Chapter 3
Determinants of Data Science Adoption in Organizations:
Insights From Analyzing the Digital Voice of Practitioners

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ABSTRACT

While the hype around data science and its key role in driving business and industry change is pervasive, there is scant insight into the factors underlying its successful and widespread adoption in organizations. This chapter presents a systematic approach that integrates text analytics with technology-organization-environment (TOE) framework to analyze the digital voice of practitioners and identify the factors driving data science adoption in organizations. The authors collected 4100 user-generated reviews for 13 prominent data science platforms from Gartner.com and then categorized them into different topics using Latent-Dirichlet Allocation (LDA) model. From the identified topics, 48 factors were derived and synthesized into a model for data science adoption using the TOE framework. The results reveal that alongside technological capabilities, several organizational and environmental factors can significantly influence data science adoption. The results also provide evidence on the potential impact of data science adoption on various aspects of business performance.

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INTRODUCTION

The proliferation of digital technologies such as social media platforms, smartphones, cloud-based data storage and the Internet of Things (IoT) have enabled companies to accumulate a wealth of data of various types and characteristics. As a result, most companies do not suffer from a lack of data on their customers, products, business operations or competitors. On the contrary, the ever-growing data silos that organizations are accumulating present them with a significant challenge in deriving knowledge and actionable insights from this data in a timely manner. This is particularly important now, as products, services, and business cycles become shorter; therefore, faster, better, and more informed decision making has become a competitive imperative (Chatterjee, Chaudhuri, & Vrontis, 2021; Daradkeh, 2019a). In this competitive environment, characterized by increasing demand for evidence-based decision-making and the proliferation of big data, data science has quickly become a mainstream practice used by many organizations to unlock the value of big data, support decision-making at the strategic and operational levels, and improve various aspects of business performance and operations (Cybulski & Scheepers, 2021; Medeiros, Hoppen, & Maçada, 2020; Oussous, Benjelloun, Ait Lahcen, & Belfkih, 2018; Sharda, Delen, & Turban, 2021).

The potential value and impact of data science has been extensively demonstrated in various business and industry applications and has been promoted by many academic and research communities (Cybulski & Scheepers, 2021; Donoho, 2017; Medeiros et al., 2020; Vicario & Coleman, 2020). While this constitutes a leap forward in the realm of data science, the challenge for researchers and industry is that the development of data science tools and technologies has not adequately addressed the subtleties and factors that are critical to the successful and effective adoption of data science in enterprises (Cybulski & Scheepers, 2021; Wimmer & Aasheim, 2019). At the same time, data science tools are becoming more sophisticated and important for business applications and decision making (Brous & Janssen, 2020; Latif et al., 2020), making the issue of adoption and acceptance even more pressing (Wimmer & Aasheim, 2019). Medeiros et al. (2020) emphasized that it is critical to understand enterprise users and the factors that could influence the adoption process when bringing data science solutions into widespread use. Understanding these factors is not only of great value to the successful adoption of data science capabilities in the workplace, but also helps reduce the risk of rejection or resistance to the adoption of new and potentially disruptive data science solutions (Brous & Janssen, 2020; Vicario & Coleman, 2020; Waller & Fawcett, 2013).

This chapter aims to develop a model that prioritizes and provides insights into the underlying factors that contribute to the success of developing data science maturity and practices in organizations. To this end, we present a systematic approach that

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