

AI and Business Model Innovation: Leveraging the AI feedback loop

Evangelos Katsamakas

Gabelli School of Business, Fordham University, New York, NY

Oleg Pavlov

Worcester Polytechnic Institute, Worcester, MA

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Abstract

The article analyzes the effects of Artificial Intelligence (AI) on Business Model Innovation. It shows that AI enables key strategic feedback loops that constitute the core structure of a business model. The article provides a framework and discusses implications for managers and entrepreneurs who seek to leverage the AI feedback loop.

Keywords: AI, AI strategy, Network Effects, Business Model, Business Model Innovation, Platforms, Data, Dynamic Complexity, Feedback Loop

Introduction

AI is expected to have a transformative impact on the economy and society (Brynjolfsson & McAfee, 2016). However, companies are struggling to make sense of the business impact of AI and create a coherent AI strategy. This article brings together the concepts of AI and Business Model Innovation, analyzing the effects of AI on Business Model Innovation.

An extensive literature on business models spans across fields such as management, strategy, innovation, and information systems. In early work, (Osterwalder, Pigneur, & Tucci, 2005) called for a clarification of the business model concept. In simple terms, a business model is “a blueprint of how a company does business,” and it defines “the logic of the firm”: How a company creates and delivers value to customers and how it captures value.

Business model innovation (BMI) is crucial to business viability. Several authors propose normative frameworks for practitioners, such as the business model canvas (Osterwalder & Pigneur, 2010), a template of nine building blocks: Customer segments, value propositions, channels, customer relationships, revenue streams, key resources, key activities, key partnerships, cost structure.

Zott, Amit, & Massa (2011) note the business model concept is emerging as a new unit of analysis, emphasizing a holistic approach to how a firm does business. Moreover, firm activities play an essential role in a business model, “a system of interconnected and interdependent activities that determines the way the company does business with its customers, partners and vendors.”

In most recent reviews, (Massa, Tucci, & Afuah, 2017) suggest three interpretations of the business model (attributes of firms; cognitive schemas; formal representation of how a business functions) and discuss the relationship with the rest of strategy literature. (Foss & Saebi, 2017) identify issues of construct clarity and research gaps and recommend future research related to complexity and entrepreneurship.

The closest article to our approach is (Casadesus-Masanell & Ricart, 2010), which clarifies the difference between strategy and business model, and proposes that Causal Loop Diagrams (CLDs) are a useful representation of business models illustrating an old-economy airline example.

This article contributes to a rigorous understanding of business model dynamics in the digital economy. It provides a framework to understand AI effects on business models, adding to the literature related to the dynamic impact of technology on business (Georgantzias & Katsamakas, 2008). The key motivating question is: How can we analyze the effects of AI on BM while accounting for dynamic complexity as a feature of business that needs to be understood and leveraged?

Research Approach and Model

We build a framework to explore business models using Causal Loop Diagrams (CLDs). A positive link between two variables in a CLD means that an increase of the first variable leads to an increase of the second variable.

The research focuses on key feedback loops that drive business model performance and sheds light on the dynamic complexity of digital business models. We focus on the platform business model, which is the most important new form of business model enabled by the Internet and digital technologies (Parker & Van Alstyne, 2005; Bakos & Katsamakas, 2008).

The platform business model archetype, in its purest form, is based on the premise that more content/apps/services on a platform attract more users, which in turn attracts more content/apps/services. This mechanism of two cross-side (indirect) network effects (Economides & Katsamakas, 2006; Katsamakas & Madany, 2019) constitutes a reinforcing feedback loop, captured at the top left corner of our model (R0 feedback loop in Figure 1). But in real life, this simple

platform mechanism alone is not enough to describe a business model, as platforms come in a variety of types. Our model (Figure 1) illustrates the structure of one type of digital platform, an advertising-based content platform (think Google Search). The content platform provides users with access to content and makes revenue from advertisers.

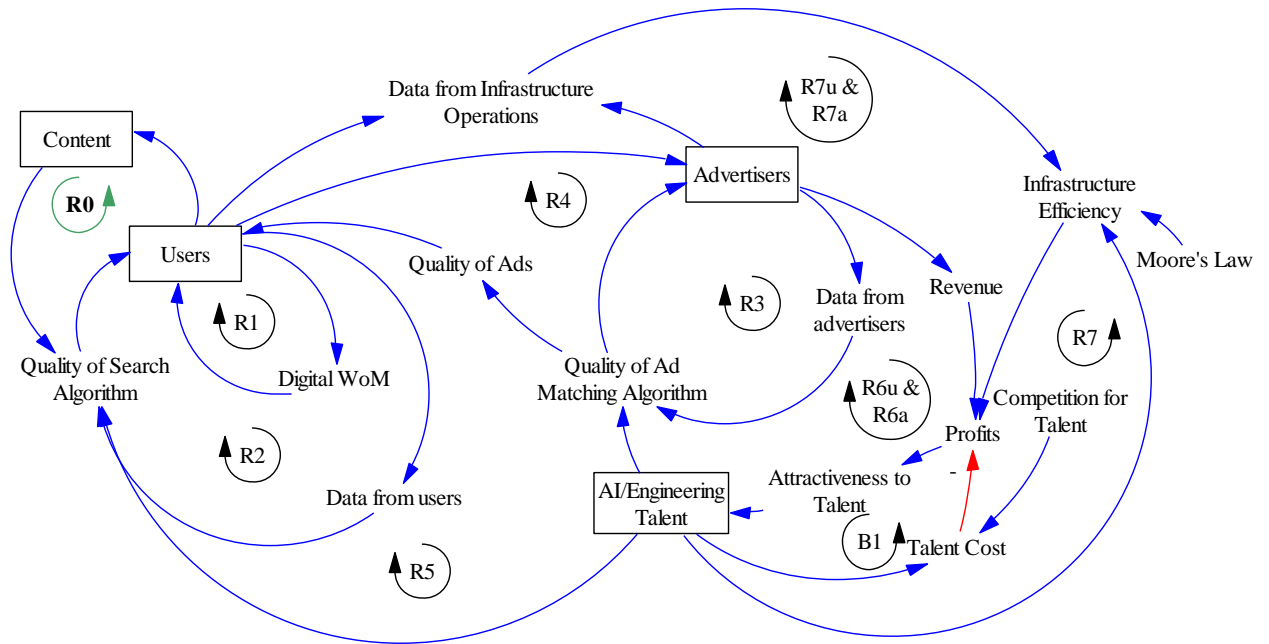


Figure 1. Ad-based content platform business model (e.g., Google Search)

We describe some of the key feedback loops that constitute the core structure of the business model. *Users* bring more users to the platform through *Digital WoM* (Word of Mouth) (R1 reinforcing feedback loop), and this is an important mechanism for platform adoption and growth.

More *Users* mean that the platform collects more *Data from users*, which drives higher *Quality of Search Algorithm*, which provides more relevant organic search results, hence attracts more users (R2 reinforcing feedback loop).

Advertisers are attracted by platform *Users*. More *Advertisers* and more *Data from advertisers* help improve the *Quality of Ad Matching Algorithm*. This has two effects: It directly attracts more *Advertisers* (R3 reinforcing feedback loop), and it improves the *Quality of Ads*, which helps attract more *Users*, thus more *Advertisers* (R4 reinforcing feedback loop).

More *Advertisers* raises the platform *Revenue* and *Profits*, which helps attract *AI/Engineering Talent*, which further helps drive a higher *Quality of Search Algorithm*, which brings even more *Users* and more *Advertisers* (R5 reinforcing feedback loop).

AI/Engineering Talent brings improvements to *Quality of Ad Matching Algorithm*, which leads to more *Advertisers* (R6a feedback loop), as well as higher *Quality of Ads* and more *Users* (R6u feedback loop).

AI/Engineering Talent is also crucial for improving *Infrastructure Efficiency*, as they optimize digital infrastructure at scale, aided by Moore's Law. This helps increase *Profits*, which helps attract even more *AI/Engineering Talent* (R7 feedback loop).

Moreover, serving more *Users* and *Advertisers* leads to more *Data from Infrastructure Operations* (e.g., running sophisticated data centers), which is used to further improve *Infrastructure Efficiency* and *Profits*, with associated positive effects on *Users* (R7u feedback loop) and *Advertisers* (R7u feedback loop).

All these reinforcing feedback loops provide the core structure of the ad-based platform business model and drive its performance, growth, and sustainability.

Figure 1 also shows one balancing feedback loop that may moderate the effect of the reinforcing loops: As the platform attracts more *AI/Engineering Talent*, and has to pay higher salaries due to *Competition for Talent*, the *Talent Cost increases* and this has a negative effect on *Profits* (B1 balancing loop).

Key Insights and Implications

Advances in AI, especially in the form of Machine Learning (ML) and neural networks (Deep Learning), has elevated the use of AI in business as a critical concern of most companies today¹. Several researchers have written about the business effect of AI, exploring issues such as the future of work, bias and trust, and the economics of AI (Raj & Seamans, 2019). For example, (Agrawal, Gans, & Goldfarb, 2018, 2019) argue that AI lowers the cost of prediction, and this has significant implications for managers. The unique perspective of our article is looking at the effect of AI at the level of business model. We use the proposed framework to understand the effects of AI on business model innovation.

Figure 1 shows that AI has a significant effect on a platform business model because it enables new reinforcing feedback loops that constitute the core structure of the business model and drive its growth and profitability. AI may also strengthen, or speed up, existing reinforcing feedback loops. Table 1 summarizes the effects of AI in a template of three elements: **AI for User**

¹ See for example: <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/an-executives-guide-to-ai>

Experience, AI for Advertiser Experience, AI for Efficient Infrastructure at scale. Each element is a cluster of feedback loops. In all three elements, data as a key resource provides a key node that connects AI with Business Model Innovation. We summarize selected insights from each element.

AIBM Template Element	Key Feedback Loops	Primary data resources	Other key resources
AI for User Experience	R0, R2, R5, R4	<i>Data from Users, Data from Advertisers</i>	<i>AI/Engineering Talent, Search Algorithm, Ad-Matching Algorithm</i>
AI for Advertiser Experience	R3, R4	<i>Data from Advertisers</i>	<i>AI/Engineering Talent, Ad-Matching Algorithm</i>
AI for Efficient Infrastructure at scale	R7, R7u, R7a	<i>Data from Infrastructure Operations</i>	<i>AI/Engineering Talent, Infrastructure Optimization Algorithms</i>

Table 1. AIBM template – Key effects of AI on platform business model

AI for User Experience: *Data from Users* is a key resource in this cluster of feedback loops that reinforces an improvement of user experience over time. *AI/Engineering talent* leverages *Data from Users* to improve the *Quality of Search Algorithm*, which improves the user experience with respect to access to *Content* (R0, R2, R5). *AI/Engineering talent* leverages *Data from Advertisers* to improve the *Quality of Ad-matching Algorithm*, which improves the user experience with respect to relevant advertising (R4). Other secondary feedback loops that help attract *AI/Engineering talent* (either through more revenues or lower infrastructure costs) also contribute to better user experience (e.g. R6u, R7u).

AI for Advertiser Experience: *Data from Users* is a key resource in this cluster of feedback loops that reinforces an improvement of user experience over time. *AI/Engineering talent* leverages *Data from Advertisers* to improve the *Quality of Ad-matching Algorithm* (R3), which enhances the targeting of *Users*. Feedback loops that increase the number of *Users* are crucial (e.g.,

R4). Other secondary feedback loops that help attract *AI/Engineering talent* also contribute to better advertising experience (e.g., R6a, R7a).

AI for Efficient Infrastructure at Scale: *AI/Engineering talent* leverages *Data from Infrastructure Operations* to improve the *Efficiency of Infrastructure*, which increases *Profits* and help attract even more *AI/Engineering talent* in a competitive market for talent (R7). Other secondary feedback loops that help attract more *Users* and more *Advertisers* help the company collect more *Data from Infrastructure Operations*, contributing to improved economies of scale (R7u, R7a).

We can now generalize these mechanisms into two high-level AI-related processes that apply to all business models: Data accumulation and data exploitation.

Data accumulation is the process of aggregating data from serving customers and other business processes and operations. Figure 1 shows how *Data from Users*, *Data from Advertisers*, and *Data from Infrastructure Operations* are accumulated in the platform business model. Data accumulation could also be supported with data from external sources (data acquisition), when necessary.

Data exploitation is the process of using Artificial Intelligence (AI) to leverage accumulated data. Overall, this may help improve platform services and business processes and the overall quality of the business model. Figure 1 shows how the platform business model exploits data to improve the *Quality of Search Algorithm*, *Quality of Ad Matching*, and *Infrastructure Efficiency*.

Another critical insight from our causal model is that data accumulation and data exploitation are two self-reinforcing processes: The more data a platform accumulates, the more data it can exploit, which helps accumulate even more data.

Discussion and conclusions

The unique contribution of this article is that it brings together BM and AI concepts, and it analyzes the effects of AI at the level of business model.

Several authors have noted that complexity theories could be useful in understanding business models (see, e.g. (Massa, Viscusi, & Tucci, 2018)). This article makes progress towards this direction by focusing on the dynamic complexity of the business model. We presented a framework for describing the structure of digital business models using causal loop diagrams (CLD). The framework brings together key platform resources, such as *data*, *algorithms*, *AI talent*,

and *infrastructure*. We proposed a three-element template (AIBM), and we showed that the feedback loop concept is vital in understanding the effects of AI at the level of business model. We generalized our discussion into data accumulation and data exploitation processes that are self-reinforcing and apply to all types of business models.

Our research provides several insights for managers and entrepreneurs. First, mapping the business model using CLDs can be very powerful in the fast-changing digital economy, where platforms and platform ecosystems are prevalent (Eisenmann, Parker, & Van Alstyne, 2006; Hagi, 2014; Katsamakas, 2014; Parker, Van Alstyne, & Choudary, 2016). A focus on feedback loops can help managers map the core structure of their business model that drives behavior and business performance. It could also help managers and entrepreneurs refine their mental models, as well as support communication (Groesser & Jovy, 2016; Moellers, von der Burg, Bansemir, Pretzl, & Gassmann, 2019).

Second, AI impact and AI transformation can be best understood as rewiring, strengthening, and speeding-up feedback loops in your business model. Managers and entrepreneurs need to ask: *Do the "AI feedback loops" work for my company? Or they work against my company? How can we leverage the "AI feedback loops" in our BMI initiatives?*

Lastly, we identify several future research directions. First, future research could map and analyze the dynamics of more business models and synthesize that knowledge into generic patterns. Second, future work could take the analysis a step forward, building computational models of selected business models and the effects of AI.

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