologies can deliver new insights by revisiting some of these theories. Recent effort in this direction—such as a forthcoming *Entrepreneurship Theory & Practice* special issue on "Biology and Entrepreneurship"[10]—supports the promises from AI integration into our research for investigating the biology assumption.

## Government Regulation: A Challenge for AI-Integrated Theory Testing

The entrepreneurship field faces various challenges in integrating AI into entrepreneurship theory testing. Government regulation on data privacy and security is a major one. For instance, new AI techniques for face recognition and emotion detection have become controversial, with critics calling for legal restrictions of these technologies in public places and in corporate practices (e.g., Crawford, 2019; Kelion, 2019). Entrepreneurial emotion—"the affect, emotions, moods, and/or feelings…that are antecedent to, concurrent with, and/or a consequence of the entrepreneurial process" (Cardon et al., 2012, p. 3)—remains a popular topic in entrepreneurship research. While we could not find scholarship that employed emotion-detection tools to study this specific topic, it is plausible that some scholars may have started to experiment with these methods and faced their own challenges. For instance, Cardon et al. (2012) highlight the reluctance of many entrepreneurs to reveal some of their emotional experiences, especially those involving passion or fear, thus calling for creative non-survey-based approaches. These creative approaches could incorporate AI techniques (e.g., applied to recordings of entrepreneurs or research participant photos). However, legal restrictions on the use of these technologies (owing to privacy rights) could significantly shrink the pool of original research prospects enabled by AI for entrepreneurship scholars.

We also envision that research ethics approvals involving the use of potentially controversial AI techniques (e.g., facial recognition), and whatever these techniques might be in the future, may dissuade researchers from pursuing promising research projects that could significantly move the field forward. Entrepreneurship scholars must therefore learn to take in stride the concerns over AI techniques and the potential disruptions of the AI research process because, eventually, new regulations for the use of certain AI-based technologies (and the resulting data) are likely to become accepted and instituted. Without such AI-readiness among our peers, accepting and valuing AI techniques as standard in the method "canon" of our field for theory testing will not become a reality, at least not in the near future.

## Debate Resolution: An Opportunity for AI-Integrated Theory Building

Our label for the move to integrate AI in theory building in entrepreneurship—the Bold Zone (Figure 2)—underlines the potential for entrepreneurship researchers to be much more adventurous and ambitious in their research. The low-risk traditional theory-building approach, which has been criticized in recent years (e.g., Shepherd, 2015; Tourish, 2019), offers little room for such boldness. Scholars might think about debate resolution by empirically testing the contenders, as is commonly done, or by using "theory elaboration" as proposed by Fisher and Aguinis (2017) to investigate a set of entrepreneurship domains (e.g., creation theory). However, AI integration in entrepreneurship theory building could resolve endless debates among scholars by, for instance, helping to identify the boundary conditions of a theory, allowing for generalizability, or facilitating the analysis of a huge amount of data.

These debates include unifying the field's definition of entrepreneurship (Shepherd, 2015). They could also include the everlasting "entrepreneurial opportunity war" regarding what an entrepreneurial opportunity is and how to measure it (e.g., Dimov, 2011) by, for instance, simulating data to test opposing theoretical views (see, e.g., Keyhani & Lévesque, 2016). In turn, this would help scholars across the entrepreneurship research field find a better and stronger identity that is highly data- and phenomenon-driven, and highly contextualized (Baker & Welter, 2017; Welter, 2011) and time sensitive (Lévesque & Stephan, 2019). As a result, we can safely predict that the distance between entrepreneurship theory and practice will shrink (Obschonka & Audretsch, 2019) because it will accelerate data gathering to inform theory development. Shrinking the time between theory development and its application is crucial for two main reasons. First, the body of entrepreneurship research must become increasingly relevant; it can become outdated if entrepreneurial practice takes place way ahead of theory. For instance, although effectuation (Sarasvathy, 2001) and bricolage (Baker & Nelson, 2005) could arguably be viewed as predecessors to the popular lean startup practice (Reis, 2011), lean startup has only recently been addressed in scholarly journals. Second, given that entrepreneurship is recognized as an inherently practice-oriented field (compared to other fields more aligned with basic research such as physics), shrinking the time between theory and practice would promote scholarship based on its timely impact (thus relevance) to practice (McMullen, 2019).

## Research Dissemination: A Challenge for AI-Integrated Theory Building

A key challenge for integrating AI in entrepreneurship theory building is research dissemination to both academic stakeholders and nonacademics, notably entrepreneurs and policymakers (e.g., Johnson et al., 2019; Wiklund et al., 2019). We anticipate that new theories developed solely by AI and big data might be difficult initially for entrepreneurship researchers and their constituents (e.g., journal editors, reviewers, academic promotion committees) to accept, partly because, as we noted above, AI-integrated research does not typically evolve from traditional theoretical paradigms. Moreover, researching and publishing new theories generated by AI (and big data), rather than based solely on scholars' own thinking, reasoning, and hand-picked data, could adversely impact their career advancement, because academic promotion committees generally use the latter to evaluate research professors' contributions and achievements (e.g., reputation, performance indicators). In effect, engaging in innovative AI (big data)-based research could impede the entire entrepreneurship field's advancement.

An analogy involves developments in the Disc Jockey (DJ) industry, specifically in techno music, a path a co-author of this editorial considered pursuing in the 1980s. Two decades ago, a DJ had to learn everything from scratch, including how to identify and find new, and sometimes rare records, and then synchronize and spin these records during a gig. But today's technology (e.g., "smart" digital sound file management) does it (almost) all—even music selection. Consequently, becoming a successful DJ today may have much less to do with imagination, talent, and music knowledge, because it requires much less of the DJ's "imaginative touch." However, even today, successful DJs must still rely on their own competencies and passion, albeit they must have more technology competencies than in the past. For instance, today's DJs must know how to set up, guide, handle, and fix glitches in the technologies that help them to play music in interaction with the audience, and they must also still have "people" skills and a "feel for" music. We see this as a useful analogy to the skill set of the future entrepreneurship researcher that we champion here.

We can safely predict that overcoming the research dissemination challenge, among other obstacles, will require significant changes in entrepreneurship stakeholders' attitudes and beliefs, along with the ability to resolve conflicts and disagreements, and engage in collegial and professional communication. Perhaps a first small step might be to ask whether the field is ready to embrace inductive, big data/AI-driven theory building that could challenge existing theories and knowledge. Accepting and valuing AI techniques as standard in the method "canon" for entrepreneurship theory building (and for theory testing) might be the next best step, but "researchers might need to constantly iterate between the data, the theoretical literature, and the phenomena" (Benbasat et al., 2020). The worse scenario, in our view, would be having two categories of new theories: more trusted traditionally generated theories and less trusted AI-generated theories. However, we view AI as a great opportunity, a powerful tool to advance entrepreneurship research and increase its relevance if used to complement traditional research. And equally important, we see it as worth the risk.

## Concrete, Next Steps

We should stress that the multiple views presented throughout this editorial are our own. Although we cannot predict how future entrepreneurship research will play out, we hope to have provided convincing arguments to support these views. As a final thought, we take the liberty to propose four short-term, concrete steps that could sway researchers to make the move to the Safe, the Bold, or the Entrepreneurial Zone (as illustrated in Figure 2). Given the importance of stakeholder *alignment*, we encourage all stakeholders in the entrepreneurship research field to take first steps simultaneously. These steps will likely require some risk taking—though shared risks are reduced risks—to prepare for the moves beyond the Status Quo Zone, thereby helping the field and its stakeholders to become AI ready. We conclude with recommendations for four major stakeholder groups in entrepreneurship research:

i. *Entrepreneurship researchers* should invest in becoming proficient in AI-based research and seek partnerships with researchers who have expertise in AI techniques. They should learn *when* and *how* to use these techniques, and/or begin integrating AI-based research approaches from other disciplines (e.g., IS, psychology, neuroscience) that use AI techniques to increase rigor and relevance. This will enable entrepreneurship researchers to initiate discussions (e.g., in their article and book or book chapters) on how to make their theory development and empirical tests more AI-ready so that new research projects can be pursued using AI for theory building and/or testing. We caution, however, inexperienced researchers from employing these techniques and inexperienced editors and reviewers from evaluating this scholarship, because as noted, this could result in (unintentionally) the dissemination of unreliable results that not only fail to move the field forward, but set it back by causing reputational harm due to faulty approaches, faulty findings, or both.[11] Moreover, given that big data is often necessary for employing AI techniques, researchers should invest time learning to identify and generate big data that can form the empirical basis for AI-supported theory building and testing. Entrepreneurship research might face unique challenges in terms of big data availability for research—since collecting big data from entrepreneurs or from startups in the nascent phase can be tricky—thereby requiring more orchestrated and intensified efforts. Using big data thus also comes with challenges in terms of scientific rigor, which requires careful consideration. Employing AI techniques strategically to stimulate theory building and testing with the necessary rigor and relevance might require more, not less, efforts and hard work from entrepreneurship scholars to ensure good scholarship.

ii. *Journal editors and editorial review board members* can call for authors to write scholarly articles that involve AI-integrated theory building and testing, create special sections in journals to promote such articles, and provide guidelines for reviewers to evaluate these articles—and identify experienced reviewers to do so. To start with, the special sections could focus on entrepreneurship topics that are most appropriate for AI-integrated theory development (e.g., entrepreneurial ecosystems, genetic tendencies of entrepreneurs, and crowdfunding). Journal editors could also regularly invite commentaries and research notes that stimulate a healthy dialog on issues related to AI-based techniques in entrepreneurship research. Moreover, they could encourage AI-supported reviews and meta-analyses assembled in real time (or close to) to tell us where the field stands regarding a certain topic, since by facilitating readability, AI could help summarize and interpret the existing body of research.[12]

iii. *Business/management schools* can start educating entrepreneurship scholars on AI processes and techniques to integrate AI with theory testing and building, particularly in the context of addressing "grand social issues" to increase the relevance and scope of entrepreneurship research. If business and management schools lack the expertise to deliver quality courses on AI-based research and theory testing, they can sponsor seminars on the topic or invite scholars for guest classes or simply send their students to universities and organizations that offer such training. Such seminars and classes should be conducted by professionals with the skills, experience, and passion for using and evaluating AI-supported research methods, and to emphasize that proper (human) understanding, insights, and reasoning are critical for revising or creating new theory.

iv. *Research funding institutions and policymakers* can develop and support the funding of research grants for projects that strongly emphasize AI-integrated theory building and testing. This approach would strongly encourage other stakeholders such as journal editors to stress the value of employing AI-based techniques in entrepreneurship research.

We conclude by noting that in making the above suggestions to the entrepreneurship field and its various stakeholders, and in offering our thoughts on this broader topic, one theme is central: as a tool, AI is a "servant" to its human masters and their goals. Therefore, let us (strategically) embrace our new grand challenge in entrepreneurship research—to rigorously integrate AI into our research to enhance its scope and relevance.

Я твой слуга
Я твой работник
(I am your servant, I am your worker)
—from "The Robots" by Kraftwerk

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## Notes

1. We prefer the term *AI* to *computational data science* or *big data analytics* because AI captures algorithms that can generate synthetic data, which can be particularly useful when data availability or data quality is a concern.
2. http://libanswers.cmich.edu/faq/25762
3. AI should not be confused with *machine learning*, which is a branch of AI (e.g., Iriondo, 2018). In turn, *deep learning* is a specific type of machine learning that relies on 'deep' neural networks.
4. https://www.gemconsortium.org/; https://www.kauffman.org/entrepreneurship/reports/kauffman- firm-survey-series/
5. For instance, researchers could 'train' an AI model to analyze facial morphology from pictures on Facebook to predict who will be an entrepreneur (and who will not), and then the researcher can link these predictions to genetic theories on entrepreneurship traits and personalities.
6. https://www.un.org/en/sections/issues-depth/global-issues-overview/
7. https://www.un.org/sustainabledevelopment/sustainable-development-goals/
8. See https://www.researchgate.net/publication/332656478_Entrepreneurial_Action_Creativity_Judgment _in_ the_Age_of_Artificial_Intelligence.
9. https://www.startupcommons.org/
10. https://journals.sagepub.com/pb-assets/cmscontent/ETP/ETP_SI_EP.pdf
11. We thank an anonymous reviewer for this important point.
12. We thank a participant at the 2020 ACERE Conference in Adelaide, Australia for this suggestion.

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