Barriers to Service Innovation Using Data Science

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Abstract. The benefits of adopting data science are increasingly clear in a variety of industries, yet adoption rates remain low. In this paper we examine the barriers faced by organizations in adopting data science approaches in the context of service innovation. We first characterize three types of barriers: legal framework, organizational challenges, and risks. The legal framework around data science is in a state of change, and certain aspects are outdated and fragmented. Organizational issues include recruitment and a lack of diversity. Finally, risk is inherent in any business, but data science investments may be especially uncertain due to the fundamental role that datasets play and the lack of familiarity that those making decisions may have with data science. We present results in which we identify and expand on the links between these barriers and service innovation using data science.

Keywords: Data science · Adoption · Service innovation · Regulatory framework

1 Introduction

The wide-spread adoption of data science by organizations is expected to improve economic productivity, create jobs, and bring significant value overall. This is only expected to grow, with Short and Todd finding 40% annual growth in the volume of stored data [11]. We define data science, broadly, as an interdisciplinary scientific approach that provides methods to understand and solve problems in an evidence-based manner, using data and experience. Recent studies confirm that mastering big data affords strategic advantages to corporate users, and that early adopters of the most advanced analytics capabilities outperform their competitors [7, 9]. As technologies around data platforms evolve and mature, the opportunities for local, national, and international economies to apply data science as a competitive edge will increase. Yet business leaders and legal and policy analysts around the world are also grappling with the risks and potential negative, disruptive effects that would arise from the adoption of data-driven technologies. Between 41% and 55% of work activities around the world could be automated through currently available data-driven technologies resulting in extensive job losses [5]. What's more, as these technologies advance, the impact on the existing workforce will only increase in speed. There is a potential for a digital divide across economies and socioeconomic and gender classes. Adoption of these new technologies also raises far-reaching social and ethical questions.

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Service science research has a role to play in addressing these challenges. Within service science, there is increasing interest in big data, data analytics, and artificial intelligence; in the context of service innovation and design [2]; for addressing specific service innovation contexts [10]; and, for supporting value [8]. There is also an understanding that service innovations through data science are associated with challenges such as ethical concerns [3]. Barriers to applying data science broadly in service innovation include: the need for a regulatory framework that builds trust yet allows innovation; a workforce with the skills and experience to create, apply, and maintain increasingly complex models; and, the creation of new datasets that are nonetheless reliable and train models with humanity [1]. We characterize three types of barriers: legal frameworks, organizational challenges, and risks.

In this paper, we present each of these barriers to data science adoption and discuss how service science is well-positioned to help address challenges associated with these barriers.

2 Legal Framework

The legal framework around data science is in need of change. Certain aspects, especially around privacy and consent, are outdated and fragmented [4]. And the distributed aspect of many data science applications means that the legal framework in any one state, province, or country must interact with other frameworks.

There is considerable interest in updating privacy laws. As technology advances, there is a need for the legal framework to evolve with these changes. For instance, as facial recognition software becomes more accurate and less expensive to deploy, having an appropriate legal framework in place becomes more pressing. While changing and updating the legal framework is necessary, the uncertainty that it creates is a barrier to service innovation through data science.

Innovation in data science comes from three areas: 1) new datasets; 2) new models; and 3) new applications. Those that are able to take advantage of Google-, Facebook-, or Amazon-scale datasets can quickly generate valuable results. But the capacity of many in academia and business to generate new training datasets and new models is limited because of the specialized knowledge and investment that these require. A legal and regulatory framework in which data were strictly regulated may make it difficult to create new services. However, a framework in which consumer-driven sharing happens with explicit consent, such as various open banking regulations, could allow service innovation in that area.

One difficulty with enacting legislation is that governments may simply lack the expertise to be able to evaluate the claims of leading data science businesses and are not well placed to properly forecast data science developments. Legislation that is focused on the requirements for today would place considerable barriers to service innovation in the near future as technology evolves and the economics of data science applications change.

3 Organizational Challenges

There are a variety of challenges to service innovation using data science that come from organizational constraints. These include leadership that may be less experienced with data science, specific cultural practices, a lack of an experienced workforce and associated recruitment difficulties, and, finally, a lack of diversity.

3.1 Leadership

Often the current leadership of service firms do not have extensive experience with using data science, let alone having implemented and evaluated data science approaches themselves. This may influence the strategic decisions of service innovation firms. In terms of implementing a business strategy, it can be difficult for leaders to appropriately manage teams and decide on tactics when they have little or no experience in the area. While this is a traditional management issue, it exists within this new context of data science and is a barrier to service innovation using data science.

3.2 Culture

Traditional business structures tend to become siloed because of the gains from specialization. But not only are the tools of data science largely 'silo agnostic' and able to be applied across a variety of them (in contrast to, say, accounting techniques, which tend to be largely confined to the accounting department), but they can benefit from the additional context for the data and techniques.

Domain expertise is a critical aspect in the success of any data science project. Creating short-term, high-impact, partnerships between data scientists and domain experts can be a challenge in overly siloed service businesses because of cultural mismatches.

3.3 Lack of Experience and Recruitment Challenges

The combination of skills needed to apply data science successfully in-service innovation means that there are gaps between the employees that are available and the positions. A typical data science application involves data gathering and cleaning, statistical modelling, and finally evaluation and iteration. Although some of these skills can be taught, there is a lack of experienced data scientists, relative to demand.

3.4 Lack of Diversity

Data science has traditionally been dominated by people with a relatively homogeneous background. As the applications of data science broaden there is a need to similarly broaden the community of data scientists. There is considerable benefit to doing this because usually the challenges of data science applications are context specific and there is substantial value from subject-matter expertise and a diversity of experience.

It is particularly important to increase participation of underrepresented groups, for example, women, indigenous peoples, and youth as both developers and consumers of data-driven technologies. Ensuring inclusiveness, equity and diversity in data infrastructure, data-collection processes, education and the workforce will benefit all stakeholders (including the general public) with better, more useful, and more equitable outcomes from data-science innovations.

4 Risks

Investment risk exists for any service innovation; however data science projects are especially risky for various reasons, including the fundamental role that datasets play, challenges associated with delivering on promised expectations, and ensuring equity, diversity, inclusion when implementing significantly disruptive technologies.

4.1 Availability of Appropriate Datasets

Creating, cleaning, updating, and securing datasets are difficult processes that often require substantial investment of resources. And while these are essential processes in order to extract value from data, they rarely provide value themselves which can be a challenge when making a business case and investment decision, and adds risk to the decision to adopt data science practices especially for small- and medium-sized service organizations.

Furthermore, even when algorithms exist that can help with these processes, the relevant software has to be deployed and configured in the particular environment, and, in order for the process to be of actual value, the constructed models have to be embedded in the activities of the organization.

4.2 Delivering on Expectations

The expected gains from data science adoption are significant and organizations are drawn to the promise of tremendous innovation potential. However, there is often a misunderstanding between expectations of what organizations want to do and what can actually be done. There is a risk that investments will not result in expected gains because either the underlying datasets are of insufficient quality or the associated algorithms and models are not deployed appropriately or both. In the case of AI replacing humans, for example in self-driving cars, a widespread appreciation of the benefits will only occur when the capability of the technology becomes substantially better than that of humans.

4.3 Implementing Disruptive Technologies

A unique risk of data science adoption is the potential for disruption to current jobs, including knowledge work. For instance, there is a difference between the skills that are in demand due to data science and the skills of the existing workforce. While some of the existing workforce will be able to retrain, many will not, and the social challenges of such change has been substantial in the past. It is important to understand the kinds of new skills that will be needed for the future workforce and to create new training and education materials and modules that can support those needs. This need for training and knowledge building goes beyond academic training, requiring new ways of thinking about helping employees in the workforce embark on new career paths or job transitions. A related risk is the potential that the disruptions will disproportionately negatively impact specific sub-populations, create a data divide, and increase existing wage disparities in the workforce.

5 Conclusion

A world-wide data-science revolution is underway, enabled by the capacity to generate massive amounts of new kinds of data from service applications, smart technologies and individuals [6]. Data-science technologies including AI, analytics, and smart service systems are increasing in importance as diverse, off-the-shelf tools become widely available. Data-science innovations are expected to generate substantial productivity gains, efficiencies and inclusiveness of services, and create more competitive markets and economic growth; however, there exists a variety of barriers to service innovation using data science.

Service science is well positioned to contribute to a multidisciplinary, cross-institutional, cross-border research agenda that pursues world-changing data-science research, increases productivity, efficiency, and inclusiveness across industries, furthers the transformation of existing operational systems with advanced data-science capabilities, delivers transparency, explainability, fairness, and ethics in all aspects of data-science deployment, equips policy makers and industry leaders with tools for predicting, managing, and surviving the pending disruption and economic and social consequences of adopting data science at scale.

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