Research Policy 51 (2022) 104315

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

A new tool for policymakers: Mapping cultural possibilities in an emerging AI entrepreneurial ecosystem

Timothy R. Hannigan, Anthony R. Briggs, Rodrigo Valadao, Marc-David L. Seidel, P. Devereaux Jennings *

ARTICLE INFO

Keywords:
Ecosystems
Emergence
Entrepreneurs
Networks
Culture
Textual analysis
Mapping
AI

ABSTRACT

Ecosystems are typically evaluated and understood using standard visible material metrics, such as new products, patents, startups, VC funding, jobs, and successful exits. Yet emerging entrepreneurial ecosystems (EEEs) provide many possibilities for members not signaled by such visible markers. Consequently, policymakers may have a difficult time making informed decisions about incentives and regulations to foster economic growth through ecosystem emergence. To address this methods and measurement issue, we conceptualize emerging systems using both cultural and material approaches to develop a comparative typology and apply it to an emerging regional ecosystem growing around artificial intelligence (AI). We render cultural and material maps using topic modeling of Twitter feeds versus well-placed others, identify strategies in each, and discuss relevant policies for enhancing EEEs to realize various economic opportunities. This method adds to policy analytics and suggests policies for building cultural infrastructure in EEEs.

Policymakers have a strong interest in entrepreneurial and innovation ecosystems as a means for systemic wealth creation, economic well-being, and tackling grand challenges facing society (Autio et al., 2014; Feldman et al., 2019; Ferraro, Etzion & Gehman, 2015). But emerging entrepreneurial ecosystems, such as those in digital technology (Nambisan et al., 2019) or around COVID-19 responses (Kuckertz et al., 2020), are not easily examined theoretically (Spigel, 2020), nor have they been sufficiently studied empirically (van Rijnsoever, 2020). The macro entrepreneurial context is too often treated as exogenous (Stam & Van de Ven, 2019), even though policy can directly shape the context, leaving many local cultural possibilities untapped. This is exasperated in early nascent periods when traditional entrepreneurial metrics are even less informative. Consequently, policymakers have a difficult time making locally informed decisions to foster unique economic opportunities during an ecosystem's nascent period (Brown & Mawson, 2019; Isenberg, 2010; Lam & Seidel, 2020). Instead, policymakers are driven to inappropriately copy policies from other successful regions (Wurth, Stam & Spigel, 2021), which can create policies not well suited to the local macro entrepreneurial context. We provide a new policy analytics tool and approach that helps address this issue for policymakers, and illustrate their usefulness in an emerging AI entrepreneurial ecosystem.

One reason emerging systems are difficult to study is that existing material resource and knowledge ties do not track closely with more radical innovations underpinning new systems, such as social enterprise innovations in older technological spaces (Autio et al., 2018; Thompson et al., 2018). Another is that in emerging ecosystems, the entrepreneurs' cultural mindsets may actually precede, not follow, patterns of tangible resource investment (Lounsbury & Glynn, 2019; Porac, Wilson, Paton & Kanfer, 1995). Furthermore, these mindsets are not reducible to local knowledge-based processes (Autio et al., 2018) or material patterns of innovation, and instead may be more dependent on cultural, field configuring events (Zilber, 2011) or subtle new specialist arrangements (Croidieu & Kim, 2018). Additionally, the speed of development in emerging entrepreneurial ecosystems is on a different scale than in most established ones (Markman et al., 2005; Stam, 2017). Being virtual and sometimes ephemeral makes direct observation of such systems and stable planning for them troublesome (Thompson et al., 2018). It is no surprise, then, that special issues, such as this one, and recent reviews (Acs et al., 2017; Feldman et al., 2019; O'Connor et al., 2018; Teece et al., 2019), call for refining our conceptualizations and measurement of emerging ecosystems to build better informed policies for nurturing innovation and entrepreneurial opportunities. Measuring and understanding the inter-relatedness of the macro entrepreneurial context is key to enabling and enhancing ultimate entrepreneurial outcomes

Revised submission to Special Issue in Uncommon Methods and Metrics for Local Entrepreneurial Ecosystems *Research Policy*.
* Corresponding author.
E-mail address: dev.jennings@ualberta.ca (P.D. Jennings).

https://doi.org/10.1016/j.respol.2021.104315
Received 27 November 2019; Received in revised form 22 April 2021; Accepted 15 June 2021
Available online 21 July 2021

through policy.

In this paper we refine the conceptualizations and measures of emerging entrepreneurial ecosystems in a way that goes beyond the more stable and concrete – "material" or resource – approach by simultaneously using a cultural one. This stereoscopic cultural and material approach combines two relevant streams of theoretical work with a methodological one. We build theoretically on the new structuralist approaches to culture (Lounsbury & Ventresca, 2002; Mohr et al., 2020; Mohr & Duquenne, 1997), cultural entrepreneurship (DiMaggio, 1997; Lounsbury & Glynn, 2019; Navis & Glynn, 2010; Thompson, Purdy & Ventresca, 2018), and strands of the cultural approach found in entrepreneurial ecosystems theory (Autio et al., 2014; Spigel, 2015; Thomas & Ritala, 2021; Wurth et al., 2021). In order to provide newer measures and metrics, we apply an interpretive data science approach (Hannigan et al., 2019; Kennedy, 2008; Nelson, 2019), which "renders" theory from big data to capture dynamics and nuances in evolving systems.

We highlight that emerging entrepreneurial ecosystems, like any nascent fields, depend not just on material resources but also on the evolving cultural understandings of *possibilities* among system members that contour that domain. Field-based understandings – that is, cultures - are reflected in field discourse (Huff, 1990; Porac et al., 1995). Discourse mapping using interpretive data science methods helps capture the emerging and evolving cultural topology of a field (Kennedy, 2008; Mohr & Duquenne, 1997; Thompson et al., 2018). Big textual data can help modellers track the evolving discourse in an emerging ecosystem (see Hannigan & Casasnovas, 2020; Kirsch et al., 2013; Powell & Oberg, 2017), and give a window to emerging possibilities for policymakers. Such data informed early insights can help policymakers move past having to place material bets on particular technologies that other regions have had success with, and instead identify new unique high potential emerging possibilities (Seidel et al., 2020).

Combining these streams of research allows us to pursue a fundamental cultural proposition - that *cultural holes catalyze entrepreneurial possibilities in an emerging ecosystem* (Baker & Nelson, 2005; Lounsbury & Glynn, 2019; Pachucki & Breiger, 2010), and if properly identified, can serve as excellent emerging policy targets. As a concept, cultural holes parallels that of structural holes (Burt, 2004; 2005) in social networks, which is used to map material possibilities. To develop our cultural holes proposition for entrepreneurial ecosystems, we first conceptualize the nature of emerging entrepreneurial ecosystems from a cultural perspective, relying on the aforementioned approaches in organizational sociology (e.g., Lounsbury & Glynn, 2019; Mohr et al., 2020) and contextual views of entrepreneurial ecosystems (e.g., Feldman et al., 2019; Spigel, 2020). We then theoretically isolate and elaborate key elements of an emerging ecosystem by developing a typology that compares ecosystem boundaries, levels of analysis, network tie types, forms of representation, notions of agency, key mechanisms, and effects on accumulation (Wurth et al., 2021). In a theoretical move similar to Spigel's (2015, 2017) and Thompson et al.'s (2018), we compare the cultural side of such an ecosystem with its material side. Guided by this twin application of the typology, we examine an emerging regional entrepreneurial ecosystem in Artificial Intelligence (AI). We combine new forms of cultural mapping with big textual data from social media and traditional forms of resource tie mapping to identify entrepreneurial possibilities and culturally informed strategies. In doing so, we uncover early cultural markers in emergent ecosystems for both policy analysts and policymakers and develop a method of cultural mapping to add to policy analytics and help customize policy to emergent ecosystems.

1. Conceptualizing emerging entrepreneurial ecosystems

Given their economic and policy importance, entrepreneurial ecosystems have received increasing attention in the last decade (Autio et al., 2014; Brown et al., 2019; Feldman et al., 2019; Spigel, 2020; Wurth, Spigel & Stam, 2021). Related to concepts such as regional innovation networks (Cooke et al., 1997; Powell, White, Koput & Owen-Smith, 2005; Saxenian, 1990), innovation clusters (Bresnahan et al., 2001; Porter, 1998) and innovation ecosystems (Oh et al., 2016), the entrepreneurial ecosystem concept is distinct in considering, on the one hand, a broader set of elements in the region, and, on the other, focusing in on entrepreneurial action (Malecki, 2018).[1]

A prominent example, one to which we subscribe, is Spigel's view: "[e]ntrepreneurial ecosystems are combinations of social, political, economic, and cultural elements within a region that support the development and growth of innovative start-ups and encourage nascent entrepreneurs and other actors to take the risks of starting, funding, and otherwise assisting high-risk ventures" (Spigel, 2017, p. 50). As such, ecosystem policy components cannot be understood without a more complete comprehension of the wider context embedding the nascent ecosystem which helps that ecosystem arise (Autio et al., 2014). The actors within it, whether individuals, networks or organizations, conceptualize possibilities and risks in that context, shaping the resulting pattern of economic activity. A distinct aspect of this approach is the concept of support for early or "prenatal" ventures (Clough et al., 2019). In this and other ways, entrepreneurial ecosystems differ from "innovation ecosystems" (Oh et al., 2016).

While entrepreneurial ecosystems are clearly distinctive, many conceptualizations and studies of ecosystems are still tilted towards more established, rather than nascent or emerging ecosystems. Established systems, like Silicon Valley, may have been heavily entrepreneurial in their earlier stages but are no longer as nascent and entrepreneurial (Audrestch, 2021; Brown et al., 2019; Feld, 2020; Isenberg, 2010; Lam & Seidel, 2020). In established entrepreneurial ecosystems, organizations and individual actors are likely to spend a great deal of time in standard organizational maintenance activity, not just building products or processes or creating new knowledge and innovating (Autio et al., 2018; Spigel, 2020). Established systems likely have most key elements and theoretical processes materially visible, and more easily measurable using established metrics (Heaton, Siegel & Teece, 2019). At this established stage the ecosystem is framed as helping entrepreneurial actors find established partners who will provide necessary resources (van Rijnsoever, 2020) and help the local regions further grow (Stam, 2015; 2017).

In contrast, emerging entrepreneurial ecosystems systems (EEEs) are not as likely to display material elements and properties to the same degree (Malecki, 2018). They may even lack some materially observable characteristics or processes, such as dedicated financing units or marketing groups (Forbes & Kirsch, 2011). This means that classic material measures of entrepreneurial outputs such as start-up counts, IPOs, acquisitions, or other exits may be less meaningful and evident in the emergence stage (Seidel & Greve, 2017). Instead, these emerging entrepreneurial ecosystems may seem more akin to knowledge systems, with their focus on innovation and not yet on material output (Kay et al., 2018; Powell & Snellman, 2004). Typical ecosystem supporting infrastructure in this mode is likely to be absent, low, or even simply a function of university institutional systems (Heaton et al., 2019; Powell & Oberg, 2017; Thomas & Ritala, 2021). This is particularly true for standard entrepreneurial financing, such as venture capital (Florida & Kenney, 1990; Hannah & Eisenhardt, 2018). Yet, policy aims to influence these emerging systems without fully understanding or observing them (Brown et al., 2019; Lam & Seidel, 2020; Nambisan et al., 2019). For this we need to add a more cultural approach, and data tools that enable policymakers to better identify and unleash the cultural possibilities appropriately.

[1] In the debate about the difference between entrepreneurial versus innovation ecosystems (see Acs, 2017; O'Connor et al., 2018; Stam, 2015), we favor viewing the former as being innovative in intent, process and often in outcomes.

1.1. A cultural approach to EEEs

A cultural approach is particularly useful for understanding and measuring the configurations of these emerging entrepreneurial ecosystems where material markers are less meaningful. Early work on entrepreneurial clusters discussed differences in cultures in places like Silicon Valley versus Boston's Route 128 (Saxenian, 1994), in mindsets (Huff, 1990) or how field level understandings (DiMaggio, 1997) underpin actors' ability to see opportunities (Alvarez, Barney, McBride & Wuebker, 2014) and willingness to take risks (Aldrich, 1994; McMullen, Shepherd & Jennings, 2007). Cognitive mindsets can temper the competitive-cooperative dynamic, allowing industries like Scottish knitwear to thrive (Porac et al., 1995). Critically, these mindsets can develop well before any material markers of such activity surface.

Broadly speaking – while acknowledging that any definition is likely to be debated - culture for us is the underlying pattern of beliefs, ideas, and practices in a social space (Mohr et al., 2020, p. 4). The pattern may be coherent or highly fragmented, but it is not shared by all people as a homogenous system (Martin, 1992; Mohr & Rawlings, 2018). The cultural pattern may be evident at different levels of analysis, from the group to field to society, and expressed through or maintained by actors at each (Mohr et al., 2020). The pattern has been theorized and modelled around five different key conceptual system elements – values, stories, frames, categories, and toolkits (Giorgi et al., 2015).

Common to these five elements and the patterns of culture they express is the meaning and meaning-making by the actors in the system (Hallett, 2003; Mohr et al., 2020). Collective meanings are produced and consumed by individual actors, the EEE's groups and the ecosystem as a field (Bourdieu, 1993; Rawlings & Childress, 2019). This implies that cultural processes in and around EEEs are highly endogenous and agentic (Kaufman, 2004). Indeed, in entrepreneurship, compared to cultural sociology, culture is viewed in more actor-focused and actor-driven terms. As such, there has been an effort to show how stories, frames, and categories are actually deployed by entrepreneurs and related actors (Giorgi et al., 2015; Lounsbury & Glynn, 2019). Founders, startup teams, intermediary actors such as professionals, VCs, universities, and governments all deploy cultural devices to shape the culture of a field (Clayton et al., 2018; Jennings et al., 2013). In doing so, they ensconce deeper values in the field and shape collective meanings (Friedland, 2013), even if new meanings continue to emerge and old ones continue to evolve (Soublière & Gehman, 2019).

At the same time, various actors, practices, and cultural elements combine to exhibit deeper patterns. Those patterns are structural arrangements that shape – both constrain and provide affordances for – activities in the cultural system (Giddens, 1984). The patterns are evident if one zooms out to higher levels, such as to the level of organizational fields, or of society. At these higher levels, the patterns can be discerned in the interaction among key actors around culturally meaningful objects in the field (Mohr et al., 2020).

1.1.1. Cultural holes

When zooming out, one key cultural pattern in an entrepreneurial ecosystem that can be seen is around cultural holes. Structural holes have previously been used to conceptualize material opportunity space for entrepreneurial activity (Burt, 2005). As an analog to structural holes, cultural holes are the spaces between clusters of understandings or practices (Pachucki & Breiger, 2010). In the words of Pachuki & Breiger (2010), "…[they are] the contingencies of meaning, practice, and discourse that enable social structure" (p. 213). The cultural spaces, being between such clusters, provide *new possibilities* for ideas, practices or values to emerge (Lounsbury & Glynn, 2019). Indeed, in this sense, key structural holes in an EEE may well just be a material subset of cultural holes, because such structural holes likely garner their meaning and worth from the cultural contingencies around existing material ties.

Nevertheless, even more so than structural holes, cultural holes are likely to go initially unnoticed by field members, only gradually being discovered (Pachucki & Breiger, 2010; Mohr & Bogdanov, 2013; Powell & Snellman, 2004). Powerful field members may push their various understandings into parts of the system, becoming salient bulwarks in and around the discourse as it coalesces. Mohr and colleagues have traced types of idea contestation by watching how participants operating in different positions within the organizational field negotiate localized and regional topographies (maps) of meanings and resources (Mohr & Duquenne, 1997). In doing so, they generated new possibilities and programs for handling poverty. Goldberg (2011) and Lizardo (2014) have shown how "cultural omnivores" consume and connect disparate cultural genres, creating new underlying categories (also see Navis & Glynn, 2010). The cultural approach and cultural holes in particular, then, appear to offer important precursors to more materially observable entrepreneurial outcomes in EEEs, such as new venture formation. These elements can be conceptualized, measured and mapped as part of policy analytics to yield a fuller picture of the emerging possibilities.

2. A cultural versus material ecosystem typology and measurements

Per this special issue's call, how might one use this culturally grounded-approach? Put slightly differently, how might one use cultural holes to measure and map new possibilities and potential material outcomes in an EEE? Entrepreneurial ecosystem researchers, as already noted, acknowledge the importance of culture and the wider milieu – or *context* – around entrepreneurial actors (Feldman et al., 2019; Stam, 2017). Many see culture as one dimension –or important characteristic – of entrepreneurial ecosystems (Autio et al., 2014; Wurth, Stam & Spigel, 2021).

Among entrepreneurial ecosystems researchers, Spigel (2015, 2020) has probably gone furthest in this direction of trying to explicitly capture the cultural and the material interaction (also see Stam 2015; 2017), and in this way bridging economic geography views of ecosystems with socio-cultural ones (Powell and Oberg, 2017; Thomas & Ritala, 2021; Thompson et al., 2018). Spigel has proposed that ecosystems can be understood and studied using their material, social, and cultural attributes, and that these attributes can be stacked from the material down to the cultural as dimensions or layers, giving each EEE its unique configuration. In his 2015 article, he displayed these configurations as side-by-side pyramids for Calgary and Waterloo (Canada) entrepreneurial ecosystems.

This unique local macro configuration is the motivating policy challenge we are attempting to address with this paper, as policies informed by and designed for a different configuration are by definition non-optimal. To delineate the power of a cultural approach, while avoiding the creation of a "straw person" on the material side, we draw on Spigel's ecosystem conceptualization and notion of mapping levels or layers. Thompson et al.'s (2018) have a similar move in their work, if less in measurement terms. For the purpose of this article, which is focused on theorizing and capturing the cultural dimension, we will limit ourselves to elaborating and contrasting that cultural layer with the material, but allude to the social along the way and in the discussion section. In keeping with our broader cultural approach, by "culture" we mean the pattern of ideas, values and practices in the emerging ecosystem around entrepreneurship, which is then evident in the various faces of culture (from toolkits to values). A key structure is the set of cultural holes as forms of entrepreneurial possibilities that can materialize as a set of tangible or intangible resources in the system. The material refers, in contrast, to the set of tangible yet also somewhat intangible resources in that system (Spigel, 2015: 6). In Spigel's social layer, he has "the resources composed of or acquired through the social networks within a region" (p. 6), which we include here in the material sides the network of resource ties among actors (Burt, 2005).

Using this dimensionalization of cultural and material layers, we consider theoretically grounded components that are common across the dimension of layers of the ecosystem (also see O'Connor et al., 2018;

Table 1
Cultural and material characteristics and measures of emerging entrepreneurial ecosystems.

Characteristics	*Cultural*	*Material*
Systems boundaries & membership	Virtual boundaries around coherent discourse spaces, with members define by identities, new norms or conventions, and meaningful objects • Using leading edge databases (Crunchbase) on local startups, social media members (Twitter accounts) who discuss ecosystem group of the city + others. Often via public data.	Geo-physical boundaries around emerging clusters with new, concentrated resource flows indicating boundaries. Membership formally defined by local schemes (industrial, govt., alliance ties). • Counting new AI starts within Edmonton city boundary, focus on concentrated entrepreneurial activity and funding (e.g., around key firms. Often via private data.
System levels	The virtual community, cliques within it, and its linkage to specific entrepreneurs and their startups. • The community constituted by the active, higher attention (#followed city AI orgs), specific handles and specific AI orgs in sub-communities.	The regional ecosystem nodes and flows, and the dyads of exchange within it. • All the organizations tied to AI startups and indicating whether there is some form of exchange among each (dyad level).
Network ties	Discourse-based ties linking actors via commentary, especially about meaningful events. • Twitter discourse about startups and founders.	Resource (money, materials, knowledge) ties; first- and second-order ones. • Recognized relationships and material support for startups.
Forms of representation & roles	Identity-based associations of diverse actors in discursive space (promoters, players) or network roles (bridgers, intermediaries). • Types of virtual actors, active/ passive accounts, assigned cultural roles and identities.	Central actors, brokers, peripheral players. • Key local players and sources of support (corporate, not-for-profit, govt.) in the system.
Agency	Agency is distributed and varies by ecosystem; cultural entrepreneurs agentically employ toolkits. • Evidence of toolkit use, some sense of distribution of agency using key cultural activit(ies).	Organizational interest reflected in positioning in the ecosystem; entrepreneurs are founders & key actors are startups. • Evidence that a founder or central actor is active in this way.
Dynamics & mechanisms	Building cultural understanding discursively, particularly by making sense of events and relationships. Cultural spaces appear for new meaning and practice possibilities. • Mapping local discursive ties, communities of understanding, and cultural holes between them.	Balancing cooperation and competition using structural reconfigurations, esp. brokering structural holes or complementarities. • Mapping ties, locating complementarities & bottlenecks, then examining key actors and their behavior around resources.
Manner of accumulation & outcomes	Expansion of discursive community, intensification of "buzz" (meaning) in it & around potential new players & products. • Examining growth in Twitter handles in system and buzz about AI firms and innovations, along with other local social media and event data.	Growth of the overall system, degree of innovation, diversity in membership, and number of "exit events." • Same measures gathered via event participation and media data.

Stam, 2017; Stam & van de Ven, 2019). Given recent work on digitization and ecosystems, such as Autio et al.'s (2018) and Nambisan et al.'s (2019), the typological components must also be sensitive enough to capture virtual and digital aspects of the system, as well as their emergence. As a result, our typology for each dimension has seven components: 1) system boundaries & membership; 2) levels for analysis; 3) network ties & types; 4) forms of actor representations & roles; 5) the nature of agency; 6) mechanisms & processes; and 7) manner of accumulation & outcomes. Table 1 shows the seven components (i.e., rows 2-8) for the cultural and material dimensions as columns 2 & 3, respectively. We display and discuss the operationalizations of these dimensions in the next section on empirics.

As can be seen for the first two components, in rows 2 & 3 of Table 1, the cultural side of the emerging entrepreneurial ecosystem is broad and only partially local, certainly less so than the material side of the system, even if both are local in their focus and contain many local systems actors. Both the cultural and the material slices or "layers" (Spigel, 2020, p. 10) have sublayers; as shown in rows 4-6, the tie types, roles, and forms of agency overlap between the cultural and material conceptualizations, but the actors who are central and complexity of the ties differ, as do their interests. Consequently, as displayed in row 7 of Table 1, the mechanisms and processes for bridging cultural holes formed by different groups (bound by shared identity) develop in different ways and only partially map on the structural holes material mapping. The latter are around competitive and cooperative processes involved in bridging structural holes and closing (or opening up) networks. Finally, as captured in row 8 of the table, the more immediate outcomes of these mechanisms and processes are dissimilar: the cultural being focused on buzz and mindshare; the material on markers such as start-ups and IPOs.

3. Empirics

Having theorized the cultural approach to EEEs and ways to typify the cultural dimension, our next step is to demonstrate the cultural dimension's differences and complementarities with the material one. To do so, we examine the emerging Artificial Intelligence (AI) ecosystem in Edmonton, a large regional city in western Canada, which we argue is a modal case of regional ecosystem emergence. In the 2013-15 era, the local anchor university had several machine learning (ML) and AI organizations. These were of sufficient quality to garner some attention of global players in the AI/ML field, such as Google Deepmind and Google Brain, Apple, Microsoft and IBM (Bouslama, 2020). The ecosystem was also recognized outside of industry outlets by traditional media (Financial Post, 2017; Globe and Mail, 2017), by the provincial government (Globe Newsire, 2020), and in global rankings of AI "ecosystems to watch" (Startup Genome, 2019). Nevertheless, many of the material trappings of larger established ecosystems, such as local venture capital, dedicated marketing groups, government development arms for AI, were lacking (Davenport, 2019). In 2015, the provincial government, in recognition of the system's importance, earmarked $100 million Can. for companies over five years, half of which found its way into the system (CBC News, 2019). This smaller scale, local focus, and efforts at self-sustaining growth paths are characteristic of regional emerging systems (e.g., see Malecki, 2018; Stam, 2015; 2017).

3.1. Rendering the Ecosystem

To form the cultural and material representations, respectively, of the emerging entrepreneurial ecosystem, we used the *three-stage rendering method* elaborated by Hannigan et al. (2019). The process of rendering refers to compiling a corpus, using mixed methods analysis on the corpus, and theorizing artifacts (constructs, linkages, processes) from those analyses – all in iterative and transparent fashion. Rendering is particularly effective with big textual data such as that from social media, which require substantial wrangling to build a corpora, open-ended analyses and more abductive theorization (Schmiedel et al.,

Fig. 1. Sample tweets involving important Edmonton AI ecosystem actors.

2019). We build on this approach by showing, at each of the three rendering stages, the cultural versus material elements of the Edmonton EEE.

3.1.1. *Rendering the ecosystem's cultural and material corpora*

The cultural dimension of the ecosystem, as shown in Table 1 (column 2; row 2 & 3[2]), is captured by examining virtual boundaries around coherent discourse spaces, with members defined by identities, new norms or conventions, and meaningful objects (Mohr et al., 2020). In this case, the meaningful objects are "AI" and "ML" (Nambisan et al., 2020). The cultural boundary is still anchored to a physical boundary (Table 1, row 3), which is the place with which actors pursing AI/ML identify (Mohr & Duquenne, 1997; Thompson et al., 2018).

The cultural approach to measuring and mapping this locally anchored entrepreneurial ecosystem relies on some of the same key actors as a material (or social) ecosystem dimension (Table 1, rows 4 & 5) – i.e., investors, intermediaries, the government, universities, startups - but uses different information. The cultural corpus is based on discourse (communication via talk, text and visuals) used by and focused around AI/ML new ventures (Navis & Glynn, 2010; Thomas & Ritala, 2021; Thompson et al., 2018). These new ventures include startups or formal initiatives (e.g., spin-ins or special new units) launched by incumbent organizations. In measurement terms, this means it would include key emerging entrepreneurial actors and others in and around the local ecosystem who communicate with or about one another (Table 1, column 2; row 4-6). The outcome of this interaction is the amount of "buzz" about new possibilities from these actors (rows 7 & 8).

Here we build our corpora using discourse in the form of tweets among ecosystem actors, although we acknowledge that other forms of communication (emails, newspapers, private conversations, meetings) are also valuable sources of information. Twitter has been used in other studies of cultural dynamics in fields (Shi et al., 2014; Zhao et al., 2011). Twitter is spontaneous, real time, and mostly public (i.e., there are some private facing features like direct messaging, but the platform is mostly used for public communication). While somewhat performative in nature (Thomas & Ritala, 2021), Twitter also enables entrepreneurial actors to find each other and evolving opportunities (Fischer & Reuber, 2011; van Rijnsoever, 2020). For example, in the fall of 2020, several prominent Silicon Valley based venture capitalists and entrepreneurs openly speculated about moving to Miami. The mayor of Miami, Francis Suarez directly responded on Twitter to this speculation, saying "How can I help?" (Suarez, 2020). The New York Times recently documented Suarez' efforts on Twitter suggesting that "the glass door to his office has his mayoral seal and his Twitter handle" (Bowles, 2021).

Tweets in the local Edmonton AI EEE appear to operate similarly. Three linked tweets among important actors are displayed below in Fig. 1. Two of these tweets – those from well-known AltaML CEO, Cory Janssen, and from Innovate Edmonton lead, Cheryll Watson – raise the issue of AI-related applications to health in Edmonton. A third tweet comes from the Provincial Minister of Jobs, Economy, and Innovation, Doug Schweitzer, in which he attempts to start an offline conversation with entrepreneurs in the ecosystem regarding economic recovery relating to "traditional and emerging sectors". These three tweets are clearly intended as public facing messaging; they connect politicians, system entrepreneurs, and local initiatives. Public messaging by Tweet enables quick sharing of information and a mindset with the central actors, diffusion of the understanding to others.

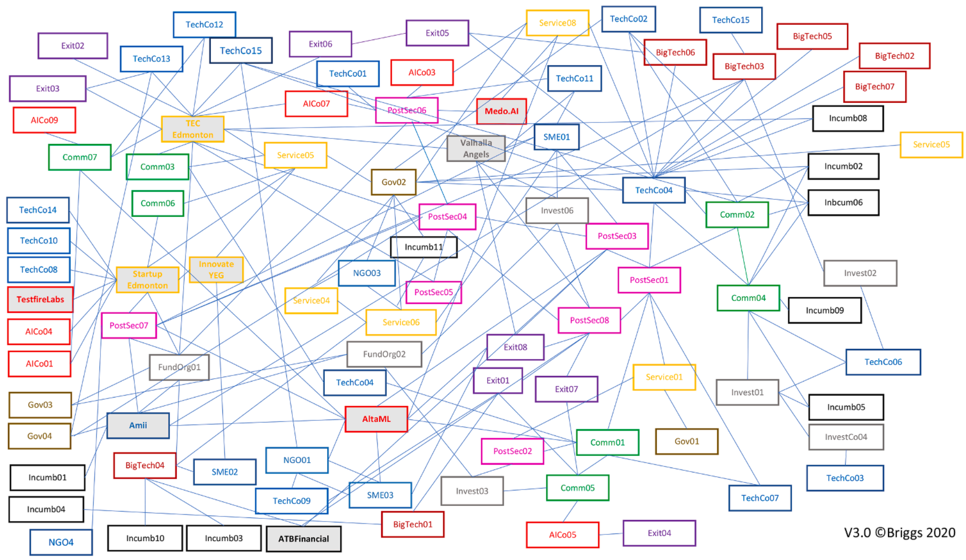
In constructing our corpora and analysis of topics, we examined both *who* said something and *what* was said by those actors in and around the ecosystem (see Table 1: column 2, rows 3-4). In our case, to capture "the *who*", we first used Crunchbase, augmented by local media mentions, to identify the 40 AI ecosystem new ventures, as of 2019, in the local ecosystem. Crunchbase has been used by other researchers studying ecosystems and entrepreneurial networks (Ter Wal et al., 2016). Of these, 29 were fully operational by the time of this study and had an active account on Twitter. Scraping of all followers on Twitter (via Twint in Python and using the official Twitter Developer API) yielded a total of 33,200 Twitter accounts following any of the 29 AI new ventures. These ventures and their tweets are displayed in Appendix Table A1.

An important rendering move to manage this corpus was then to select *all Twitter handles that were following four or more (4+) AI start-ups* in the system, *plus the 29 AI* new ventures handles that were sending out virtual ties. We made this decision by inspecting the maps of 2+, 4+, and 6+ sent and/or received (all directional) links to followers to set up corpus selection criteria in order to identify more coherent networks and bundles of tweets flowing through their ties (Borgatti et al., 2018; Owen-Smith & Powell, 2004). This yielded 135 nodes, the most active sending and receiving ones being listed in Appendix Table A1.

In the case of "the *what*" (Table 1, rows 6 & 7), we examined up to the most recent tweets (up to 200) by the 135 actors (i.e., the nodes in the cultural network). These nodes' handles had tweeted, in total, 23,532 times in the past two years about the ecosystem. We used these tweets to form the documents for our study's corpus (see Appendix Table A1). To render this corpus, we preprocessed the documents by lemmatizing the texts (Schmiedel et al., 2019). We lemmatized the words in these Tweets using the Stanford CoreNLP toolkit (v. 3.9.2 in Manning et al., 2014; see Goldenstein & Poschmann, 2019 for an application in social science) to create tokens for analysis. Of the 218,025 words 30,341 were unique tokens. These lemmatized tweets with unique tokens included AI/ML specific references, such as: "@deepmindai neurips18 head deepmind recruitment stand meet edmonton team group focus fun" and "This is really cool. Awesome to see #AI #MachineLearning in traditional industries in #yeg and Alberta. Cool project." They also included entrepreneurship related Tweets, e.g., "Among the dreamers and the doers at @INVENTUREScan #yeg #researchinnovation #Entrepreneurship." Other tweets in the corpus were about lifestyle and other municipal area topics. The population of all tweets in this time period about the AI system formed the corpora to topic model "the what" in the model rendering stage.

The Material Dimension's Corpus. The material ecosystem, as shown in Table 1 (column 3; rows 2 & 3), is captured by examining members in

[2] If one counts the characteristics' column and dimensions' row, per the prior discussion of dimensionalization.



Category type	Description
InvestCo	Angel investor
FundOrg	Venture or program funder
AICo	AI at core of product or service
SME	Small or medium company not AI
TechCo	AI Adjacent with capabilities
Incumbent	Large local company not tech
BigTech	Non-local, large tech with AI capabilities
NGO	AI linked non-governmental organization
Community	Entrepreneurial community
Service	Government entrepreneurship service provider
Govern	City or provincial government
PostSec	Post-secondary faculty or unit
Exit	Exited techco

Fig. 2. Composite material map of Edmonton AI ecosystem.

geo-physical boundaries around emerging clusters with new, concentrated resource flows indicating boundaries. The boundary for the material map is based on government determined municipalities. The area includes surrounding suburbs, satellite towns, and the core city. Like membership in most material maps, members in the ecosystem can be defined by relevant tangible and intangible resource activities around identifiable actors in the local main city's ecosystem (Table 1, rows 3-5).

We encoded these members and their ties in the regional ecosystem via reports by well-placed others (Borgatti et al., 2018). Each well-placed other was requested to discuss key actors and the others in the system with whom they were tied (Borgatti et al., 2018; Marsden, 2005). We then asked them to build upon these insights and draw a map that contained the key actors and their tangible and intangible resource ties (Mehra et al., 2001; Schiffer & Hauck, 2010). The respondents included a director of a local service organization for entrepreneurship in the regional ecosystem, the head of a health-based AI firm, a government service lead, and a prominent local investor in the ecosystem. Consistent with Schiffer & Hauck (2010), we then built a composite material map from these four maps. The composite contained all nodes and ties mentioned (the union of nodes), and had the most important (well-linked and critical resource) actors positioned more centrally. To systematize that map, we read the node list of bi-directional ties as an . xls symmetric matrix of ties among actors into UCINET (Ver. 6.7) and generated a map display (see Fig. 2). Most nodes, at the request of respondents and coordinating author, were anonymized by coding them into broader categories, such as "InvestCo" and "FundCo". A select number of nodes were, with permission, revealed to match up the key organizations from the material map with those from the cultural one.

Somewhat centrally are TechCo 4, PostSec 1, Invest 5 [Valhalla Angels], Service 3 [Startup Edmonton], and Gov2. Less central are Incumbents 4 & 11, TechCo 3, BigTech 1, and Invest 2. In between these two groups are several moderately linked and clustered actors, such as those around AICo 8 [AltaML], Service 3 [Startup Edmonton], and FundOrg 2. The map itself looks moderately dense and seems to have a diversity of organizations (AI startups, funders, government agencies and service providers, university units). Importantly, the organizations recognized for doing AI or ML research and application themselves vary, from broader tech companies (such as TechCo4), to AI-specific firms (the respected AICo8 [AltaML]), to AI-NGO type research-oriented units (NGO 2 [Amii], a prominent player). On the whole, the map contains organizations and patterns that look similar to those found in other EEE maps (Autio, 2017; Heaton et al., 2019; Spigel, 2020).

3.1.2. *Rendering the ecosystem's cultural & material (structural) holes*

Rendering topics and models – in particular, cultural and structural holes – from the corpora was our next major task (Hannigan et al., 2019). In the case of the cultural holes map and analysis, this required three steps. The first was to parse down and organize the set of 135 nodes of "*who was linked to whom*" in network terms (i.e., those in Appendix Table A1). The second was to find "the what" was being said as sets of topics and themes. The third was to link these parsed down and organized network members and topics together into a cultural holes map. As the first step, to capture the core group of actors shaping the local cultural discourse, we tried to identify the most stable bi-directional (two-way) ties among actors, which, in network terms indicates reciprocity and mutual engagement (Borgatti et al., 2018;

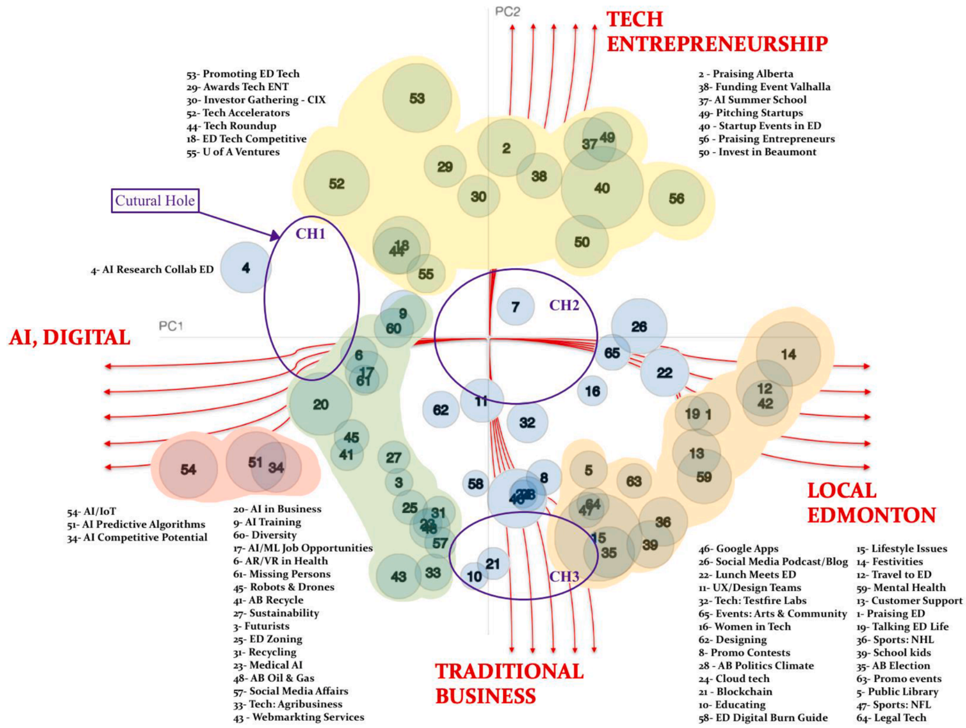


Fig. 3. The cultural map of topic clusters and holes.

Tasselli & Kilduff, 2020). Using a rendering move similar to that for creating the 4+ networks in corpora stage, we examined 3+, 4+, and 5+ tweet following networks, and created bi-directional network graphs for each, and, upon visual inspection settled on the 4+ bi-directional as the most coherent and balanced network underlying the tweets in the "what" corpus. That 4+ map is displayed in Appendix Fig. A1, rendered via Gephi (Ver. 9.2) with betweenness centrality and modularity of Q=.58 (Wang et al., 2017).

To then understand *what* was being said about entrepreneurial possibilities by this core set of cultural actors, as our second step we applied topic modeling analysis (Mohr & Bogdanov, 2013). Topic modeling using Latent Dirichlet Allocation (LDA) is becoming the standard go-to analysis in management of big textual data (Hannigan et al., 2019). However, when each document (i.e., a tweet, in our current case) has a small number of words, LDA is not optimal. The distribution of topics across the documents was too sparse, making estimation of the LDA parameters for a document particularly difficult. Recently, analysts have advocated rendering topics using bi-term (concurrence of two tokens) analysis, otherwise known as "BTM" (Jonsson & Stolee, 2019; Yan, Liu, Chen & Tong, 2013). Like LDA, it uses a Bayesian iterative approximation of the distribution of words across documents, but considers the whole collection of documents, not each individual one, as its starting point. We used the R coding of BTM (Wijffels, 2019) to generate topics across the corpus of tweets. To find the optimal set of topics, given a large or small number can be generated, consistent with LDA best practice, we plotted the loglikelihoods of each BTM model, in 5 topic steps (from 5, 10, 15, up to 70 topics), to find this downward inflection point in the LL. In this rich cultural space, there were 65 topics.

We still needed to generate some sense of meaning for those topics and relate the topics to one another. To do so, we needed to rely on both machine and human interpretation. Following Hannigan et al. (2019), three well-placed, co-author observers in the ecosystem axial coded the topics using three items: 1) the top twenty most probable words per topic; 2) the matrix of topics weighted by cleaned tweets about the topic, and 3) the LDAvis tool (Sievert & Shirley, 2014) applied to the topics and outputs produced the BTM package[3]. Each observer independently coded topic meanings, compared and the adjusted codes and generated a list of first-order topics. They then examined the agreed upon meanings and the LDAvis of all 65 topics to come up with relative groupings and second-order codes for those topics. Toggling relevance scores of words in the LDAvis helped ferret out this meaning. The details on these first-order axial 65 coded topics and the four second-order conversation spaces are available upon request.

As our third step, we combined "*the who*" 4+ bi-directional network and "*the what*" 65 topics into a novel artifact: *a cultural map of discourse* (see Fig. 3 below). We normalized the matrix of tweets by collapsing the distribution of topics across the 23,532 documents (the tweets) that were being jointly followed by the 135 handles (nodes). We then generated a cluster map of topics proximities based on the underlying network of bi-directional tweeters (see Fig. 3). The sets of 65 topics cluster into the four areas: AI/ML SciTech, AI to Business, AI Entrepreneurship, and Local Lifestyle & Community Issues. Each of these four areas appears to have somewhat coherent topics and active tweeting within them; that is, they may reveal subcultures of discourse in the cultural (Audretsch et al., 2021; Mohr et al., 2020). Among those four groups and other subgroups of clustered topics are spaces; that is cultural holes where new entrepreneurial possibilities may exist (Lounsbury & Glynn, 2019; Pachuki & Breiger, 2010). In Fig. 3, using circles in purple, we have identified a few of these cultural holes. We discuss the theoretical importance of the map and the cultural holes in the rendering theory section.

The Material Dimension. Parallel to our model rendering step for cultural holes, we rendered structural holes with a material map of entrepreneurial actor ties. In keeping with Burt's well-known work on structural holes (Burt, 2004; 2005), we used our material map's symmetric matrix in UCINET (Ver. 6.7) to generate centrality, constraint and

[3] One of the co-authors developed software for this project to extend the BTM R package for the LDAvis functionality.

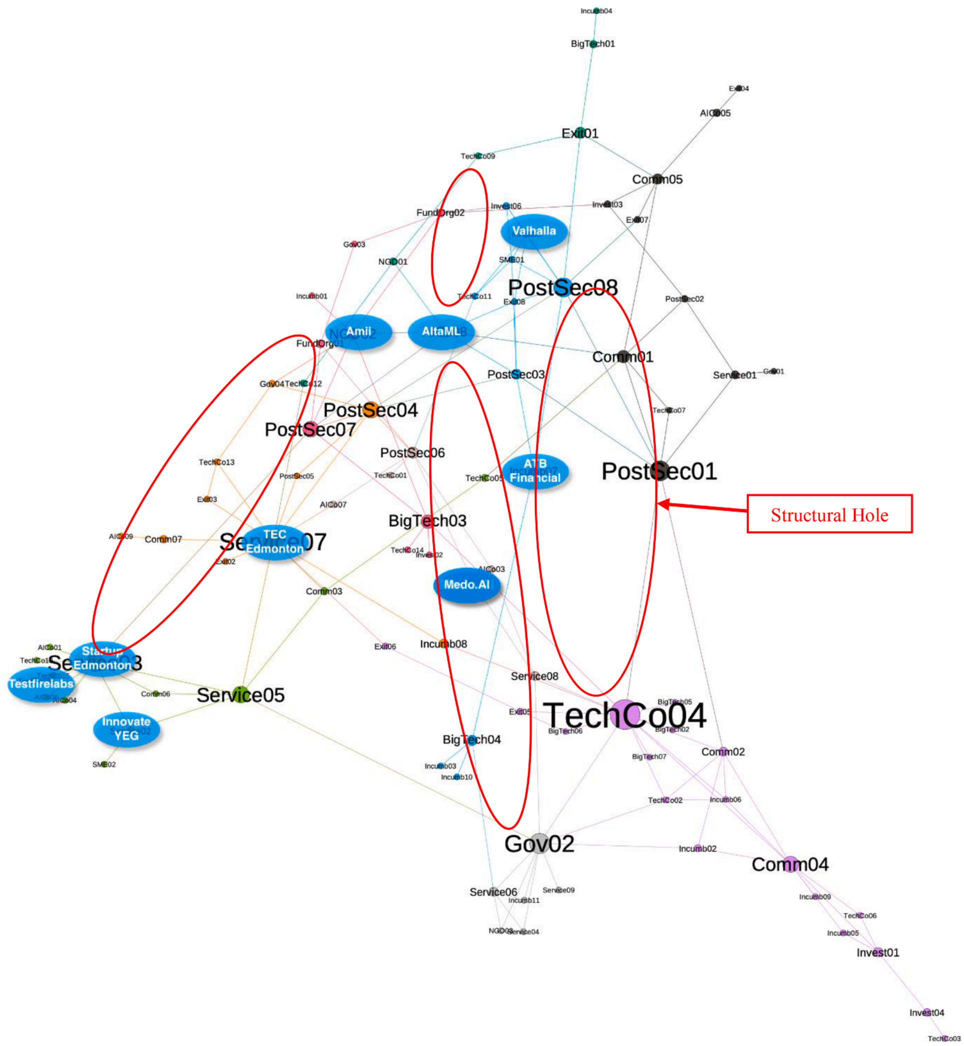


Fig. 4. Material map of weighted nodes, group tie types, and a few structural holes.

autonomy measures for actors in the map. A sample of these measures is displayed in Appendix Table A2. The highest centrality score in terms of sheer tie count (10) and betweenness (1228) is TechCo 4, followed by main city unit (10 and 730, respectively), and the post-secondary units 1 & 8 (7, 9; 726, 738). The AI specific firms, such as the well-regarded (AICo-08, AltaML) have lower degree and moderate betweenness scores.

Next, we generated a more focused, distillate material map of the resource power and centrality of key actors in the network (Burt, 2004). To do so, we converted the betweenness centrality of actors to be represented as node size (Borgatti et al., 2018; Wang et al., 2017). Applying betweenness modularity (again at Q=.58) to parse down the number of ties and determine main cliques, as we did with the cultural map, reveals seven clusters of organizations (Fig. 4). Each is indicated by a color: black, blue, red, orange, green, pink and grey.

Finally, using the scores per actor regarding centrality and number of structural holes (Appendix Table A2), along with the all-important visual inspection of the distillate material map in Fig. 4, we identified spaces that represented large or important structural holes. The most important structural holes are those spaces between the dense cliques and are signalled by the constraint scores (reversed by 1-constraint), per Burt (2004, 2005). We display three large structural holes in the figure, with a smaller one for contrast. A large structural hole appears between TechCo 4 (a tech med startup) and PostSec 8 (a university mentoring unit linking alumni to students). Currently, that hole is primarily bridged by PostSec 1. However, PostSec 1 is not a funder or a specialist group per se, whereas PostSec 8 is a specialist group, suggesting opportunities exist for less constrained actors who have relevant funding or knowledge skills to enter this space and potentially to become "brokers" between actors in different cliques (Burt, 2005). One of these potential brokers is an external very large tech firm, BigTech 3, (effsz=4.6, cnstr =.30), another is a bank, Incumbent 7 (ATB Financial's new AI venture), (effsz=3.0, cnstr=.33). Yet whether these spaces will be noticed and bridged, as we have argued above, depends on how the cultural map and its holes (possibilities) align with the material map and its holes.

3.1.3. Rendering relevant entrepreneurship and policy theory

In the corpus and model rendering steps we crafted EEE maps of cultural and structural holes. Based on these, we were then able to interrogate the maps theoretically to generate insights and additional theoretical artifacts (Hannigan et al., 2019). In Fig. 3's cultural map, as mentioned above, we see four conversation areas - *AI/digital, tech entrepreneurship, local/lifestyle,* and *traditional industry*. Theoretically

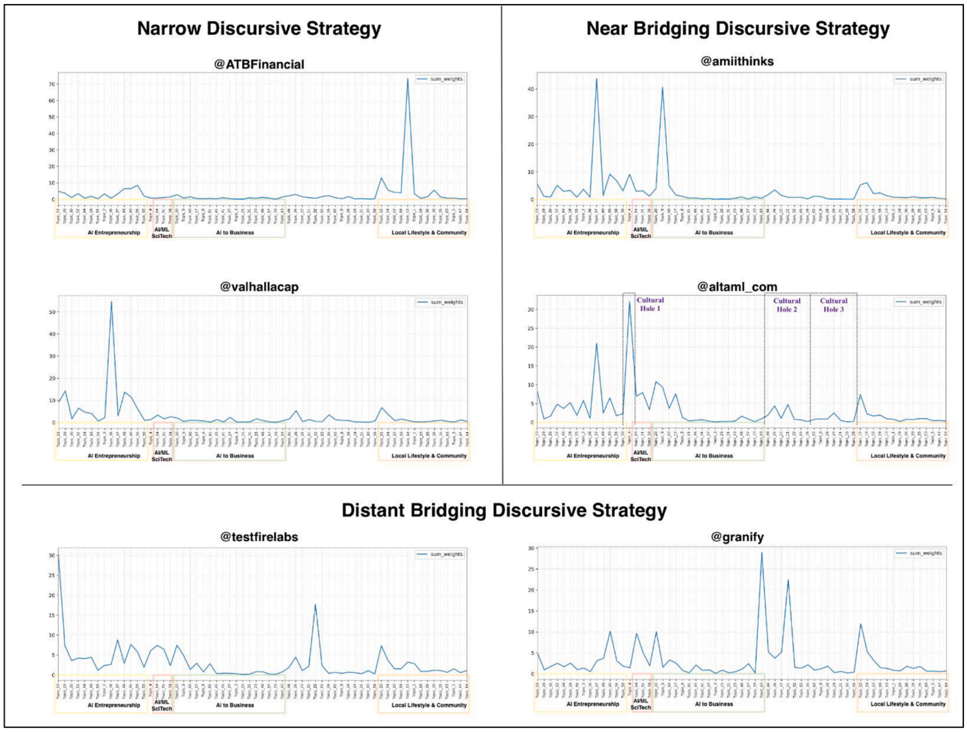


Fig. 5. Discursive signatures.

they seem to represent different cultural conversation clusters, and perhaps indicate cultural subgroups or subculture in the AI industry (Audretsch et al, 2019; Mohr et al., 2020). Based on the direction of the tweets and the nature of the tweets, four areas appear to pull in different directions. On the one hand, this means that within subcultures topics are pulling in a similar direction; e.g., the core conversation of AI/ML research groups and applied engineering firms in the AI Digital space appear to have some discourse and likelihood of filling nearby cultural holes. On the other hand, this outward pull of the four groups leaves a sparser center in the map– some form of low gravity well in the EEE. One might argue that this cultural hole is significant enough to represent some institutional or logics void (Thornton, Ocaio & Lounsbury, 2012). There is insufficient dialogue among the poles to fill this space with joint understanding (Lounsbury & Glynn, 2019). There may even be some degree of polarization. This may imply that these larger cultural holes and places of polarity are early traces of market failures (Heaton et al., 2019), which policymakers should evaluate and potentially redress with pre-emptive action.

A second theory-inducing observation about the cultural map is around the arc of topics or conversations in the map. There is a prominent arc (in green) on the map's left-hand side representing engineering AI/ML clustered conversations. That cluster is only loosely touching on the large nebula of conversation about technology entrepreneurship at the map's top, many tweets of which are generated by service providers. A great deal of policy work in EEEs is around connecting technology applications and knowledge to entrepreneurial opportunities and service provision (Heaton Siegel & Teece, 2019; Nambisan, Thomas & Wright, 2018; Stam, 2017). The cultural map clearly captures these two important clusters and their evolving relationship in the two-year snapshot. It suggests that more work needs to be done to connect these two important sets of discourse – another potential policy target.

Turning to theory that might emerge from the material map in Fig. 4, interestingly, the three large structural holes displayed show evidence of big voids in the map between several cliques, at least at that map's level of granularity. But there is no evidence of one major or central void that defines a central axis of potential polarization. Observations of the material map, therefore, might lead policymakers to construct generic connecting policies, like joint conferencing or funding pools, without recognizing the polarities across the subcultures and misaligned resource cliques might lead to failures. Policymakers might also focus on particular structural holes and fund resource players based on their proximities, but without understanding the cultural tensions among proximate actors. As a result, event equal funding might be viewed as unequal because some critical segment of actors view their virtual position as being more important (Audretsch, 2021).

Looking at the specific actors in the material map, we also see that the most central players are not necessarily the tech firms, but universities and service providers, a point that researchers have made (Heaton et al., 2019; Grimaldi et al., 2020). These actors provide human capital and maintain many social ties with tech firms, but the university and service firms do not often have enough fungible resources to help linked cliques in more substantial ways. On that point, in the material map we see some very long linked areas, such as to the lower left and right. Granted, this is partly a function of arbitrary map rotation, but the network indicates that there are disconnected AI/ML players in resource terms, yet these same actors appear in Fig. 3 to be more connected in

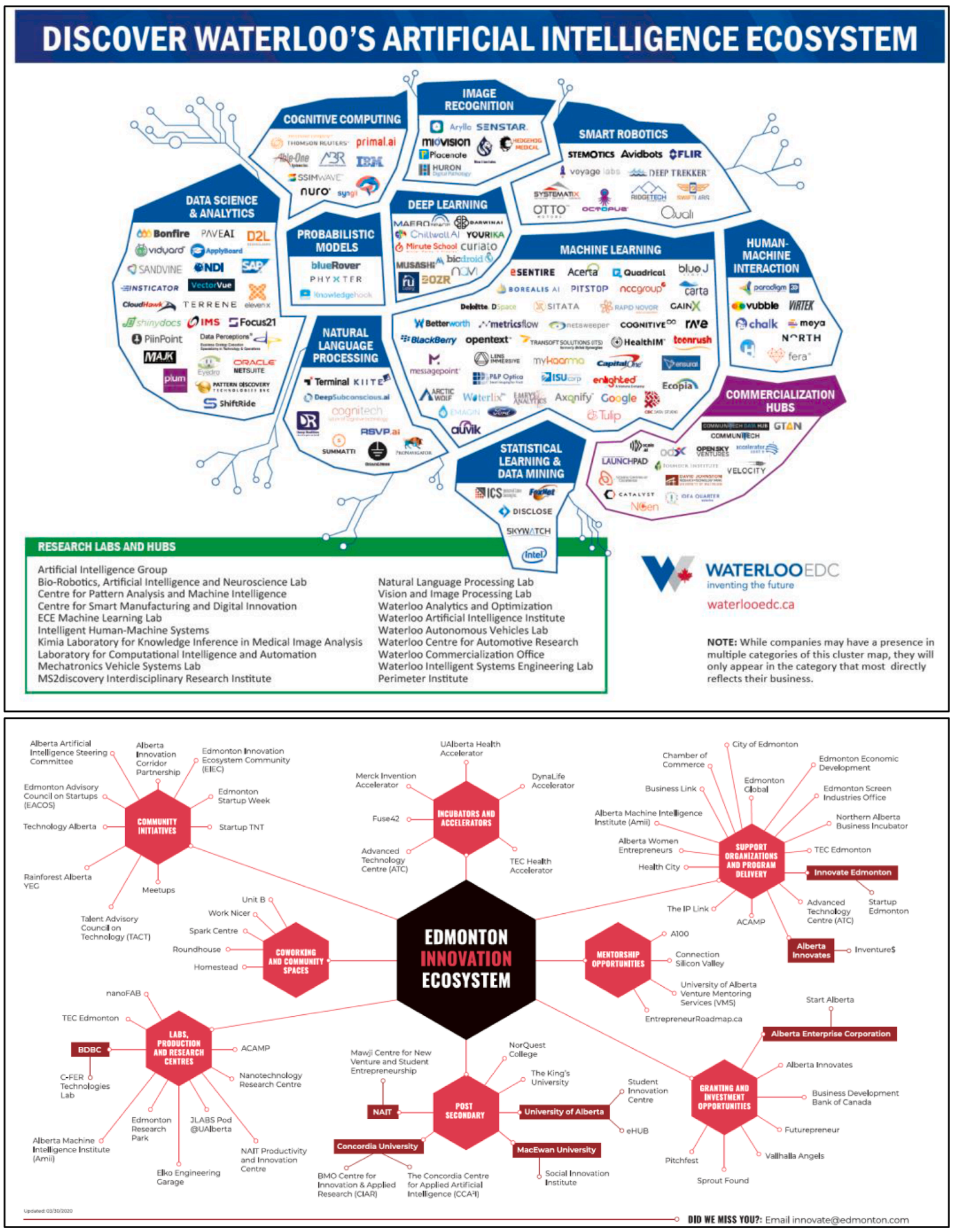


Fig. 6. Two examples of current regional ecosystem maps.

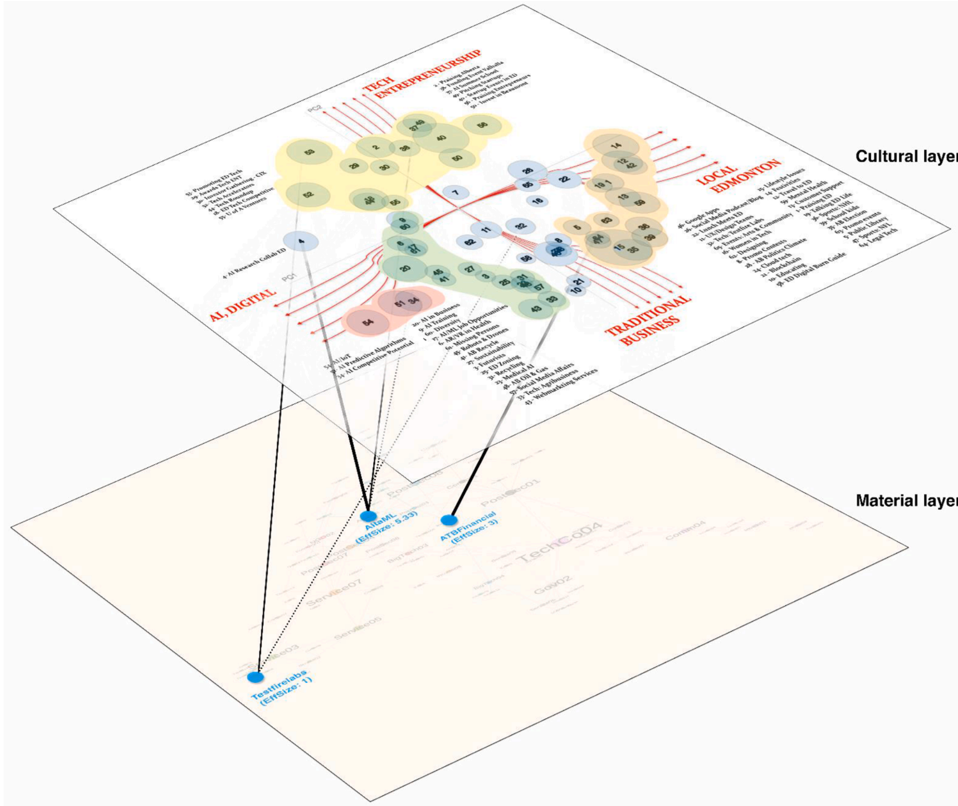


Fig. 7. A two-layer, cultural-material map of Edmonton's emerging AI entrepreneurial ecosystem.

discursive (cultural conversation) ones. This suggests policymakers should consider how these different actors might be linked to new resources via conversations.

3.1.4. Discursive strategies

To capture how firms in the cultural map might actually not just locate and signal possibilities – but exploit them by bridging – we generated a new theoretical artifact: *spectrograms of discursive strategy bridging*. To do so, we arranged the topics that actors tapped via tweets according to the major conversation clusters (color grouping) in Fig. 3 and recorded the frequency of that topic tweeting by the actor. Fig. 5 shows the sets of topics on the x-axis of the spectrograms from Fig. 3's the upper left-hand conversation spaces (AI digital & tech entrepreneurship) down to those in the lower right-hand (traditional industry & lifestyle). Each spectrogram represents a linear order of topics that we rendered in order to focus attention on clusters of topics and cultural holes. The clusters are highlighted with colors to help distinguish holes between them. In Fig. 5, we focused on displaying actors who seemed to be in positions to exploit cultural holes and tried to identify the key patterns of how they did so.

Some actors' discursive strategies have a singular (*narrow*) tweeting focus. The top left in this figure shows ATB Financial (a provincial bank) with topic weights predominantly in Local Lifestyle & Community Conversations. Another example of this strategy is situated on the top left-hand side of Fig. 5. One organization – Valhalla Angels – has a predominate focus on the left-side of the spectrum, representing AI digital and tech entrepreneurship. The narrowness of the foci for the actors is also manifest in the lack of topic clusters that they seem to bridge. Valhalla, while able to bridge between tech entrepreneurship topics and ML/AI science ones via Topic 4, does not actually have much discourse (frequency of tweeting) in that linking space. So, in cultural, mapping and strategic terms, we can label this localized form of cultural conversation as a "*narrow discursive strategy*."

Other actors seem to pursue discursive strategies that are more clearly about bridging cultural holes. One signature is specifically about cases where organizations are explicitly attempting to fill cultural holes that are immediately adjacent to them. AltaML and Amii –unlike Valhalla – clearly both tweet in the bridging Topic 4 space, as shown by the frequency of tweets in that spot and the vertical rectangle used to highlight the link placed on the x-axis of the spectrogram. We labeled such signature types as a "*near bridging discursive strategy*." In contrast, some firms tweet into a very different space from their own, trying to draw together two (or more) disparate discourses clusters. Two notable examples are Testfire Labs and Granify. Via topic 11 (UX-Design Teams) in Fig. 3, each has the opportunity to bridge between the AI to Business clusters of topics in green and the Local/Lifestyle topics in orange. We labelled this a "*distant bridging discursive strategy*".

This distinction of near and distant bridging cultural holes reflects an important property of possibility space – that cultural structures constituted by discourse are more or less distant from one another (Goldberg, 2011; Mohr et al., 2020). In related strategy research, for some years, related diversification (Markides & Williamson, 1994) and proximate spatial dispersion (Kim et al., 2015) have been lauded. In knowledge-based approaches to firms, drawing on notions of evolutionary biology, Felin et al. (2014) have developed the concept of the "adjacent possible" as a way of understanding the emergence of economic opportunities in proximity terms. Proximity in this cultural map and bridging strategies may make it more likely that bridging strategies will be effective in the cultural map.

3.1.5. Discursive strategy's material outcomes?

A critical question, of course, is whether these three generic cultural (discursive) strategies will have systematic material effects? While this question is beyond the scope of an article devoted to conceptualizing and developing metrics for a novel mapping measure, we must discuss ways for systematic research with the construct to address the issue. If we re-examine the centrality-based material-clique map in Fig. 4, we see in blue-grey transparent bubbles with their actual names in the material map the six firms whose discursive strategies we just theorized about with regard to Fig. 5. Of the organizations actively using discursive strategies, at the end of our data collection in 2019, two were well-positioned in the material map around various structural holes: Amii (36 holes, low constraint), and AltaML (26 holes, low constraint). Two were moderately well-positioned: Valhalla Angels (10 holes, low constraint), ATB Financial (6 holes, low constraint). And two were not well-positioned materially on the material map: Testfire Labs and Granify..

As a follow up on this pattern, in early 2020, before covid, we found that AltaML and Amii were still doing well. Since covid, AltaML has been even more ascendant (Globe Newswire, 2020) and Amii has been granted additional funding from the provincial government (Joannou, 2020). In contrast, ATB Financial retreated some from the AI space, and Valhalla seems to have shifted efforts to British Columbia. Granify has survived, but repositioned culturally and materially, and Testfire is no longer actively tweeting. There appears, then, to be a simple correlation between firms employing near bridging discursive strategies and presence around structural holes (Amii and AltaML). In contrast, a distant bridging strategy either is associated with low material presence, or not even remaining on our material map. More detailed study, of course, would need to be done to systematically link these cultural discursive strategies to exploitation of these structural and cultural holes.

4. Policy implications & research contributions

Our cultural approach to EEEs has shown value in considering it as a distinct dimension in emerging ecosystems. We see this as one way to conceptualize and measure the characteristics of the cultural dimension, and as a novel mapping technique for identifying cultural holes and discursive bridging strategies. In the remainder of this article, we consider the implications of our measurement and mapping approach for policy analytics and for policymakers.

4.1. Implications for policy analytics

Policy analytics, as an area of data analytics, is becoming more prominent in both research and practice (De Marchi et al., 2016; Nambisan et al., 2019). Governments have always created and relied on data for decision making; but the volume and velocity of data – big data – combined with the human-machine algorithms from computer science have created an array of new tools for policy analysts to apply and policymakers to deploy (Pencheva et al., 2020). Here we have focused on cultural mapping as one such tool. In the current approaches to emergent entrepreneurial ecosystems, it is common to see mapping done of ecosystem actors as a means of categorizing and organizing different spaces. Fig. 6 displays two recent maps of regional ecosystems in Canada, one of the AI entrepreneurial ecosystem in the Waterloo area, a respected hub of high tech (e.g., Spigel & Vinodrai, 2020; Bramwell & Wolfe, 2008), and the other for the wider innovation ecosystem (not just the AI entrepreneurial one) in Edmonton, Alberta the region examined here.

Policy analysts generated each map based on their relevant local knowledge; i.e., in theoretical terms, they acted as well-placed others in local context (Autio et al., 2014). The analysts' maps were designed to capture the main actors and relationship in the ecosystems. The maps foreground material (resource) ties and considerations, backgrounding cultural understanding of these relationships. Looking at the AI ecosystem map of Waterloo, we see topic clusters, such as "Machine Learning" and "Data Science and Analytics." We also see key research labs boxed below the brain-shaped map. These clusters, their labels, and their proximities are arranged based on the contextualized understanding of the system, partly based on iterative discussions with local others about the best arrangements to depict the system. Similar to the Waterloo map, the Edmonton innovation ecosystem map is quite clear and captures key hubs of activity, with some agreed-upon labels. It goes a step further and displays the links within and across hubs, suggesting innovation opportunity spaces, the main one being in the center of the map.

Both maps displayed in Fig. 6 have a winning expressiveness and are good talking points; but they would be difficult to use them systematically as policy analytic tools. The proximities may or may not mean much; it is difficult to know ex ante whether being close to one cluster or another in the Waterloo map matters, or whether being remotely connected to actors in the Edmonton map is a problem. In addition, the new opportunity spaces (possibilities) are not obviously identified in either map. Hence, better and worse possibilities are difficult to locate in each figure. For policymakers, these drawbacks have implications on where and how to distribute funds – and to whom specifically. In the AI ecosystem map, the hubs below the map seem critical, but policymakers lack map metrics to prioritize them and to spread funds to nearby organizations.

In contrast, we have argued that a good policy analytic tool would be to rely on Fig.s 3 and 4 in some combination. One possibility, similar to work in ecosystems by Spigel (2015) and Stam (2015), Wurth et al. (2021) is to layer the maps (also see Mohr et al., 2020). The key firms and possibilities discussed in each map layer can be linked across levels via "pipes." These are forms of vertical or modal network ties (Padgett & Ansell, 1993; Tasselli & Kilduff, 2020). For illustrative purposes, we have displayed just three firms already discussed above: Testfire, ATB AI Financial, and AltaML. By observing the overall congruence of clusters and cliques across the two maps, and then carefully examining the positioning and discursive strategies of specific firms (or of similar types), policy analysts should be able to isolate better and worse spaces for attention and funding, and actors who might be encouraged (steered) towards or away from these areas. For example, AltaML has a discursive bridging position between the AI Digital and Tech Entrepreneurship spaces and in the material map, high centrality and a position besides several structural holes. It would appear to be an actor worth some culturally and materially informed policy attention, as would the joint spaces beside it in the two-layers. In contrast, in spite of Testfire's location in the Tech Entrepreneurship cluster and high tweeting propensity, its far bridging strategy and incongruent material map location at the far edge of a distant clique may make its layered locations less auspicious.[4]

4.1.1. Policies to enable mapping analytics

In order to use such multilayered possibility maps, policy would be required for accessing, assembling and analyzing big cultural data along with more standard resource map data. As a precursor to such policies, it is important for policy analysts and policymakers first to embrace some of this cultural approach and combine it with the material or resource-focused one. That stereoscopic view of EEEs would not only allow for a deeper understanding of the ecosystems and their co-evolutionary dynamics (Johnson et al., 2019; Thompson et al., 2018), but also lead policymakers to prioritize collecting such data. As we have seen, cultural

[4] Of course, additional on site, contemporary due diligence would be needed to confirm these policy analytic points.

markers are carried in social conversations, such as those found in Twitter and other social media data (Obschonka et al., 2020). These tweets and are, in Nambisan et al.'s words (2019), "digital affordances" – virtual world enablers of various system facets. Some social media data are in the public domain or for purchase, but with the marketization of such data, it is not clear that will be true for long. Over the course of writing this paper, we shifted from collecting data manually using Python tools to working directly with Twitter through their academic developer program. The ease by which data was collected dramatically shifted as a result.

Looking forward, it is conceivable that the company will continue to find ways to make this data more accessible for policy audiences. However, provisions for collecting and accessing the data as part of the package of tech company regulations would be useful if the public and policymakers are to benefit from these data as much as private business has to this point. Policy analysts need help from funders and policymakers to secure some of the corpora in order to use them for the business ecosystem and public's behalf. Other open data efforts targeting such corpora will help as well (Perkmann & Schildt, 2015). Policy enabling local forms of federated learning (Bonawitz et al., 2019) may even enable such cultural mapping of more private communications within an ecosystem while preserving individual privacy.

The ability to use such data in analyses and in policy formation is equally important to getting access to and assembling those data in corpora. In particular, the ability to generate and work with the various measures and metrics captured in Table 1 is important. Here, we employed a contemporary suite of computational social science tools (e.g., see Edelmann et al., 2020; Goldenstein & Poschmann, 2019), but took strides to recognize the localized knowledge of the author team in determining reasonable methodological decisions such as transparency and replicability (Nelson, 2019). To effectively render an EEE using our toolkit and approach requires, then, both well-placed quasi-ethnographic abilities *and* computational tools on the part of policy analysts. Training in these tools to capture the stereoscopic nature of EEEs seems to be important in the world of emerging policy analytics.

4.2. Implications for EEE policy

Policymakers guide regional and global economic opportunities. In recent years, there have been critiques of entrepreneurial ecosystem policy, highlighting conceptual and measurement issues (Autio, 2017; Spigel, 2020) as well as applicability challenges (Brown et al., 2017; Isenberg, 2010). Past policy analysis and thought about ecosystems appears to have been built upon some flawed assumptions. In the area of EEE policy, there are well-known success models: the Rainforest Model (Hwang & Horowitt, 2012) and similar depictions of the Silicon Valley (Isenberg, 2010). But not every region can be – or wants to be – a Silicon Valley (Audretsch, 2021; Feld, 2020; Isenberg, 2010). The bias towards this success model has been intensified by only measuring the material markers of success established in systems such as Silicon Valley with its hypergrowth exit mindset (Brown & Mawson, 2019; Lam & Seidel, 2020).

Policymakers can address this past oversight and unlock numerous previously untapped possibilities hidden in previously unobserved cultural holes. Ecosystems can flourish in unique ways with differing sets of cultural assumptions, such as those found in northern Italy (Tracey et al., 2018), Singapore (The Economist, 2014), the UK (Brown et al., 2017) or Finland (Autio, 2017). These locales have each benefitted from different local cultural infrastructures where some unique cultural cliques and conversations, key events and rollouts, and pre-venture mishmashes can thrive (Beltagui et al., 2020; Tracey et al., 2018). Without that, policy efforts to encourage that local cultural infrastructure, the material side of the ecosystem will rapidly become inflexible and ossify – or perhaps never emerge in the first place.

But before creating policies to foster cultural infrastructure and co-evolutionary paths, we think policymakers and government should ask whether they *should be* directly, rather than indirectly, involved in fostering emergent entrepreneurial processes. Today most of the policy world accepts that some involvement is important (Heaton et al., 2019; O'Connor et al., 2018). This particularly holds where collective action failures hinder early stage ecosystem activities that can serve the public good in the long term but are unlikely to generate short term profits and are thus generally not properly addressed by the private sector without policy support (Seidel et al., 2020). But we believe that setting up the cultural and material infrastructure less directly is potentially more beneficial.

Universities are just one example, and are part of a broader set of cultural and institutional possibilities that could be coordinated to help address the collective action failures in the more traditionally market reliant sectors (Heaton et al., 2019). In addition, efforts to coordinate across university and business sectors, such as via formal partnerships, like the HIBAR Research Alliance, can help catalyze policy solutions and cultural changes to solve such collective action failures in innovation ecosystems. They do so by more tightly culturally integrating universities with broader innovation ecosystems (Whitehead et al., 2020). Funding agencies are another critical component for EEEs. For example, an NSF Assistant Director recently outlined a shift demonstrating the importance of an "honest assessment of possible and likely outcomes rather than on the probability of specific outcomes." (Social Science Space, 2021). This shift away from specific outcome bets is well-aligned with our cultural possibilities approach. Successful ecosystem policy intervention requires building a strong cultural fabric across sectors instead of simply focusing on material entrepreneur support.

These points imply that EEEs should not be "over-engineered" and that "reform" of bureaucratic approaches to them is needed (Isenberg, 2010: p. 9). The historical context of the regional EEE becomes crucial here, as Isenberg himself notes. Some systems in some countries have a history of more direct involvement of local or non-local government. Such is the case of our focal emerging AI ecosystem, and the same for some in Europe (Stam, 2017) and China (Armanios et al., 2017). Unfortunately, in the recent past, this has also led government, under public pressure to justify EEE infrastructure funding and political support, to try to pick winners (Autio et al., 2014; Bresnahan et al., 2001; Isenberg, 2010; Reif, 2020). Today policymakers continue to do so, as evidenced by one example of how the emerging Endless Frontier Act in the United States. That acts makes major policy bets on future technologies instead of focusing on the possibilities of addressing longer term societal problems (Prahbakar, 2020; Seidel et al., 2020). But conceiving the government as successfully strategically guiding innovation ecosystems is outdated (Flagg & Harris, 2020). Understanding cultural holes can help policymakers more broadly identify the core problems and possibilities ecosystems can likely address, as opposed to placing large bets based on guesses of future technological winners informed by metrics and trends originating in other ecosystems.

4.3. Limitations and next steps

In this article we have contributed to research on policy regarding

EEEs by reconceptualizing entrepreneurial ecosystems (Shipilov & Gawar, 2019; Wurth, Stam & Siegel, 2021), using a cultural approach (Audretsch et la., 2020; Lounsbury & Glynn, 2019; Powell & Oberg, 2017), one based on interpretive data science and big data (Hannigan et al., 2019; Mohr et al., 2020; Schmiedel et al., 2019). We have done so developing cultural-based theory around EEEs, with a dimensionalization of the cultural layer, and a methodology for comparing and contrasting the cultural map to a material one in a sample emerging AI. This, in turn, has allowed us to offer suggestions for policy analytics and for policymakers who wish to use this cultural approach and mapping tool methodology.

Being a measurement article, our study has some obvious research limitations, the first of which is the restrained ability to fully demonstrate the impact of the measurement system's usefulness for capturing long term system evolution. In this respect, we follow recent directions in entrepreneurship research (Obschonka & Audretsch, 2020; Lounsbury & Glynn, 2019) that propose applying big data tools to enhance the articulation of entrepreneurial possibilities, particularly at early stages of an ecosystem. Instead of arguing for the technology alone, we explicitly emphasized how this new approach paired with a cultural perspective can be a valuable form of mapping EEEs. This moves beyond other big data studies that continue to carry forward the attribute-based framing to social media, such as Obschonka et al. (2020) that found correlations between tweets and psychological traits of a region. Our approach is a first step in pushing for cultural and material dimensions as intertwined and co-evolving in a particular configuration. But this is based on capturing a snapshot in time. We envision capturing more panels of the cultural and materials dimension's evolution over time in a subsequent study to track some of these effects, and elaborate on the co-evolution of the dimensions.

A second noticeable drawback is capturing the full dynamism of cultural discourse and artifacts in the cultural layer. We acknowledge that other important cultural activities take place in an emerging entrepreneurial ecosystem, such as field configuring events, like conferences, or regularly organized meetups. Related work in management has demonstrated how key events generate cultural discourse (Hannigan & Casasnovas, 2020; Seidel, 2018; Hardy & Maguire, 2010; Zilber, 2011), and we have reason to believe the same is true in entrepreneurial ecosystems. The key criteria are whether sufficient sets of relevant actors are involved with (and paying attention to) the discourse, and whether it can be effectively captured. This points to our perspective as ultimately being relational. In planning this article, we conducted initial exploratory field work and determined that the Edmonton ecosystem was actively using Twitter. But this discourse was also in part fueled by conferences such as the SingularityU Canada Summit and other local events being organized on the *meetup.com* platform. Further work could study these events in more detail, considering the discourse produced, as well as the network of actors attending.

A third drawback is that our methodology, while state-of-the-art, still needed to be adapted to the short, burstiness of tweets, and the topics that were rendering were thus only approximated and only if the system itself for that two-year period was adequately stable. Our central argument was based on the premise that tweets over a two-year period carried patterns and regularities of meaning. This was the basis of rendering meaning structures that form cultural holes. While we examined varieties of topic model numbers and cut-offs as forms of sensitivity analyses in our two-year panel, further work might disentangle whether an adequate corpus is based on a minimum threshold of time, or is more a function of key events that generate discourse in that space. Our review of recent computer science work on the subject (i.e., Jonsson & Stolee, 2019) pointed to BTM as the leading approach for modeling short texts. Newer methods are continuing to be developed for the purpose of topic modeling twitter data with more structural assumptions. For example, stLDA-C (Tierney, Bail & Volfovsky, 2021) is an emerging approach that shifts from modeling topics in individual tweets to mapping distributions of topics for users. Our modeling of discursive strategy signatures (spectrograms) is a contribution to that literature and suggests that a similar set of patterns within the time periods by user sets may be a way to capture stable discourse. Clearly, this is an area for future research.

5. Conclusion

These limitations not withstanding, we hope that our work will still encourage EEE researchers to embrace less literal or concrete readings of ecosystems and their processes, in favor of a more cognitive and societally-grounded one anchored on cultural analysis (Audretsch et al., 2020; Lounsbury & Glynn, 2019) that reflects a systematic and technological bent (Mohr et al., 2020; Powell & Oberg, 2017). Introducing this new tool will enable policy analysts to provide policymakers with a more comprehensive data informed understanding of their local possibilities. This reframing enables new insights on earlier stages of system emergence that are difficult to consider when only considering material markers. Local thought leaders (O'Conner et al., 2018) and intermediary organizations (Clayton et al., 2018; Heaton et al., 2019) become important in part because of the visions and local buzz they create and promote in the cultural map (Nambisan et al., 2019). In addition, as demonstrated above, discursive strategies are a key component in their entrepreneurial toolkit (Lounsbury & Glynn, 2019; Swidler, 1986). These strategies help bridge these possibilities in the form of cultural holes (Pachucki & Breiger, 2010). Bridging, in turn, attracts attention and resources - personnel, funding, complementary technology, and other startups, helping turn "lead into gold" (Clough et al., 2019).

Credit author statement

Timothy R. Hannigan – conceptualization, data collection, measurement, analysis (esp. of cultural models), core writing, and response letter. Anthony R. Briggs – some conceptualization, material data collection and some analysis, some editing and some writing. Rodrigo Valadao – some conceptualization, cultural data collection and analysis, editing, reference checking, some writing. Marc-David L. Seidel – some conceptualization, core writing on policy sections, some editing. P. Devereaux (Dev) Jennings – team coordination, corresponding author, conceptualization, data collection, measurement, analysis (esp. of material models), core writing, and response letter. All in all, we worked as a team, and our contributions reflect our team's effort.

Declaration of Competing Interest

None.

Acknowledgement

We would like to acknowledge the suggestions and reactions to this paper by the IDeaS (Interpretive Data Science) Group, the probing questions of Jennifer Jennings, the design assistance of Debjani Hannigan, the theoretical considerations raised by Mike Lounsbury, the friendly review by Marc Ventresca and the scraping code from Chris Cliff. This research was supported by the Social Science and Humanities Research Council (SSHRC), including grants #430-2018-01061 and #435-2017-0046.

Appendix

Table A1
Most active and mentioned tweeters

Alphabetical sorting	Most Active Tweeters (sent out)		Most Mentioned (received in)			
New ventures anchor list	New ventures[a]	Followers of new ventures[b]	New ventures	# Mentions	Followers of new ventures	# Mentions
altaml_com	ATBFinancial	allantaylor	altaml_com	131	amiithinks	320
ATBFinancial	altaml_com	buzzilinear	testfirelabs	117	startupedmonton	307
bixscdn	bixscdn	cixcommunity	ATBFinancial	75	innovateyeg	257
BizPlanWorld	gabbi_ai	yegtweetup	Medo_ai	58	tecedmonton	171
boardeeapp	honest_door	yrrabyrrab	granify	40	valhallacap	159
BuddyTracker_io	testfirelabs	startupcalgary	SAM_Desk	34	nform	143
capstoneitdev	whitespark	startupedmonton	profilze	30	yeghealthcity	139
dhanalytics	StreamTechInc	take_roots	honest_door	28	taprootyeg	135
gabbi_ai	trustscience	donaterecycleit	dhanalytics	25	flyeia	112
granify	BizPlanWorld	innovateyeg	StreamTechInc	23	futurecite	105
honest_door	granify	themetaspaceyyc	boardeeapp	23	dbayeg	98
howtocreateart	SAM_Desk	govkid	mobiledatatech	17	inventurescan	86
innovills_tech	mymatchwork	bitcoinbrains	bixscdn	17	cheryllyeg	82
Medo_ai	boardeeapp	dbayeg	trustscience	12	edmontonglobal	81
mobiledatatech	Medo_ai	crowncathy	webdataguru	12	scaleupyeg	81
mpowered_tech	sportingcharts	chrislabossiere	touchmetric	11	worknicer	79
mymatchwork	innovills_tech	yeghealthcity	BizPlanWorld	11	valhallaangels	74
PitchSixty	dhanalytics	futurecite	ZanInitiative	6	rainforestyeg	74
profilze	WyvernSpace	worknicer	sportingcharts	6	cixcommunity	64
SAM_Desk	mobiledatatech	abudnick	mymatchwork	5	gethendrix	63
sportingcharts	ZanInitiative	sellarcast	gabbi_ai	5	fscammells	60
StreamTechInc	PitchSixty	flyeia	whitespark	4	justinc_ai	57
testfirelabs	webdataguru	clairemacyeg	WyvernSpace	2	albertaventure	44
touchmetric	capstoneitdev	naitmawjicentre	innovills_tech	2	startupcalgary	43
trustscience	profilze	clintonsenkow	PitchSixty	2	reg_joseph	37
webdataguru	touchmetric	amiithinks	howtocreateart	1	alondrac_ai	36
whitespark	BuddyTracker_io	planedmonton	capstoneitdev	0	williamsengca	35
WyvernSpace	howtocreateart	katesversion	BuddyTracker_io	0	ashifmawji	35
ZanInitiative	mpowered_tech	visibilitypower	mpowered_tech	0	naitmawjicentre	32

[a] From most to least active
[b] From most to least

Table A2
Selected set of structural hole measures for edmonton AI ecosystem organizations[a]

	Degree	EffSize	Efficiency	Constraint	Hierarchy	EgoBet	Ln(Constraint)	Indirects	Density	AvgDeg	Numholes
AICo01	1	1	1	0	1	0	0	0	0	0	0
AICo02	2	2	1	0.5	0	2	-0.693	0	0	0	2
AICo03	2	2	1	0.5	0	2	-0.693	0	0	0	2
AICo04	1	1	1	0	1	0	0	0	0	0	0
AICo05	2	2	1	0.5	0	2	-0.693	0	0	0	2
AICo06	1	1	1	0	1	0	0	0	0	0	0
AICo07	2	2	1	0.5	0	2	-0.693	0	0	0	2
AICo08	6	5.333	0.889	0.306	0.032	26	-1.186	0.333	0.133	0.667	26
AICo09	1	1	1	0	1	0	0	0	0	0	0
BigTech01	2	2	1	0.5	0	2	-0.693	0	0	0	2
BigTech02	1	1	1	0	1	0	0	0	0	0	0
BigTech03	5	4.6	0.92	0.3	0.05	18	-1.204	0.2	0.1	0.4	18
BigTech04	4	4	1	0.25	0	12	-1.386	0	0	0	12
BigTech05	1	1	1	0	1	0	0	0	0	0	0
BigTech06	2	1	0.5	1.125	0	0	0.118	0.5	1	1	0
BigTech07	1	1	1	0	1	0	0	0	0	0	0
Comm01	6	5.667	0.944	0.236	0.045	28	-1.443	0.167	0.067	0.333	28
Comm02	6	3.667	0.611	0.487	0.063	9.667	-0.719	0.661	0.467	2.333	16
Comm03	3	2.333	0.778	0.611	0.052	4	-0.492	0.333	0.333	0.667	4
Comm04	8	6.5	0.813	0.31	0.052	41	-1.172	0.531	0.214	1.5	44
Comm05	5	5	1	0.2	0	20	-1.609	0	0	0	20
Comm06	2	1	0.5	1.125	0	0	0.118	0.5	1	1	0
Comm07	2	2	1	0.5	0	2	-0.693	0	0	0	2
Exit01	4	4	1	0.25	0	12	-1.386	0	0	0	12
Exit02	1	1	1	0	1	0	0	0	0	0	0
Exit03	2	1	0.5	1.125	0	0	0.118	0.5	1	1	0
Exit04	1	1	1	0	1	0	0	0	0	0	0

(continued on next page)

Table A2 (*continued*)

	Degree	EffSize	Efficiency	Constraint	Hierarchy	EgoBet	Ln(Constraint)	Indirects	Density	AvgDeg	Numholes
Exit05	3	2.333	0.778	0.611	0.052	4	-0.492	0.333	0.333	0.667	4
Exit06	2	2	1	0.5	0	2	-0.693	0	0	0	2
Exit07	2	2	1	0.5	0	2	-0.693	0	0	0	2
Exit08	4	3	0.75	0.563	0	8	-0.575	0.5	0.333	1	8
FundOrg01	4	3.5	0.875	0.406	0.055	10	-0.901	0.25	0.167	0.5	10
FundOrg02	4	4	1	0.25	0	12	-1.386	0	0	0	12
Gov01	1	1	1	0	1	0	0	0	0	0	0
Gov02	10	8.8	0.88	0.218	0.062	75	-1.522	0.425	0.133	1.2	78
Gov03	2	2	1	0.5	0	2	-0.693	0	0	0	2
Gov04	3	3	1	0.333	0	6	-1.099	0	0	0	6
Incumb01	1	1	1	0	1	0	0	0	0	0	0

[a] The full set is available upon request.

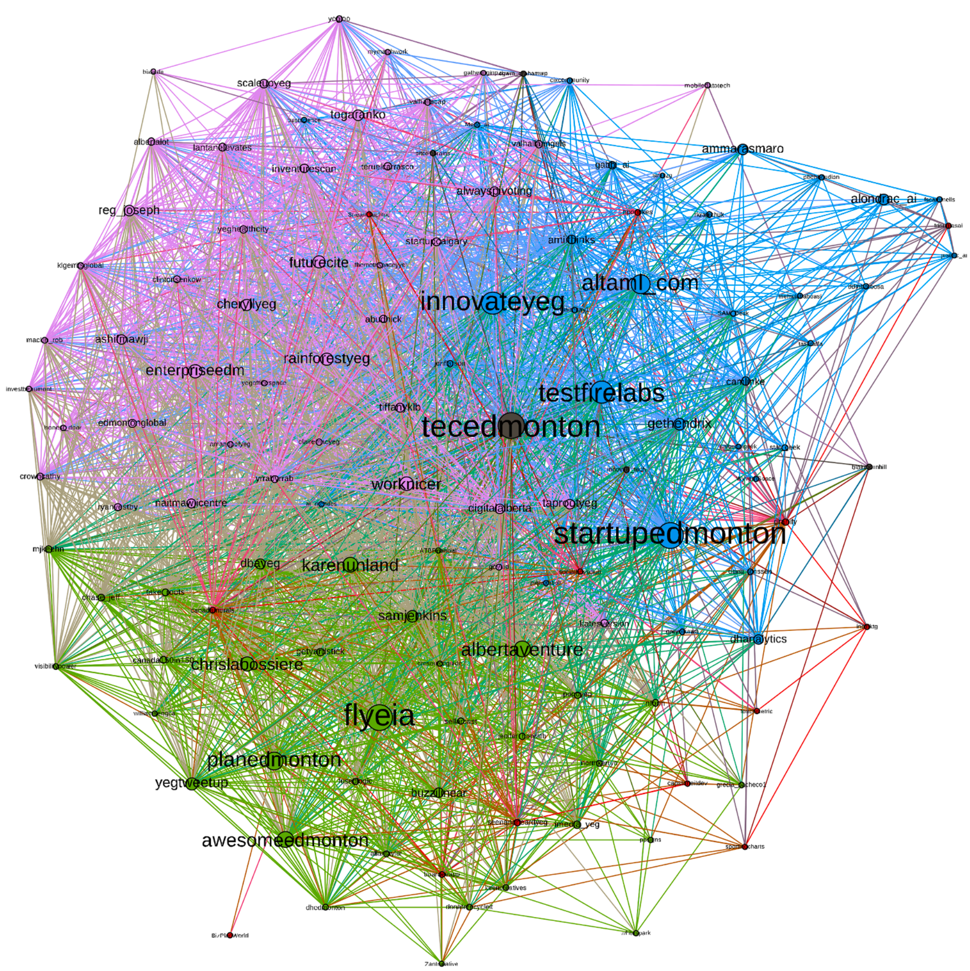


Fig. A1. Bi-Directed (Mutual) Network Graph of 4+ Twitter Handles.

References

Acs, Z.J., Stam, E., Audretsch, D.B., O'Connor, A, 2017. The lineages of the entrepreneurial ecosystem approach. Small Bus. Econ. 49 (1), 1–10. https://doi.org/10.1007/s11187-017-9864-8.

Aldrich, H.E., 1994. Fools Rush in? The Institutional Context of Industry Creation, p. 27.

Alvarez, S.A., Barney, J.B., McBride, R., Wuebker, R., 2014. Realism in the Study of Entrepreneurship. Acad. Manage. Rev. 39 (2), 227–231.

Armanios, D.E., Eesley, C.E., Li, J., Eisenhardt, K.M., 2017. How entrepreneurs leverage institutional intermediaries in emerging economies to acquire public resources. Strateg. Manage. J. 38 (7), 1373–1390. https://doi.org/10.1002/smj.2575.

Audretsch, D.B., 2021. Have we oversold the Silicon Valley model of entrepreneurship? Small Bus. Econ. 56 (2), 849–856.

Audretsch, D.B., Cunningham, J.A., Kuratko, D.F., Lehmann, E.E., Menter, M., 2019. Entrepreneurial ecosystems: Economic, technological, and societal impacts. J. Technol. Transfer 44 (2), 313–325.

Autio, E., 2017. Strategic Entrepreneurial Internationalization: A Normative Framework. Strateg. Entrepreneurship J. 11 (3), 211–227. https://doi.org/10.1002/sej.1261.

Autio, E., Kenney, M., Mustar, P., Siegel, D., Wright, M., 2014. Entrepreneurial innovation: The importance of context. Res. Policy 43 (7), 1097–1108.

Autio, E., Nambisan, S., Thomas, L.D.W., Wright, M, 2018. Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. Strateg. Entrepreneurship J. 12 (1), 72–95. https://doi.org/10.1002/sej.1266.

Baker, T., Nelson, R.E., 2005. Creating Something from Nothing: Resource Construction through Entrepreneurial Bricolage. Adm. Sci. Q. 50 (3), 329–366. https://doi.org/10.2189/asqu.2005.50.3.329.

Beltagui, A., Rosli, A., Candi, M., 2020. Exaptation in a digital innovation ecosystem: The disruptive impacts of 3D printing. Res. Policy 49 (1), 103833. https://doi.org/10.1016/j.respol.2019.103833.
... & Bonawitz, K., Eichner, H., Grieskamp, W., Huba, D., Ingerman, A., Ivanov, V., Roselander, J., 2019. Towards federated learning at scale: System design. arXiv preprint arXiv:1902.01046.
Borgatti, S.P., Everett, M.G., Johnson, J.C., 2018. Analyzing social networks. Sage.
Bourdieu, P., 1993. The Field of Cultural Production: Essays on Art and Literature. Columbia University Press.
Bouslama, S., 2020. Join Edmonton Global at World Summit AI. Edmonton Global. https://edmontonglobal.ca/join-edmonton-global-at-the-world-summit-ai/.
Bowles, N, 2021. Join Us in Miami! Love, Masters of the Universe. New York Times. https://www.nytimes.com/2021/01/29/technology/join-us-in-miami-love-masters-of-the-universe.html.
Bramwell, A., Wolfe, D.A., 2008. Universities and regional economic development: The entrepreneurial University of Waterloo. Res. Policy 37 (8), 1175–1187.
Bresnahan, T., Gambardella, A., Saxenian, A., Wallsten, S., 2001. Old Economy" Inputs for "New Economy" Outcomes: Cluster Formation in the New Silicon Valleys. Industr. Corp. Change 10 (4), 835–860. https://doi.org/10.1093/icc/10.4.835.
Brown, R., Mawson, S., 2019. Entrepreneurial ecosystems and public policy in action: A critique of the latest industrial policy blockbuster. Cambridge J. Regions Economy Soc. 12 (3), 347–368. https://doi.org/10.1093/cjres/rsz011.
Brown, R., Mawson, S., Lee, N., Peterson, L., 2019. Start-up factories, transnational entrepreneurs and entrepreneurial ecosystems: Unpacking the lure of start-up accelerator programmes. Eur. Plann. Stud. 27 (5), 885–904. https://doi.org/10.1080/09654313.2019.1588858.
Brown, R., Mawson, S., Mason, C., 2017. Myth-busting and entrepreneurship policy: The case of high growth firms. Entrepreneurship Regional Dev. 29 (5–6), 414–443. https://doi.org/10.1080/08985626.2017.1291762.
Burt, R., 2005. Brokerage and closure: An introduction to social capital.
Burt, R.S., 2004. Structural Holes and Good Ideas. Am. J. Sociol. 110 (2), 349–399. https://doi.org/10.1086/421787.
News, CBC, 2019. Alberta's high-tech sector to get $100M boost over 5 years | CBC News. CBC. https://www.cbc.ca/news/canada/calgary/notley-bilous-alberta-innovates-funding-ai-artificial-intelligence-calgary-amii-1.5017785.
Clayton, P., Feldman, M., Lowe, N., 2018. Behind the Scenes: Intermediary Organizations that Facilitate Science Commercialization Through Entrepreneurship. Acad. Manage. Perspect. 32 (1), 104–124. https://doi.org/10.5465/amp.2016.0133.
Clough, D., Fang, T., Vissa, B., Wu, A., 2019. Turning lead Into gold- How do entrepreneurs mobilize resources to exploit opportunities. Academy of Management Annals.
Cooke, P., Gomez Uranga, M., Etxebarria, G., 1997. Regional innovation systems: Institutional and organisational dimensions. Res. Policy 26 (4–5), 475–491. https://doi.org/10.1016/S0048-7333(97)00025-5.
Croidieu, G., Kim, P.H., 2018. Labor of love: Amateurs and lay-expertise legitimation in the early U.S. radio field. Adm. Sci. Q. 63 (1), 1–42.
Davenport, T., 2019. Learning From The Canadian Model Of AI. Forbes. https://www.forbes.com/sites/tomdavenport/2019/11/19/learning-from-the-canadian-model-of-ai/?sh=40748b1c2300.
De Marchi, G., Lucertini, G., Tsoukiàs, A., 2016. From evidence-based policy making to policy analytics. Ann. Oper. Res. 236 (1), 15–38.
DiMaggio, P.J., 1997. Culture and cognition. Ann. Rev. Sociol. 23, 263–287.
Edelmann, A., Wolff, T., Montagne, D., Bail, C.A., 2020. Computational Social Science and Sociology. Ann. Rev. Sociol. 46 (1), 61–81.
Feld, B., 2020. Startup Communities: Building an Entrepreneurial Ecosystem in Your City. John Wiley & Sons.
Feldman, M., Siegel, D.S., Wright, M., 2019. New developments in innovation and entrepreneurial ecosystems. Industr. Corp. Change 28 (4), 817–826. https://doi.org/10.1093/icc/dtz031.
Felin, T., Kauffman, S., Koppl, R., Longo, G., 2014. Economic Opportunity and Evolution: Beyond Landscapes and Bounded Rationality. Strateg. Entrepreneurship J. 8 (4), 269–282.
Ferraro, F., Etzion, D., Gehman, J., Al, O.S.E., 2015. Tackling Grand Challenges Pragmatically: Robust Action. *Revisited*.
Financial Post, 2017. Revolution AI: How Edmonton is gaining ground as a research and innovation hub for AI. Financial Post. https://financialpost.com/entrepreneur/revolution-ai-how-edmonton-is-gaining-ground-as-a-research-and-innovation-hub-for-ai.
Fischer, E., Reuber, A.R., 2011. Social interaction via new social media:(How) can interactions on Twitter affect effectual thinking and behavior? J. Bus. Venturing 26 (1), 1–18.
Flagg, M., & Harris, P. (2020, September). *September 2020*. How to Lead Innovation in a Changed World. https://intangibleeconomy.wordpress.com/2020/09/.
Florida, R., Kenney, M., 1990. High-Technology Restructuring in the USA and Japan. Environ. Plann. A 22 (2), 233–252. https://doi.org/10.1068/a220233.
Forbes, D.P., Kirsch, D.A., 2011. The study of emerging industries: Recognizing and responding to some central problems. J. Bus. Venturing 26 (5), 589–602. https://doi.org/10.1016/j.jbusvent.2010.01.004.
Friedland, R., 2013. The gods of institutional life: Weber's value spheres and the practice of polytheism. Crit. Res. Religion 1 (1), 15–24. https://doi.org/10.1177/2050303213476104.
Giddens, A., 1984. The constitution of society: Outline of the structuration theory. Polity Press.
Giorgi, S., Lockwood, C., Glynn, M.A., 2015. The Many Faces of Culture: Making Sense of 30 Years of Research on Culture in Organization Studies. Acad. Manage. Ann. 9 (1), 1–54. https://doi.org/10.1080/19416520.2015.1007645.
Globe and Mail, 2017. It's time to make the Canadian AI ecosystem bloom. https://www.theglobeandmail.com/report-on-business/rob-commentary/its-time-to-make-the-canadian-ai-ecosystem-bloom/article35559957/.
GlobeNewsWire. (2020a). $57 million to Alberta researchers and innovators. . GlobeNewswire News Room. https://www.globenewswire.com/news-release/2020/05/25/2038229/0/en/57-million-to-Alberta-researchers-and-innovators.html.
Goldberg, A., 2011. Mapping shared understandings using relational class analysis: The case of the cultural omnivore reexamined. Am. J. Sociol. 116 (5), 1397–1436.
Goldenstein, J., Poschmann, P., 2019. Analyzing Meaning in Big Data: Performing a Map Analysis Using Grammatical Parsing and Topic Modeling. Sociol. Methodol. 49 (1), 83–131. https://doi.org/10.1177/0081175019852762.
Hallett, T. (2003). Symbolic Power and Organizational Culture. *Sociological Theory*, 21 (2), 128–149. https://doi.org/10.1111/1467-9558.00181.
Hannah, D.P., Eisenhardt, K.M., 2018. How firms navigate cooperation and competition in nascent ecosystems. Strateg. Manage. J. 39 (12), 3163–3192. https://doi.org/10.1002/smj.2750.
Hannigan, T.R., Casasnovas, G., 2020. New structuralism and field emergence: The co-constitution of meanings and actors in the early moments of social impact investing. Res. Sociol. Org. 68, 147–184.
Hannigan, T.R., Haans, R.F.J., Vakili, K., Tchalian, H., Glaser, V.L., Wang, M.S., Kaplan, S., Jennings, P.D, 2019. Topic Modeling in Management Research: Rendering New Theory from Textual Data. Acad. Manage. Ann. 13 (2), 586–632. https://doi.org/10.5465/annals.2017.0099.
Hardy, C., Maguire, S., 2010. Discourse, Field-Configuring Events, and Change in Organizations and Institutional Fields: Narratives of DDT and the Stockholm Convention. Acad. Manag. J. 53 (6), 1365–1392.
Heaton, S., Siegel, D.S., Teece, D.J., 2019. Universities and innovation ecosystems: A dynamic capabilities perspective. Industr. Corp. Change 28 (4), 921–939. https://doi.org/10.1093/icc/dtz038.
Huff, A., 1990. Mapping strategic thought. John Wiley & Sons.
Hwang, M.V.W., Horowitt, M.G, 2012. The Rainforest: The Secret to Building the Next Silicon Valley. Regenwald.
Isenberg, D.J., 2010. How to Start an Entrepreneurial Revolution. Harv. Bus. Rev. 10.
Jennings, P.D., Greenwood, R., Lounsbury, M.D., Suddaby, R., 2013. Institutions, entrepreneurs, and communities: A special issue on entrepreneurship. J. Bus. Venturing 28 (1), 1–9. https://doi.org/10.1016/j.jbusvent.2012.07.001.
Joannou, A., 2020. Alberta government giving $9 million in funding to Edmonton AI company. Edmonton J. https://edmontonjournal.com/news/politics/alberta-government-to-give-9-million-in-funding-to-edmonton-ai-company.
Johnson, D., Bock, A.J., George, G., 2019. Entrepreneurial dynamism and the built environment in the evolution of university entrepreneurial ecosystems. Industr. Corp. Change 28 (4), 941–959.
Jonsson, E., Stolee, J., 2019. An Evaluation of Topic Modelling Techniques for Twitter 11.
Kaufman, J., 2004. Endogenous Explanation in the Sociology of Culture. Ann. Rev. Sociol. 30 (1), 335–357. https://doi.org/10.1146/annurev.soc.30.012703.110608.
Kay, N.M., Leih, S., Teece, D.J., 2018. The role of emergence in dynamic capabilities: A restatement of the framework and some possibilities for future research. Industr. Corp. Change 27 (4), 623–638. https://doi.org/10.1093/icc/dty015.
Kennedy, M.T., 2008. Getting Counted: Markets, Media, and Reality. Am. Sociol. Rev. 73 (2), 270–295.
Kim, H., Hoskisson, R.E., Lee, S.H., 2015. Why strategic factor markets matter: "New" multinationals' geographic diversification and firm profitability. Strateg. Manage. J. 36 (4), 518–536.
Kirsch, D., Moeen, M., Wadhwani, R.D, 2013. Historicism and Industry Emergence: Industry Knowledge from Pre-emergence to Stylized Fact. In: Bucheli, M., Wadhwani, R.D. (Eds.), Organizations in Time. Oxford University Press, pp. 217–240. https://doi.org/10.1093/acprof:oso/9780199646890.003.0009.
Kuckertz, A., Brändle, L., Gaudig, A., Hinderer, S., Morales Reyes, C.A., Prochotta, A., Steinbrink, K.M., Berger, E.S.C, 2020. Startups in times of crisis – A rapid response to the COVID-19 pandemic. J. Bus. Venturing Insights 13, e00169. https://doi.org/10.1016/j.jbvi.2020.e00169.
Lam, L., Seidel, M.-D.L., 2020. Hypergrowth Exit Mindset: Destroying Societal Wellbeing through Venture Capital Biased Social Construction of Value. J. Manage. Inquiry 29 (4), 471–474. https://doi.org/10.1177/1056492620929085.
Lizardo, O., 2014. Omnivorousness as the bridging of cultural holes: A measurement strategy. Theory Soc. 43 (3–4), 395–419. https://doi.org/10.1007/s11186-014-9220-9.
Lounsbury, M., Glynn, M.A., 2019. Cultural Entrepreneurship: A New Agenda for the Study of Entrepreneurial Processes and Possibilities, 1st ed. Cambridge University Press. https://doi.org/10.1017/9781108539487.
Lounsbury, M., Ventresca, M., 2002. Social structure and organizations revisited. JAI.
Malecki, E.J., 2018. Entrepreneurship and entrepreneurial ecosystems. Geograph. Compass 12 (3), e12359. https://doi.org/10.1111/gec3.12359.
Manning, C., Surdeanu, M., Bauer, J., Finkel, J., Bethard, S., McClosky, D., 2014. The Stanford CoreNLP Natural Language Processing Toolkit. In: Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations, pp. 55–60. https://doi.org/10.3115/v1/P14-5010.
Markides, C.C., Williamson, P.J., 1994. Related diversification, core competences and corporate performance. Strateg. Manage. J. 15 (S2), 149–165.
Markman, G.D., Gianiodis, P.T., Phan, P.H., Balkin, D.B., 2005. Innovation speed: Transferring university technology to market. Res. Policy 34 (7), 1058–1075. https://doi.org/10.1016/j.respol.2005.05.007.
Marsden, P., 2005. Recent developments in network measurement. Models and methods in social network analysis, p. 30.

Martin, J., 1992. Cultures in Organizations: Three Perspectives. Oxford University Press, USA.

Shepherd, D.A., McMullen, J.S., Jennings, P.D., 2007. The formation of opportunity beliefs: Overcoming ignorance and reducing doubt. Strateg. Entrepreneurship J. 1 (1–2), 75–95.

Mehra, A., Kilduff, M., Brass, D.J., 2001. The Social Networks of High and Low Self-Monitors: Implications for Workplace Performance. Adm. Sci. Q. 46 (1), 121–146.

Mohr, J.W., Bail, C.A., Frye, M., Lena, J.C., Lizardo, O., McDonnell, T.E., Mische, A., Tavory, I., Wherry, F.F., 2020. Measuring Culture. Columbia University Press.

Mohr, J.W., Bogdanov, P., 2013. Introduction—Topic models: What they are and why they matter. Poetics 41 (6), 545–569. https://doi.org/10.1016/j.poetic.2013.10.001.

Mohr, J.W., Duquenne, V., 1997. The Duality of Culture and Practice: Poverty Relief in New York City, 1888-1917. Theory Soc. 26 (2/3), 305–356.

Mohr, J.W., Rawlings, C., 2018. The Oxford Handbook of Cultural Sociology. Four Ways to Measure Culture: Social Science, Hermeneutics, and the Cultural Turn.

Nambisan, S., Lyytinen, K., Yoo, Y., 2020. Digital innovation: Towards a transdisciplinary perspective. Handbook Digital Innovation. https://www.elgaronline.com/view/edcoll/9781788119979/9781788119979.00008.xml.

Nambisan, S., Wright, M., Feldman, M., 2019. The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. Res. Policy 48 (8), 103773. https://doi.org/10.1016/j.respol.2019.03.018.

Navis, C., Glynn, M.A., 2010. How New Market Categories Emerge: Temporal Dynamics of Legitimacy, Identity, and Entrepreneurship in Satellite Radio, 1990–2005. Adm. Sci. Q. 55 (3), 439–471. https://doi.org/10.2189/asqu.2010.55.3.439.

Nelson, L.K., 2019. To Measure Meaning in Big Data, Don't Give Me a Map, Give Me Transparency and Reproducibility. Sociol. Methodol. 49 (1), 139–143.

Oh, D.-S., Phillips, F., Park, S., Lee, E., 2016. Innovation ecosystems: A critical examination. Technovation 54, 1–6.

Obschonka, M., Audretsch, D.B., 2020. Artificial intelligence and big data in entrepreneurship: A new era has begun. Small Bus. Econ. 55 (3), 529–539.

Obschonka, M., Lee, N., Rodríguez-Pose, A., Eichstaedt, J.C., Ebert, T., 2020. Big data methods, social media, and the psychology of entrepreneurial regions: Capturing cross-county personality traits and their impact on entrepreneurship in the USA. Small Bus. Econ. 55 (3), 567–588.

O'Connor, A., Stam, E., Sussan, F., Audretsch, D.B., 2018. Entrepreneurial Ecosystems: The Foundations of Place-based Renewal. In: O'Connor, A., Stam, E., Sussan, F., Audretsch, D.B. (Eds.), Entrepreneurial Ecosystems. Springer International Publishing, pp. 1–21. https://doi.org/10.1007/978-3-319-63531-6_1. Vol. 38.

Owen-Smith, J., Powell, W.W., 2004. Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community. Org. Sci. 15 (1), 5–21.

Pachucki, M.A., Breiger, R.L., 2010. Cultural Holes: Beyond Relationality in Social Networks and Culture. Ann. Rev. Sociol. 36 (1), 205–224. https://doi.org/10.1146/annurev.soc.012809.102615.

Padgett, J.F., Ansell, C.K., 1993. Robust Action and the Rise of the Medici, 1400-1434. Am. J. Sociol. 98 (6), 1259–1319. https://doi.org/10.1086/230190.

Pencheva, I., Esteve, M., Mikhaylov, S.J., 2020. Big Data and AI – A transformational shift for government: So, what next for research? Pub. Policy Admin. 35 (1), 24–44.

Perkmann, M., Schildt, H., 2015. Open data partnerships between firms and universities: The role of boundary organizations. Res. Policy 44 (5), 1133–1143.

Porac, J.F., Thomas, H., Wilson, F., Paton, D., Kanfer, A., 1995. Rivalry and the Industry Model of Scottish Knitwear Producers. Adm. Sci. Q. 40 (2), 203. https://doi.org/10.2307/2393636.

Porter, M., 1998. Clusters and the New Economics of Competition. http://marasbiber.com/wp-content/uploads/2018/05/Michael-E.-Porter-Cluster-Reading.pdf.

Powell, W.W., Oberg, A., 2017. Networks and Institutions. In: Greenwood, R., Oliver, C., Lawrence, T.B., Meyer, R.E. (Eds.), The Sage Handbook of Organizational Institutionalism, 2nd ed. Sage, London, pp. 446–476.

Powell, W.W., Snellman, K., 2004. The Knowledge Economy. Ann. Rev. Sociol. 30 (1), 199–220. https://doi.org/10.1146/annurev.soc.29.010202.100037.

Powell, W.W., White, D.R., Koput, K.W., Owen-Smith, J., 2005. Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences. Am. J. Sociol. 110 (4), 1132–1205. https://doi.org/10.1086/421508. JSTOR.

Rawlings, C.M., Childress, C., 2019. Emergent Meanings: Reconciling Dispositional and Situational Accounts of Meaning-Making from Cultural Objects. Am. J. Sociol. 124 (6), 1763–1809. https://doi.org/10.1086/703203.

Reif, L.R., 2020. MIT President on US Competitiveness and the Endless Frontier Act. Issues Sci. Technol. https://issues.org/to-compete-with-china-america-needs-the-endless-frontier-act-mit-rafael-reif/.

Saxenian, A., 1994. Regional Networks: Industrial Adaptation in Silicon Valley and Route 128.

Saxenian, A., 1990. Regional Networks and the Resurgence of Silicon Valley. Calif. Manage. Rev. 33 (1), 89–112. https://doi.org/10.2307/41166640.

Schiffer, E., Hauck, J., 2010. Net-Map: Collecting Social Network Data and Facilitating Network Learning through Participatory Influence Network Mapping. Field Methods 22 (3), 231–249. https://doi.org/10.1177/1525822x10374798.

Schmiedel, T., Müller, O., vom Brocke, J., 2019. Topic Modeling as a Strategy of Inquiry in Organizational Research: A Tutorial With an Application Example on Organizational Culture. Org. Res. Methods 22 (4), 941–968. https://doi.org/10.1177/1094428118773858.

Seidel, M.-D.L., 2018. The Role of Conferences in the Emergence of Developmental Professional Culture. J. Manage. Inquiry 27 (2), 149–153.

Seidel, M.-D.L., Greve, H.R., 2017. Emergence: How Novelty, Growth, and Formation Shape Organizations and Their Ecosystems. In: Seidel, M.-D.L., Greve, H.R. (Eds.), Research in the Sociology of Organizations. Emerald Publishing Limited, pp. 1–27. https://doi.org/10.1108/S0733-558x20170000050020. Vol. 50.

Seidel, M.-D.L., Schwartz, L.H., Jordan, G.B., 2020. Innovation Isn't a Frontier—It's an Ecosystem. Issues Sci. Technol. https://issues.org/the-endless-frontier-legislation-hibar-research-innovation-ecosystem/.

Shi, Z., Rui, H., Whinston, A.B., 2014. Content sharing in a social broadcasting environment: evidence from twitter. MIS Q. 38 (1), 123–142.

Shipilov, A., Gawer, A., 2019. Integrating Research on Inter-Organizational Networks and Ecosystems. Acad. Manage. Ann. https://doi.org/10.5465/annals.2018.0121.

Sievert, C., & Shirley, K. (2014). LDAvis: A method for visualizing and interpreting topics. *Proceedings of the Workshop on Interactive Language Learning, Visualization, and Interfaces*, 63–70. https://doi.org/10.3115/v1/W14-3110.

Social Science Space. (2021). NSF Letter Frames Concept of 'Broader Impact'. https://www.socialsciencespace.com/2021/03/nsf-letter-frames-concept-of-broader-impact/.

Soublière, J.-F., Gehman, J., 2019. The Legitimacy Threshold Revisited: How Prior Successes and Failures Spill Over to Other Endeavors on Kickstarter. Acad. Manag. J. https://doi.org/10.5465/amj.2017.1103 amj.2017.1103.

Spigel, B., 2015. Edinburgh's Entrepreneurial and Support Ecosystem, 11.

Spigel, B., 2017. The Relational Organization of Entrepreneurial Ecosystems. Entrepreneurship Theory Pract. 41 (1), 49–72. https://doi.org/10.1111/etap.12167.

Spigel, B., 2020. Entrepreneurial Ecosystems: Theory, Practice and Futures. Edward Elgar Publishing.

Spigel, B., Vinodrai, T., 2020. Meeting its Waterloo? Recycling in entrepreneurial ecosystems after anchor firm collapse. Entrepreneurship Reg. Dev. 1–22.

Stam, E., 2015. Entrepreneurial ecosystems and regional policy: a sympathetic critique. Eur. Plann. Stud. 23 (9), 1759–1769.

Stam, E. (2017). Measuring the Entrepreneurial Ecosystem. *Utrecht School of Economics, Discussion Paper Series 17–11.*.

Stam, Erik, van de Ven, A., 2019. Entrepreneurial ecosystem elements. Small Bus. Econ. https://doi.org/10.1007/s11187-019-00270-6.

Startup Genome. (2019). *Global Startup Ecosystem Report 2019*. https://startupgenome.com/reports/global-startup-ecosystem-report-2019.

Swidler, A., 1986. Culture in Action: Symbols and Strategies. Am. Sociol. Rev. 51 (2), 273 https://doi.org/10.2307/2095521.

Suarez, F. [@francissuarez]. (2020, December 4). *How can I help?* Twitter. https://twitter.com/francissuarez/status/1335037068108554241.

Tasselli, S., & Kilduff, M. (2020). Network Agency. *Academy of Management Annals*, annals.2019.0037. https://doi.org/10.5465/annals.2019.0037.

Teece, D., Fleming, L., Feldman, M., Heaton, S., Desai, S., 2019. Special Issue Call for Uncommon Methods and Metrics for Local Entrepreneurial Ecosystems. Res. Policy.

Economist, The, 2014. All together now. *The Economist*. https://www.economist.com/special-report/2014/01/16/all-together-now.

Thomas, L.D.W., Ritala, P, 2021. Ecosystem Legitimacy Emergence: A Collective Action View. J. Manag., 0149206320986617

Thompson, T.A., Purdy, J.M., Ventresca, M.J., 2018. How entrepreneurial ecosystems take form: Evidence from social impact initiatives in Seattle. Strateg. Entrepreneurship J. 12 (1), 96–116. https://doi.org/10.1002/sej.1285.

Tierney, G., Bail, C., & Volfovsky, A. (2021) Author Clustering and Topic Estimation for Short Texts. *Working paper.*.

Tracey, P., Dalpiaz, E., Phillips, N., 2018. Fish out of Water: Translation, Legitimation, and New Venture Creation. Acad. Manag. J. 61 (5), 1627–1666. https://doi.org/10.5465/amj.2015.0264.

van Rijnsoever, F.J., 2020. Meeting, mating, and intermediating: How incubators can overcome weak network problems in entrepreneurial ecosystems. Res. Policy 49 (1), 103884. https://doi.org/10.1016/j.respol.2019.103884.

Wang, F., Mack, E.A., & Maciewjewski, R. (2017). Analyzing Entrepreneurial Social Networks with Big Data. *Annals of the American Association of Geographers*, 107(1), 130–150. https://doi.org/10.1080/24694452.2016.1222263.

Whitehead, L.A., Slovic, S.H., Nelson, J.E., 2020. Re-invigorating HIBAR research for the 21st century: Enhancing fundamental research excellence in service to society. Technol. Innovation 21 (2), 153–167.

Wijffels, J., 2019. BTM: Biterm Topic Models for Short Text. *R package version 0.2.1.*. https://cran.r-project.org/web/packages/BTM/.

Wurth, B., Stam, E., Spigel, B., 2021. Toward an entrepreneurial ecosystem research program. Entrepreneurship Theory and Practice, 1042258721998948.

Yan, X., Guo, J., Lan, Y., Cheng, X., 2013. A Biterm Topic Model Short Texts 11.

Zhao, W.X., Jiang, J., Weng, J., He, J., Lim, E.-P., et al., 2011. Comparing Twitter and Traditional Media Using Topic Models. In: Clough, P., Foley, C., Gurrin, C., Jones, G.J.F., Kraaij, W., et al. (Eds.), Advances in Information Retrieval. Springer, Berlin, Heidelberg, pp. 338–349.

Zilber, T.B., 2011. Institutional Multiplicity in Practice: A Tale of Two High-Tech Conferences in Israel. Org. Sci. 22 (6), 1539–1559. https://doi.org/10.1287/orsc.1100.0611.