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Establishing a Data Science for Good Ecosystem: The Case of ATLytiCS

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ABSTRACT

Data science for social good (DSSG) initiatives have been championed as worthy mechanisms for transformative change and social impact. However, researchers have not fully explored the systems by which actors coordinate, access data, determine goals and communicate opportunities for change. We contribute to the information systems ecosystems and the nonprofit volunteering literatures by exploring the ways in which data science volunteers leverage their talents to address social impact goals. We use Atlanta Analytics for Community Service (ATLytiCS), an organization that aids nonprofits and government agencies, as a case study. ATLytiCS represents a rare example of a nonprofit organization (NPO) managed and run by highly-skilled volunteer data scientists within a regionally networked system of actors and institutions. Based on findings from this case, we build a DSSG ecosystem framework to describe and distinguish DSSG ecosystems from related data and entrepreneurial ecosystems.

KEYWORDS

Social good, Case study, Volunteer management, Ecosystem, Data science community

INTRODUCTION

Organizations with access to both high-quality data and skilled analysts can execute effective data-driven solutions (McAfee et al., 2012). Importantly, organizational resources, including both the data analyzed and the human capital skills needed for such analysis, are not exclusively housed within organizations. Nearly half (46%) of corporations are using external data to support their analytics projects (van der Meulen and McCall, 2018). Types of data used include data from: consumer demographics, social media, weather, Internet of Things (IoT), geolocation and online news and job posts among others (Schatsky, Camhi and Muraskin, 2019). In addition, a variety of networked actors, both those organizationally employed as well as contract workers, engage in a large breadth of project-based collaborative work. The combination of data and labor resources that are not exclusively organizationally-bounded create a digital ecosystem (de Vasconcelos Gomes et al., 2018). Digital ecosystems are predicated on the idea of open innovation, whereby an organization makes available its innovation process to other firms, individuals, etc. to create collaborative arrangements (Pustovrh et al., 2020). The rise and success of these digital ecosystems has proved that companies can increasingly rely on open, modular technology and data capabilities for their analytics projects (Dietz, Hamza and Rab, 2020). It is expected that digital ecosystems will play a foundational role in a $60 trillion integrated network economy by 2025 (Chung et al., 2020).

The rising popularity and recognition of the import of data-driven decision-making is not limited to for-profit organizations. The social and public sector—including government, nonprofit organizations (NPOs), community groups and social enterprises—is utilizing data science to increase their efficiency in decision-making and the impact of their goals (Bopp, Harmon, and Voida, 2017). Organizations whose missions are focused on alleviating social inequities and injustices (i.e., crises response, healthcare disparities, crime, poverty, etc.) are increasingly seeking ways to access and leverage data to improve their products, processes and services (Benjamin, Voida and Bopp, 2018). These data science for social good (DSSG) initiatives have been championed in nearly all disciplines and industries as worthy mechanisms for transformative change and social impact (Hey, Tansley and Tolle, 2009; Catlett and Ghani, 2015; Coulton, et al., 2015; Williams, 2015; Chandy, Hassan and Mukherji, 2017). As a result, not just for-profit companies but social enterprises, governments and NPOs, are vying for the attention of data scientists and for access to third-party data sources (Niño et al., 2017).

As a result of this industry-spanning focus on data and analysis, demand for data professionals is outpacing supply across the United States (Ramachandran and Watson, 2021). Despite broad options for employment, skilled data professionals are much more likely to pursue highly paid and prestigious for-profit organizations rather than socially-driven NPOs or public sector employment. Without the talent and know-how, potentially useful data often remains trapped in the digital footprints of NPOs and government organizations, preventing it from being used to address social ills (Coulton et al., 2015; Chui et al., 2018). To ameliorate this problem, scholars have recommended that collaborative approaches between for-profit and public- and social-sector organizations are necessary. However, a framework for how this cooperation would work has not yet been proposed. We suggest that a new type of ecosystem of unbounded, networked organizations and actors can jointly share their data and human capital resources to benefit social and public sector organizations' goals. We call this ecosystem, structured around supporting social mission centered organizations engaging in data-driven initiatives, a data science for social good (DSSG) ecosystem.

We argue that a DSSG ecosystem is distinct from two well-studied ecosystems, the information systems (IS) ecosystem and entrepreneurship ecosystems. Notably, in contrast to these two ecosystems, the organizations engaging in DSSG initiatives (the NPOs, government agencies and social enterprises): exist to mitigate social ills, are focused on a limited geographic area, and depend on highly skilled volunteers to accomplish their goals. Thus, we argue that organizational missions are essential and unique to the DSSG ecosystem because it is the mission that drives the individual and institutional collaborations.

This study builds on the ecosystem literature by focusing on social sector organizations as the purveyor of DSSG initiatives. Thus, we introduce the DSSG ecosystem concept and define it as: *a set of interdependent, highly skilled volunteer actors (people), actants (places, processes and things), and assorted nonprofit, for-profit and government institutions, coordinated to enable the utilization of data science and analytics techniques for addressing social maladies within a particular locale.*

The paper continues with an overview of the literature on ecosystem and information systems to provide a context for the development of our novel ecosystem. We then discuss skills-based volunteers, as the critical actors necessary to establish a DSSG ecosystem. Next, we review our methodological approach to our case, and introduce our case study organization, ATLytiCS. We then present our DSSG ecosystem framework. We discuss several ATLytiCS initiatives, linking aspects of our framework to ATLytiCS's work. Then, we conclude the paper by identifying the unique contributions of a DSSG ecosystem and lessons learned for those interested in developing a geographic-specific DSSG ecosystem.

THEORETICAL BACKGOUND

IS and Entrepreneurship Ecosystems

The concept of ecosystems is a fruitful way to understand how various forms of open innovation are employed in modern organizations, especially given that scholars suggest open innovation is likely to replace traditional ways of innovation (Rangus and Slavec, 2017). Open innovations describe knowledge inflows and outflows of an organization (Chesbrough, 2003)—rather than any single organization harnessing all needed resources of the innovation process, open innovation provides opportunities for networked actors and institutions to collaborate by sharing resources (Pustovrh et al., 2020). This model of open innovation provides the framework for innovation ecosystems. Innovation ecosystems are comprised of knowledge ecosystems (driven by R&D) and business ecosystems (driven by market economies) (Xu et al., 2018). From an economic and strategic management perspective, ecosystems are defined as, "a set of actors with varying degrees of multilateral, nongeneric complementarities that are not fully hierarchically controlled" (Jacobides, Cennamo and Gawer, 2018, p. 2264). This definition extends the ecosystem concept by clarifying the unique differences of ecosystems from that of other inter-group firm projects. Specifically, *nongeneric* implies that customization is possible and dependent on the broader environmental context. The *not fully hierarchical* nature of the network implies that no single party can unilaterally set terms, controls or standards. And ecosystems as *multilateral complementarities* suggest that ecosystem investments or assets on behalf of actors are not completely fungible, meaning they cannot be fully deployed elsewhere without cost.

Research on IS ecosystems has focused on corporations forming flexible networks of strategic alliances with key external stakeholders (Bitran, Gurumurthi and Sam, 2007). For-profits take advantage of these "interconnected and collaborative business processes" (Guggenberger et al., 2020, p. 2) via digitally-enabled environments, resulting in the proliferation of diffuse organizational processes. Other research has focused on strengthening IS capacity for maintaining competitive advantage (Lee, Chen and Zhang, 2001; Lettieri, Borga and Savoldelli, 2004), improving agility and firm performance (Richardson et al., 2014), examining the capability of IS to meet strategic marketing goals (Laureano et al., 2018), improving employee satisfaction (Lane, 1996) or revealing tensions caused by increasing demands for data-driven practices within mission-driven organizations (Bopp, Harmon and Voida, 2017). More recently, the concept of data ecosystems, defined as "socio-technical complex networks in which actors interact and collaborate with each other to find, archive, publish, consume, or reuse data as well as to foster innovation, create value, and support new businesses" (Oliveira, Lima, and Lóscio, 2019, p. 519), has gained traction in IS due to advances in IoT and web-based technologies facilitated by open data movements (Tarkkala et al., 2020). IS literature has made note of the value of NPOs, but only to the extent that they may act as mechanisms or recipients of IS or data science service-learning projects for educational purposes (Hoxmeier and Lenk, 2003; Leidig, Ferguson and Leidig, 2006; Anslow et al., 2016; Uys, 2019).

Another relevant arm of the ecosystem literature relates to entrepreneurship (Stam and Spigel, 2016). While a digital entrepreneurship ecosystem suggests individuals can create geographically dispersed communities by leveraging existing technology tools (Elia, Margherita and Passiate, 2020), often entrepreneurial ecosystems are discussed according to regional specificity, where geographic proximity enables collaboration between multiple stakeholders to foster innovation (Radziwon and Bogers, 2019). Despite adverse economic and social conditions, entrepreneurial ecosystems have generated significant economic returns in multiple global contexts (i.e., Mexico, Argentina, China, and the U.S.) (Suresh and Ramraj, 2012). Isenberg (2010) identified nine principles and emphasized tailoring the ecosystem to meet local demands and styles. Others acknowledged this trend, finding that interconnected, historically generated, place-based characteristics are what created the conditions for long-term entrepreneurial success in select cities around the globe, including Silicon Valley (Saxenian, 1996), Kyoto (Aoyama, 2009) and Washington, DC (Feldman, 2014).

Entrepreneurial ecosystems require unique dynamics among a variety of actors and institutions (Pustrovrh et al., 2020). The Kauffman Foundation provides a detailed outline of the key elements of any successful entrepreneurial ecosystem, including entrepreneurs (i.e., those who aspire to start and grow new businesses), talent, knowledge and resources, champions and conveners, onramps (or access points), intersections (between people, ideas and resources), stories and social capital (i.e., collaboration, cooperation, trust, reciprocity and a focus on the common good) (Absher et al., 2019). Ultimately, according to Spigel (2017), key attributes of an ecosystem include culture (i.e., culture of risk taking and prominent local examples of successful ventures), social (i.e., talent, investment, networks, mentors, role models) and material (i.e., infrastructure, policies, universities, support services).

Despite ample research on entrepreneurship ecosystems (see Tsujimoto et al., 2018 for a review of 90 previous works), this literature is still limited. Scholarship focusing on specific types of market actors, namely social enterprises, is scarce and much needed. Researchers suggest digital applications, community involvement, and networked relationships between social enterprises, nonprofits, for-profits, government agencies and research institutions are needed to tackle social problems, from emergency management (Díaz, Onorati and Aedo, 2017) to food waste and malnourishment (Bolwig et al., 2001). Such digital social innovation (DSI), linking digital platforms developed by professionals and a community of loosely connected volunteers who use the technology (Rodrigo and Palacios, 2021) is an important start. But understanding how to create social innovation ecosystems to meet a broad range of social needs is a critical next step (Mason, 2017). The ecosystem characteristics that foster social enterprise at the national or local levels is less well-studied. Early findings suggest that the factors of primary importance involve socio-cultural and economic forces (Isenberg, 2011) or social-economy hybridity (Roundy, 2017; Okuneviciute and Pranskeviciute, 2021). These studies provide us with some initial insight into the factors that may enable a DSSG ecosystem.

Skills-Based Volunteering in the Social Sector

Most DSSG initiatives receive ample support from or are housed within academic institutions (e.g., Columbia University's Data Science Institute; Carnegie Mellon's Data Science for Social Good Fellowship) or have data supplied by federally funded institutes (e.g., CDC, NIH) (Barlow, 2015). These initiatives typically have a national or global social issue focus (e.g., DataKind) that is often agnostic to regional or localized issues and less concerned with cultivating a community of data science professionals.

Given that most DSSG initiatives are managed within academia or the public sector, there is less known about how the DSSG movement functions within the social sector, which is mainly driven by volunteer efforts. Volunteering itself has generally been defined as working for no monetary gain (Waikayi et al., 2012) despite having clear economic value for collective and societal good (Menchik and Weisbrod, 1987). There is a vast literature focused on the incentives, motivations, limited expectations, recruitment and management strategies of volunteers (Farny et al., 2019), particularly within the social enterprise and NPO contexts. Similarly, although a unified volunteering theory remains elusive (Hustinx, Cnaan and Handy, 2010), the stereotypical view portrays volunteers as less credentialed, having little job training and have few opportunities for professional development (Ashcraft and Kedrowicz, 2002; Lewis, 2013). The volunteer management literature contends that volunteers need to be given ample support (in carrying out tasks, training, involvement, etc.) so that they become embedded in the social structure of the NPO, thereby fostering positive attitudes and behaviors (Alfes, Antunes and Shantz, 2017). Furthermore, evidence suggests that piecemeal support and advice through well-meaning board members, fragile networks and higher education institutes, do not provide a strong framework for growth and sustainability in managing human resources in social enterprises (Royce, 2007).

A subset of the volunteering literature is focused on highly skilled volunteers who use '"work-related knowledge and expertise in a volunteer opportunity"' (Steimel, 2018, p.2, citing Americorps). These professional, skills-based volunteers are often highly trained and can bring tremendous value to the organizations they work with. Highly-skilled volunteers challenge the traditional literature in which there is: (1) a clear separation between work and volunteer projects; (2) a low barrier to volunteer entry and exit; (3) low-level managerial power or control over volunteer behaviors; and (4) an altruistic focus of volunteer work (Steimel, 2018). Social sector organizations have increasingly sought out highly-skilled professionals, drawing volunteers explicitly from the corporate world (Zappalà, 2001). In turn, corporations have teamed up with social enterprises and NPOs to create project-based volunteer opportunities where loyalty is no longer a priority and regularity of service is not required (Zappalà, 2001). For corporate citizenship programs, this skills-based volunteering has been fast-growing, and 50% of companies now direct the talents of their employees to NPOs (Letts and Holly, 2017).

METHODS

Case Site

In order to explore the effectiveness of highly-skilled volunteers and develop a framework for a DSSG ecosystem, we focus on the organizational and environmental context (Bozeman and Bretschneider, 1986) of the Atlanta Analytics for Community Service (ATLytiCS), a volunteer-led DSSG social enterprise based in Atlanta, Georgia. It is an NPO that offers data science solutions primarily to Atlanta-area public and social sector organizations (ATLytiCS, 2022). ATLytiCS's vision statement is "… a connected analytics community, conscientious of its role in society and aware that humanity's well-being should be at the core of our technological progress. We aspire to help build a world powered by data and analytics to provide others access to basic human rights so that we all have a choice in shaping our individual and collective future." (ATLytiCS, 2022).

According to its founders, ATLytiCS had a goal of completing at least one hackathon per year and one additional project each quarter. In practice, the organization has been successful at hosting an annual hackathon, and completing three data science projects per year. ATLytiCS typically has two major projects occurring at any given time. Many of these projects have multiple team engagements, each team consisting of approximately eight volunteers. In total, ATLytiCS boasts over 1800 volunteer members that it can reach out to on as-needed, depending on the expertise, availability, networks and other volunteer resources required for any given project.

To our knowledge, this is the first study to investigate the role of the data science organization as a means of creating social value from the regional ecosystem development perspective. In an attempt to fill gaps (Alvesson and Sandberg, 2011) in the existing IS, entrepreneurial ecosystems and skills-based volunteering literatures, the sections that follow describe our case study research design in order to develop an understanding and framework for the characteristics of a DSSG ecosystem.

Research Design

The case study design is the most widely used qualitative method in IS research and has been used to describe phenomena, develop theory or test theory (Darke, Shanks and Broadbent, 1998). Case study research is most appropriate when: the phenomenon of interest cannot be studied outside its natural setting, the study is focused on contemporary events, the control or manipulation of subjects or events is unnecessary or when the phenomenon of interest does not enjoy an established theoretical base (Benbasat, Goldstein and Mead, 1987).

The primary unit of analysis is the organization. The methodology employed is a descriptive, unique single-case explanatory design (Dubé and Paré, 2003; Yin, 2017) with the aim of describing a phenomenon that is not well-understood using the existing ecosystem and volunteering literatures. This approach reflects the recommendations by Leidner (2020) to fill a gap in existing theories, importing and extending them into IS in the context of an emerging phenomena (i.e., analytics and data science). The ATLytiCS site was selected based on the characteristics of the organization—an NPO, DSSG organization, led and operated by highly-skilled volunteers. In line with previous case studies and qualitative studies of social enterprise and DSSG initiatives (Radziwon and Bogers, 2019), data collection consisted of archival records (organizational charts, slide decks, presentation material and previous and current website content) and semi-structured interviews with the organization founders.

Interviews of all three founders served as a primary means of capturing information in a manner that would not be immediately observable by researchers themselves (Baskerville and Myers, 2014). The interview protocol was developed to capture founder narratives (Gartner, 2007) and identify key intra- and inter-organizational components utilized in DSSG initiatives. The protocol was arranged into six content areas: personal profile, founder's story, common challenges, evaluating the impact on social good, ethical dilemmas and closing thoughts about the organization and the nonprofit field. Repeated interviews lasted 30 to 60 minutes and were conducted within a one-month period (approximately 10 hours of interview time in total). Interviews were recorded via Zoom and transcribed prior to analysis. Transcribed files were later audited by the research team for accuracy and cross-checked against the audio recording in cases where missing words or phrases were present.

Two members of the research team analyzed these data using an inductive process of allowing themes to emerge from the raw data (Zhang and Wildemuth, 2009). The unit of analysis was defined as a "chunk of text" representing a theme relevant to our primary research question. Qualitative analysis was conducted via iterative (descriptive and interpretive) coding to identify overarching themes with thick descriptions and anonymized quotes (Miles and Huberman, 1994; Charmaz, 2014; Myers, 2019). Categories and coding schemes were developed such that one chunk of text could be assigned to multiple categories. A constant comparative method was used to ensure consistency throughout the coding process. Data were analyzed in Microsoft Excel and Microsoft Word (Meyer and Avery, 2009; Ose, 2016). Examples of initial first-order themes that led directly to the development of our DSSG framework included: access (data and funding), trust and accountability, impact, networks, human capital and technical expertise. Discussion amongst the research team helped to refine and clarify relationships between the practices, experiences and implications of internal and external DSSG organizational processes and networks. Codes were added to our list of themes as needed and this process was repeated for two additional rounds to ensure that the final set of codes were consistent between coders and comprehensive across all interviews. Examples of more refined second-order themes, as it pertains to funding access for example, included: funding sources from private sector, funding sources from public sector, funding and conflict of interest, and funding and data results impact. Affinity diagramming was used to identify cross-cutting themes to highlight the unique considerations and concerns of the founders. Striking quotes were lifted and included in this narrative to contextualize the findings presented.

Archival records, in addition to providing supporting documentation for qualitative insights, also provided a mechanism for understanding a range of project types offered to promote and facilitate DSSG. In accordance with suggestions by Yin (2017), these two sets of data (interviews and archival records) allowed for the triangulation of findings and for capturing the contextual complexity of the case. By examining the internal structure of the organization and the types of DSSG programming offered we are able to explain the unique value of a DSSG organization.

THE ATLytiCS CASE

In this section, ATLytiCS is discussed. We introduce the organization, the motivations of the founding triad and provide detail of the chronological progression of events in the organizations' establishment. Next, we discuss the ATLytiCS structure, its broad networked members and organizational connections, and how together these elements support the emergence of the Atlanta DSSG ecosystem. In addition, we describe three types of organically-developed ATLytiCS DSSG projects which exemplify how the DSSG ecosystem functions and provides value to DSSG, its institutional partners and its volunteers.

Founding ATLytiCS: Early Motivations

ATLytiCS was founded in 2017 by Andreea Popescu, PhD, Beverly Wright, PhD and Khalifeh Al Jadda, PhD with the aim to bring together analytics professionals to help solve critical societal problems. These three individuals were professional acquaintances, coming from strong corporate backgrounds, and joined together in 2016 after Popescu's plea to the data science community on LinkedIn. Popescu was both concerned and frustrated by the homeless man that she passed by at the transit station on her way to work every day. She wondered, "How do we have so many shelters in this city, and this man is never able to find a bed to sleep in?" Her solution was to try and identify other analytics-minded people in the Atlanta community who wanted to use their analytical skills to address problems like this.

A Litmus Test: The First Hackathon Event

The founders' first step toward starting the organization was to gauge available talent and altruistic interest within the Atlanta-Metro area. The founders wanted to ensure that there was a large enough volunteer base with the relevant set of skills needed to sustain the caseload that they envisioned. Moreover, they wanted to understand what skills were the most available in this niche volunteer labor market. Data analytics skills can cover a wide range of specialties, with professionals having different experiences using techniques such as structural equation modeling, predictive modeling and machine learning. In order to better understand local talent and humanitarian interest, the team decided to host a community hackathon in 2017 titled: "Data for Hope - Understanding Drivers of Homelessness Shelter Utilization". They focused on housing insecurity because of its widespread visibility in the Atlanta community.

One of the founders learned of a publicly available data source through a colleague at a local NPO. The data were from the Atlanta Regional Commission which reported information on the use of shelter beds in the Atlanta area. The hackathon received marketing and dissemination support from an affiliated organization of Al Jadda's, the Southern Data Science Conference. Administrative task work was also required, including refining the question posed by the hack, establishing rules, addressing technology needs, recruiting and prepping judges, reviewing submissions and other logistical details. Financial partners were used to fund the prizes and awards, and NPO partners functioned as subject matter experts (SMEs) for finalizing problem statements and to serve as judges.

NPO partners were recruited via the founders' professional networks. Ultimately, both Habitat for Humanity International and United Way of Greater Atlanta were asked to participate as SMEs and were the beneficiaries of the analytics insights generated by the hack. Leading up to the hack, the founders worked with the SMEs at these NPOs to identify a specific problem that had not previously been addressed and that could be answered using data.

The final question posed to hackers was, "What attributes tend to drive shelter usage?" The analytical goal was to understand why some shelters are underutilized while housing insecure persons are still sleeping on the street. Hackathon judges were recruited from NPOs, the corporate data science community and academic institutions. Of the 12 independently-formed participating teams (consisting of approximately 2-4 members each), less than 50% consisted of students from academic institutions and the remaining teams were affiliated with other area NPOs or corporations (including several teams from Fortune 500 companies who chose to use the hack as a team-building exercise). Teams used applied analytics techniques (e.g., dimension reduction, EDA, machine learning and predictive modeling among other approaches) to answer the question posed. The winning team was comprised of corporate volunteers (and one member of this team ultimately became a client for a future hack). By many measures, this event was a success and proved to the founders that there was certainly a community of data science individuals and institutions that could support their mission.

Despite the fact that all hackathon teams presented novel and mathematically sound insights at the end of the hack, it was difficult getting the NPOs that could have had the largest impact in the community to understand how these insights could be applied toward actionable decisions. As one founder explained: "We [realized that we] could also get better at dissemination of information to the public when it makes sense to do so. As data scientists, we can tend to focus just on the analysis and not enough on the implementation."

For this reason, the co-founders decided that future hackathons and engagements would aim to build awareness for the social cause and cause-based analytics, rather than attempting to solve a systemic issue through a hack alone.

Legal Formation, Mission And Vision

The success of the hackathon led the founders to conclude that the Atlanta community was ripe for a DSSG NPO. Ample participation and engagement at the event suggested that the community was brimming with talented analytics professionals with some degree of altruistic motivation. The founders were also encouraged by the participation of Habitat for Humanity and United Way, which could potentially help drive actionable solutions from participants' work. Procurement of company sponsorships also hinted that there could be potential interest in funding projects in the future. The combination of these positive outcomes pushed the founders to formally incorporate the organization as a 501(c)(3). This designation was chosen so that all donations or sponsorships would be tax deductible and easier to facilitate. Legal documentation would also add credibility to the ATLytiCS name and future efforts. Moreover, the founders believed that their prior corporate experiences were easily translatable into an NPO fueled by highly skilled volunteers. As one founder explained: "Previous experiences with companies have been key to running ATLytiCS...[We were] familiar with how consulting firms worked, and so we were able to apply that process when consulting NPOs. Another founder and myself have many years of experience as traditional data scientists and that experience has helped us match the right talent to the right project."

The founders' vision was to build a connected analytics community with a shared goal of progressing humanity's well-being, which would focus on improving and saving human life through analytics solutions. Today, the organization's focus on establishing and nurturing a DSSG community is supported by three ideological pillars, "Community", "Impact" and "Awareness" (See Figure 1).

The concept of "community" describes ATLytiCS's goal of bringing together data scientists, social experts and good-hearted people to create social change. This concept is interwoven into every effort within ATLytiCS, but is primarily accomplished by organizing networking events within the community. "Impact" encompasses all initiatives that influence social good using data-driven insights. This goal is directly addressed through custom consultations where data is used to assist NPOs. This of course is not always an easy task. As one founder explained: "[W]e…[realized that we have] to spend a lot of time teaching NPOs, especially smaller ones, how analytics can improve their organizations. Many times these NPOs don't even know what 'data' means. With one organization we realized that if we talked about data as information, spreadsheets or logs in notebooks, it finally clicked." Analytical findings are used in areas such as driving organizational decisions, applying for grant funding and disseminating information to the public to influence social change.

Finally, the "Awareness" pillar describes an intention to educate the public on the power that DSSG can have in the community. Hackathons are one way of accomplishing this goal as they inspire individuals to create social change through data science. This personal empowerment is also promoted through presentations and panel discussions with the general public. When addressing corporations, the "Awareness" function aims to inform companies on the power they have to influence social change through data science, whether by starting an internal project or allowing employees to volunteer their time. The goal when speaking with NPOs is to enlighten stakeholders on how data insights can be used and the degree to which those insights will help the NPO's mission.

There was a discussion early on among the founders about the possibility of "not involving volunteers but instead using funding to hire staff to complete projects. However, since we [the founders] wanted to deliberately build a data science community, raise awareness of the issues we set out to solve and awareness that data science can be used to solve complex social problems, we opted to go this route with the three connected pillars.” Thus, the ATLytiCS founders deliberately sought to develop an organization that was fundamentally structured to help fuel and take advantage of an ecosystem that included community engagement in the form of volunteers as well as corporate, university and government collaborations; local impact through critical geographic specific networks and localized social issues; and awareness of both the power that data science can offer and the benefit the community can derive from data driven solutions.

Organizational Structure and Core Values

ATLytiCS adjusted its organizational structure three times since its inception. Figure 1 outlines the most current structure. In order to maintain both top quality of project work and continuous motivation among high-value volunteers, as one founder explained: “Autonomy in project management will be needed if we want to keep growing, or even maintain our current size. Volunteers are complicated machines, but since we fill leadership roles with people who have real leadership experience, we should be able to hand off these projects to teams exactly like a company would.”

In order to succeed with this type of structural and cultural approach, each organizational iteration included more hierarchy and ownership initiative. These changes were largely motivated by an influx in interest and volunteer labor in response to ATLytiCS community events. To optimize the volume of workflow the organization could process, the structure needed to allow autonomous execution of projects by a team of volunteers without the founders’ direct involvement.

ATLytiCS’s current organizational structure aims to optimize management of the three ideological pillars, “Impact”, “Awareness” and “Community” alongside a “Shared Services" pillar which includes the variety of tasks required to logistically support the organization. Examples of projects within each category are listed beneath each pillar in Figure 1. Individual projects are assigned a Coordinator, who oversees a team of volunteers to assist with executing the work. The Coordinator is responsible for all deliverables to the client. Unit Heads manage a team of Coordinators. Heads are responsible for functions within their corresponding pillar and ensuring processes are implemented at all levels. Heads are also responsible for reporting project updates to the Board of Directors. The Board of Directors is composed of the three co-founders and a fourth board member who joined as a volunteer data scientist in 2018 and gradually took on more responsibilities as the organization grew. This executive level group makes decisions for all new initiatives as well as develops long term strategy.

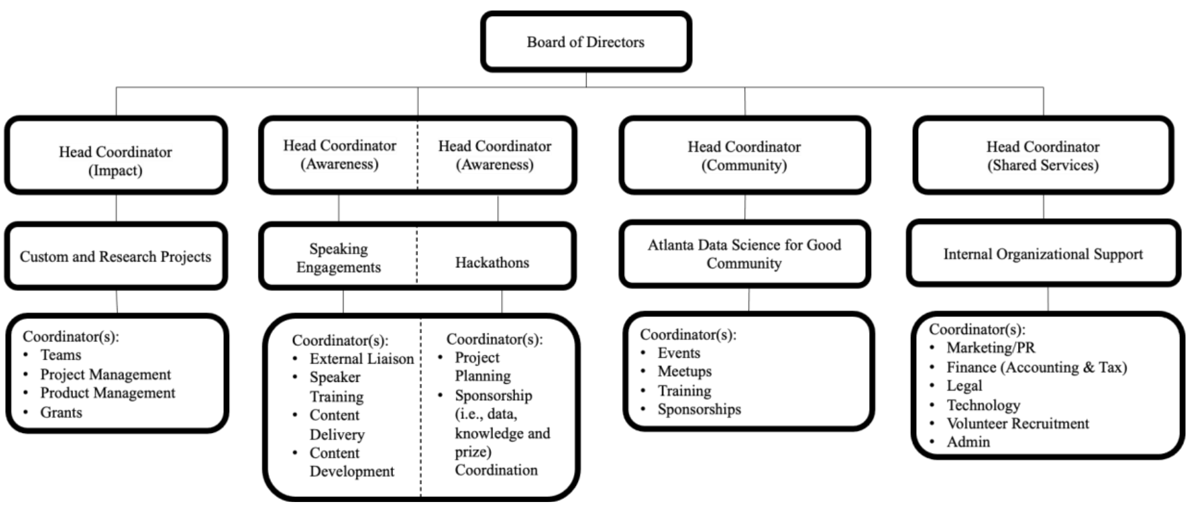

Figure 1. The Present ATLytiCS Organizational Structure

A 100% Volunteer Workforce

ATLytiCS operates using volunteer labor at every level of the organization. Although this was an intentional approach, the rapid growth of the organization also led to a recognition about the reality of a voluntary workforce and its relationship with project quality. As one founder put it: “We are trying to adjust to how quickly the organization has grown without sacrificing the quality of work. Quality isn’t going to be perfect when produced solely by volunteers.” Nevertheless, the organization has assumed a number of steps and adjusted its protocols to accepting volunteers to ensure high quality deliverables. In its early days, the organization recruited volunteers using pen and paper sign-up sheets that were passed around at community events. However, the attention sparked by hackathons and other community events made volunteering a competitive process, with the current network consisting of over 1800 members. Those interested must now formally apply through the website and complete an interview to determine if they have the right skillset to be placed on a team. Volunteers in Unit Head and Coordinator positions tend to have advanced degrees in business, technology, or quantitative fields, and ten to fifteen years of relevant professional experience, while Board Members have more than twenty years of experience. Volunteers in technical roles tend to have experience managing and leading data science and analytics projects in their paid employment. Since members typically have little to no prior volunteer history, it was expected that most individuals would burn out quickly in the organization. Although this may have been true of some team members at the bottom of the organizational structure, overall volunteer retention is relatively high (>75%). This is especially true of Unit Heads who have never turned down an offered position or been unable to complete a full year's commitment. This is a greater proportion than some research findings, which suggest more than one-third of those who volunteer one year do not donate their time in the following year to any nonprofit (Einolf and Yung, 2018).

Recruitment and Retention

Upon reflecting on the success of the ATLytiCS model, the founders realized that in their experience, volunteers often come with a set of self-interested motivations. This is natural for those who prioritize personal and professional growth. Projects offer unique opportunities to manage a team, try a new analytical technique or answer a question that would not typically occur in volunteers' work environment. These endeavors are ultimately items to be added as a new experience on a resume and discussed in job interviews. Additionally, the organization offers an excellent network for those wanting to make connections with aspiring and experienced data scientists who work at established companies. Providing these incentives is one of the ways ATLytiCS is able to secure competitive talent for its progressive projects. However, it can become problematic when the social cause is not the primary motivation for volunteers. Those with genuine altruistic motivations, especially those in leadership, were imperative to enable ATLytiCS to pursue its mission. Unit Heads are responsible for vetting and onboarding the Coordinators, who oversee the team of workers that execute the project. Onboarding consists of an introductory meeting between the two levels of members before any physical work is started.

Building a DSSG Ecosystem

A large part of the success of ATLytiCS has to do with the broader ecosystem of internal and external supports, detailed in Figure 2. Internal resources (i.e., volunteers, analytics expertise, legal support, marketing and technology) are those that the organization leverages to accomplish its mission. The variety of professional skills from its volunteer base are by far the community's most important resource. Analytics expertise is leveraged throughout the organization. Volunteers execute required tasks for deliverables in data science, speaking engagements or community events. In leadership positions, volunteers manage workflow and content quality to assure that products are in alignment with the project goals. Leaders with marketing experience promote the organization by fostering relationships with partners, facilitate community outreach through social media, update the website and other initiatives to expand ATLytiCS's reach.

Various technologies are also utilized at every level in the organization. Volunteers get an ATLytiCS email address and have access to shared data. Tools such as Tableau, RStudio, Jupyter Notebook and more are used by teams for analysis and insight reporting. The various platforms and communications between volunteers does create privacy concerns that for-profit partners are still navigating. As one founder explained: "[I]t can be difficult to get certain organizations to trust us with their data… even though we have credentials and sign NDAs." Another founder added: "Getting quality data is difficult, but that is why we have data experts who have ways of overcoming bad data. We try to be very sensitive with the data we touch and leverage public datasets as much as possible." The organizations with the largest, most reliable datasets often have difficulty trusting volunteer-run organization to maintain the privacy of sensitive information. ATLytiCS's establishment as a 501(c)(3) NPO won some trust with these partner organizations, but more legal practices and privacy-protection systems will need to be put into place before volunteers can gain access to larger proprietary datasets.

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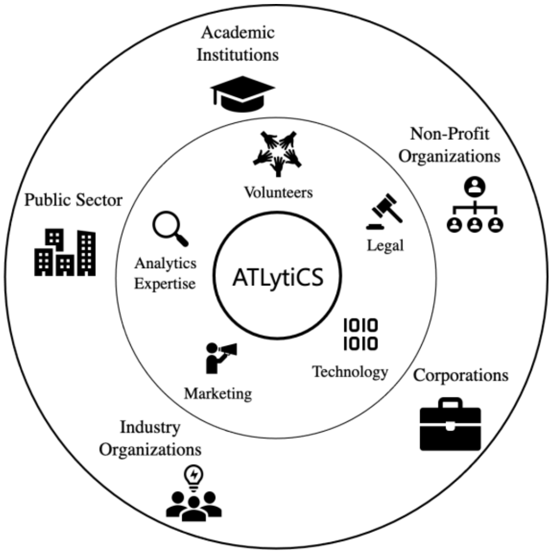

Figure 2. The ATLytiCS Ecosystem

External resources include relationships with organizations that ATLytiCS collaborates with to fulfill its mission. NPOs and public sector entities are the focal point of the work produced. These entities provide data for use in research, as well as deeper insights into the systemic problems that custom consulting projects and hackathons aim to solve. These institutions are also the primary vehicles for facilitating societal change once the insights are delivered. ATLytiCS also leverages partnerships with universities and private sector organizations, such as software providers and data science conferences. These partnerships help promote ATLytiCS, spread DSSG awareness and recruit volunteers. Sometimes these partnerships lead to the execution of initiatives themselves such as when custom consultations are handed off to a university classroom and managed primarily by a professor, or when conferences assist in managing hackathons.

Corporate partnerships are another critical component of the ATLytiCS ecosystem, especially for funding purposes. Funding is required for technology subscriptions, various legal fees, hackathon prize money and other basic operational functions. However, corporate partnerships can become problematic when a for-profit corporation seeks out DSSG expertise to tackle an analytics project with "fuzzy" social aims. ATLytiCS's ultimate goal is to generate funding through grants so that they can function independently of corporate sponsorships.

THE DSSG ECOSYSTEM FRAMEWORK

Table 1 is the DSSG ecosystem framework we derived from analyzing our data. It identifies two sets of general criteria (dimensions and values) determined to be of central importance for realizing DSSG project success and growing a robust DSSG ecosystem. In line with prior ecosystem research, we find that a combination of social, technical, and environmental factors are necessary to establish and maintain a DSSG ecosystem. These factors are captured as *dimensions* in our framework. Each dimension relates to either a broader environmental (e.g., network), social (e.g., socio-economic, human capital) or technical consideration. In addition to these dimensions, we identify important sets of *values* that capture the tensions and considerations in project selection, evaluation and impact. Values are of great importance to IS scholarship and can be intrinsic (e.g., justice or altruism) or instrumental (e.g., privacy or trust) (Parameswaran and Whinston, 2007; Shilton, Koepfler and Fleischmann, 2014).
The four key values we identify as necessary for a DSSG ecosystem to thrive are: 1) contextual knowledge of the problem and understanding of the data, access to quality data, people and financial support; 2) access to the right resources (i.e., skilled data scientists, data sources and datasets of reasonable quality, and adequate funding to sponsor events and to incentivize participation); 3) partners that trust the DSSG project team to use data, models and software in ways that do not violate good stewardship norms, organizational policies or laws (i.e., HIPPA, FERPA etc.) and 4) the scope and the scale of the project's impact is in line with partner goals with reasonable expectations for social impact that fit with the overarching objectives of the DSSG sponsor organization. This can be modified to meet the specific needs or conditions of the DSSG community in ways that align with the types of DSSG projects being undertaken.

		DSSG Ecosystem - Dimensions			
		D1. Network (e.g., professional and organizational networks and sense of community)	**D2. Socio-Economic** (e.g., organizational mission, organizational structure and leadership)	**D3. Human Capital** (e.g., leadership and staff, onboarding, training, hiring and managing of volunteers)	**D4. Technical** (e.g., problem framing, data, models, software tools and legal expertise)
DSSG Ecosystem - **Values**	**V1. Context and Understanding** (i.e., understanding data and problem context)	Partners endorse project insights as meeting their needs	Problem aligns with org. mission (e.g., poverty, human trafficking, etc.)	Teams are trained to understand the problem context to ensure relevance to partners	Project questions can be answered given time, modeling and data constraints
	V2. Access and Quality (i.e., access to quality data, people and funding)	Community partners are a source of teams	Sponsorship is available to promote, host and incentivize participation	A sufficient number of skilled data science teams participate	Data are accessible (i.e., publicly available)
	V3. Trust and Accountability (i.e., trust and accountability of data, teams and partners)	Partners trust teams to produce quality insights from their analyses	The software and data sources are adequate measures of the social phenomena under investigation	Leadership and teams are trained to protect PII and other sensitive data	Provision of data and models does not violate federal, local or organizational policies
	V4. Impact (i.e., unit, scale or level of impact)	Community support for the cause	Social sector constituents will be served by this work if implemented	Scale and scope of project suitable for team size	Potential for model deployment

Table 1. A DSSG Ecosystem Framework

ATLytiCS DSSG Projects

The Board of Directors evaluates all initiatives and assigns approved projects to a relevant pillar for execution. Table 2 outlines the Board of Directors' criteria used for approving new projects. The project approval process is either reactive (i.e., responding to a request by a Unit Head, sponsor or organization) or proactive (i.e., pursuing new projects that promote strategic goals). The primary requirement is that ATLytiCS's work aligns with its vision of improving and saving human lives. Impact is evaluated based on the work's intended application, type of impact created and level of impact in the community. Another crucial consideration is whether or not ATLytiCS has adequate resources, including labor, technology and promotional platforms, to produce the quality of work desired. Data availability, resources and involvement of NPOs and corporate partners are also important factors. In custom projects, partners must be comfortable sending data to volunteers for analysis. It is also favorable if these organizations can provide additional resources such as a product owner or a point person to communicate directly with the analytics team.

CRITERIA	EXAMPLE QUESTIONS POSED AMONG BOARD MEMBERS
Alignment with vision	• How does the project, event, or initiative accomplish the mission of "establishing a data science community for good?"
Application of work	• Will the results be used to create change in the community? If so, how will they be used? • Which pillar, Impact, Awareness, or Community, does the work support?
Type of impact	• Will the work directly save human life or improve quality of life? • Will it directly affect individuals or society as a whole?
Level of impact	• How many people will be directly impacted? • Does the work target local or global causes and organizations?
Available resources	• Does ATLytiCS have volunteer labor with the skills required to complete the work? • Is there enough funding to supply materials? • What can NPOs and sponsors provide? • What might sponsors want in exchange for funding? • What resources are available to market the event in the community?
Availability of data	• What kind of data is available? • Can the NPO trust information in the hands of volunteers?
Partner involvement	• Does the NPO have a primary point of contact to communicate with ATLytiCS teams? • What other NPOs, companies, or institutes will be involved?

Table 2. Rubric for Project Approval Process

The succeeding sections outline three projects that met the board's approval, based on Table 1 Rubric, and exemplify the impact sought. In addition, we identify aspects of each project that link to the key characteristics of the DSSG Ecosystem Framework we developed in Table 1. As identified in Table 1, the various *dimensions* (D) and *values* (V) are designated with the notations D1 through D4 and V1 through V4, respectively. We categorize the details of these examples with these labels to demonstrate the utility of our framework.

Project 1: Dekalb Fire and Rescue Custom Build Project

On fire and rescue calls, intelligence is a resource that saves not just time but also lives and property. Insights into high-risk areas could exponentially improve the effectiveness of entities such as the Dekalb County Fire and Rescue Department (DCFR), which responded to 34,690 fire related calls in 2018 in the Metro-Atlanta area. Until 2020, DCFR could only make vague connections about high-risk fire areas based on firefighters' experiences. ATLytiCS was able to introduce a data-driven model to improve DCFR's incident response system [V1, D1, D2].

Data was compiled from nineteen diverse sources. The Census, Dekalb Government, Zillow Real Estate, USPS Vacancy, and DCFR reports were some of the sources used to analyze patterns at varying levels of residency outlined in Figure 3 [V2]. The ATLytiCS team constructed machine learning and random forest models, and compared the effectiveness of these two techniques at varying residential levels [D3]. Results indicated that machine learning analysis at the block level was the most effective at predicting fire risk [D4]. The model was used to develop a visual tool for DCFR to quickly identify high risk areas that may require intervention. Key drivers from analysis were also used in an educational infographic to disseminate among community members. The final phase of the project was to develop a streamlined process for DCFR to store internal data, access external data and regularly update the machine learning model. This would support the use of data-driven decision making after the conclusion of ATLytiCS's work [V3, V4].

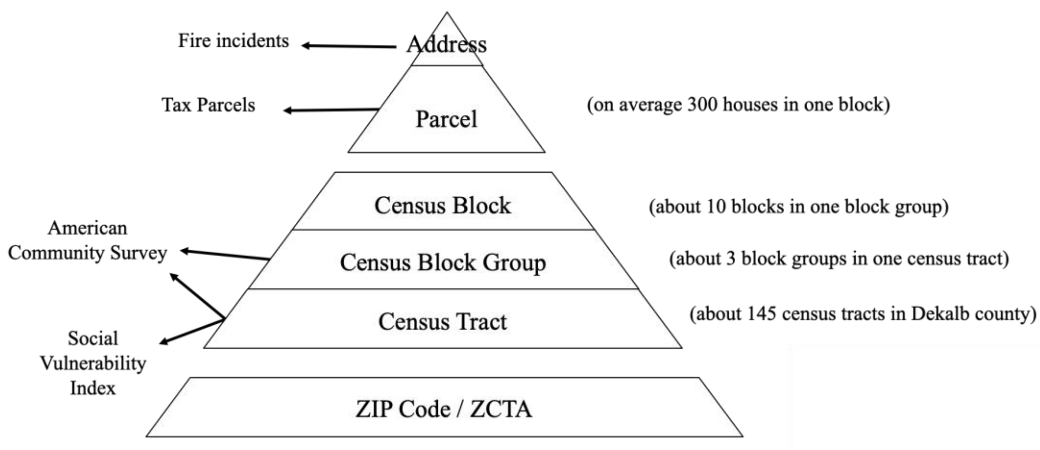

Figure 3. Importance of Data Aggregations

Project 2: Equifax Speaking Engagement

Highly successful DSSG projects may require access to corporations' big data resources [V1]. ATLytiCS regularly speaks with corporations in an attempt to influence the company's involvement in the community [V2, V3]. The Equifax Spark Conference, which took place in March 2019, is one example of an event that provided a platform to spread these ideas [D1, D4]. The invitation-only event brought together an elite group of product executives, data scientists and analytics experts from around the globe to discuss the latest innovations in technology [D3]. ATLytiCS shared their advanced analytics work from three previous custom projects and one hackathon. To establish relevance within the advanced analytics audience, the audience was presented with the background for each case, analytical approach to solving the problem and specific resources that were used [D2, V4]. The closing slides communicated to the audience how DSSG adds value to the decision-making process that facilitates social change [V4].

Project 3: Human Trafficking Hackathon

The human trafficking crisis is a global systemic issue, but one that disproportionately affects the Atlanta community because of the amount of international traffic that passes through the city [D2, V4]. It is estimated that more than half of all housing insecure youth in Atlanta have previously experienced human trafficking (Wright et al., 2021). In 2019, ATLytiCS hosted a hackathon [V2] to see what insights the Atlanta community could identify about this critical problem [V1]. The hack consisted of 15 participating teams [D1]. The winning team used an xgboost machine learning algorithm to identify that sex trafficking amongst Cambodian citizens was significantly greater than other countries [D3, D4]. Market basket analysis was also used to identify common abuses associated with each type of exploitation [V3].

LESSONS LEARNED/BEST PRACTICES

One great benefit of a case study is its ability to present information that is both useful for theory and practice (Gioia, 2021). In Table 3 we summarize a few critical aspects of the DSSG ecosystem, some practical problems ATLytiCS has encountered in these areas and their solutions. We believe this summary will be useful, particularly for practitioners seeking to emulate some of the success of ATLytiCS and the development of a DSSG ecosystem.

Ecosystem Function	Problems Encountered	Recommended Solutions
Volunteer Workforce	• Motivations may be self-interest related (e.g., to gain technical expertise, networks, resume-building experience, etc.) which has resulted in lower-than expected quality of work and retention issues • Operations areas like accounting, marketing, and legal lacked adequate volunteer capacity • Many were interested in offering technical assistance, but few were interested in leadership roles	• Be selective in the recruitment process • Create clear expectations within roles • Advertisements for volunteer positions should include expectations of skills, prior experience, and anticipated hours • Create a formal application and interview process • Have an engaging and information-driven onboarding process to connect new volunteers to the client organization's mission and culture • Create volunteer advancement paths and identify talented and dedicated volunteers for leadership opportunities
Partnerships	• Effectively leverage NPO, government, and college/university partnerships • Obtaining corporate funding and concerns of "fuzzy" aims	• Be clear about your relationships and the purpose of engagement • Identify universities and professors with the right resources who are eager to execute on findings and initiatives • Focus on generating funding from grants to function independent of corporate sponsorship
Data Sources	• As a privacy concern, for-profit companies remain hesitant to share data	• All volunteers should sign NDAs • Reiterate to private partners the organizations' NPO status and service in the name of social good • Prioritize and leverage public and university collected data sets whenever possible
Project Selection	• Mission creep • Emotionally-fueled conversations among internal board members and between the NPO and partners	• Create a written charter with consistent alignment about what the organization aims to do, how they plan to accomplish goals, and what sorts of activities the organization does not perform • Create a clear system or rubric and criteria for project selection (e.g., Table 2) • Stay apolitical and religiously agnostic (unless these are criteria built into your organization's mission) • Continuously remind organizational leaders and volunteers what your cause is—have this as a mantra

Table 3. Lessons Learned: Ecosystem Functions, Potential Problems, and Practical Solutions

Conclusion

This article makes valuable contributions to our understanding of data and entrepreneurial ecosystems by connecting this scholarship to the skills-based volunteer and nonprofit management literature. Furthermore, we extend these existing theoretical frames to include the actors (people), actants (places, processes and things) and institutions (NPO, for-profit and government bodies) that have been excluded from prior research. However, the rising demand and cost of analytics talent in the face of short supply means that NPOs and the public sector are entering a competitive marketplace for skilled data analysts, drawing on the same pool of potential candidates as well-resourced for-profit firms. Most social sector organizations would benefit from traditional analytics insights requiring less resources to implement and whose feature effects are directly explainable (Bughin et al., 2018). The importance of organizations like ATLytiCS and DSSG services—whose target audience are precisely those who stand to benefit the most from analytics awareness, community building and impact services—should not be under appreciated. Although entrepreneurial ecosystems have long been recognized as powerful forces for change (Stam and Spigel, 2016), the rising importance of data science and analytics services for social good has the potential to become an ever-important phenomena for regional nonprofit and public sector analytics needs.

To advance DSSG ecosystems research, we need more examples of functioning DSSG organizations and their broader ecosystems, along with a more in-depth understanding of the privacy and accountability concerns of organizations whose data are less accessible to capable and well-meaning DSSG organizations and teams. More work is also needed to understand how highly-skilled and dedicated data scientist volunteers should be recruited and the motivations they need to remain dedicated to collaborative projects. This information would help us understand what makes some DSSG ecosystems thrive and others fail, especially because we anticipate more NPOs and public sector organizations turning to highly-skilled volunteers to address their analytics needs. Ultimately, this study calls for greater attention to the unique contributions of DSSG ecosystems in their efforts to address long-standing social inequities and welcomes others to engage in this important conversation.

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