

# Artificial Intelligence, Consumers, and the Experience Economy

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## INTRODUCTION

The term Artificial Intelligence (AI) was first used by McCarthy, Minsky, Rochester, and Shannon in a proposal for a summer research project in 1955 (Solomonoff, 1985). It is widely and commonly defined to be “the science and engineering of making intelligent machines” (McCarthy, 2006). Recent technological advances and methodological developments have made AI pervasive in new marketing offerings, ranging from self-driving cars, intelligent voice assistants such as Amazon’s Alexa, to burger-making robots at restaurants and rack-moving robots inside warehouses such as Amazon’s family of robots (Kiva, Pegasus, Xanthus) and delivery drones. There is optimism, and perhaps even over-optimism, of the potential heralded by AI as a source of greater customizability and personalization and reduced operational costs.

For many businesses planning to develop and deploy AI (and more generally, machine learning algorithms underlying this technology), a promising context is marketing decisions (Davenport, Guha, Grewal, & Bressgott, 2020) in experiential products and services (McKinsey Quarterly, 2021). Experiential products and services are those that are characterized by the sensory experiences they provide to users and consumers (Holbrook & Hirschman, 1982). Common examples include entertainment (e.g., real-life concert performances, movies and shows on Netflix and Disney+), hospitality (e.g., fine-dining restaurants, hotel resorts), and tourism (e.g., amusement parks, travel packages).

Understanding what customers want in experiential products and services is a fundamental challenge for businesses catering to the “experience economy” (Pine & Gilmore, 2011). Given that the primary value of an experiential product lies in the sensory experience that it provided to consumers, experiential products tend to have complex, nuanced, and rich features (Mukherjee & Kadiyali, 2018). There are almost limitless possibilities as businesses aim to develop new experiential products that appeals to the market. For example, Netflix has been reported to hire human coders to develop a proprietary classification system of over 76,000 micro-genres to describe its movies and television shows (Madrigal, 2014), which power both the development of its new entertainment offerings and its recommendation engine that promotes its existing offerings. Examples of such tags include “spy action and adventure movies from the 1930s,” “critically-acclaimed emotional underdog movies,” and ‘British set in Europe Sci-Fi & Fantasy from the 1960s’ (Madrigal, 2014). While this process was required for product management and customer experience management, it is likely very expensive and time-consuming to setup and to maintain (to keep up with the fast-changing consumer preferences and wide range of product options in the entertainment industry). Fortunately, recent developments in the AI and machine learning literature present several exciting new possibilities to help businesses better and more effectively cater to the

DOI: 10.4018/978-1-7998-9220-5.ch033

experience economy, though exactly how they can manifest in business operations is still largely being discussed and explored (PwC, 2017).

Crucially, the successful development and deployment of AI-based experiential products and services depends on the consumer's willingness to accept and adopt AI technologies and solutions. Current anecdotal evidence, however, suggests that the consumer's receptivity of AI is complex, multiply determined, and hard to anticipate. For example, during the COVID-19 pandemic, Pan Pacific Singapore expanded the functions of its AI digital concierge Mika to handle guest needs (e.g., requests for housekeeping items) (Vouch, 2020), while Henn-na Hotel in Japan drastically reduced its robot services due to escalating guest complaints (Haddad, 2020). Though both hotels deployed AI to provide better lodging experiences, the dramatic difference in AI deployment outcomes is illustrative of the uncertainty that surrounds the acceptance and success of AI products and services in the experiential economy.

The nascent scientific (academic) evidence corroborates the anecdotal evidence. For example, extant research has found that people place lower trust in dating services that are based on AI algorithms (Castelo, Bos, & Lehmann, 2019), callers to customer service centers end calls early and report lower satisfaction if they realize they are interacting with an AI (Luo, Tong, Fang, & Qu, 2019), and patients are unwilling to utilize health care provided by AI (Longoni, Bonezzi, & Morewedge, 2019), relative to equivalent services offered by human agents. These findings challenge the general assumption (and hope) that customers will adopt AI products and services if these products and services lower search costs and/or increase consumer utility and consumer welfare. In contrast, the anecdotal evidence and emerging empirical findings suggest that consumers may be unwilling to accept and adopt AI solutions—even when such solutions provide superior benefits at a reasonable cost—due to people's fundamental mistrust of, and reticence towards, AI.

Accordingly, the present book chapter discusses the nascent literature on consumers and AI, particularly in the context of experiential products and the experience economy, which are key marketing application contexts (Pine & Gilmore, 2011; McKinsey Quarterly, 2021). The present chapter further draws upon the formal academic literature and leading practitioner press to synthesize current evidence, with suggestions and recommendations for marketing managers and policymakers tasked with driving the deployment and success of AI in the experience economy.

## **BACKGROUND**

Experiential products and services are those that consumers choose, buy, and use solely to experience and enjoy (Holbrook & Hirschman, 1982). The key benefit of an experiential product is “hedonic consumption, that is the feelings, emotions and sensations experienced during product usage” (Cooper-Martin, 1992). Examples of experiential products include going to watch a movie (Mukherjee & Kadiyali, 2011), taking a vacation (Chang & Pham, 2018), and attending a concert (Table 3, Loureiro et al., 2020). As consumers place increasing emphasis on experiences over material possessions (Euromonitor International, 2017), the experience economy is growing in prominence and importance to many nations' overall gross domestic product (Pine & Gilmore, 2011). Recognizing the increasing significance of managing consumer experiences for businesses' long-term success, practitioners are increasingly focusing on customer experiences and experiential marketing—the marketing of a product by emphasizing its experiential benefits. For example, BMW markets its automobiles based on driving experience; the tourism boards of many countries and cities advocate the emotional benefits that visitors derive by experiencing the culture, history, and scenery of specific destinations.

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