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Is Artificial Intelligence a Double-Edged Sword? Insights from Three Essays on its Impacts

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Is Artificial Intelligence a Double-Edged Sword? Insights from Three Essays on its Impacts

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Abstract

> "If we do it right, we might be able to evolve a form of work that taps into our uniquely human capabilities and restores our humanity. The ultimate paradox is that this technology may become a powerful catalyst that we need to reclaim our humanity." – John Hagel

Artificial intelligence (AI) is viewed as a disruptive technology that some executives believe will take over a lot of jobs. However, others believe that AI will bolster growth, improve business processes, and create new business opportunities. This dissertation focuses on the tension arising from such contrasting expected impacts of AI. Extant research has investigated the algorithm development eye of AI and neglected the implications eye of AI on the users of AI and organizations. This dissertation seeks to address this gap by examining the impacts at individual and firm levels. It uses data on publicly-traded US companies, interviews, and surveys, to address this broad question through three essays on the impacts of AI on individuals, firms, and society. The essays use multiple data collection methods, including crawling social media (essay 1), archival data (essays 1 and 2), interviews (essay 3), and a mixed-method study based on interviews and longitudinal surveys involving three rounds of data collection (essay 3). More specifically, using signaling and automation-augmentation theories as foundations, **Essay 1** examines the impact of the nature of AI investments and investors' concerns related to layoffs and ethics, and optimism about hiring arising from the nature of AI investments on a firm's long-term abnormal returns. We find that investors positively react to AI investment for both automation and augmentation. Moreover, the positive effects of automation AI investment are amplified by optimism that they would lead to hiring and attenuated by concerns that they would lead to layoffs or ethical issues. By contrast, the positive effects of augmentation AI investment are amplified by concerns that they would lead to layoffs. Using dynamic capabilities and exploration-exploitation strategic theories, **Essay 2** examines the interplay among strategic AI

orientation, overall IT strategy of the firm, and industry environment on firm performance. We find that a firm's strategic AI orientation has one-year positive lagged effect on its performance with the effect being stronger when the firm's strategic AI orientation aligns with the firm's overall IT strategy – revenue-focused and cost-focused. Such an effect becomes more pronounced in dynamic environment especially for firms focusing on revenue generation and pursuing exploration AI strategy. Drawing upon needs-affordances-features (NAF) theory and the IS success model, **Essay 3** examines the adoption of a specific AI product, namely a recommender system (RS), and underscores the importance of alignment between action opportunities enabled through the features of RS and the user's psychological needs. It adds to the methodological rigor by providing a novel measure of alignment. We find that the alignment between RS affordances and users' psychological needs significantly impacts the use of recommendations. Moreover, users of RS seem information hungry about generated recommendations and feel positive about RSs that consider their preferences. Our findings suggest that current RSs might lack good design features related to engagement with users as our sample of RS users perceive their interactive features negatively. To the best of our knowledge, this dissertation is the first to investigate AI's implications on different performance metrics at the firm and the individual level. Each essay offers theoretical and practical insights, and directions for future research.

Dedication

To my papa, Yogendra Nath Arora, whose dream of getting himself a Ph.D. could not be accomplished due to finances. This work is dedicated in his honor. It's also for my mummy, Sushma Arora, whose blessings kept me healthy and going in the entire Ph.D. journey, and my sister, Rinki, who sent affectionate Rakhi every year from India with full of love, care, and encouragement that inspired me never to drift away from the path. Love them, as, without their support, this work would not have started in the first place, and the completion of the work would not have been possible!

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Chapter 1: Introduction

> "Some people worry that artificial intelligence will make us feel inferior, but then, anybody in his right mind should have an inferiority complex every time he looks at a flower." – Alan Kay[1]

The advancements in the field of artificial intelligence (AI) are impacting society at an unprecedented rate. The impacts of AI are quite diverse, causing much optimism as well as fear. AI-enabled digital capabilities are being embraced by companies across numerous industries, and bring economic growth and prosperity. McKinsey estimated in 2018 that AI will add $13 trillion to the global economy in the next decade (McKinsey 2018). However, AI is also feared to take jobs, exacerbate societal inequalities, and create fundamental ethical issues (e.g., layoffs, biased and inaccurate results, privacy concerns) (Executive Office of the President 2016). We have also been warned about the blackbox nature of the AI products (Rai 2020), such as recommender systems attenuating the impact of potential benefits of the systems. This tension from the contrasting nature of the effects of AI is the focus of this dissertation. In other words, does AI act as a double-edged sword in terms of its consequences? This dissertation addresses this broad question by using data on publicly-traded US companies for the years 2010-2020 along with primary data from individuals, across three essays on the impacts of AI on individuals, firms, and society. The essays use multiple data collection methods, including crawling social media (essay 1), archival data (essays 1 and 2), and interviews and longitudinal surveys (essay 3).

Building upon signaling theory and automation-augmentation perspective, **Essay 1** focuses on the tension among potentially contrasting expectations – the fear of job losses, the optimism about new jobs, and the ethical concerns – associated with the investment in AI by the firms. Actions and announcements by firms convey signals that reduce information asymmetry between

[1] https://www.goodreads.com/quotes/9232851-some-people-worry-that-artificial-intelligence-will-make-us-feel

them and outsiders (Havakhor et al. 2022). Signals are "activities or attributes of individuals in a market, which by design or accident, alter the beliefs of, or convey information to, other individuals in the market" (Spence 1974, pp. 2). A corporate announcement about specific IT investments (e.g., AI) is one such signal. The nature of the announced AI investment conveys information to the stock market and people interested in the firm, including those commenting on social media. Anticipated consequences resulting from the AI investments in the form of layoffs or ethical issues and hiring can moderate these effects. The automation-augmentation perspective complements signaling theory as firms can invest in AI to automate their business processes to improve efficiency or to augment business processes by having AI work with humans, enabling mutual learning and enhancing each other capabilities (Raisch and Krakowski 2021). This dual nature of AI – for automation or augmentation – could affect investors in different ways and elicit varying responses on social media about the firms that, in turn, could impact firm performance (Luo et al. 2013). Therefore, essay 1 addresses the following questions using data on 169 AI announcements by 142 unique U.S. publicly-traded companies during years 2000-19:

> RQ1. How does the nature of AI investment influence the long-term abnormal returns of the firm?
> RQ2. How do investor sentiments about potential consequences from an AI investment, specifically sentiments related to (i) concerns about layoffs; (ii) optimism about hiring; and (iii) concerns about ethics (including bias and diversity) moderate the effects mentioned in RQ1?

Essay 2 draws upon the exploration-exploitation strategic perspective (March 1991) to examine how a firm's strategic AI orientation to create differential value impacts its performance and how the relationship between strategic AI orientation and firm performance is influenced by the firm's overall IT strategy. It draws upon dynamic capabilities theory (Teece et al. 1997), further examining the impact of environment dynamism. AI can empower firms to undertake various strategic actions to create differential value. For example, a firm could automate its business processes to improve efficiency or foster product innovation (Daugherty and Wilson 2018, p. 67), undertaking different strategic actions to create business value.

Firms invest in IT to reduce costs or increase revenues (Mithas and Rust 2016). A cost-focused IT strategy involves improving productivity and efficiency. By contrast, a revenue-focused IT strategy involves using IT to explore new business ventures and find or create new products/services. Although BVIT literature highlights the effects of a firm's IT strategy on its performance (Leidner et al. 2011), little is known about how a firm's overall IT strategy impacts its ability to leverage investments in a particular IT, such as AI, for improving performance. A firm's strategic investment in AI could help in difficult environmental conditions by enabling the firm to quickly leverage new knowledge through the analysis of the copious amount of data to reveal hidden patterns and improve or gain efficiency and productivity (Shrestha et al. 2019). However, if the firm's strategic investment in AI does not conform with its overall IT strategy, a firm may lose the competitive edge it could have gained or sustained. In light of this, our last research question investigates the interplay between a firm's AI strategic orientation through exploration or exploitation and overall IT strategy in a dynamic environment on its performance. Accordingly, essay 2 addresses the following questions:

> RQ1. How does a firm's strategic AI orientation affect its performance?
> RQ2. How does a firm's IT strategy moderate the effect of the firm's strategic AI orientation on its performance?
> RQ3. How does the environment dynamism moderate the moderate effect mentioned in RQ2?

Essay 3 focuses on the use and adoption of a specific AI product, namely recommender systems (RSs). RSs are information filtering tools that provide users with personalized content online as recommendations (Schafer et al. 2001). By analyzing users' data, they shape users' experiences and interactions. Essay 3 draws upon the needs-affordances-features (NAF) (Karahanna et al. 2018) perspective and the IS success model (Sabherwal et al. 2006) to examine the effects of the user's psychological needs, the RS features, and the alignment between user's psychological needs and RS affordances on RS success. The NAF perspective complements IS success literature in helping us understand how the user's different needs are fulfilled by RS affordances that influence the actions users perform, such as using RS and continuing to use RS.

Individuals use RSs to satisfy their needs. Moreover, a RS has several affordances enabled by its features that could help fulfill the user's psychological needs. However, these features could also raise concerns (Adomavicius et al. 2018). For instance, anthropomorphic features of a RS can increase users' engagement (Qiu and Benbasat 2009), but also engender an oppressive feeling (Kane et al. 2021). Thus, these features of a RS could enhance or attenuate users' perception of the quality of the RS and thereby could affect the success of the RS. The paradoxical tension arising from one's desire to fulfill needs by using a RS but not subject to any risks from doing so has been recognized yet not holistically investigated (Milano et al. 2020). Thus, essay 3 seeks to address the following research questions:

RQ1. How do the features of the RS affect its success?
RQ2. What affordances does a RS provide, and how do they satisfy user's psychological needs?
RQ3. How does the alignment between the user's psychological needs and affordances provided by a RS affect its success?

Table 1 provides an overview of the three essays.

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Tables of Chapter 1

Table 1. An overview of three essays

	Essay 1	Essay 2	Essay 3
Research Questions	RQ1: How does the nature of AI investment influence the long-term abnormal returns of the firm? RQ2: How do investor sentiments about potential consequences from an AI investment, specifically sentiments related to (i) concerns about layoffs; (ii) optimism about hiring; and (iii) concerns about ethics (including bias and diversity) moderate the effects mentioned in RQ1?	RQ1. How does a firm's strategic AI orientation affect its performance? RQ2. How does a firm's IT strategy moderates the effect of the firm's strategic AI orientation on its performance? RQ3. How does the environment dynamism moderate the moderate effect mentioned in RQ2?	RQ1. How do the features of a RS affect its success? RQ2. What affordances does a RS provide, and how do they satisfy user's psychological needs? RQ3. How does the alignment between the user's psychological needs and affordances provided by a RS affect its success?
Theoretical Foundations	Word-of-Mouth; Signaling Theory; Automation-Augmentation Perspective	Exploration-Exploitation Strategic Perspective; Dynamic Capabilities Theory	Needs-Affordances-Features Perspective; IS Success
Unit of analysis	AI announcement	Firm-year observations	An individual's use of a recommender system
Methods	Quantitative (text mining, regression analysis)	Quantitative (text mining, regression analysis)	Quantitative (Structure Equation Modeling, Cluster analysis)
Data sources	Crawled data from webpages, Archival data from COMPUSTAT and Twitter	Archival data from COMPUSTAT and Hoberg-Phillips	Longitudinal survey (two surveys, one week apart)
Sample	169 AI announcements (by 142 unique U.S. publicly-traded companies) during years 2000-19	464 firm-year observations related to AI investment belonging to 326 unique firms for the years 2010-2020	Two survey responses (one week apart) from 355 full-time working individuals

Chapter 2: Understanding the Societal Implications of Artificial Intelligence

> "In our business, we talk about emerging technologies and how they impact society. We've never seen a technology move as fast as AI to impact society and technology. This is by far the fastest moving technology that we've ever tracked in terms of its impact and we're just getting started." - Paul Daugherty, Chief Technology and Innovation Officer, Accenture (Honjo 2019).

Introduction

Having already been adopted by companies across various industries, including healthcare, finance, retail, government, education, and so on, to create business value through AI-enabled digital capabilities (McKinsey 2018), artificial intelligence (AI) is ushering a new era of digital transformation and may be defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein 2019). A survey of 250 executives whose companies are embarking on the path of AI showed its expected benefits across a number of business areas (Davenport and Ronanki 2018). McKinsey estimated in 2019 that AI will add $13 trillion to the global economy in the next decade (Fountaine et al. 2019).

Firms invest in AI systems to either automate their business processes for improvement in efficiency or work in close relationships with humans, enabling mutual learning and enhancing each other's capabilities. Such close collaboration between AI systems and human is termed as augmentation by scholars (see Raisch and Krakowski 2021). Automation and augmentation figure at either end of the human-machine spectrum in current debates on the investment in AI systems. For example, Robotic Process Automation tools (based on rule-based engines) is an example of the use of AI for automation, and speech recognition and conversational agents used for first line customer interaction (based on Natural Language Processing techniques) illustrate the use of AI for augmentation. While automation of a human worker's tasks may result in replacement of the human worker altogether, more often there is a partial automation of specific tasks, resulting in a division of labor between the human and the technology, where novel tasks also emerge and ensure a continued need for the human worker resulting in enhancing knowledge of human and exploration of new ventures for the organizations (Raisch and Krakowski 2021). Thus, firms can invest in AI to automate their processes in which AI substitute humans or invest in AI in which tasks are mutually carried out by AI and humans and both AI and humans function as an integrated unit (Rai et al. 2019; von Krogh 2018).

The automation of activities can enable businesses to improve performance by reducing errors and improving quality and speed, and in some cases achieving outcomes that go beyond human capabilities. Augmentation is more suited to ambiguous tasks in which AI systems' abilities complement humans' unique capabilities, such as intuition and common-sense reasoning (Daugherty and Wilson 2018, pp. 191) resulting into organizational knowledge building. Prior research has shown that capital markets respond positively to IT investments (Hayes et al. 2001; Sabherwal and Sabherwal 2007). With this backdrop, our first research question is:

> RQ1. How does the nature of AI investment influence the long-term abnormal returns of the firm?

In order to address RQ1, we examine the following effects: (a) the direct effect of a firm's AI investment in automation on the firm's long-term abnormal returns; (b) the direct effect of a firm's AI investment in augmentation on the firm's long-term abnormal returns. To account for the possibility that the market takes a long time to figure out the performance consequences of the IT investments, we made use of long-term abnormal returns.

However, predictions remain mixed regarding the societal impacts of AI investments by the firms. For example, a report by Capgemini says companies are creating new jobs after implementing AI,[2] and a report by World Economic Forum says that by 2022 about net 58 million new jobs will be created by AI.[3] In contrast to creation of new jobs due to AI investments, there is a fear that AI may also exacerbate fundamental and ethical issues (Fjeld et al. 2020) – societal inequalities by reducing employment and wages (Executive Office of the President 2016), biasedness and diversity issues,[4] layoffs. For example, Microsoft's announcement on laying off journalists and replacing them with AI.[5] Thus, AI systems could impact society in several ways. AI can induce both positive and negative effects on the public related to employment and ethical use of IT. Investors' perception about the firm investing in AI could change depending on the potential consequences arising from the investment in AI technologies. For example, when a firm announces an investment in AI, public sentiments related to hiring may change – a Capgemini study of 1000 organizations, who have implemented AI, highlights the creation of new jobs from AI;[6] layoffs – AI is expected to take 40 percent of the jobs as said by Dr. Lee on CBS '60 minutes' show;[7] ethical concerns – Amazon's AI recruiting software tool found to be biased against women (Reuters 2018).[8] As a result, these sentiments might provide insights into the subsequent effect of the AI investment on firm value. With this backdrop, our next research question is:

> RQ2. How do investor sentiments about potential consequences from an AI investment, specifically sentiments related to (i) concerns about layoffs; (ii)

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[2] https://www.capgemini.com/service/digital-services/insights-data/data-science-analytics/artificial-intelligence-where-and-how-to-invest/.

[3] https://www.forbes.com/sites/amitchowdhry/2018/09/18/artificial-intelligence-to-create-58-million-new-jobs-by-2022-says-report/?sh=1e7eed444d4b.

[4] https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G.

[5] https://www.theverge.com/2020/5/30/21275524/microsoft-news-msn-layoffs-artificial-intelligence-ai-replacements

[6] https://www.capgemini.com/service/digital-services/insights-data/data-science-analytics/artificial-intelligence-where-and-how-to-invest/

[7] https://www.cbs.com/shows/60_minutes/video/hhs9AtEaPo52m531tKM_1Fy3lGjlnVm_/facial-and-emotional-recognition-how-one-man-is-advancing-artificial-intelligence/

[8] https://www.reuters.com/article/uk-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUKKCN1MK08K?edition-redirect=uk

optimism about hiring; and (iii) concerns about ethics (including bias and diversity) moderate the effects mentioned in RQ1?

This study builds on theoretical foundations of signaling theory (Spence 1973, 2002; Connelly et al. 2011; Havakhor et al. 2022) and automation-augmentation perspective (Raisch and Krakowski 2021) to investigate tension among potentially contrasting expectations – the fear of job losses, the optimism about new jobs, and ethical concerns – on the effect of nature of AI investment on firm's long-term abnormal-returns. Firms' AI investment announcements signal to stakeholders about their potential business improvements and innovations, and stakeholders access the information to get insights about the firm planning and strategies. Signaling theory complements the automation-augmentation perspective as firms' signals affect both the public and the firms. Since a firm could use AI products for either automating or augmenting employees' capabilities, the announcement of AI could result in different consequences affecting investors in different ways and elicit varying responses on social media, which, in turn, could impact the firm's stock price (Luo et al. 2013).

The rest of the chapter is organized as follows. The next section discusses the theoretical foundations for the paper. The subsequent sections develops the theoretical model followed by description about the data, including the sample and the measures. A description of the analyses and results follows. The chapter concludes with a discussion of the emergent findings and their implications for future research and practice.

Theoretical Foundations

Signaling Theory and the Implications of AI Investment Announcements

Signaling theory examines the communication between the sender and the receiver (Spence 1974; Connelly et al. 2011; Roztocki and Weistroffer 2015). The theory aims to address the problem of information asymmetry that arises when different people know different things. For example, executives or managers know specifics about the organization's aspects, such as the firm's investment in products or services that may not be known to outsiders creating an information gap between the firm's management and the outsiders. This information asymmetry is reduced by signals from the firms (Connelly et al. 2011; Havakhor et al. 2022).

Signals are "activities or attributes of individuals in a market, which by design or accident, alter the beliefs of, or convey information to, other individuals in the market" (Spence 1974, pp. 2). Signals could be in the form of corporate announcements about specific IT investments that affect perceptions about firm strategy, performance, and strategy alignment (Roztocki and Weistroffer 2015; Sabherwal et al. 2019). Here, we focus on AI investment announcement as a form of signal. This study benefits from the application of signaling theory as the firm's announcement of AI would convey information to the stock market and people interested in the firm in general, including those commenting on the firm on social media. The next subsection discusses the implications of AI investment.

Implications of AI Investment

AI investments vary in terms of the impact they could have on society. AI seems to be a double-edged sword as, although AI is helping organizations to improve business processes, thereby creating optimism about the usefulness of AI systems and technologies, it is also posing ethical issues resulting in fear in society about the use and adoption of AI systems. Researchers and practitioners have both stressed enormous potential yet excessive implications for society. For example, if Facebook's CEO Mark Zuckerberg thinks AI will make lives better, Tesla CEO Elon Musk links AI to doomsday scenarios.[9]

[9] https://www.cnbc.com/2017/07/24/mark-zuckerberg-elon-musks-doomsday-ai-predictions-are-irresponsible.html

This paradoxical nature of AI has created uncertainty in the minds of the public about AI because AI help organizations and individuals with efficiency and augmenting knowledge (Manyika et al. 2017; Metcalf et al. 2019; Raisch and Krakowski 2021), but also poses fundamental and ethical issues – biasedness (e.g., Amazon's AI recruiting system discrimination against women),[10] culturally inappropriate content (Souali et al. 2011), privacy concerns (Koene et al. 2015), job losses (Muro et al. 2019), lack in diversity (Kane et al. 2021), oppression (Kane et al. 2021). Such potential issues could influence the public faith toward the company, thereby impacting firm value. Next, we discuss about the theoretical base for the nature of AI investment.

The Automation-Augmentation Perspective and the Nature of AI Investment

Raisch and Krakowski (2021) put forth the automation-augmentation perspective stressing the need for giving importance to contradictory yet interdependent dual elements causing the persistent tension. Organizations apply AI in two broad areas – automation and augmentation. Whereas automation is a machine taking over a human task, augmentation is the collaboration between humans and machines to execute a task. The automation-augmentation perspective highlights the need for organizations to understand the tension caused by the dual nature of AI applications and states that without acknowledge the dynamic interdependencies of the duality of AI applications, firms would risk in falling into vicious cycles. Organizations use AI for automation to allow comprehensive and efficient processing. By contrast, they apply AI to augment human intelligence and gain performance (Raisch and Krakowski 2021).

AI is a burgeoning technology and disrupting work practices in various ways across numerous sectors. Also, unlike other ITs, AI is anthropomorphic in nature, imitating human form and behavior and providing myriad benefits and many ethical issues. Signaling theory helps our

[10] https://www.lexalytics.com/lexablog/stories-ai-failure-avoid-ai-fails-2020

study as we examine the effect of signals on stakeholders (Spence 1973). For example, a firm's announcing an AI investment could elicit divergent responses as some investors may view the investment as the firm's discourse toward growth, while others may view the firm as engaging in unethical practices. For example, Apple and Goldman Sachs were accused of gender bias on social media when it was found that Apple's credit card algorithm was providing higher credit limits to males than females.[11] The automation-augmentation perspective complements signaling theory by providing us a lens to study the use of the AI by the firms in the form of automation or augmentation and the sentiments investors feel about the potential actions firm could take from AI investment. These actions in the form of responses on social media could affect firm stock market returns (Luo et al. 2013). The next subsection discusses the nature of AI investment.

The Nature of AI Investment

AI investments have been broadly classified into two types based on the role they perform in organizations (Raisch and Krakowski 2021). Organizations invest in AI to automate business processes (e.g., chatbots) (Davenport and Ronanki 2018) or augment human capabilities (Metcalf et al. 2019). In automation, AI takes over the task of humans with little or no intervention of humans. Organizations involved in automation aim to keep humans out to allow for efficient processing (Davenport and Kirby 2016, pp. 21). In augmentation, close interaction happens between humans and AI systems, complementing each other capabilities. For example, humans' intuition and common sense collaborate with AI abilities resulting in innovation and reduction in search costs (Bergstein 2019). This study adopts the automation-augmentation perspective to examine the effects of dichotomous AI product roles – automation or augmentation based on their application in organizations. The next section develops the theoretical model for the paper.

[11] https://www.washingtonpost.com/business/2019/11/11/apple-card-algorithm-sparks-gender-bias-allegations-against-goldman-sachs/

Theoretical Development

When a firm announces an IT investment, it reduces the information asymmetry between its management and potential investors (Connelly et al. 2011). Studies have shown that such announcements have an impact on firm's stock market returns (Dos Santos et al. 1993; Sabherwal and Sabherwal 2007). The cost-effective solutions and business-process enhancements from AI have led to firms' adoption of AI products in several business areas (Davenport and Ronanki 2018). Firms engage in AI adoption in two areas – automate the business processes or augment the human capabilities by making AI work in conjunction with the workforce (Raisch and Krakowski 2021). AI offers great promise in terms of benefits, such as improvement in efficiency, helping people to "punch above their weight" by offloading tedious work and enabling them to perform faster (Daugherty and Wilson 2018), but also presents challenges and risks, such as the possibility of biasedness and privacy concerns (Lyons 2018). Owing to this paradoxical nature of AI, the announcements on AI investments by the firms could have unintended consequences and impact the sentiments of the investors toward the firms. Figure 1 depicts the overall research model to investigate the research questions, and Table 1 mentions key constructs used in the research model.

---Insert Figure 1 about here---

---Insert Table 1 about here---

Main Effects of the Announcement of AI Investment

Motivated by the productivity paradox, IS researchers have examined the organizational performance impacts of IT investments over the past three decades. IT spending by the firms has increased over time, but firms still face a dilemma about whether and when it will generate business value (Mithas and Rust 2016). Studies in the late 2000s found that IT investments contribute to firm productivity and higher returns than non-IT investments (Brynjolfsson and Hitt 1996; Dedrick et al. 2003). The value generated from IT investments could be through automated business processes, effective decision making, and transformed business processes leading to new modes of value creation (Zuboff 1988). Later studies argue that the value generated from IT investments depends on the attributes and strategic role of IT, management practices, and the macro environment (Brynjolfsson et al. 2002; Mithas et al. 2012; Sabherwal et al. 2019).

Announcing an IT investment is a way for a firm to communicate to its stakeholders, such as customers and investors. Relative to top managers, most other stakeholders have limited information about the firm's true position. Signals in the form of announcements are meant to address the information scarcity problem (Connelly et al. 2011). For example, the declaration of a dividend may signal superior financial performance and attract investors. AI is an innovative technology that is close to the arch-nemesis of human working and behavior as it facilitates human action and also influences humans and organizations (Orlikowski 1992). It is expected that AI will bolster growth, improve business processes, and create new job opportunities (Ransbotham et al. 2018). Although a report by Manyika et al. (2017) suggests that AI will generate significant benefits for users, businesses, and economies, it would also take some time to reap substantial benefits from AI investments (Barro and Davenport 2019). Although researchers have examined the short-term firm performance from IT investments by examining changes in cumulative abnormal returns (CARs) (Fornell et al. 2006; Sabherwal and Sabherwal 2007), researchers have also stressed that realization of IT value takes longer time and thus long-term firm performance, such as buy and hold abnormal return (BHAR), becomes important to investigate as well (Havakhor et al. 2022). IS research has examined the positive impacts on stock returns from embracing new technology (see Shea et al. 2019, pp. 216). Dos Santos et al. (1993) argued that the stock market reacts positively to IT investments.

Firms use AI to either automate processes or augment human capabilities (Raisch and Krakowski 2021). Automation is mainly used for repeatable and measurable tasks, and can improve efficiency and productivity (Manyika et al. 2017) through labor substitution (Riley 2018). Automation can help perform a range of routine physical work activities better and more cheaply than humans. Analysts suggest that use of AI for automation can help the banking industry save more than US$1 trillion by 2030 by reducing 22 percent of operating expenses (Joyce 2018). McKinsey Global Institute has reported that AI-enabled automation can provide an additional $13 trillion per year to the global economic output by 2030 (Bughin et al. 2018).

By contrast, augmentation is used for reimagining of business processes, and involves human intuition and judgment (Daugherty and Wilson 2018). It helps human capabilities in three broad areas of human-machine collaboration – amplification, interaction, and embodiment (Daugherty and Wilson 2018, pp. 138). AI can *amplify* human capabilities by providing data-driven insights, thereby enhancing the effectiveness of their activities. For instance, AI is helping radiologists by providing patients' health data in an easy-to-see format, thereby helping in the accuracy of diagnoses. In *interaction,* AI takes the role of customer-facing by interacting with many customers at once and freeing employees to work on other tasks that require tacit knowledge. For example, SEB, a Swedish Bank, uses 'Aida', a virtual IT help-desk agent, to interact with its 1 million customers directly while employees work on other bank-related tasks that require judgment. In *embodiment*, AI takes the form of humans and works alongside them. For example, in the BMW car manufacturing facility, robots are equipped with sensors and electric arms and work with humans in painting and lifting windows.

Therefore, using the automation-augmentation perspective, we posit the following hypotheses on the impact of AI investment on firm performance:

> H1a: A firm's announcement of AI for automation is associated with higher long-term abnormal returns.
> H1b: A firm's announcement of AI for augmentation is associated with higher long-term abnormal returns.

Web word-of-mouth (WOM) plays a key role in the digitized era and is being used by firms in various business streams such as predicting consumer behavior (Martens et al. 2016), responses to data breaches (Goode et al. 2016), and used-goods markets (Ghose 2009). Studies have examined the impact of sentiments on a firm's stock market performance (e.g., Luo et al. 2013 studied the role of sentiments on firm equity). Some other studies that have investigated the sentiments in the textual content have argued the importance of public sentiments in influencing key firm's performance metrics (Heston and Sinha 2017; Huang et al. 2018).

AI is a multifaceted technology with wider implications unlike previous technologies. It is viewed as disruptive technology as some executives believe that it will take over the jobs, while others expect it to bring economic prosperity and growth (Manyika et al. 2017). Proponents of AI see it as a great servant helping managers in decision making, whereas its opponents see it as a terrible master causing fundamental and ethical issues (Fjeld et al. 2020). This paradoxical nature of AI has wider implications for society. Next, we discuss about the implications of investors' sentiments about the potential consequences of the announced AI investment.

Moderating Effects of Sentiments About the Potential Consequences of the AI Investment

AI acts as a double-edged sword as the contrasting nature of the effects of AI investment by the firm could influence the investors' trust in the firm. Investors may feel optimistic about hiring as AI investment could result in the creation of jobs (Manyika et al. 2017) or become concerned about AI investment as AI could bring unemployment (Muro et al. 2019) and ethical issues (Kane et al. 2021) impacting society at a large scale. Next, we discuss the impacts of investors' optimism about hiring and concerns about layoffs and ethics arising from AI investment.

Moderating Effects of Optimism about Potential Hiring

AI-enabled automation in the service industry is benefitting firms in creating good quality output providing higher wages to the employees. For example, the Marlin Steel factory in Baltimore created high-paying jobs after adopting AI-enabled automation that not only helped the firm in creating a high-quality product but also helped employees in getting higher wages and from becoming unemployed.[12] Augmentation helps enhance the effectiveness of human capabilities and leads to innovation and better-personalized offerings (Raisch and Krakowski 2021). For example, Symrise employs AI to provide insights on customer demographics to its master perfumers, who then use their judgment to decide on the type of personal fragrance to create for customers. Augmentation also open doors for diversification of business portfolios and create avenues for business opportunities. With automation taking over the routine tasks, human capacity is freed to work on knowledge enhancements and taking over non-routine tasks. Similarly, with augmented AI humans can learn from machine abilities and overall create new knowledge for the organization. Potential hiring would signal a growth trajectory for the organizations as investors would sense firms venturing into new business areas, diversifying portfolio of products offering, creating new knowledge sharing between new hires and existing AI systems and workforce. Thus potential hiring sentiments would strengthen the relationship between investment in AI for automation and augmentation on firm performance. So, we posit:

[12] https://venturebeat.com/2017/09/07/automation-replaced-800000-workers-then-created-3-5-million-new-jobs/

H2a: Investor optimism about potential hiring by a firm due to an AI investment by it strengthen the positive relationship between investment in AI for automation and long-term abnormal returns.
H2b: Investor optimism about potential hiring by a firm due to an AI investment by it strengthen the positive relationship between investment in AI for augmentation and long-term abnormal returns.

Moderating Effects of Concerns about Potential Layoffs

In contrast to the optimism about potential hiring, AI can also cause feelings of worry and fear among employees.[13] Although AI is expected to create future jobs, a majority of the population in the U.S. works in sectors that are highly vulnerable to automation and, as a result, apprehensive about AI-enabled automation. Because AI-enabled automation could potentially replace humans working on highly structured and predicable tasks (Manyika et al. 2017), it leads to fear of potential layoffs and firing and cause strikes and protests, thereby hampering firm reputation.[14] By contrast, potential layoffs may not result in trouble when the firm invests AI in augmentation as it involves working closely with machines, creating a shared knowledge repository, and mutual learning among machines and humans. Anticipated layoffs from the use of AI for augmentation may signal that the firm is getting rid of non-learning workers who do not contribute much to the firm's benefits and growth. Investors would feel positive about it as potential layoffs on AI-enabled augmentation would signal that the firm is more responsive to its markets. It would also show the proactiveness of the mindset of the management and the leadership (Daugherty and Wilson 2018). Thus, we posit:

H3a: Investor concerns about potential layoffs by a firm due to an AI investment by it weaken the positive relationship between investment in AI for automation and long-term abnormal returns.
H3b: Investor concerns about potential layoffs by a firm due to an AI investment by it strengthen the positive relationship between investment in AI for augmentation and long-term abnormal returns.

[13] https://www.theatlantic.com/technology/archive/2019/01/automation-hotel-strike-ai-jobs/579433/
[14] https://www.japantimes.co.jp/news/2019/07/11/business/walmart-workers-strike-retailers-robot-push-chile/

Moderating Effects of Concerns about Potential Ethical Issues

Research has stressed the importance of explainable AI and the potential ethical issues that may get amplified from the blackbox nature of AI (Rai 2020; Kane et al. 2021), resulting in unintended consequences, such as automated AI system bias against Black defendants (Daugherty and Wilson 2018, p. 179) and Amazon AI hiring tool discrimination against females for technical jobs (Dastin 2018).[15] Ethical incidents arising from AI adoption are mostly associated with AI-enabled automation in which AI system was entirely vested with decision-making.[16] Thus, the concerns about potential ethical issues arising from adoption of AI could have detrimental effect on the benefits from AI-enabled automation. So, we posit:

> H4: Investor concerns about potential ethical issues by a firm due to an AI investment by it weaken the positive relationship between investment in AI for automation and long-term abnormal returns.

Methods

Data

The study uses announcements made by the U.S. publicly-traded firms on AI using Lexis-Nexis data source from 2010-2019. We exclude the year 2020 from our dataset as 2020 was hit by COVID and the year witnessed layoffs at an unprecedented rate. This will confound with the potential consequences resulting from AI investments if we include the year 2020 for the analysis. Appendix 1 provides the search string used for pulling the announcements from the PR Newswire and Business Wire sections of Lexis-Nexis. The search string was developed in a 4-step process: (1) the initial search string was developed using keywords related to artificial intelligence; (2) a senior faculty and a junior faculty reviewed, and provided minor suggestions

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[15] https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazonscraps-secret-ai-recruiting-tool-that-showed-bias-againstwomen-idUSKCN1MK08G

[16] https://www.npr.org/2022/01/18/1073857310/tesla-autopilot-crash-charges

on the search string; (3) we revised the search string accordingly; (4) the same senior faculty and the junior faculty reviewed the revised search string again, and approved it. We then used the approved search string to extract AI investment announcements from Lexis-Nexis. This produced an initial set of 569 announcements. Consistent with prior event studies (e.g., Sabherwal and Sabherwal 2007), we removed 98 AI announcements where a merger, acquisition, divestiture, or change in CEO occurred in a 14-trading-day event window around the AI investment announcement [-7d, +7d] (Havakhor et al. 2022). After text mining the announcement text using LIWC 2022 (v 1.0.0)[17] to identify the other ITs, we excluded 112 announcements that mentioned another IT (e.g., cloud computing) in addition to AI. Appendix 2 provides the list of keywords used for other ITs.[18] Finally, to avoid an announcement being in another IT or AI announcement's 365-day event window, similar to other event studies (Chatterjee et al. 2001; Havakhor et al. 2022), we excluded 190 additional announcements. This made sure to study only those firms who have made an AI investment announcement in a year and not any other IT investment announcement. This exclusion of a total of 400 announcements led to a final sample of 169 unique AI announcements by 142 unique U.S. publicly-traded companies. Next section discusses about the measurement of study variables.

Measurement

Measures of the Nature of AI Investment

We measure the nature of AI investment using LIWC 2022 (v 1.0.0). We created custom dictionaries for AI investments (automation and augmentation) shown in Appendix 3 using the same process as discussed above for the search string for AI announcements, with the initial

[17] https://www.liwc.app/

[18] This list was taken from https://www.kaggle.com/tahahavakhor/search-keywords-for-each-information-technology. Blockchain, Virtual Reality, and Augmented Reality ITs were added to the list.

dictionaries based on prior literature (Brynjolfsson and McAfee 2016; Daugherty and Wilson 2018; Davenport and Kirby 2016; Raisch and Krakowski 2021). Appendix 3 shows the refined dictionaries for automation and augmentation, which we used for text mining the AI announcements. We also manually coded the entire announcements to verify the reliability of the software. Two individuals – a doctoral candidate and a senior faculty – independently coded 10 randomly-selected announcements. The results of their coding were in complete agreement, and consistent with the LIWC measures in all cases, thus showing the reliability of the LIWC coding. Therefore, we proceeded to use the measures based on LIWC (shown in Table 2) for nature of AI investment (automation and augmentation).

Automation and augmentation scores for each entire AI announcement by the firm are computed as the ratio of the number of sentences in the entire AI announcement mentioning automation and augmentation keywords (shown in Appendix 3), respectively, to the number of sentences in the entire AI announcement. Appendix 4 provides further details on the measurement of the nature of AI investment variables (automation and augmentation).

Measures of the Sentiments about Potential Consequences from AI Investments

We extracted tweets for each firm making an AI investment in our sample set using Twitter API obtained through academic research account of Twitter in the period ranging from [-10d,+10d] using the focal firm ticker symbol in the search string, in which 'd' is the date of AI investment announcement. We choose the tweets in the range [-10d,+10d] because we noticed that mean number of tweets for hiring, layoffs, and ethics starts to pick ten days before the AI announcement date and starts to decline 10 days after the AI announcement date. Figure 2 depicts the trend in the tweets. Using the firm's ticker symbol allows us to capture the tweets from the investors and discard the non-financial social media talks on Twitter. For example, to get tweets about Apple, we used “$AAPL” in the search string. This resulted into 1,896,244 tweets about the sample firms in our dataset.

---Insert Figure 2 about here---

We used LIWC 2022 (v 1.0.0) to measure the sentiments about potential consequences from AI investments – optimism about hiring, concerns about layoffs, and concerns about ethics. We created custom dictionaries for (a) optimism about hiring, (b) concerns about layoffs, and (c) concerns about ethics (see Appendix 5) using the same process as discussed above for the dictionaries for automation and augmentation, with the initial dictionaries based on prior literature (Brynjolfsson and McAfee 2016; Daugherty and Wilson 2018; Davenport and Kirby 2016; Fjeld et al. 2020; Hosanagar 2020; Kane et al. 2021; Raisch and Krakowski 2021). Appendix 5 shows the refined dictionaries for hiring, layoffs, and ethics, which we used for text mining the tweets by the investors about the firm that made an AI investment announcement.

Optimism about hiring for each tweet is computed as the degree of positive tone in the tweet multiplied with the proportion of hiring related keywords (shown in Appendix 5); concerns about layoff for each tweet is computed as the degree of negative tone in the tweet multiplied with the proportion of layoffs related keywords (shown in Appendix 5); and concerns about ethics for each tweet is computed as the degree of negative tone in the tweet multiplied with the proportion of ethics related keywords (shown in Appendix 5). Overall optimism about hiring, concerns about layoffs, and concerns about ethics for the firm that year for all the tweets in the range [-10d,+10d], in which ‘d’ is the date of AI investment announcement, are computed as the weighted average (weighted by the length of each tweet) of the optimism about hiring, concerns about layoffs, and concerns about ethics score for each tweet by the investors about the firm, respectively. Appendix 6 describes the computation of sentiments about potential consequences related to hiring, layoffs, and ethical issues from the AI investment, using sample of tweets from the investors on the firms announcing AI investments.

Measures of the Long-term Abnormal Returns

To measure the long-term abnormal returns of the firm, we use the one-year buy-and-hold abnormal returns (BHAR) from the day on which the AI investment is publicly announced. Short-term market reaction measures, such as abnormal returns cumulated over a window of a few days after the announcement, are limited in their ability to see results from a major IT investment. The longer time period used for BHAR addresses this issue. Additionally, BHAR accounts for the uncontrolled impact of other confounding factors by finding matched firms with no investment and adjusting the focal firm’s market performance by removing the gains accrued to a similar no-investment firm during the same period. To estimate BHAR, we follow Bessembinder and Zhang (2013) and first find a matching firm for each event observation (i.e., a firm investing in IT). Matched firm was identified using propensity matching algorithm and we follow a two-step process. (1) We consider the closest book-to-market ratio (BM) among firms with a market capitalization of 70 percent to 130 percent of the focal firm, based on the values of BM and size (market capitalization) in the latest December before the announcement. Further, we ensure the matching firms has the same 4-digit SIC code as the focal firm. (2) Out of those matched firms, we select the one that has about 70 percent to 130 percent of focal firm tweets in the same event window of [-10d, +10d]. After finding a matching firm, we estimate the abnormal return as the difference between the daily compounded returns of the sample firm and its match over a one-year period using COMPUSTAT.

Measures of Control Variables

We control for environment dynamism, complexity, and environment hostility. Following prior literature (Keats and Hitt 1988; Xue et al. 2011), we measure environment dynamism by quantifying the volatility of industry sales using COMPUSTAT. For each firm, we regress the natural log of total sales of the four-digit SIC industry code to which a firm belongs against an index variable of years, for a period of five years (t-1, t-5), where *t* is the year of examining the firm performance. We then use the antilog of the standard error of the regression coefficient to measure sales volatility as a proxy for a firm's environment dynamism.

We measure environment complexity as the reciprocal of industry concentration. Following Xue et al. (2011), we use the log value of the reciprocal of the industry Herfindahl index (i.e., the sum of the squares of the market shares of the four firms with the highest sales in the industry) to measure complexity. We measure environment hostility based on the growth in industry's sales (Keats and Hitt 1988; Xue et al. 2011). To do so, we regress the natural log of total sales of the four-digit SIC industry code to which the firm belongs against an index variable of years, for a period of five years (t-1, t-4), where *t* is the year of examining the firm performance. We then use the reciprocal of the antilog of the regression coefficient to measure hostility.

We also control for industry performance (Sabherwal et al. 2019), industry capital intensity (Mithas et al. 2012), firm size (Faleye 2007), firm cash flow ratio (Xue et al. 2021), organization slack (Iyer and Miller 2008), firm profitability (Mithas et al. 2012), firm capital expenditure (Xue et al. 2021), and firm R&D intensity (Uotila et al. 2009) for the year *t-1*, where *t* is the year of AI investment announcement. Table 2 summarizes the variables used in the study along with their measures. We discuss the analyses and results in the next section.

---Insert Table 2 about here---

Analyses and Results

We reduce the potential threat of artificial multicollinearity by first standardizing all the variables in the model and then creating the interaction terms (Aiken et al. 1991; Cohen et al. 2014). The *t*-test indicate that for firms announcing an AI investment mean BHAR ($t = 2.07$) is significantly ($p < 0.05$) above zero. Table 3 presents the means, standard deviations, and correlations for the study variables.

---Insert Table 3 about here---

To test hypotheses H1-H4, we conduct regression analyses. We estimate robust standard errors to correct for potential bias in standard errors due to heteroskedasticity. We also check for variance inflation factor (VIF) and all the values were below 10 (Hair et al. 1998; Mathieson et al. 2001), suggesting multicollinearity is not a major concern in our models. Table 4 presents the results. We find support for H1, H2a, H3, and H4. We find that both investment in AI for automation and augmentation result in positive impact on BHAR. We find that optimism about hiring when firm uses AI for automation results in improving BHAR whereas concerns on layoffs and ethics have negative effect on BHAR when firm uses AI for automation. We also find that investors feel optimistic about the layoffs when firm uses AI for augmentation. However, hiring doesn't seem to create any optimism among investors when firm uses AI for augmentation as H2b was not supported. Table 4 presents the results, while Table 5 summarizes the findings in the context of the hypotheses. Figure 3 depicts the interaction plots.

---Insert Table 4 about here---

---Insert Table 5 about here---

---Insert Figure 3 about here---

From Figure 2, we observe that at as the use of AI for automation increases, long-term abnormal returns - increases as the optimism about hiring increases, and decreases as the concerns about layoffs and ethics increases. On the contrary, as the use of AI for augmentation increases, long-term abnormal returns increases as the concerns about layoffs increases. The next subsection discusses about various robustness tests performed to check the generalizability of our findings using alternate measures of variables.

Supplemental Analyses

We conduct a series of robustness tests, as summarized in Table 6. The supplemental analyses include nine robustness tests to address potential concerns regarding our estimation and inclusion of variables within the main model. Table 7 provides the results of robustness tests. All nine robustness tests provide results consistent with the main result.

---Insert Table 6 about here---

---Insert Table 7 about here---

To address the generalizability of our findings across the different measures of firm long-term abnormal returns, we use value-weighted (R1) values of BHAR as alternative measures of dependent variable from COMPUSTAT. Value-weighted index assigns weights based on each stock's market capitalization. We find results consistent with the main results (Model M4, Table 4). To address potential concerns related to the measures of various variables used in our study, we used alternative measures of firm size – natural log of sales (R2), alternative measure of organization slack – debt to assets ratio (R3); alternate measures of the nature of AI investment using - binary measures of automation and augmentation (R4), and the ratio of the total number of automation and augmentation keywords in the entire AI announcement to the total number of words in the entire AI announcement (R5). The alternative measures of the nature of AI investment are consistent with the results of the main model (Model M4, Table 4). This lends credibility to our text-mining methodology of measuring nature of AI investments.

We also use an alternative measure of environment dynamism – industry's operational income volatility (R6); an alternative measure of environment complexity - log value of the reciprocal of the Herfindahl index of the market shares of all firms in the industry (R7); and an alternative measure of environment hostility – industry's operating income growth (R8). We find results to be consistent with our main model (Model M4, Table 4). Next subsection, we discuss how we address potential endogeneity concerns.

Test for Endogeneity

The AI investments by the firms in our sample may be the result of AI investments by their peer firms. Thus, our focal independent variable – the nature of AI investment – might not be purely exogenous as firms tend to follow their peer firms when making product-related investments (Bustamante and Frésard 2021). So, we test for endogeneity by using instrument variables for automation and augmentation as an average of automation and augmentation score of all the firms, belonging to the same four-digit SIC code, making AI investment before the AI investment announcement date of any given firm in our sample set, respectively (R9).

We perform 2SLS using the *ivreg2* command in Stata 17.0 for the endogeneity test. First, we perform an underidentification test to check whether our choice of instrument variables is correlated with endogenous variables (see Qi et al. 2021; Windmeijer 2021). The underidentification test checks whether the equation is identified, i.e., that the excluded instruments are relevant, meaning correlated with the endogenous regressors. In other words, the test examines the null hypothesis that the instruments have insufficient explanatory power to predict the endogenous variable(s) in the model for identification of the parameters. For the underidentifcation test, Kleibergen-Paap rk LM statistic obtained from 2SLS results was 4.92 ($p < 0.05$), implying that our choice of instrument variables have sufficient explanatory power to predict endogenous variables and there is no underidentification. Next, we test whether our endogenous regressors can be treated as exogenous. To test that, we use the *endog* option in the 2SLS ivreg2 command in Stata. The endogeneity test of endogenous regressors statistic ($\chi^2 = 3.11$, $p > 0.05$) was non-significant. Thus, we fail to reject the null hypothesis that 2SLS and OLS estimates are the same. This indicates that our specified endogenous regressors can be treated as exogenous. We find 2SLS results (R9) consistent with our main model (Model M4, Table 4). The next section throws light on key findings, limitations of our study, and implications to both research and practice.

Discussion

AI is viewed as a revolutionary technology impacting society at an unprecedented rate. Some view AI as a technology providing superpowers to human civilization, while others view it as doom for the human race. Prior literature attributes improvement in business processes to AI, but also sheds light on the unwanted issues resulting from AI, such as discriminatory workforce hiring, bias toward the males for credit limits, etc. This paradox associated AI has motivated this investigation of the perception society feels about the potential consequences from the investment in AI by the organizations. The study explores the interaction between two emergent AI types – augmentation and automation, and perception of the investors about the potential consequences from AI investment on the long-term abnormal returns of the firm.

Using a sample of 169 AI announcements, we theorized and empirically tested the AI investment in automation and augmentation on long-term abnormal returns (H1). Use of AI for automation relates to efficiency, growth productivity, and obsolescence of old legacy. Use of AI for augmentation creates a knowledge building and mutual learning environment between machines and human. We find that both AI investments - automation and augmentation create a bullish market. Despite the fact that AI is expected to bring prosperity and new business opportunities, there is fear that the AI investments by the organizations could engender societal issues – layoffs, and ethical problems. The study investigates the perception in the market about potential consequences resulting from AI – hiring, layoffs, and ethical problems by analyzing the market sentiments from social media and how those sentiments interact with the AI investments.

The results indicate that investors positively react to the AI-enabled automation if there is a strong belief of hiring taking place after AI implementation by the firm (H2a). However, the market concerns about layoffs and ethical issues arising from the AI investments attenuate the bullish sentiment of AI-enabled automation on the firm's long-term abnormal returns (H3a and H4). By contrast, the effect of AI-enabled augmentation on firm's long-term abnormal returns tends to be strengthened when the market is concerned with layoffs (H3b). This could be due to investors feeling buoyant that the firm is getting rid of workforce that do not contribute toward learning as augmentation involves a symbiosis between human and machines creating a learning environment in which both parties complement each other's abilities and fosters growth.

Limitations

The above results should be viewed in the light of the study's limitations. First, like other event studies, it is based on public announcements. The effect of AI investments that are not publicly announced is thus not assessed. Second, we examined the effects of the announced AI investments on long-term abnormal returns of the firm and the market sentiments about potential consequences resulting from the AI investment. We used text-mining approach to measure the AI investment and sentiments of the market by developing a corpus of words related to automation, augmentation, hiring, layoffs, and ethics using prior literature because we do not have data on these aspects. While acknowledging these limitations, we believe our findings, which are robust to several alternative specifications, would be useful for the field.

Implications for Research

This study is an initial attempt to examine the fundamental and ethical issues arising from the investment in AI by organizations. To our knowledge, this study is the first to investigate the impact of AI investment on firm's long-term abnormal returns. The study makes some key theoretical contributions. First, it extends the application of automation-augmentation perspective by investigating the impacts of different types of AI investments by the firm on its long-term abnormal returns. Prior research has provided insights on the improvement in stock-market returns resulting from IT investments. Our work extends the work in the business value of IT literature using AI as context.

AI is known to be a blackbox (Rai 2020; Kane et al. 2021) with algorithms working behind the scenes generating recommendations on products (e.g., amazon), making decisions on hiring (Tambe et al. 2019), solving custom queries via bots, and many more. Such autonomous and non-explainable traits have more often than not resulted into ethical issues – diversity, biasedness, gender, and racial discrimination, thereby creating an oppressive society for the humans. Second, our study contributes to the ethics literature by understanding the fundamental and ethical issues arising from the investment in AI that have wider implications for society.

Third, it extends the application of signaling theory by investigating the implications of public AI investment announcements. Information is a key facet to decision making by the investors. Investors act on public information, often conveyed through either firms' annual reports or through public announcements. Corporate announcements have been viewed as signals that reduce asymmetry between the firm's executives and outsiders, thereby affecting perceptions about future firm performance. This is true for announcements about IT investments. Some BVIT studies view the announcement of an IT investment as a signal to investors about change in the firm's future cash flow (e.g., Shea et al. 2019) or as signals for investors to determine a firm's business strategy, IT strategy, and strategic alignment (Sabherwal et al. 2019). Our study makes use of signals in the form of AI investments, potential hiring, layoffs, and ethical issues resulting from AI investments.

Fourth, it contributes to accounting literature by investigating the interplay between nature of AI investment and sentiments of investors about potential consequences resulting from AI investments on its long-term abnormal returns. Studies have stressed the importance of looking over long-term abnormal returns, e.g., BHAR, instead of short-term abnormal returns as IT investments take time to provide transparent results.

Last, it provides methodological rigor by employing text-mining algorithm through the use of a custom-built dictionary to measure the AI investment – automation and augmentation from the announcement text; and to measure sentiments from the tweets about optimism about hiring, concerns about layoffs, and concerns about ethics. The study employs propensity score matching algorithm to identify the comparable matching firm, not investing in AI, both in terms of market capitalization and twitter reputation to help measure the one-year buy-and-hold abnormal returns (BHAR). Future research could use this custom-built dictionary in studying the role of sentiments in various contexts.

Implications for Practice

This study also has implications for practice. First, our results suggest that investors feel positive about the effects of the firm's AI investment in improving efficiency and productivity through automating repetitive tasks, and on fostering a learning environment in which human and machines complement each other capabilities through using AI for augmentation. Although investment in AI bestows improvement in firms' performance, the performance gains may be reinforced or subdued by the perception of the investors about the potential consequences from the AI investment.

Second, there is a widespread fear that AI would take away the jobs. Most of the workforce in U.S. belong to sectors vulnerable to automation (Manyika et al. 2017). AI-enabled automation is used mainly for repetitive and mechanical tasks to reduce the time and improve efficiency. The feeling of potential hiring by the firm investing in AI for automation would allay the fears of layoffs in the society and engender a positive feeling toward the firm. Firm would gain investors' confidence boosting firm value further from the AI investment in automation. However, if investors feel concerned about the potential layoffs happening from AI investment in automation, it generates a melancholy feeling among the investors resulting into weakening of the positive impact of AI investment in automation. Management needs to be careful with the AI investment in automation. The transition to AI investment toward automation should happen in a planned way. Management should employ the workforce vulnerable to automation in skill development training thereby sending signals about engaging workforce in new creative tasks. This would avoid any bad reputation on social media and subsequently gain investors' confidence fostering growth.

Third, in contrast to concern about the potential layoffs from AI investment in automation, investors feel optimistic about potential layoffs happening from AI investment in augmentation. Augmentation involves a symbiosis between human and machines in which both the parties work closely together fostering an environment of mutual learning thereby enhancing organizational knowledge. Workforce that averts such learning tend to be a liability for the organization and thus do not contribute much to the overall profitability of the organization. Getting rid of such workforce sends strong signal to the market that firm is serious about improvements in its overall operations. Such potential layoffs ensuing from AI investment in augmentation bolsters the faith among the investors toward the company.

Last, management should understand the functioning of the AI system, how AI will be used by the end-users, and what implications it would have on society before deploying the systems. Ethical issues has arisen when AI system was given sole discretion to act on its own. Firms need to carefully monitor the tasks associated with AI-enabled automation and should not vest responsibility to AI system on tasks that could have serious repercussions. For example, in deciding the hiring of a candidate, profiling could be done by the system but human need to be involved in the final decision making so that system do not discriminate the candidate based on race, gender, or color when hiring. Otherwise, firms should make sure to maintain their AI system by updating with the correct data as failing to do so may pose ethical issues and termination of the system. For example, hiring AI system was terminated by the employers as the system was favoring candidates with name as Jared and who played lacrosse in high school.[19]

[19] https://www.americanbar.org/groups/business_law/publications/blt/2020/10/ai-in-hiring/

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Figures of Chapter 2

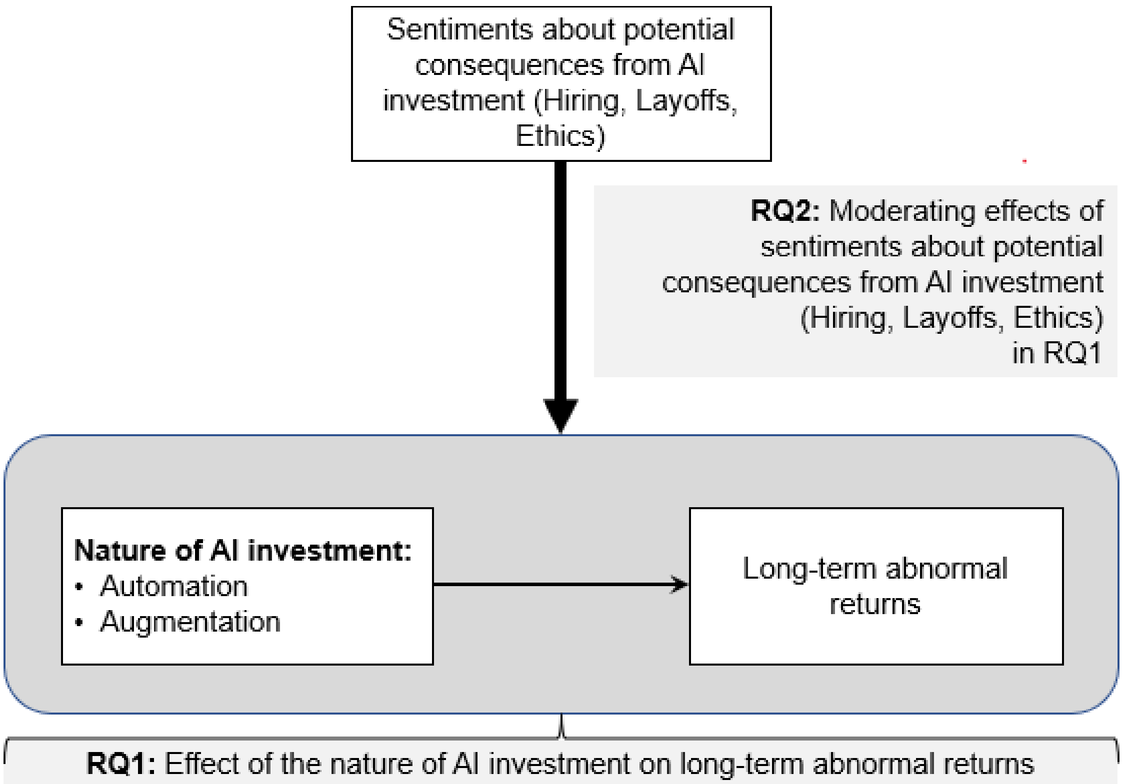

Figure1. Research model

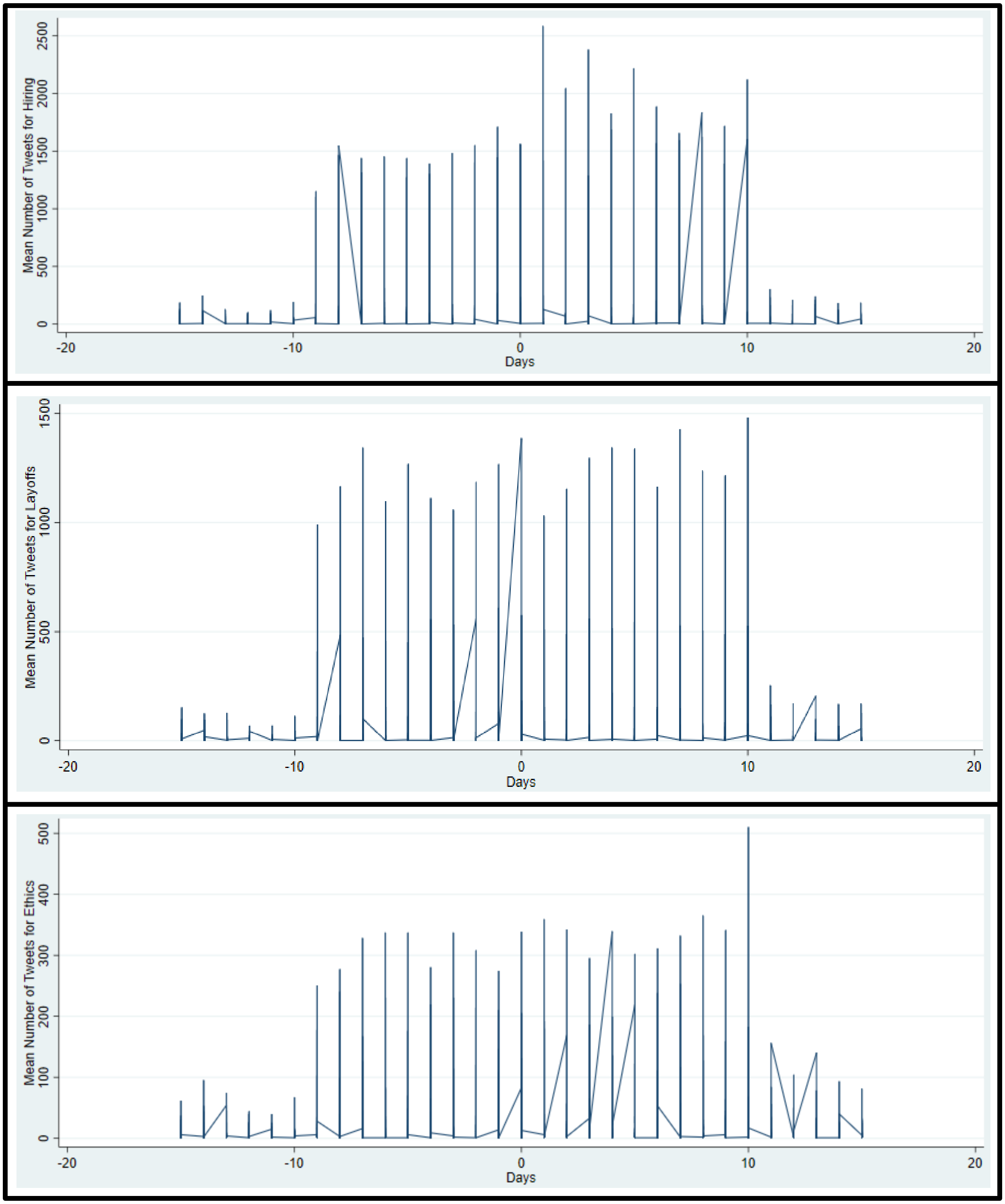

Figure 2. Trend in mean number of tweets across days

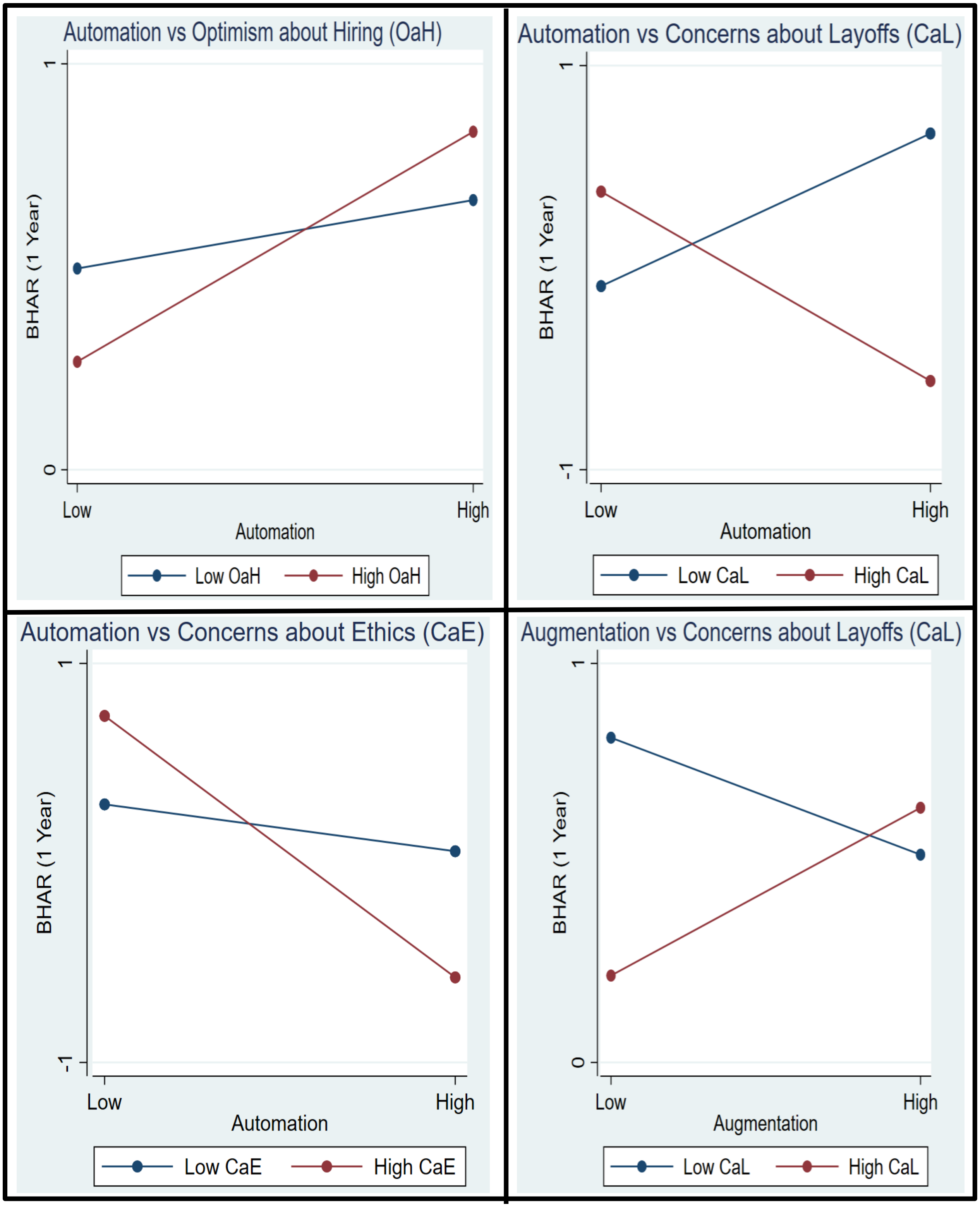

Figure 3. Interaction plots

Tables of Chapter 2

Table 1. Key constructs and definitions

Construct	Definition
Nature of AI investment	Nature of AI investment based on its application either for automation or augmentation (Raisch and Krakowski 2021).
Automation	AI product takes over human task with no little involvement of humans (Raisch and Krakowski 2021).
Augmentation	AI product collaborates with human complementing each other capabilities (Raisch and Krakowski 2021).
Sentiments about potential consequences from AI investment	People's affective expression about a firm related to optimism about hiring or concerns about layoffs or concerns about ethics arising from AI investment by the firm on social media (adapted from Hillman and Trier 2013).
Long-term abnormal returns	Reflection of the anticipated changes in firm's future expected cash flows (adapted from Pauwels et al. 2004).

Table 2. List of variables and measures used in the study

Variables	Measures	Sources
Main		
Long-term Abnormal Returns	buy-and-hold abnormal returns (BHAR)	Havakhor et al. (2022)
Automation	ratio of the number of sentences in the entire AI announcement text mentioning automation related keywords (shown in Appendix 3) to the number of sentences in the entire AI announcement text.	
Augmentation	ratio of the number of sentences in the entire AI announcement text mentioning augmentation related keywords (shown in Appendix 3) to the number of sentences in the entire AI announcement text.	
Optimism about Hiring	weighted average (weighted by the length of each tweet) of the degree of positive tone in the tweet multiplied with the proportion of hiring related keywords (shown in Appendix 5) in the tweet, across all the tweets in the period [-10d, +10d]	
Concerns about Layoffs	weighted average (weighted by the length of each tweet) of the degree of negative tone in the tweet multiplied with the proportion of layoffs related keywords (shown in Appendix 5) in the tweet, across all the tweets in the period [-10d, +10d]	
Concerns about Ethics	weighted average (weighted by the length of each tweet) of the degree of negative tone in the tweet multiplied with the proportion of ethics related keywords (shown in Appendix 5) in the tweet, across all the tweets in the period [-10d, +10d]	
Control		
Industry Performance	median of the q ratios of the firms in that industry	Sabherwal et al. (2019)
Industry Capital Intensity	median of the capital intensities of the firms in that industry	Sabherwal et al. (2019)
Firm Size	natural log of employees.	Faleye (2007)
Firm Cash Flow Ratio	cash flow from assets in place to the total assets	Xue et al. (2021)

Table 2. (Cont.)

Variables	Measures	Sources
Control		
Organization Slack	debt to equity ratio	Iyer and Miller (2008)
Profitability	return on sales	Mithas et al. (2012)
Firm Capital Expenditure	capital expenditure to total assets	Xue et al. (2021)
Firm R&D Intensity	natural log of the firm R&D expense divided by its sales	Uotila et al. (2009)
Environment Munificence	growth in industry sales	Xue et al. (2011)
Environment Dynamism	volatility of industry sales	Xue et al. (2011)
Environment Complexity	log value of the reciprocal of the industry Herfindahl index	Xue et al. (2011)

Table 3. Summary statistics and correlations[a]

Variables	Mean	S.D.	1	2	3	4	5
1. Automation	0.16	0.48					
2. Augmentation	0.14	0.81	0.05				
3. Optimism about Hiring	0.17	0.28	0.14	0.11			
4. Concerns about Layoffs	0.02	0.07	-0.13	0.16*	0.02		
5. Concerns about Ethics	0.32	0.62	-0.19*	-0.11	0.07	0.02	
6. BHAR	0.45	0.38	0.27**	0.23**	0.13	-0.29***	-0.17*

[a] Correlations are reported as: ***p < 0.001; **p < 0.01; *p < 0.05; n = 169.

Table 4. Results of regressions for H1-H4[a,b]

	DV = 1 Year BHAR			
Variables	**M1**	**M2**	**M3**	**M4**
Industry Performance	0.128 (0.043)	0.053 (0.044)	0.050 (0.045)	0.032 (0.044)
Industry Capital Intensity	-0.096 (0.004)	-0.111⁺ (0.004)	-0.107 (0.005)	-0.131⁺ (0.005)
Firm Size	0.096 (0.015)	0.123 (0.015)	0.125 (0.016)	0.138 (0.016)
Firm Cash Flow	-0.050 (0.390)	-0.062 (0.390)	-0.062 (0.395)	-0.082 (0.391)
Organization Slack	-0.054 (0.008)	-0.059 (0.008)	-0.060 (0.009)	-0.061 (0.009)
Profitability	-0.071 (0.256	-0.094 (0.261)	-0.094 (0.266)	-0.072 (0.264)
Firm Capital Expenditure	0.037 (0.048)	0.100 (0.058)	0.100 (0.058)	0.103 (0.060)
Firm R&D Intensity	0.246** (0.015)	0.240** (0.015)	0.250** (0.016)	0.251** (0.016)
Environment Munificence	-0.047 (0.356)	-0.044 (0.330)	-0.039 (0.340)	-0.035 (0.325)
Environment Dynamism	-0.145* (1.01)	-0.144* (0.903)	-0.151* (0.952)	-0.120* (0.857)

Table 4. (Cont.)

	DV = 1 Year BHAR			
Variables	**M1**	**M2**	**M3**	**M4**
Environment Complexity	-0.076 (0.029)	-0.129 (0.029)	-0.127 (0.030)	-0.153^{+} (0.032)
Automation		0.098* (0.007)	0.101* (0.007)	0.365* (0.026)
Augmentation		0.192* (0.167)	0.186* (0.169)	0.390*** (0.196)
Optimism about Hiring (OaH)			0.010 (2.086)	0.047 (2.210)
Concerns about Layoffs (CaL)			0.020 (0.042)	-1.531** (0.651)
Concerns about Ethics (CaE)			-0.049* (1.923)	-0.071 (2.916)
Automation X OaH				0.172* (1.712)
Automation X CaL				-1.430** (0.865)
Automation X CaE				-0.207** (3.263)
Augmentation X OaH				0.042 (1.947)
Augmentation X CaL				0.602** (0.866)
R^2 (%)	18.30	21.53	22.04	26.43
F-value	2.79**	3.01***	2.39**	6.09***

[a] Standardized regression coefficients are reported with robust standard errors. Significance levels reported are two-tailed and are indicated as: ***p < 0.001; **p < 0.01; *p < 0.05; $^{+}$ < 0.10; n = 169 for all models. *OaH* refers to Optimism about Hiring; *CaL* refers to Concerns about Layoffs; *CaE* refers to Concerns about Ethics.

[b] We also test the impact of non-hypothesized relationship - interaction between Augmentation and Concerns about Ethics (CaE) on BHAR by including in the model. We did not find any significance of *Augmentation X CaE* on BHAR. The significance of all other relationships remain the same as in model M1-M4. This supports our argument in the context of hypothesis H4 that ethical issues from AI are the results of AI investment for automation. We did not include *Augmentation X CaE* in the table to not complicate the table.

Table 5. Summary of results

Hypothesis	Result
H1a: A firm's announcement of AI for automation is associated with higher long-term abnormal returns.	Supported
H1b: A firm's announcement of AI for augmentation is associated with higher long-term abnormal returns.	Supported
H2a: Investor optimism about potential hiring by a firm due to an AI investment by it strengthen the positive relationship between investment in AI for automation and long-term abnormal returns.	Supported
H2b: Investor optimism about potential hiring by a firm due to an AI investment by it strengthen the positive relationship between investment in AI for augmentation and long-term abnormal returns.	Not Supported
H3a: Investor concerns about potential layoffs by a firm due to an AI investment by it weaken the positive relationship between investment in AI for automation and long-term abnormal returns.	Supported
H3b: Investor concerns about potential layoffs by a firm due to an AI investment by it strengthen the positive relationship between investment in AI for augmentation and long-term abnormal returns.	Supported
H4: Investor concerns about potential ethical issues by a firm due to an AI investment by it weaken the positive relationship between investment in AI for automation and long-term abnormal returns.	Supported

Table 6. Summary of robustness tests

Model	Potential biases and alternative arguments	Alternate measure for Robustness test	Results compared to main model
R1	Are the results generalizable to alternative dependent variables?	▪ Value-weighted measure of BHAR (R1)	Consistent
R2	Are the results generalizable to alternative measure of firm size?	▪ Natural log of sales.	Consistent
R3	Are the results generalizable to alternative measure of organization slack?	▪ Debt to assets ratio	Consistent
R4, R5	Are the results generalizable to alternative measure of nature of AI investment?	▪ Use of binary measures of automation and augmentation ▪ Ratio of the total number of automation and augmentation keywords in the entire AI announcement to the total number of words in the entire AI announcement	Consistent
R6	Are the results contingent on the estimation of Munificence?	▪ Industry's operational income growth.	Consistent
R7	Are the results contingent on the estimation of Dynamism?	▪ Industry's operational income volatility.	Consistent
R8	Are the results contingent on the estimation of Complexity?	▪ Natural log value of the reciprocal of the Herfindahl index of the market shares of all firms in the industry.	Consistent
R9	Are the independent variables endogenous?	▪ Test for endogeneity	Consistent

Table 7. Robustness Tests[a,b]

Variables	M4	R1	R2	R3	R4	R5	R6	R7	R8	R9
IP	0.032 (0.044)	0.033 (0.044)	0.083 (0.044)	0.036 (0.046)	0.041 (0.044)	0.066 (0.043)	0.037 (0.046)	0.045 (0.046)	0.083 (0.045)	0.088 (0.044)
ICI	-0.131+ (0.005)	-0.132+ (0.005)	-0.144* (0.005)	-0.153* (0.005)	-0.126+ (0.005)	-0.139+ (0.005)	-0.154* (0.005)	-0.146* (0.005)	-0.149* (0.005)	-0.149* (0.005)
FS	0.138 (0.016)	0.139 (0.016)	0.187+ (0.017)	0.151 (0.016)	0.135 (0.017)	0.170 (0.017)	0.152 (0.015)	0.145 (0.016)	0.177+ (0.017)	0.213+ (0.018)
FCFR	-0.082 (0.391)	-0.084 (0.389)	-0.011 (0.415)	0.104 (0.437)	-0.080 (0.356)	-0.040 (0.432)	0.101 (0.435)	0.095 (0.395)	0.134 (0.496)	0.019 (0.419)
OS	-0.061 (0.009)	-0.061 (0.009)	-0.070 (0.009)	0.251* (0.100)	-0.055 (0.009)	-0.066 (0.009)	0.249* (0.099)	0.234* (0.095)	0.199+ (0.093)	-0.074 (0.010)
Profitability	-0.072 (0.264)	-0.073 (0.263)	0.177 (0.280)	-0.304 (0.354)	-0.079 (0.244)	-0.132 (0.272)	-0.303 (0.353)	-0.296 (0.329)	-0.342 (0.370)	-0.224 (0.299)
FCE	0.103 (0.060)	0.103 (0.060)	0.138 (0.059)	0.043 (0.054)	0.096 (0.059)	0.134 (0.060)	0.043 (0.054)	0.039 (0.053)	0.078 (0.056)	0.119 (0.058)
FRDI	0.251** (0.016)	0.250** (0.016)	-0.239* (0.001)	0.298** (0.017)	0.246** (0.016)	0.244* (0.001)	0.297** (0.017)	0.290** (0.017)	0.259* (0.001)	0.229* (0.001)
EM	-0.035 (0.325)	-0.035 (0.325)	-0.024 (0.311)	-0.053 (0.305)	-0.023 (0.323)	-0.036 (0.311)	-0.052 (0.304)	-0.039 (0.305)	-0.039 (0.297)	-0.018 (0.310)
ED	-0.120* (0.857)	-0.120* (0.855)	-0.094+ (0.794)	-0.139* (0.843)	-0.122* (0.848)	-0.104 (0.809)	-0.140* (0.842)	-0.140* (0.840)	-0.113* (0.811)	-0.093+ (0.789)
EC	-0.153+ (0.032)	-0.155+ (0.032)	-0.135 (0.032)	-0.140 (0.031)	-0.154+ (0.032)	-0.140 (0.032)	-0.142+ (0.031)	-0.142 (0.031)	-0.120 (0.032)	-0.121 (0.032)
Aut	0.365* (0.026)	0.366* (0.026)	0.397* (0.028)	0.441* (0.032)	0.354* (0.026)	0.360* (0.026)	0.441* (0.033)	0.425* (0.032)	0.406+ (0.034)	-0.418* (0.028)
Aug	0.390*** (0.196)	0.391*** (0.195)	0.414*** (0.211)	0.383** (0.228)	0.365*** (0.188)	0.390*** (0.198)	0.384** (0.227)	0.359** (0.217)	0.368** (0.241)	0.409*** (0.211)
OaH	0.047 (2.210)	0.048 (2.209)	0.030 (1.989)	0.043 (2.308)	0.071 (2.264)	0.040 (2.021)	0.043 (2.306)	0.067 (2.350)	0.036 (2.105)	0.034 (1.986)
CaL	-1.531** (0.651)	-1.533** (0.651)	-1.696** (0.743)	-1.793** (0.887)	-1.497** (0.652)	-1.516** (0.652)	-1.794** (0.886)	-1.743* (0.873)	-1.690* (0.950)	-1.755* (0.744)
CaE	-0.071 (2.916)	-0.072 (2.909)	-0.100+ (2.657)	-0.099 (2.961)	-0.071 (2.871)	-0.097+ (2.629)	-0.099 (2.959)	-0.097 (2.918)	-0.123* (2.817)	-0.111* (2.595)
Aut X OaH	0.172* (1.712)	0.172* (1.711)	0.169* (1.564)	0.171* (1.696)	0.180* (1.774)	0.177* (1.593)	0.170* (1.694)	0.178* (1.749)	0.173* (1.632)	0.168* (1.544)
Aut X CaL	-1.430** (0.865)	-1.432** (0.865)	-1.580** (0.988)	-1.662** (1.176)	-1.378** (0.866)	-1.425** (0.867)	-1.662** (1.174)	-1.595** (1.156)	-1.570* (1.261)	-1.631** (0.989)

Table 7. (Cont.)

Variables	M4	R1	R2	R3	R4	R5	R6	R7	R8	R9
Aut X CaE	-0.207** (3.263)	-0.208** (3.261)	-0.230** (3.242)	-0.218** (3.355)	-0.205** (3.309)	-0.223** (3.170)	-0.218** (3.355)	-0.216** (3.379)	-0.236** (3.425)	-0.234*** (3.229)
Aug X OaH	0.042 (1.947)	0.041 (1.887)	0.029 (1.182)	0.031 (1.104)	0.035 (1.871)	0.034 (1.368)	0.030 (1.045)	0.025 (1.,143)	0.021 (1.383)	0.026 (1.042)
Aug X CaL	0.602** (0.866)	0.603** (0.867)	0.673** (0.590)	0.712** (0.598)	0.594** (0.875)	0.596** (0.867)	0.713* (0.587)	0.697* (0.492)	0.669* (0.072)	0.694** (0.577)
R^2 (%)	26.43	26.51	25.08	28.10	25.31	24.76	28.08	26.62	24.96	25.75
F-value	6.09***	6.08***	5.85***	3.93***	5.18***	6.29***	3.96***	3.89***	3.73***	5.57***

[a] Standardized regression coefficients are reported with robust standard errors. For endogeneity test (R9), we use *betacoeff* module in stata to get standardized coefficients and centered R square is reported. Significance levels reported are two-tailed and are indicated as: ***p < 0.001; **p < 0.01; *p < 0.05; $^{+} < 0.10$; n = 169 for all models (M4 and R1-R8); n=141 for R9. *IP* refers to Industry Performance; *ICI* refers to Industry Capital Intensity; *FS* refers to Firm Size; *FCFR* refers to Firm Cash Flow Ratio; *FCE* refers to Firm Capital Expenditure; *FRDI* refers to Firm R&D Intensity; *EM* refers to Environment Munificence; *ED* refers to Environment Dynamism; *EC* refers to Environment Complexity; *Aut* refers to Automation; *Aug* refers to Augmentation; *OaH* refers to Optimism about Hiring; *CaL* refers to Concerns about Layoffs; *CaE* refers to Concerns about Ethics.

[b] We also test the impact of non-hypothesized relationship - interaction between Augmentation and Concerns about Ethics (CaE) on BHAR by including in all the robustness tests models. We did not find any significance of *Augmentation X CaE* on BHAR.The significance of all other relationships remain the same as in model M4. We did not include *Augmentation X CaE* in the table not to make complicate the table.

Appendices

Appendix 1. Search String for AI Announcements on Lexis Nexis

(“artificial intelligence” or “deep learning” or “machine learning” or “cognitive systems” or “cognitive computing” or “intelligent systems” or “chatbots” or “virtual assistants” or “recommender systems” or “pattern recognition”) or hlead(“algorithms” or “image processing” or “image recognition” or “speech recognition” or “object recognition” or “object tracking” or “face recognition” or “facial recognition” or “ biometric*” or “robot” or “computer vision” or “driverless” or “autonomous vehicles”) and hlead((“invest” or “purchase” or “buy” or “acquire” or “implement” or “install” or “adopt” or “alliance” or “partner” or “collaborat*” or “develop” or “build*” or “create” or “launch” or “merge*” or “acquisition”)) and (“NASDAQ” OR “NYSE” or “AMEX”) and not (“Comtex SmarTrend® Alert” or “conference” OR “exhibit” or “exhibitor” or “exhibition” or “annual reports” or “q* earnings” or “industry report” or “research” or “divest” or “university”) and not hlead (“news commentary” or “stocks update”) and not title(“initial public offering” or “stock option”)

Appendix 2. Keywords for Blockchain and Virtual and Augmented Reality added to Other ITs List[20]

Blockchain[21]: AlphaPoint, Axcore, Axoni, B2Broker, Bankchain, BigChainDB, bitcoin, Blockchain, Blockchain Evidence Locker, Blocko, Blockstream, Brainbot, Bubichain, Chain Core, Chainalysis KYT, Corda, cryptocurrency, Digital Asset Platform, Domus Tower Blockchain, Ethereum, Factom Harmony, GemOS, Hydrachain, Hyperledger, Hyperledger Fabric, Hyperledger Indy, Hyperledger Iroha, Hyperledger Sawtooth, IBM Blockchain, Kaleido, Microsoft Azure Blockchain, Monax, MultiChain, NEM, NEO, Nexledger, Nxt Platform, Omni, Onchain, OpenCSD, Oracle Blockchain Cloud Service, ParallelChain, pNetwork, Polkadot, Quorum, Ripple, RSK, SettleMint, Signchain Signature, Stellar, StreamCore, Swirlds, Symbiont Assembly, Tangle, Tendermint, VeChain ToolChain, Velas, Waves, Zeeve, Zilliqa

Virtual and Augmented Reality[22]: 1trip2, 3D Anatomy Viewer 4 Artists, 3-in-1 Ruler, 4D Sight, 6D.AI, 8th Wall, Absco , Absco Sheds, Admix, Adobe Aero, Adobe Lightroom 4.3, After Ice, Aglet, AI Scry, Air Museum, AirMeasure, AKUNA-TX EARBUD, ALAIRA, Alipay AR Red Envelopes (Hong Bao), Ameyt World, Ammazza, ANI, AnimateYou, Appfity, AR, Augment* reality, AR Alphabets, AR Chess by BrainyChess, AR Chief Trump, AR Distance, AR Docs, AR Educational Toys, AR Experiments, AR FaceFighter, AR fart app, AR Fly Ruler, AR Grimoire, AR History, AR Hockey Ultra, AR LOKA, AR Lyrics, AR MeasureKit, AR Planes, AR Pong, AR Search, AR Social, AR Stickers, AR Studio Player, AR Translator, AR Warriors, AR Zyion Invasion, AR.fx, AR.js, AR/VR Today, Arbi , ARBOOX, Archeology,

[20] This list was taken from https://www.kaggle.com/tahahavakhor/search-keywords-for-each-information-technology. Blockchain, Virtual Reality, and Augmented Reality ITs were added to the list. Keywords include ITs and product names of respective ITs.

[21] Blockchain IT words are based using Lacity (2020) and https://www.gartner.com/reviews/market/blockchain-platforms.

[22] Virtual Reality and Augment Reality words are based using https://www.producthunt.com/topics/augmented-reality

ARChess, ARcraft.me, Arcus, Aremi, Aremo, AREmoji , AR-GO, ARiddle, arjoy, Arkerobox, ARKit2, ARKit-Emperor, ARKitty, ARMA APP, ARMeasureApp, ARQ Editor, ARscape, Art.com, Arthouse, Articcio, Artios, ARToolkit, ARTX, ARWAY, AR-XR, Aryel, Aryzon AR/MR, ARZombi 2, ASH, Assemblr, Asteroid, Asteroid 2, Astral, Astrophilia, Augment Desktop, Augmented AR Jungle Adventure, Augmented Halloween, Augmented Human, Augray, Augspace, Avvnue, Bacydar, Bad Screenprints Dot Com, Balloon Invaders: Pop Balloons in AR, Banuba Face Filters SDK, Barty App, Bazar, BBC Civilisations AR, Beard Live - Beard Cam Live, Beatsy, Beem, BeyondPass AR, bicoco, BioHazard AR Escape Room, Biometrics Input Kit for XR, Bitcoin AR, Blackbox, BlindGuide Maps / KLIC, Blippar, Blocker, BlocSide Sports, Bloxels Build Your Own Video Games, BlueScore, Bold Poker, Bookful, boomApp, BOSE Audio AR platform, Bose Frames, Bridge, BRIO, Bubbles, Bubo - AR Social Network, Bunny Run AR, Butterfly Story, Byond, CalculatAR Beta, Camera IQ, Cannabis Viewer AR, CAPTUR3D, Capture, Carafes Letter, Carbon 0, Cardlet, Carloudy, Cat Tiny Homes, Catchar, Changes, Cheapshot, Cheddar Live News on Magic Leap, chem3D, Chroma, Cibo, CifiPowa, CINEMOOD 360, Citizen, Clean Hero AR!, Client Finda Commercial, Clik Shop, Climb Designer, ClipDrop, Clothes Filters, Coachy, Coachy 2.0, Coin Hunter, ColdSpotting, Conekton, Convergence, Cosmos Creator, Crafter: AR Build Battle, Craftle, Creator Cam, CrittARs, Crypto Lingo, CUBE, Cubiques AR, Customized Videos!, CVRNT Podcast, CYBER, Da Vinci Eye, Dance Nation, DAQRI Smart Glasses, DecorMatters, DEVAR, DictionARy, DigiBets, Digital Art, dilium, Dimension - Explore AR Worlds, display.land, Dog Identifier, domFire, DominanceAR, doodlar, DoodleLens, DopeBalls, Doppler, Dot Go, DottyAR App, DRAFT, Dragon Federation, Draki Hero, DrawmaticAR - Writing Magic, DrillRoom, Echotags, Eclipse Ares, Edgybees, EeziShop, ElementClip (App Clip), Embla

Candles, Entrance Architect, Envision Glasses, Escape The Room: AR, eurecaStudio™, Everything VR & AR, exaQuark, Exploratu, Explore Nearby, Fabric - Social AR, Fabrik, Face in the Hole, Face Maker, Facebook AR Studio, FacefARt, FaceMock, Fantasmo, fARtjacker, Fascroll, Figment AR, Filtroo.com, FitaDo, FitaDo AR, Fitly.ai, Fitness AR, Flame, Flappy Box, Flashcards + AR, FlippAR, Flotogram, FocalHub, Focals Showroom, FoodNoms, Foodvisor, For All Mankind: Time Capsule, Forbes' The Premise - Designing Future Things, FORM Swim Goggles, Fractoz, frankie, Frimousse, FringeFM Podcast, Fritz AI for Snap Lens Studio, Fulldive VR, FunAR, fuse.it, Galaxy Explorer Project, GallARy, Gallery AR, Game Face, Gameboard-1, Gantri AR View, GEENEE, Geenee AR, Geoga, GeoGeek AR, Geography quiz in , Geopogo, GHeight, Ghost, Ghost Seeker, GIPHY World, Glimpse AR, Glitché NFT Tool, Glowing Gloves, Gold Coast Motorcycles, GoodVision Video Insights, Google ARCore, Google Lookout, Gorillaz, Graphmented, Grapic, Guess The Person CEO Quiz, Guidance Internal, Gyroscope v3.5, hakus, HandX, Happy Snap, HAPTICAL, Hawkeye Access, HearHere, HeartsBridges, Heijar, HelloAR, Help Me Read This, heymesh, Hidden Secrets: Mobile Treasure Hunt, HideNHunt, Hiface: Explore Your Style, HIGHTYPE, HillaryDonald Go, hire.AR, Holo, HoloCam, HolodeckVR, Hologo, Holographica, Hololamp, Hololens 2, Holon, Holosports, Holotoolkit, Home AR, Hootsy, Horizon Explorer, HorrorMasks, Hotdog face snapchat lens, House Shfiting Service, Housecraft, Hoverlay, Hybri, Hyper Online, ICON, Ideal Reality, ifcXR, Imagina Books: The Human Body, ImmerseAR, IMMY Mark 1, In Wonder ~Prologue~, InAssist, Iron HUD, Is this place good?, iTagged, IUnknown, JackOxr, Jarit, Jevar, JFK Moonshot, Jig Pro by JigSpace, JigSpace, Jobs in XR, Kalkul [proto]Type 1, KAMP, Kavtek, Ketogram, King Children, Kivisense AR Sneaker, Klub, Klues, Knockout Boxing VR: Ring Fight, Kodama 3DGo, Koka v1.0, KUBE, Kustom AR, Lalinga, Lampix, Layar, Legal Graffiti, LEGO AR Studio, LEGO Hidden Side, Leo Video Camera, Lexting: Hands- 3D Rapid Text Entry, Lifecast, Lifeliqe, Lightform LF2, Lightship ARDK, Little Engineer, Little Rebels, Live Home 3D for iOS, Live Link Face, LivePaper, LivePics, Loly, LoopLeap, Lucyd Loud 2020 Smartglasses, Lumo, LUNAR, MAD Gaze, Made With ARKit, MagePrints, Magic Chess AR, Magic Leap Creator Portal, Magic Leap One, Magic Photos, Magic Sudoku , Magicplan, Maguss, Makebox AR, makeSEA, Makeup Genius, Marketing New Realities, Marsbot for AirPods, Mask Fashions, MASSIVE, Measure, MeasureKit 2.0 with LiDAR Scanner, MechFightAR, Medici, Meet Diana Danko, Megastores.com, Mem Place, Memeois World, MemoAR, Memojis, Merge Cube, Meta 2 Dev Kit, Metal 2, Metaverse, Micro Breaker, Microsoft Hololens, mimesys, Minecraft Earth, Minsar Studio, Mint and List your NFT, MIX, Moatboat, MoCap, Modelified 3D Scanner, Modiface, Mokosh Simple Gallery, moonmoons AR, MR Builder, Mudra Inspire, Muglife, Music Kit V.3, MY DARE BOX, My Virtual Girlfriend AR, myHouseby, n3xt, Neatsy, Nerdeo, New School VR - The Five E's of VR Learning, Nexto, NFTs 2.0, Nodesk, NOMone AR/VR desktop on the GO, nosedive BETA, Notable Me, noteit AR, NoteStorm, Observer Analytics, Octi 2.0, Open Villas, Opuscope, ORA-X, Orbit-Ed, Orboot, Orbu, Osmo Pizza Co., Paint the City, Paint3r - Coloring in 3D, Paint-AR, PairPlay Audio Adventures, Panda, Paperframe, Paperplane, Pastie, PeakFinder AR, PeakVisor, Periodic Table Chemistry 4 app, Personal Sticker Maker for WhatsApp, Phantom Augmented Robotality, Photo Find, PhotoCatch, PianoVision, PicAlive, Pictarize, Pictofit, PictureThat, Pikmin Bloom, Pin Club, Pinmyspot, Placie, Plane Finder AR, Planet Attack AR, PlayCanvas, PlayCrowd, Playmoji: Childish Gambino, PlayTable, PlayVisit, PLNAR, PlugXR, Pokemon Go, POLARIS, Pong AR, POP AR, Portalble, Possessions., Pretia, Primepads, Primer, Prism, Product Hunt Collection of Media Tech, Project Clear, Prompto, Properly, Proximie, PubFighters, Qhanu, Qibla Finder, Qlone, Quartz Brief, WRain It!, Rainbrow, REAL cARds™, Reality Filters, Reality Tasks, Reality Tasks macOS, Really Make, Recyclinator, Reliance MET Industrial Plots, RemoteMac.io, Render People, Research VR Podcast, ResearchVR 006 - Drones, , HMD's and ZUI, resources.AR, Respond, REWILD, RideOn, Rini, Roav, RocketXR, RoCo, Rovr, RP-FX, rumii, Run an Empire 3.0, SAFARI CENTRAL, SatelliteSkill5, Scavengar, SceneShot, SearchCam, Seat360, Sebela, Seek, SeeSignal, Selfie Fixer, Sellar Listing Tool, Sephora Virtual Artist, Shazam Codes, Shepard Fairey AR exhibition, Sherpa Tours, ShiShi TryOn, ShowMe Assist, Shuffle Cups AR, SIMO AR, sippBOX , SiteScape, SketchAR, Sketchfab, Skip, Skrite, Sky Guide RA, Skyway, Slidrs, Smart AR Home, SmartLens, Smash Tanks!, SmileFun, Snatch, SNOW, Social Bee Adventures, Society, Solar3D glasses, Soundmaze, Space Era, Spatial, Spatial Computing Platform, Speak To Anything, Spellbound, Spheroid Universe, Spiff 3D, Spotlight, Squavel, Stack AR, Stambol VR, Stellart, Sticker It!, StickLing, SticStac, Stories AR View, Suggestic, Sun Locator Lite, Sun Seeker, SureMDM, Surreal Words, Talkie OCR, Tangar, TekRevol, TeleStory, Terace 2.0, tethr, The Don, The Fidj, The Fourth Transformation, The Future Wave Newsletter, The Ghost Howls, The Legend of Jack-o'-Lantern, The Lookout, The Machines By Directive Games, The Mona Lisa, Augmented, THE RAW SPACE EXPERIENCE, TheParallaxView, TikTok, Tilt Five, TIME Immersive, Timelense, TinkerNote, TomToons, Tooder, toolbox, Torch, Touristerguide Wand, Trail of Treasures, Tribe XR DJ School, Trickshot League, Triffic, TRIPP, TRY BUY, TryAR, TurboHire, TV Size AR, TweetReality, UBeBot, Ultraman Kaiju Kombat, UniteAR, Unity AR+GPS Location, Unity3D, Universal AR, Unomi 3D , unspun, VAIR, VAM/R, VIBZ, Victorise, Vigilante, Virtlo, Virtual Reality, VR, Virtual Travel Experience, Virtual Try On, Virtuhunt, Virus Hunters, Visao, Visual Money, Visual Shazam, Visualist, Vived Learning, Vossle, voxelizeAR, VR Maker, Vrumble

2.0, Vuzix Blade, Wacky Face, Waggle Words, Walk the Property Lines, Walker of Aldenor, WallaMe, Wallary, Wallr, Wand, War of the AI, Warby Parker Virtual Try-On, warpAR, watAR, Wayfarer Stories, WEbXR Experiments by Google, WebXR Viewer, Weird Cuts, WiDAR, Wildeverse, WiTag, Woah AR, Wonderscope, WooCommerce AR, Worldopo, WrldCraft, WYD Pride, Xiaomi Smart Glasses, Xibit, Xmas Card AR, XO, XR Loaded, XR Typography Guidelines 1.0, YAS, Yaw2, Yeehaw Wand, YoPuppet, You Gun Die AR, ZapBox, ZapWorks, ZapWorks Studio 6, ZINE LOOP, Zumbio

Appendix 3. Keywords for Nature of AI Investment

Augmentation: amplif* * *worker*, amplif* * *workforce*, amplif* * *workman*, amplif* * employee*, amplif* * human*, amplif* * labor*, amplif* * people*, amplif* * person*, amplif* * staff*, amplif* *worker*, amplif* *workforce*, amplif* *workman*, amplif* employee*, amplif* human*, amplif* labor*, amplif* people*, amplif* person*, amplif* staff*, assist* * *worker*, assist* * *workforce*, assist* * *workman*, assist* * employee*, assist* * human*, assist* * labor*, assist* * people*, assist* * person*, assist* * staff*, assist* *worker*, assist* *workforce*, assist* *workman*, assist* employee*, assist* human*, assist* labor*, assist* people*, assist* person*, assist* staff*, augment* * *worker*, augment* * *workforce*, augment* * *workman*, augment* * employee*, augment* * human*, augment* * labor*, augment* * people*, augment* * person*, augment* * staff*, augment* *worker*, augment* *workforce*, augment* *workman*, augment* employee*, augment* human*, augment* labor*, augment* people*, augment* person*, augment* staff*, boost* * *worker*, boost* * *workforce*, boost* * *workman*, boost* * employee*, boost* * human*, boost* * labor*, boost* * people*, boost* * person*, boost* * staff*, boost* *worker*, boost* *workforce*, boost* *workman*, boost* employee*, boost* human*, boost* labor*, boost* people*, boost* person*, boost* staff*, cobot*, collaborat* * *worker*, collaborat* * *workforce*, collaborat* * *workman*, collaborat* * employee*, collaborat* * human*, collaborat* * labor*, collaborat* * people*, collaborat* * person*, collaborat* * staff*, collaborat* *worker*, collaborat* *workforce*, collaborat* *workman*, collaborat* employee*, collaborat* human*, collaborat* labor*, collaborat* people*, collaborat* person*, collaborat* staff*, complement* * *worker*, complement* * *workforce*, complement* * *workman*, complement* * employee*, complement* * human*, complement* * labor*, complement* * people*, complement* * person*, complement* * staff*, complement* *worker*, complement* *workforce*, complement* *workman*, complement* employee*, complement* human*, complement* labor*, complement* people*, complement* person*, complement* staff*, decision-making, employee* * amplif*, employee* * assist*, employee* * augment*, employee* * boost*, employee* * collaborat*, employee* * complement*, employee* * enhanc*, employee* * expand*, employee* * extend*, employee* * help*, employee* * improv*, employee* * increas*, employee* * increment*, employee* * interact*, employee* * supplement*, employee* * support*, employee* amplif*, employee* assist*, employee* augment*, employee* boost*, employee* collaborat*, employee* complement*, employee* enhanc*, employee* expand*, employee* extend*, employee* help*, employee* improv*, employee* increas*, employee* increment*, employee* interact*, employee* supplement*, employee* support*, enhanc* * *worker*, enhanc* * *workforce*, enhanc* * *workman*, enhanc* * employee*, enhanc* * human*, enhanc* * labor*, enhanc* * people*, enhanc* * person*, enhanc* * staff*, enhanc* *worker*, enhanc* *workforce*, enhanc* *workman*, enhanc* employee*, enhanc* human*, enhanc* labor*, enhanc* people*, enhanc* person*, enhanc* staff*, expand* * *worker*, expand* * *workforce*, expand* * *workman*, expand* * employee*, expand* * human*, expand* * labor*, expand* * people*, expand* * person*, expand* * staff*, expand* *worker*, expand* *workforce*, expand* *workman*, expand* employee*, expand* human*, expand* labor*, expand* people*, expand* person*, expand* staff*, extend* * *worker*, extend* * *workforce*, extend* * *workman*, extend* * employee*, extend* * human*, extend* * labor*, extend* * people*, extend* * person*, extend* * staff*, extend* *worker*, extend* *workforce*, extend* *workman*, extend* employee*, extend* human*, extend* labor*, extend* people*, extend* person*, extend* staff*, help* * *worker*, help* * *workforce*, help*

* *workman*, help* * employee*, help* * human*, help* * labor*, help* * people*, help* * person*, help* * staff*, help* *worker*, help* *workforce*, help* *workman*, help* employee*, help* human*, help* labor*, help* people*, help* person*, help* staff*, human* * amplif*, human* * assist*, human* * augment*, human* * boost*, human* * collaborat*, human* * complement*, human* * enhanc*, human* * expand*, human* * extend*, human* * help*, human* * improv*, human* * increas*, human* * increment*, human* * interact*, human* * supplement*, human* * support*, human* amplif*, human* assist*, human* augment*, human* boost*, human* collaborat*, human* complement*, human* enhanc*, human* expand*, human* extend*, human* help*, human* improv*, human* increas*, human* increment*, human* interact*, human* supplement*, human* support*, improv* * *worker*, improv* * *workforce*, improv* * *workman*, improv* * employee*, improv* * human*, improv* * labor*, improv* * people*, improv* * person*, improv* * staff*, improv* *worker*, improv* *workforce*, improv* *workman*, improv* employee*, improv* human*, improv* labor*, improv* people*, improv* person*, improv* staff*, increas* * *worker*, increas* * *workforce*, increas* * *workman*, increas* * employee*, increas* * human*, increas* * labor*, increas* * people*, increas* * person*, increas* * staff*, increas* *worker*, increas* *workforce*, increas* *workman*, increas* employee*, increas* human*, increas* labor*, increas* people*, increas* person*, increas* staff*, increment* * *worker*, increment* * *workforce*, increment* * *workman*, increment* * employee*, increment* * human*, increment* * labor*, increment* * people*, increment* * person*, increment* * staff*, increment* *worker*, increment* *workforce*, increment* *workman*, increment* employee*, increment* human*, increment* labor*, increment* people*, increment* person*, increment* staff*, insights*, interact* * *worker*, interact* * *workforce*, interact* * *workman*,

interact* * employee*, interact* * human*, interact* * labor*, interact* * people*, interact* * person*, interact* * staff*, interact* *worker*, interact* *workforce*, interact* *workman*, interact* employee*, interact* human*, interact* labor*, interact* people*, interact* person*, interact* staff*, labor* * amplif*, labor* * assist*, labor* * augment*, labor* * boost*, labor* * collaborat*, labor* * complement*, labor* * enhanc*, labor* * expand*, labor* * extend*, labor* * help*, labor* * improv*, labor* * increas*, labor* * increment*, labor* * interact*, labor* * supplement*, labor* * support*, labor* amplif*, labor* assist*, labor* augment*, labor* boost*, labor* collaborat*, labor* complement*, labor* enhanc*, labor* expand*, labor* extend*, labor* help*, labor* improv*, labor* increas*, labor* increment*, labor* interact*, labor* supplement*, labor* support*, people* * amplif*, people* * assist*, people* * augment*, people* * boost*, people* * collaborat*, people* * complement*, people* * enhanc*, people* * expand*, people* * extend*, people* * help*, people* * improv*, people* * increas*, people* * increment*, people* * interact*, people* * supplement*, people* * support*, people* amplif*, people* assist*, people* augment*, people* boost*, people* collaborat*, people* complement*, people* enhanc*, people* expand*, people* extend*, people* help*, people* improv*, people* increas*, people* increment*, people* interact*, people* supplement*, people* support*, person* * amplif*, person* * assist*, person* * augment*, person* * boost*, person* * collaborat*, person* * complement*, person* * enhanc*, person* * expand*, person* * extend*, person* * help*, person* * improv*, person* * increas*, person* * increment*, person* * interact*, person* * supplement*, person* * support*, person* amplif*, person* assist*, person* augment*, person* boost*, person* collaborat*, person* complement*, person* enhanc*, person* expand*, person* extend*, person* help*, person* improv*, person* increas*, person* increment*, person* interact*, person* supplement*, person* support*, staff* * amplif*, staff* * assist*, staff* * augment*, staff* * boost*, staff* * collaborat*, staff* * complement*, staff* * enhanc*, staff* * expand*, staff* * extend*, staff* * help*, staff* * improv*, staff* * increas*, staff* * increment*, staff* * interact*, staff* * supplement*, staff* * support*, staff* amplif*, staff* assist*, staff* augment*, staff* boost*, staff* collaborat*, staff* complement*, staff* enhanc*, staff* expand*, staff* extend*, staff* help*, staff* improv*, staff* increas*, staff* increment*, staff* interact*, staff* supplement*, staff* support*, supplement* * *worker*, supplement* * *workforce*, supplement* * *workman*, supplement* * employee*, supplement* * human*, supplement* * labor*, supplement* * people*, supplement* * person*, supplement* * staff*, supplement* *worker*, supplement* *workforce*, supplement* *workman*, supplement* employee*, supplement* human*, supplement* labor*, supplement* people*, supplement* person*, supplement* staff*, support* * *worker*, support* * *workforce*, support* * *workman*, support* * employee*, support* * human*, support* * labor*, support* * people*, support* * person*, support* * staff*, support* *worker*, support* *workforce*, support* *workman*, support* employee*, support* human*, support* labor*, support* people*, support* person*, support* staff*, work* * *worker*, work* * *workforce*, work* * *workman*, work* * employee*, work* * human*, work* * labor*, work* * people*, work* * person*, work* * staff*, *worker* * amplif*, *worker* * assist*, *worker* * augment*, *worker* * boost*, *worker* * collaborat*, *worker* * complement*, *worker* * enhanc*, *worker* * expand*, *worker* * extend*, *worker* * help*, *worker* * improv*, *worker* * increas*, *worker* * increment*, *worker* * interact*, *worker* * supplement*, *worker* * support*, *worker* amplif*, *worker* assist*, *worker* augment*, *worker* boost*, *worker* collaborat*, *worker* complement*, *worker* enhanc*, *worker* expand*, *worker* extend*, *worker* help*, *worker* improv*, *worker* increas*, *worker* increment*, *worker* interact*, *worker* supplement*, *worker* support*, *workforce* * amplif*, *workforce* * assist*, *workforce* * augment*, *workforce* * boost*, *workforce* * collaborat*, *workforce* * complement*, *workforce* * enhanc*, *workforce* * expand*, *workforce* * extend*, *workforce* * help*, *workforce* * improv*, *workforce* * increas*, *workforce* * increment*, *workforce* * interact*, *workforce* * supplement*, *workforce* * support*, *workforce* amplif*, *workforce* assist*, *workforce* augment*, *workforce* boost*, *workforce* collaborat*, *workforce* complement*, *workforce* enhanc*, *workforce* expand*, *workforce* extend*, *workforce* help*, *workforce* improv*, *workforce* increas*, *workforce* increment*, *workforce* interact*, *workforce* supplement*, *workforce* support*, *workman* * amplif*, *workman* * assist*, *workman* * augment*, *workman* * boost*, *workman* * collaborat*, *workman* * complement*, *workman* * enhanc*, *workman* * expand*, *workman* * extend*, *workman* * help*, *workman* * improv*, *workman* * increas*, *workman* * increment*, *workman* * interact*, *workman* * supplement*, *workman* * support*, *workman* amplif*, *workman* assist*, *workman* augment*, *workman* boost*, *workman* collaborat*, *workman* complement*, *workman* enhanc*, *workman* expand*, *workman* extend*, *workman* help*, *workman* improv*, *workman* increas*, *workman* increment*, *workman* interact*, *workman* supplement*, *workman* support*

Automation: automate, automated, automatic, automation, autonomous, ax* * *worker*, ax* * *workforce*, ax* * *workman*, ax* * employee*, ax* * human*, ax* * labor*, ax* * people*, ax* * person*, ax* * staff*, ax* *worker*, ax* *workforce*, ax* *workman*, ax* employee*, ax* human*, ax* labor*, ax* people*, ax* person*, ax* staff*, computerized, discharg* * *worker*, discharg* * *workforce*, discharg* * *workman*, discharg* * employee*, discharg* * human*, discharg* * labor*, discharg* * people*, discharg* * person*, discharg* * staff*, discharg* *worker*, discharg* *workforce*, discharg* *workman*, discharg* employee*, discharg* human*, discharg* labor*, discharg* people*, discharg* person*, discharg* staff*, discontinu* * *worker*, discontinu* * *workforce*, discontinu* * *workman*, discontinu* * employee*, discontinu* * human*, discontinu* * labor*, discontinu* * people*, discontinu* * person*, discontinu* * staff*, discontinu* *worker*, discontinu* *workforce*, discontinu* *workman*, discontinu* employee*, discontinu* human*, discontinu* labor*, discontinu* people*, discontinu* person*, discontinu* staff*, dismiss* * *worker*, dismiss* * *workforce*, dismiss* * *workman*, dismiss* * employee*, dismiss* * human*, dismiss* * labor*, dismiss* * people*, dismiss* * person*, dismiss* * staff*, dismiss* *worker*, dismiss* *workforce*, dismiss* *workman*, dismiss* employee*, dismiss* human*, dismiss* labor*, dismiss* people*, dismiss* person*, dismiss* staff*, displac* * *worker*, displac* * *workforce*, displac* * *workman*, displac* * employee*, displac* * human*, displac* * labor*, displac* * people*, displac* * person*, displac* * staff*, displac* *worker*, displac* *workforce*, displac* *workman*, displac* employee*, displac* human*, displac* labor*, displac* people*, displac* person*, displac* staff*, dissolv* * *worker*, dissolv* * *workforce*, dissolv* * *workman*, dissolv* * employee*, dissolv* * human*, dissolv* * labor*, dissolv* * people*, dissolv* * person*, dissolv* * staff*, dissolv* *worker*, dissolv* *workforce*, dissolv* *workman*, dissolv* employee*, dissolv* human*, dissolv* labor*, dissolv* people*, dissolv* person*, dissolv* staff*, downsiz* * *worker*, downsiz* * *workforce*, downsiz* * *workman*, downsiz* * employee*, downsiz* * human*, downsiz* * labor*, downsiz* * people*, downsiz* * person*, downsiz* * staff*, downsiz* *worker*, downsiz* *workforce*, downsiz* *workman*, downsiz* employee*, downsiz* human*, downsiz* labor*, downsiz* people*, downsiz* person*, downsiz* staff*, efficien*, employee* * ax*, employee* * discharg*, employee* * discontinu*, employee* * dismiss*, employee* * displac*, employee* * dissolv*, employee* * downsiz*, employee* * fire*, employee* * firing, employee* * free*, employee* * furlough*, employee* * laid, employee* * laid-off, employee* * lay*, employee* * lay-off, employee* * layoff, employee* * oust*, employee* * reduc*, employee* * releas*, employee* * replac*, employee* * retir*, employee* * sack*, employee* * substitut*, employee* * suspend*, employee* * take over, employee* * take-over, employee* * terminat*, employee* * unemploy*, employee* ax*, employee* discharg*, employee* discontinu*, employee* dismiss*, employee* displac*, employee* dissolv*, employee* downsiz*, employee* fire*, employee* firing, employee* free*, employee* furlough*, employee* laid, employee* laid-off, employee* lay*, employee* lay-off, employee* layoff, employee* oust*, employee* reduc*, employee* releas*, employee* replac*, employee* retir*, employee* sack*, employee* substitut*, employee* suspend*, employee* tak* over, employee* take-over, employee* terminat*, employee* unemploy*, fire* * *worker*, fire* * *workforce*, fire* * *workman*, fire* * employee*, fire* * human*, fire* * labor*, fire* * people*, fire* * person*, fire* * staff*, fire* *worker*, fire* *workforce*, fire* *workman*, fire* employee*, fire* human*, fire* labor*, fire* people*, fire* person*, fire* staff*, firing * *worker*, firing * *workforce*, firing * *workman*, firing * employee*, firing * human*, firing * labor*, firing * people*, firing * person*, firing * staff*, firing *worker*, firing *workforce*, firing *workman*, firing employee*, firing human*, firing labor*, firing people*, firing person*, firing staff*, free* * *worker*, free* * *workforce*, free* * *workman*, free* * employee*, free* * human*, free* * labor*, free* * people*, free* * person*, free* * staff*, free* *worker*, free* *workforce*, free* *workman*, free* employee*, free* human*, free* labor*, free* people*, free* person*, free* staff*, furlough* * *worker*, furlough* * *workforce*, furlough* * *workman*, furlough* * employee*, furlough* * human*, furlough* * labor*, furlough* * people*, furlough* * person*, furlough* * staff*, furlough* *worker*, furlough* *workforce*, furlough* *workman*, furlough* employee*, furlough* human*, furlough* labor*, furlough* people*, furlough* person*, furlough* staff*, human* * ax*, human* * discharg*, human* * discontinu*, human* * dismiss*, human* * displac*, human* * dissolv*, human* * downsiz*, human* * fire*, human* * firing, human* * free*, human* * furlough*, human* * laid, human* * laid-off, human* * lay*, human* * lay-off, human* * layoff, human* * oust*, human* * reduc*, human* * releas*, human* * replac*, human* * retir*, human* * sack*, human* * substitut*, human* * suspend*, human* * take over, human* * take-over, human* * terminat*, human* * unemploy*, human* ax*, human* discharg*, human* discontinu*, human* dismiss*, human* displac*, human* dissolv*, human* downsiz*, human* fire*, human* firing, human* free*, human* furlough*, human* laid, human* laid-off, human* lay*, human* lay-off, human* layoff, human* oust*, human* reduc*, human* releas*, human* replac*, human* retir*, human* sack*, human* substitut*, human* suspend*, human* tak* over, human* take-over, human* terminat*, human* unemploy*, labor* * ax*, labor* * discharg*, labor* * discontinu*, labor* * dismiss*, labor* * displac*, labor* * dissolv*, labor* * downsiz*, labor* * fire*, labor* * firing, labor* * free*, labor* * furlough*, labor* * laid, labor* * laid-off, labor* * lay*, labor* * lay-off, labor* * layoff, labor* * oust*, labor* * reduc*, labor* * releas*, labor* * replac*, labor* * retir*, labor* * sack*, labor* * substitut*, labor* * suspend*, labor* * take over, labor* * take-over, labor* * terminat*, labor* * unemploy*, labor* ax*, labor* discharg*, labor* discontinu*, labor* dismiss*, labor* displac*, labor* dissolv*, labor* downsiz*, labor* fire*, labor* firing, labor* free*, labor* furlough*, labor* laid, labor* laid-off, labor* lay*, labor* lay-off, labor* layoff, labor* oust*, labor* reduc*, labor* releas*, labor* replac*, labor* retir*, labor* sack*, labor* substitut*, labor* suspend*, labor* tak* over, labor* take-over, labor* terminat*, labor* unemploy*, laid * *worker*, laid * *workforce*, laid * *workman*, laid * employee*, laid * human*, laid * labor*, laid * people*, laid * person*, laid * staff*, laid *worker*, laid *workforce*, laid *workman*, laid employee*, laid human*, laid labor*, laid people*, laid person*, laid staff*, laid-off * *worker*, laid-off * *workforce*, laid-off * *workman*, laid-off * employee*, laid-off * human*, laid-off * labor*, laid-off * people*, laid-off * person*, laid-off * staff*, laid-off *worker*, laid-off *workforce*, laid-off *workman*, laid-off employee*, laid-off human*, laid-off labor*, laid-off people*, laid-off person*, laid-off staff*, lay* * *worker*, lay* * *workforce*, lay* * *workman*, lay* * employee*, lay* * human*, lay* * labor*, lay* * people*, lay* * person*, lay* * staff*, lay* *worker*, lay* *workforce*, lay* *workman*, lay* employee*, lay* human*, lay* labor*, lay* people*, lay* person*, lay* staff*, lay-off * *worker*, lay-off * *workforce*, lay-off * *workman*, lay-off * employee*, lay-off * human*, lay-off * labor*, lay-off * people*, lay-off * person*, lay-off * staff*, lay-off *worker*, lay-off *workforce*, lay-off *workman*, lay-off employee*, lay-off human*, lay-off labor*, lay-off people*, lay-off person*, lay-off staff*, layoff * *worker*, layoff * *workforce*, layoff * *workman*, layoff * employee*, layoff * human*, layoff * labor*, layoff * people*, layoff * person*, layoff * staff*, layoff *worker*, layoff *workforce*, layoff *workman*, layoff employee*, layoff human*, layoff labor*, layoff people*, layoff person*, layoff staff*, mechanical, motorized, nonmanual, optimiz*, oust* * *worker*, oust* * *workforce*, oust* * *workman*, oust* * employee*, oust* * human*, oust* * labor*, oust* * people*, oust* * person*, oust* * staff*, oust* *worker*, oust* *workforce*, oust* *workman*, oust* employee*, oust* human*, oust* labor*, oust* people*, oust* person*, oust* staff*, people* * ax*, people* * discharg*, people* * discontinu*, people* * dismiss*, people* * displac*, people* * dissolv*, people* * downsiz*, people* * fire*, people* * firing, people* * free*, people* * furlough*, people* * laid, people* * laid-off, people* * lay*, people* * lay-off, people* * layoff, people* * oust*, people* * reduc*, people* * releas*, people* * replac*, people* * retir*, people* * sack*, people* * substitut*, people* * suspend*, people* * take over, people* * take-over, people* * terminat*, people* * unemploy*, people* ax*, people* discharg*, people* discontinu*, people* dismiss*, people* displac*, people* dissolv*, people* downsiz*, people* fire*, people* firing, people* free*, people* furlough*, people* laid, people* laid-off, people* lay*, people* lay-off, people* layoff, people* oust*, people* reduc*, people* releas*, people* replac*, people* retir*, people* sack*, people* substitut*, people* suspend*, people* tak* over, people* take-over, people* terminat*, people* unemploy*, person* * ax*, person* * discharg*, person* * discontinu*, person* * dismiss*, person* * displac*, person* * dissolv*, person* * downsiz*, person* * fire*, person* * firing, person* * free*, person* * furlough*, person* * laid, person* * laid-off, person* * lay*, person* * lay-off, person* * layoff, person* * oust*, person* * reduc*, person* * releas*, person* * replac*, person* * retir*, person* * sack*, person* * substitut*, person* * suspend*, person* * take over, person* * take-over, person* * terminat*, person* * unemploy*, person* ax*, person* discharg*, person* discontinu*, person* dismiss*, person* displac*, person* dissolv*, person* downsiz*, person* fire*, person* firing, person* free*, person* furlough*, person* laid, person* laid-off, person* lay*, person* lay-off, person* layoff, person* oust*, person* reduc*, person* releas*, person* replac*, person* retir*, person* sack*, person* substitut*, person* suspend*, person* tak* over, person* take-over, person* terminat*, person* unemploy*, reduc* * *worker*, reduc* * *workforce*, reduc* * *workman*, reduc* * employee*, reduc* * human*, reduc* * labor*, reduc* * people*, reduc* * person*, reduc* * staff*, reduc* *worker*, reduc* *workforce*, reduc* *workman*, reduc* employee*, reduc* human*, reduc* labor*, reduc* people*, reduc* person*, reduc* staff*, releas* * *worker*, releas* * *workforce*, releas* * *workman*, releas* * employee*, releas* * human*, releas* * labor*, releas* * people*, releas* * person*, releas* * staff*, releas* *worker*, releas* *workforce*, releas* *workman*, releas* employee*, releas* human*, releas* labor*, releas* people*, releas* person*, releas* staff*, replac* * *worker*, replac* * *workforce*, replac* * *workman*, replac* * employee*, replac* * human*, replac* * labor*, replac* * people*, replac* * person*, replac* * staff*, replac* *worker*, replac* *workforce*, replac* *workman*, replac* employee*, replac* human*, replac* labor*, replac* people*, replac* person*, replac* staff*, retir* * *worker*, retir* * *workforce*, retir* * *workman*, retir* * employee*, retir* * human*, retir* * labor*, retir* * people*, retir* * person*, retir* * staff*, retir* *worker*, retir* *workforce*, retir* *workman*, retir* employee*, retir* human*, retir* labor*, retir* people*, retir* person*, retir* staff*, robot*, rules-based, sack* * *worker*, sack* * *workforce*, sack* * *workman*, sack* * employee*, sack* * human*, sack* * labor*, sack* * people*, sack* * person*, sack* * staff*, sack* *worker*, sack* *workforce*, sack* *workman*, sack* employee*, sack* human*, sack* labor*, sack* people*, sack* person*, sack* staff*, self-acting, self-operate, self-operating, self-regulate, self-regulating, semi-automatic, staff* * ax*, staff* * discharg*, staff* * discontinu*, staff* * dismiss*, staff* * displac*, staff* * dissolv*, staff* * downsiz*, staff* * fire*, staff* * firing, staff* * free*, staff* * furlough*, staff* * laid, staff* * laid-off, staff* * lay*, staff* * lay-off, staff* * layoff, staff* * oust*, staff* * reduc*, staff* * releas*, staff* * replac*, staff* * retir*, staff* * sack*, staff* * substitut*, staff* * suspend*, staff* * take over, staff* * take-over, staff* * terminat*, staff* * unemploy*, staff* ax*, staff* discharg*, staff* discontinu*, staff* dismiss*, staff* displac*, staff* dissolv*, staff* downsiz*, staff* fire*, staff* firing, staff* free*, staff* furlough*, staff* laid, staff* laid-off, staff* lay*, staff* lay-off, staff* layoff, staff* oust*, staff* reduc*, staff* releas*, staff* replac*, staff* retir*, staff* sack*, staff* substitut*, staff* suspend*, staff* tak* over, staff* take-over, staff* terminat*, staff* unemploy*, structured, substitut* * *worker*, substitut* * *workforce*, substitut* * *workman*, substitut* * employee*, substitut* * human*, substitut* * labor*, substitut* * people*, substitut* * person*, substitut* * staff*, substitut* *worker*, substitut* *workforce*, substitut* *workman*, substitut* employee*, substitut* human*, substitut* labor*, substitut* people*, substitut* person*, substitut* staff*, suspend* * *worker*, suspend* * *workforce*, suspend* * *workman*, suspend* * employee*, suspend* * human*, suspend* * labor*, suspend* * people*, suspend* * person*, suspend* * staff*, suspend* *worker*, suspend* *workforce*, suspend* *workman*, suspend* employee*, suspend* human*, suspend* labor*, suspend* people*, suspend* person*, suspend* staff*, tak* over, tak* over *worker*, tak* over *workforce*, tak* over *workman*, tak* over employee*, tak* over human*, tak* over labor*, tak* over people*, tak* over person*, tak* over staff*, take over * *worker*, take over * *workforce*, take over * *workman*, take over * employee*, take over * human*, take over * labor*, take over * people*, take over * person*, take over * staff*, take-over, take-over * *worker*, take-over * *workforce*, take-over * *workman*, take-over * employee*, take-over * human*, take-over * labor*, take-over * people*, take-over * person*, take-over * staff*, take-over *worker*, take-over *workforce*, take-over *workman*, take-over employee*, take-over human*, take-over labor*, take-over people*, take-over person*, take-over staff*, terminat* * *worker*, terminat* * *workforce*, terminat* * *workman*, terminat* * employee*, terminat* * human*, terminat* * labor*, terminat* * people*, terminat* * person*, terminat* * staff*, terminat* *worker*, terminat* *workforce*, terminat* *workman*, terminat* employee*, terminat* human*, terminat* labor*, terminat* people*, terminat* person*, terminat* staff*, unemploy* * *worker*, unemploy* * *workforce*, unemploy* * *workman*, unemploy* * employee*, unemploy* * human*, unemploy* * labor*, unemploy* * people*, unemploy* * person*, unemploy* * staff*, unemploy* *worker*, unemploy* *workforce*, unemploy* *workman*, unemploy* employee*, unemploy* human*, unemploy* labor*, unemploy* people*, unemploy* person*, unemploy* staff*, *worker* * ax*, *worker* * discharg*, *worker* * discontinu*, *worker* * dismiss*, *worker* * displac*, *worker* * dissolv*, *worker* * downsiz*, *worker* * fire*, *worker* * firing, *worker* * free*, *worker* * furlough*, *worker* * laid, *worker* * laid-off, *worker* * lay*, *worker* * lay-off, *worker* * layoff, *worker* * oust*, *worker* * reduc*, *worker* * releas*, *worker* * replac*, *worker* * retir*, *worker* * sack*, *worker* * substitut*, *worker* * suspend*, *worker* * take over, *worker* * take-over, *worker* * terminat*, *worker* * unemploy*, *worker* ax*, *worker* discharg*, *worker* discontinu*, *worker* dismiss*, *worker* displac*, *worker* dissolv*, *worker* downsiz*, *worker* fire*, *worker* firing, *worker* free*, *worker* furlough*, *worker* laid, *worker* laid-off, *worker* lay*, *worker* lay-off, *worker* layoff, *worker* oust*, *worker* reduc*, *worker* releas*, *worker* replac*, *worker* retir*, *worker* sack*, *worker* substitut*, *worker* suspend*, *worker* tak* over, *worker* take-over, *worker* terminat*, *worker* unemploy*, *workforce* * ax*, *workforce* * discharg*, *workforce* * discontinu*, *workforce* * dismiss*, *workforce* * displac*, *workforce* * dissolv*, *workforce* * downsiz*, *workforce* * fire*, *workforce* * firing, *workforce* * free*, *workforce* * furlough*, *workforce* * laid, *workforce* * laid-off, *workforce* * lay*, *workforce* * lay-off, *workforce* * layoff, *workforce* * oust*, *workforce* * reduc*, *workforce* * releas*, *workforce* * replac*, *workforce* * retir*, *workforce* * sack*, *workforce* * substitut*, *workforce* * suspend*, *workforce* * take over, *workforce* * take-over, *workforce* * terminat*, *workforce* * unemploy*, *workforce* ax*, *workforce* discharg*, *workforce* discontinu*, *workforce* dismiss*, *workforce* displac*, *workforce* dissolv*, *workforce* downsiz*, *workforce* fire*, *workforce* firing, *workforce* free*, *workforce* furlough*, *workforce* laid, *workforce* laid-off, *workforce* lay*, *workforce* lay-off, *workforce* layoff, *workforce* oust*, *workforce* reduc*, *workforce* releas*, *workforce* replac*, *workforce* retir*, *workforce* sack*, *workforce* substitut*, *workforce* suspend*, *workforce* tak* over, *workforce* take-over, *workforce* terminat*, *workforce* unemploy*, *workman* * ax*, *workman* * discharg*, *workman* * discontinu*, *workman* * dismiss*, *workman* * displac*, *workman* * dissolv*, *workman* * downsiz*, *workman* * fire*, *workman* * firing, *workman* * free*, *workman* * furlough*, *workman* * laid, *workman* * laid-off, *workman* * lay*, *workman* * lay-off, *workman* * layoff, *workman* * oust*, *workman* * reduc*, *workman* * releas*, *workman* * replac*, *workman* * retir*, *workman* * sack*, *workman* * substitut*, *workman* * suspend*, *workman* * take over, *workman* * take-over, *workman* * terminat*, *workman* * unemploy*, *workman* ax*, *workman* discharg*, *workman* discontinu*, *workman* dismiss*, *workman* displac*, *workman* dissolv*, *workman* downsiz*, *workman* fire*, *workman* firing, *workman* free*, *workman* furlough*, *workman* laid, *workman* laid-off, *workman* lay*, *workman* lay-off, *workman* layoff, *workman* oust*, *workman* reduc*, *workman* releas*, *workman* replac*, *workman* retir*, *workman* sack*, *workman* substitut*, *workman* suspend*, *workman* tak* over, *workman* take-over, *workman* terminat*, *workman* unemploy*

Appendix 4. Measures of Automation and Augmentation using AI Announcement

Below, we provide as an example a snippet of an AI investment announcement by HSBC bank listed in New York Stock Exchange under the ticker symbol HSBC.[23]

> *"With Pepper at HSBC Bank's flagship retail branch, we're marking several noteworthy firsts: Pepper's first deployment at a retail bank in the United States, Pepper's first opportunity to help customers in New York City, and the first time a* <u>*robot will be engaging in conversational interactions with banking customers*</u>*, said Steve Carlin, Chief Strategy Officer, SBRA. Humanoid robots* <u>*helping people and working alongside human coworkers*</u> *is an idea no longer relegated to the realm of popular culture and science fiction. Pepper will bring real benefits to HSBC banking customers."*

We use LIWC to measure nature of AI investment (automation and augmentation). In the above snippet of an AI announcement, total number of sentences are 3. The underlined phrase of the first sentence mentions use of a robot in helping customers. This sentence signifies automating conversations with customers through the use of robots and belongs to the list of keywords in automation (see Appendix 3). The underlined phrase of the second sentence mentions helping people and working alongside coworkers. This sentence signifies the use of robots in augmentation and belongs to the list of words in augmentation (see Appendix 3). The third sentence does not signify use of AI neither in automation or augmentation and there is no word in the snippet of an announcement shown that belongs to automation or augmentation list of keywords (shown in Appendix 3). Thus, the measure of the nature of AI investment in automation computed by LIWC is: *1/3 = 0.33*, and the measure of the nature of AI investment in augmentation computed by LIWC is: *1/3 = 0.33*, in this part of the announcement.

[23] For space limitations, we provide a snippet of an AI investment announcement made by HSBC bank in June 2018 as mentioned in Lexis-Nexis. Text mining was done on the entire announcement.

Appendix 5. Keywords about Potential Consequences from AI Investment

Hiring: appoint* * *worker*, appoint* * *workforce*, appoint* * *workman*, appoint* * employee*, appoint* * human*, appoint* * labor*, appoint* * people*, appoint* * person*, appoint* * staff*, appoint* *worker*, appoint* *workforce*, appoint* *workman*, appoint* employee*, appoint* human*, appoint* labor*, appoint* people*, appoint* person*, appoint* staff*, contract* * *worker*, contract* * *workforce*, contract* * *workman*, contract* * employee*, contract* * human*, contract* * labor*, contract* * people*, contract* * person*, contract* * staff*, contract* *worker*, contract* *workforce*, contract* *workman*, contract* employee*, contract* human*, contract* labor*, contract* people*, contract* person*, contract* staff*, draft* * *worker*, draft* * *workforce*, draft* * *workman*, draft* * employee*, draft* * human*, draft* * labor*, draft* * people*, draft* * person*, draft* * staff*, draft* *worker*, draft* *workforce*, draft* *workman*, draft* employee*, draft* human*, draft* labor*, draft* people*, draft* person*, draft* staff*, employ*, employ* * *worker*, employ* * *workforce*, employ* * *workman*, employ* * employee*, employ* * human*, employ* * labor*, employ* * people*, employ* * person*, employ* * staff*, employ* *worker*, employ* *workforce*, employ* *workman*, employ* employee*, employ* human*, employ* labor*, employ* people*, employ* person*, employ* staff*, employee* * appoint*, employee* * contract*, employee* * draft*, employee* * employ*, employee* * enlist*, employee* * enroll*, employee* * fetch*, employee* * headhunt*, employee* * hire*, employee* * hiring, employee* * leas*, employee* * procur*, employee* * recruit*, employee* appoint*, employee* contract*, employee* draft*, employee* employ*, employee* enlist*, employee* enroll*, employee* fetch*, employee* headhunt*, employee* hire*, employee* hiring, employee* leas*, employee* procur*, employee* recruit*, enlist*, enlist* * *worker*, enlist* * *workforce*, enlist* * *workman*, enlist* * employee*, enlist* * human*, enlist* * labor*, enlist* * people*, enlist* * person*, enlist* * staff*, enlist* *worker*, enlist* *workforce*, enlist* *workman*, enlist* employee*, enlist* human*, enlist* labor*, enlist* people*, enlist* person*, enlist* staff*, enroll*, enroll* * *worker*, enroll* * *workforce*, enroll* * *workman*, enroll* * employee*, enroll* * human*, enroll* * labor*, enroll* * people*, enroll* * person*, enroll* * staff*, enroll* *worker*, enroll* *workforce*, enroll* *workman*, enroll* employee*, enroll* human*, enroll* labor*, enroll* people*, enroll* person*, enroll* staff*, fetch* * *worker*, fetch* * *workforce*, fetch* * *workman*, fetch* * employee*, fetch* * human*, fetch* * labor*, fetch* * people*, fetch* * person*, fetch* * staff*, fetch* *worker*, fetch* *workforce*, fetch* *workman*, fetch* employee*, fetch* human*, fetch* labor*, fetch* people*, fetch* person*, fetch* staff*, headhunt*, headhunt* * *worker*, headhunt* * *workforce*, headhunt* * *workman*, headhunt* * employee*, headhunt* * human*, headhunt* * labor*, headhunt* * people*, headhunt* * person*, headhunt* * staff*, headhunt* *worker*, headhunt* *workforce*, headhunt* *workman*, headhunt* employee*, headhunt* human*, headhunt* labor*, headhunt* people*, headhunt* person*, headhunt* staff*, hire*, hire* * *worker*, hire* * *workforce*, hire* * *workman*, hire* * employee*, hire* * human*, hire* * labor*, hire* * people*, hire* * person*, hire* * staff*, hire* *worker*, hire* *workforce*, hire* *workman*, hire* employee*, hire* human*, hire* labor*, hire* people*, hire* person*, hire* staff*, hiring, hiring * *worker*, hiring * *workforce*, hiring * *workman*, hiring * employee*, hiring * human*, hiring * labor*, hiring * people*, hiring * person*, hiring * staff*, hiring *worker*, hiring *workforce*, hiring *workman*, hiring employee*, hiring human*, hiring labor*, hiring people*, hiring person*, hiring staff*, human* * appoint*, human* * contract*, human* * draft*, human* * employ*, human* * enlist*, human* * enroll*, human* * fetch*, human* * headhunt*, human*

* hire*, human* * hiring, human* * leas*, human* * procur*, human* * recruit*, human* appoint*, human* contract*, human* draft*, human* employ*, human* enlist*, human* enroll*, human* fetch*, human* headhunt*, human* hire*, human* hiring, human* leas*, human* procur*, human* recruit*, labor* * appoint*, labor* * contract*, labor* * draft*, labor* * employ*, labor* * enlist*, labor* * enroll*, labor* * fetch*, labor* * headhunt*, labor* * hire*, labor* * hiring, labor* * leas*, labor* * procur*, labor* * recruit*, labor* appoint*, labor* contract*, labor* draft*, labor* employ*, labor* enlist*, labor* enroll*, labor* fetch*, labor* headhunt*, labor* hire*, labor* hiring, labor* leas*, labor* procur*, labor* recruit*, leas* * *worker*, leas* * *workforce*, leas* * *workman*, leas* * employee*, leas* * human*, leas* * labor*, leas* * people*, leas* * person*, leas* * staff*, leas* *worker*, leas* *workforce*, leas* *workman*, leas* employee*, leas* human*, leas* labor*, leas* people*, leas* person*, leas* staff*, people* * appoint*, people* * contract*, people* * draft*, people* * employ*, people* * enlist*, people* * enroll*, people* * fetch*, people* * headhunt*, people* * hire*, people* * hiring, people* * leas*, people* * procur*, people* * recruit*, people* appoint*, people* contract*, people* draft*, people* employ*, people* enlist*, people* enroll*, people* fetch*, people* headhunt*, people* hire*, people* hiring, people* leas*, people* procur*, people* recruit*, person* * appoint*, person* * contract*, person* * draft*, person* * employ*, person* * enlist*, person* * enroll*, person* * fetch*, person* * headhunt*, person* * hire*, person* * hiring, person* * leas*, person* * procur*, person* * recruit*, person* appoint*, person* contract*, person* draft*, person* employ*, person* enlist*, person* enroll*, person* fetch*, person* headhunt*, person* hire*, person* hiring, person* leas*, person* procur*, person* recruit*, procur* * *worker*, procur* * *workforce*, procur* * *workman*, procur* * employee*, procur* * human*, procur* * labor*, procur* * people*, procur* * person*, procur*

* staff*, procur* *worker*, procur* *workforce*, procur* *workman*, procur* employee*, procur* human*, procur* labor*, procur* people*, procur* person*, procur* staff*, recruit*, recruit* * *worker*, recruit* * *workforce*, recruit* * *workman*, recruit* * employee*, recruit* * human*, recruit* * labor*, recruit* * people*, recruit* * person*, recruit* * staff*, recruit* *worker*, recruit* *workforce*, recruit* *workman*, recruit* employee*, recruit* human*, recruit* labor*, recruit* people*, recruit* person*, recruit* staff*, staff* * appoint*, staff* * contract*, staff* * draft*, staff* * employ*, staff* * enlist*, staff* * enroll*, staff* * fetch*, staff* * headhunt*, staff* * hire*, staff* * hiring, staff* * leas*, staff* * procur*, staff* * recruit*, staff* appoint*, staff* contract*, staff* draft*, staff* employ*, staff* enlist*, staff* enroll*, staff* fetch*, staff* headhunt*, staff* hire*, staff* hiring, staff* leas*, staff* procur*, staff* recruit*, *worker* * appoint*, *worker* * contract*, *worker* * draft*, *worker* * employ*, *worker* * enlist*, *worker* * enroll*, *worker* * fetch*, *worker* * headhunt*, *worker* * hire*, *worker* * hiring, *worker* * leas*, *worker* * procur*, *worker* * recruit*, *worker* appoint*, *worker* contract*, *worker* draft*, *worker* employ*, *worker* enlist*, *worker* enroll*, *worker* fetch*, *worker* headhunt*, *worker* hire*, *worker* hiring, *worker* leas*, *worker* procur*, *worker* recruit*, *workforce* * appoint*, *workforce* * contract*, *workforce* * draft*, *workforce* * employ*, *workforce* * enlist*, *workforce* * enroll*, *workforce* * fetch*, *workforce* * headhunt*, *workforce* * hire*, *workforce* * hiring, *workforce* * leas*, *workforce* * procur*, *workforce* * recruit*, *workforce* appoint*, *workforce* contract*, *workforce* draft*, *workforce* employ*, *workforce* enlist*, *workforce* enroll*, *workforce* fetch*, *workforce* headhunt*, *workforce* hire*, *workforce* hiring, *workforce* leas*, *workforce* procur*, *workforce* recruit*, *workman* * appoint*, *workman* * contract*, *workman* * draft*, *workman* *

employ*, *workman* * enlist*, *workman* * enroll*, *workman* * fetch*, *workman* * headhunt*, *workman* * hire*, *workman* * hiring, *workman* * leas*, *workman* * procur*, *workman* * recruit*, *workman* appoint*, *workman* contract*, *workman* draft*, *workman* employ*, *workman* enlist*, *workman* enroll*, *workman* fetch*, *workman* headhunt*, *workman* hire*, *workman* hiring, *workman* leas*, *workman* procur*, *workman* recruit*

Layoffs: ax* * *worker*, ax* * *workforce*, ax* * *workman*, ax* * employee*, ax* * human*, ax* * labor*, ax* * people*, ax* * person*, ax* * staff*, ax* *worker*, ax* *workforce*, ax* *workman*, ax* employee*, ax* human*, ax* labor*, ax* people*, ax* person*, ax* staff*, axe, axed, axing, discharg*, discharg* * *worker*, discharg* * *workforce*, discharg* * *workman*, discharg* * employee*, discharg* * human*, discharg* * labor*, discharg* * people*, discharg* * person*, discharg* * staff*, discharg* *worker*, discharg* *workforce*, discharg* *workman*, discharg* employee*, discharg* human*, discharg* labor*, discharg* people*, discharg* person*, discharg* staff*, discontinu* * *worker*, discontinu* * *workforce*, discontinu* * *workman*, discontinu* * employee*, discontinu* * human*, discontinu* * labor*, discontinu* * people*, discontinu* * person*, discontinu* * staff*, discontinu* *worker*, discontinu* *workforce*, discontinu* *workman*, discontinu* employee*, discontinu* human*, discontinu* labor*, discontinu* people*, discontinu* person*, discontinu* staff*, dismiss* * *worker*, dismiss* * *workforce*, dismiss* * *workman*, dismiss* * employee*, dismiss* * human*, dismiss* * labor*, dismiss* * people*, dismiss* * person*, dismiss* * staff*, dismiss* *worker*, dismiss* *workforce*, dismiss* *workman*, dismiss* employee*, dismiss* human*, dismiss* labor*, dismiss* people*, dismiss* person*, dismiss* staff*, displac* * *worker*, displac* * *workforce*, displac* * *workman*, displac* * employee*, displac* * human*, displac* * labor*, displac* * people*, displac* * person*, displac* * staff*, displac* *worker*, displac* *workforce*, displac* *workman*, displac* employee*, displac* human*, displac* labor*, displac* people*, displac* person*, displac* staff*, dissolv* * *worker*, dissolv* * *workforce*, dissolv* * *workman*, dissolv* * employee*, dissolv* * human*, dissolv* * labor*, dissolv* * people*, dissolv* * person*, dissolv* * staff*, dissolv* *worker*, dissolv* *workforce*, dissolv* *workman*, dissolv* employee*, dissolv* human*, dissolv* labor*, dissolv* people*, dissolv* person*, dissolv* staff*, downsiz*, downsiz* * *worker*, downsiz* * *workforce*, downsiz* * *workman*, downsiz* * employee*, downsiz* * human*, downsiz* * labor*, downsiz* * people*, downsiz* * person*, downsiz* * staff*, downsiz* *worker*, downsiz* *workforce*, downsiz* *workman*, downsiz* employee*, downsiz* human*, downsiz* labor*, downsiz* people*, downsiz* person*, downsiz* staff*, employee* * ax*, employee* * discharg*, employee* * discontinu*, employee* * dismiss*, employee* * displac*, employee* * dissolv*, employee* * downsiz*, employee* * fire*, employee* * firing, employee* * furlough, employee* * jobless*, employee* * laid-off, employee* * lay* off, employee* * lay-off, employee* * layoff, employee* * oust*, employee* * reduc*, employee* * releas*, employee* * retir*, employee* * sack*, employee* * suspend*, employee* * tak* over, employee* * take-over, employee* * terminat*, employee* * unemploy*, employee* ax*, employee* discharg*, employee* discontinu*, employee* dismiss*, employee* displac*, employee* dissolv*, employee* downsiz*, employee* fire*, employee* firing, employee* furlough, employee* jobless*, employee* laid-off, employee* lay* off, employee* lay-off, employee* layoff, employee* oust*, employee* reduc*, employee* releas*, employee* retir*, employee* sack*, employee* suspend*, employee* tak* over, employee* take-over, employee* terminat*, employee* unemploy*, fire* * *worker*, fire* * *workforce*, fire* * *workman*, fire* * employee*, fire* * human*, fire* * labor*, fire* * people*, fire* * person*, fire* * staff*, fire* *worker*, fire* *workforce*, fire* *workman*, fire* employee*, fire* human*, fire* labor*, fire* people*, fire* person*, fire* staff*, firing * *worker*, firing * *workforce*, firing * *workman*, firing * employee*, firing * human*, firing * labor*, firing * people*, firing * person*, firing * staff*, firing *worker*, firing *workforce*, firing *workman*, firing employee*, firing human*, firing labor*, firing people*, firing person*, firing staff*, furlough, furlough * *worker*, furlough * *workforce*, furlough * *workman*, furlough * employee*, furlough * human*, furlough * labor*, furlough * people*, furlough * person*, furlough * staff*, furlough *worker*, furlough *workforce*, furlough *workman*, furlough employee*, furlough human*, furlough labor*, furlough people*, furlough person*, furlough staff*, human* * ax*, human* * discharg*, human* * discontinu*, human* * dismiss*, human* * displac*, human* * dissolv*, human* * downsiz*, human* * fire*, human* * firing, human* * furlough, human* * jobless*, human* * laid-off, human* * lay* off, human* * lay-off, human* * layoff, human* * oust*, human* * reduc*, human* * releas*, human* * retir*, human* * sack*, human* * suspend*, human* * tak* over, human* * take-over, human* * terminat*, human* * unemploy*, human* ax*, human* discharg*, human* discontinu*, human* dismiss*, human* displac*, human* dissolv*, human* downsiz*, human* fire*, human* firing, human* furlough, human* jobless*, human* laid-off, human* lay* off, human* lay-off, human* layoff, human* oust*, human* reduc*, human* releas*, human* retir*, human* sack*, human* suspend*, human* tak* over, human* take-over, human* terminat*, human* unemploy*, jobless*, jobless* * *worker*, jobless* * *workforce*, jobless* * *workman*, jobless* * employee*, jobless* * human*, jobless* * labor*, jobless* * people*, jobless* * person*, jobless* * staff*, jobless* *worker*, jobless* *workforce*, jobless* *workman*, jobless* employee*, jobless* human*, jobless* labor*, jobless* people*, jobless* person*, jobless* staff*, labor* * ax*, labor* * discharg*, labor* * discontinu*, labor* * dismiss*, labor* * displac*, labor* * dissolv*, labor* * downsiz*, labor* * fire*, labor* * firing, labor* * furlough, labor* * jobless*, labor* * laid-off, labor* * lay* off, labor* * lay-off, labor* * layoff, labor* * oust*, labor* * reduc*, labor* * releas*, labor* * retir*, labor* * sack*, labor* * suspend*, labor* * tak* over, labor* * take-over, labor* * terminat*, labor* * unemploy*, labor* ax*, labor* discharg*, labor* discontinu*, labor* dismiss*, labor* displac*, labor* dissolv*, labor* downsiz*, labor* fire*, labor* firing, labor* furlough, labor* jobless*, labor* laid-off, labor* lay* off, labor* lay-off, labor* layoff, labor* oust*, labor* reduc*, labor* releas*, labor* retir*, labor* sack*, labor* suspend*, labor* tak* over, labor* take-over, labor* terminat*, labor* unemploy*, laid-off, laid-off * *worker*, laid-off * *workforce*, laid-off * *workman*, laid-off * employee*, laid-off * human*, laid-off * labor*, laid-off * people*, laid-off * person*, laid-off * staff*, laid-off *worker*, laid-off *workforce*, laid-off *workman*, laid-off employee*, laid-off human*, laid-off labor*, laid-off people*, laid-off person*, laid-off staff*, lay off, lay* off * *worker*, lay* off * *workforce*, lay* off * *workman*, lay* off * employee*, lay* off * human*, lay* off * labor*, lay* off * people*, lay* off * person*, lay* off * staff*, lay* off *worker*, lay* off *workforce*, lay* off *workman*, lay* off employee*, lay* off human*, lay* off labor*, lay* off people*, lay* off person*, lay* off staff*, lay-off, lay-off * *worker*, lay-off * *workforce*, lay-off * *workman*, lay-off * employee*, lay-off * human*, lay-off * labor*, lay-off * people*, lay-off * person*, lay-off * staff*, lay-off *worker*, lay-off *workforce*, lay-off *workman*, lay-off employee*, lay-off human*, lay-off labor*, lay-off people*, lay-off person*, lay-off staff*, layoff, layoff * *worker*, layoff * *workforce*, layoff * *workman*, layoff * employee*, layoff

* human*, layoff * labor*, layoff * people*, layoff * person*, layoff * staff*, layoff *worker*, layoff *workforce*, layoff *workman*, layoff employee*, layoff human*, layoff labor*, layoff people*, layoff person*, layoff staff*, oust*, oust* * *worker*, oust* * *workforce*, oust* * *workman*, oust* * employee*, oust* * human*, oust* * labor*, oust* * people*, oust* * person*, oust* * staff*, oust* *worker*, oust* *workforce*, oust* *workman*, oust* employee*, oust* human*, oust* labor*, oust* people*, oust* person*, oust* staff*, people* * ax*, people* * discharg*, people* * discontinu*, people* * dismiss*, people* * displac* , people* * dissolv*, people* * downsiz*, people* * fire*, people* * firing, people* * furlough, people* * jobless*, people* * laid-off, people* * lay* off, people* * lay-off, people* * layoff, people* * oust*, people* * reduc*, people* * releas*, people* * retir*, people* * sack*, people* * suspend*, people* * tak* over, people* * take-over, people* * terminat*, people* * unemploy*, people* ax*, people* discharg*, people* discontinu*, people* dismiss*, people* displac*, people* dissolv*, people* downsiz*, people* fire*, people* firing, people* furlough, people* jobless*, people* laid-off, people* lay* off, people* lay-off, people* layoff, people* oust*, people* reduc*, people* releas*, people* retir*, people* sack*, people* suspend*, people* tak* over, people* take-over, people* terminat*, people* unemploy*, person* * ax*, person* * discharg*, person* * discontinu*, person* * dismiss*, person* * displac*, person* * dissolv*, person* * downsiz*, person* * fire*, person* * firing, person* * furlough, person* * jobless*, person* * laid-off, person* * lay* off, person* * lay-off, person* * layoff, person* * oust*, person* * reduc*, person* * releas*, person* * retir*, person* * sack*, person* * suspend*, person* * tak* over, person* * take-over, person* * terminat*, person* * unemploy*, person* ax*, person* discharg*, person* discontinu*, person* dismiss*, person* displac*, person* dissolv*, person* downsiz*, person* fire*, person* firing, person* furlough, person*

jobless*, person* laid-off, person* lay* off, person* lay-off, person* layoff, person* oust*, person* reduc*, person* releas*, person* retir*, person* sack*, person* suspend*, person* tak* over, person* take-over, person* terminat*, person* unemploy*, reduc* * *worker*, reduc* * *workforce*, reduc* * *workman*, reduc* * employee*, reduc* * human*, reduc* * labor*, reduc* * people*, reduc* * person*, reduc* * staff*, reduc* *worker*, reduc* *workforce*, reduc* *workman*, reduc* employee*, reduc* human*, reduc* labor*, reduc* people*, reduc* person*, reduc* staff*, releas* * *worker*, releas* * *workforce*, releas* * *workman*, releas* * employee*, releas* * human*, releas* * labor*, releas* * people*, releas* * person*, releas* * staff*, releas* *worker*, releas* *workforce*, releas* *workman*, releas* employee*, releas* human*, releas* labor*, releas* people*, releas* person*, releas* staff*, retir* * *worker*, retir* * *workforce*, retir* * *workman*, retir* * employee*, retir* * human*, retir* * labor*, retir* * people*, retir* * person*, retir* * staff*, retir* *worker*, retir* *workforce*, retir* *workman*, retir* employee*, retir* human*, retir* labor*, retir* people*, retir* person*, retir* staff*, sack* * *worker*, sack* * *workforce*, sack* * *workman*, sack* * employee*, sack* * human*, sack* * labor*, sack* * people*, sack* * person*, sack* * staff*, sack* *worker*, sack* *workforce*, sack* *workman*, sack* employee*, sack* human*, sack* labor*, sack* people*, sack* person*, sack* staff*, staff* * ax*, staff* * discharg*, staff* * discontinu*, staff* * dismiss*, staff* * displac*, staff* * dissolv*, staff* * downsiz*, staff* * fire*, staff* * firing, staff* * furlough, staff* * jobless*, staff* * laid-off, staff* * lay* off, staff* * lay-off, staff* * layoff, staff* * oust*, staff* * reduc*, staff* * releas*, staff* * retir*, staff* * sack*, staff* * suspend*, staff* * tak* over, staff* * take-over, staff* * terminat*, staff* * unemploy*, staff* ax*, staff* discharg*, staff* discontinu*, staff* dismiss*, staff* displac*, staff* dissolv*, staff* downsiz*, staff* fire*, staff* firing, staff* furlough, staff* jobless*, staff* laid-off, staff* lay* off, staff* lay-off, staff* layoff, staff* oust*, staff* reduc*, staff* releas*, staff* retir*, staff* sack*, staff* suspend*, staff* tak* over, staff* take-over, staff* terminat*, staff* unemploy*, suspend* * *worker*, suspend* * *workforce*, suspend* * *workman*, suspend* * employee*, suspend* * human*, suspend* * labor*, suspend* * people*, suspend* * person*, suspend* * staff*, suspend* *worker*, suspend* *workforce*, suspend* *workman*, suspend* employee*, suspend* human*, suspend* labor*, suspend* people*, suspend* person*, suspend* staff*, tak* over, tak* over * *worker*, tak* over * *workforce*, tak* over * *workman*, tak* over * employee*, tak* over * human*, tak* over * labor*, tak* over * people*, tak* over * person*, tak* over * staff*, tak* over *worker*, tak* over *workforce*, tak* over *workman*, tak* over employee*, tak* over human*, tak* over labor*, tak* over people*, tak* over person*, tak* over staff*, take-over, take-over * *worker*, take-over * *workforce*, take-over * *workman*, take-over * employee*, take-over * human*, take-over * labor*, take-over * people*, take-over * person*, take-over * staff*, take-over *worker*, take-over *workforce*, take-over *workman*, take-over employee*, take-over human*, take-over labor*, take-over people*, take-over person*, take-over staff*, terminat* * *worker*, terminat* * *workforce*, terminat* * *workman*, terminat* * employee*, terminat* * human*, terminat* * labor*, terminat* * people*, terminat* * person*, terminat* * staff*, terminat* *worker*, terminat* *workforce*, terminat* *workman*, terminat* employee*, terminat* human*, terminat* labor*, terminat* people*, terminat* person*, terminat* staff*, unemploy*, unemploy* * *worker*, unemploy* * *workforce*, unemploy* * *workman*, unemploy* * employee*, unemploy* * human*, unemploy* * labor*, unemploy* * people*, unemploy* * person*, unemploy* * staff*, unemploy* *worker*, unemploy* *workforce*, unemploy* *workman*, unemploy* employee*, unemploy* human*, unemploy* labor*, unemploy* people*, unemploy* person*, unemploy* staff*, *worker* * ax*, *worker* * discharg*, *worker* * discontinu*, *worker* * dismiss*, *worker* * displac*, *worker* * dissolv*, *worker* * downsiz*, *worker* * fire*, *worker* * firing, *worker* * furlough, *worker* * jobless*, *worker* * laid-off, *worker* * lay* off, *worker* * lay-off, *worker* * layoff, *worker* * oust*, *worker* * reduc*, *worker* * releas*, *worker* * retir*, *worker* * sack*, *worker* * suspend*, *worker* * tak* over, *worker* * take-over, *worker* * terminat*, *worker* * unemploy*, *worker* ax*, *worker* discharg*, *worker* discontinu*, *worker* dismiss*, *worker* displac*, *worker* dissolv*, *worker* downsiz*, *worker* fire*, *worker* firing, *worker* furlough, *worker* jobless*, *worker* laid-off, *worker* lay* off, *worker* lay-off, *worker* layoff, *worker* oust*, *worker* reduc*, *worker* releas*, *worker* retir*, *worker* sack*, *worker* suspend*, *worker* tak* over, *worker* take-over, *worker* terminat*, *worker* unemploy*, *workforce* * ax*, *workforce* * discharg*, *workforce* * discontinu*, *workforce* * dismiss*, *workforce* * displac*, *workforce* * dissolv*, *workforce* * downsiz*, *workforce* * fire*, *workforce* * firing, *workforce* * furlough, *workforce* * jobless*, *workforce* * laid-off, *workforce* * lay* off, *workforce* * lay-off, *workforce* * layoff, *workforce* * oust*, *workforce* * reduc*, *workforce* * releas*, *workforce* * retir*, *workforce* * sack*, *workforce* * suspend*, *workforce* * tak* over, *workforce* * take-over, *workforce* * terminat*, *workforce* * unemploy*, *workforce* ax*, *workforce* discharg*, *workforce* discontinu*, *workforce* dismiss*, *workforce* displac*, *workforce* dissolv*, *workforce* downsiz*, *workforce* fire*, *workforce* firing, *workforce* furlough, *workforce* jobless*, *workforce* laid-off, *workforce* lay* off, *workforce* lay-off, *workforce* layoff, *workforce* oust*, *workforce* reduc*, *workforce* releas*, *workforce* retir*, *workforce* sack*, *workforce* suspend*, *workforce* tak* over, *workforce* take-over, *workforce* terminat*, *workforce* unemploy*, *workman* * ax*, *workman* * discharg*, *workman* * discontinu*, *workman* * dismiss*, *workman* * displac*, *workman* * dissolv*, *workman* * downsiz*, *workman* * fire*, *workman* * firing, *workman* * furlough, *workman* * jobless*, *workman* * laid-off, *workman* * lay* off, *workman* * lay-off, *workman* * layoff, *workman* * oust*, *workman* * reduc*, *workman* * releas*, *workman* * retir*, *workman* * sack*, *workman* * suspend*, *workman* * tak* over, *workman* * take-over, *workman* * terminat*, *workman* * unemploy*, *workman* ax*, *workman* discharg*, *workman* discontinu*, *workman* dismiss*, *workman* displac*, *workman* dissolv*, *workman* downsiz*, *workman* fire*, *workman* firing, *workman* furlough, *workman* jobless*, *workman* laid-off, *workman* lay* off, *workman* lay-off, *workman* layoff, *workman* oust*, *workman* reduc*, *workman* releas*, *workman* retir*, *workman* sack*, *workman* suspend*, *workman* tak* over, *workman* take-over, *workman* terminat*, *workman* unemploy*

Ethics: accountab*, autonom*, bias*, blackbox, breach, concern*, control, discrimin*, distrust, divers*, emancipa*, explain*, fair*, fraud*, hide, hiding, honest*, identity, inaccura*, inclusiv*, inequalit*, issue*, lies, mistrust, opacity, opaque, privacy, racial, racis*, responsib*, safe*, secure, security, transpare*, trust*, truth*, unauthori*, unequal

Appendix 6. Computation of Potential Consequences from AI Investment using Tweets

LIWC 2022 provides the scores on hiring, layoffs, and ethics categories as a percentage of total words in a text. It creates a tone category that depicts the degree of positive or negative tone in the text. A custom dictionary was created using keywords associated with hiring, layoffs, and ethics. The custom dictionary was installed in the LIWC software. LIWC was then run on all the tweets belonging to the sample set of firms within the period [-10d, +10d]. Below, we show the computation for the measures used in the study, where i = firm, d = day of the tweet, t = tweet, N = total number of tweets, wc = total words in a tweet, hiring = proportion of hiring related keywords as percentage of total words in a tweet, layoff = proportion of layoff related keywords as percentage of total words in a tweet, ethics = proportion of ethics related keywords as percentage of total words in a tweet, and tone = degree of positive tone or negative tone present in a tweet:

$$\text{Optimism about Hiring}_i = \frac{\sum_{d=-10}^{d=+10} \sum_{t=1}^{t=\mathbb{N}} (\text{wc X hiring X positive tone})_{i\,dt}}{\sum_{d=-10}^{d=+10} \sum_{t=1}^{t=\mathbb{N}} (\text{wc})_{i\,dt}}$$

We provide as an example two tweets by the investors on the hiring from the company Talend and the company Unilever soon after they announced an AI investment.

Tweet#1: *"$TLND is hiring a Junior Software Developer in Automation (m/f)! Join #Teamtalend, be part of a."*

Tweet#2: *"$UL has been using #AI brain games for #hiring"*

In the first tweet on the company Talend (ticker symbol TLND), total word count = 16, number of words belonging to list of keywords on hiring (see Appendix 5) = 1, hiring score = 0.06 and degree of positive tone = 0.95 as computed by LIWC. In the second tweet on the company Unilever (ticker symbol UL), total word count = 9, number of words belonging to list of keywords on hiring (see Appendix 5) = 1, hiring score = 0.11 and degree of positive tone = 0.20 as computed by LIWC. Therefore the overall optimism about hiring score for these two example tweets is:

[(16 X 0.06 X 0.95) + (9 X 0.11 X 0.20)]/[16+9] = 0.04

We provide as an example two tweets by the investors on the layoffs from the company Accenture and the company United Airlines soon after they announced an AI investment.

Tweet#1: *"$ACN layoff all their salesreps!!!"*

Tweet#2: *"$UAL to reduce workforce by 2,100 thru voluntary furlough offer. #airline"*

$$\text{Concerns about Layoff}_{i} = \frac{\sum_{d=-10}^{d=+10} \sum_{t=1}^{t=\mathbb{N}} (\text{wc X layoff X negative tone})_{i\,dt}}{\sum_{d=-10}^{d=+10} \sum_{t=1}^{t=\mathbb{N}} (\text{wc})_{i\,dt}}$$

In the first tweet on the company Accenture (ticker symbol ACN), total word count = 5, number of words belonging to list of keywords on layoffs (see Appendix 5) = 1, layoff score = 0.2 and degree of negative tone = 0.79 as computed by LIWC. In the second tweet on the company United Airlines (ticker symbol UAL), total word count = 10, number of words belonging to list of keywords on layoffs (see Appendix 5) = 2, layoff score = 0.2 and degree of negative tone = 0.79 as computed by LIWC. Therefore the overall concern about layoffs score for these two example tweets is:

[(5 X 0.2 X 0.79) + (10 X 0.2 X 0.79)]/[5+10] = 0.16

We provide as an example two tweets by the investors on the ethical concerns related to the company Paypal and the company Western Union soon after they announced an AI investment.

Tweet#1: *"$PYPL This is to bring to the notice of the general public that PAYPAL is a racist platform that frustrate non US citizens, this is the second time they are doing it to me the first time l was using it for my business making payments the moments l received fund they blocked me"*

Tweet#2: *“$WU Respond! Where is the transparency? I demand the right department to contact me NOW! I am fed up of #lies and #fraudulent statements”*

$$\text{Concerns about Ethics}_i = \frac{\sum_{d=-10}^{d=+10} \sum_{t=1}^{t=\mathbb{N}} (\text{wc X ethics X negative tone})_{i\,dt}}{\sum_{d=-10}^{d=+10} \sum_{t=1}^{t=\mathbb{N}} (\text{wc})_{i\,dt}}$$

In the first tweet on the company Paypal (ticker symbol PYPL), total word count = 54, number of words belonging to list of keywords on ethics (see Appendix 5) = 1, ethics score = 0.02 and degree of negative tone = 0.99 as computed by LIWC. In the second tweet on the company Western Union (ticker symbol WU), total word count = 24, number of words belonging to list of keywords on ethics (see Appendix 5) = 3, ethics score = 0.12 and degree of negative tone = 0.99 as computed by LIWC. Therefore the overall concern about ethics score for these two example tweets is:

[(54 X 0.02 X 0.99) + (24 X 0.12 X 0.99)]/[54+24] = 0.05

Chapter 3: Impact of Strategic AI Orientation on Firm Performance

> "What all of us have to do is to make sure we are using AI in a way that is for the benefit of humanity, not to the detriment of humanity." - Tim Cook, Chief Executive Officer, Apple (Forbes 2019).[24]

Introduction

Artificial Intelligence (AI) capabilities have been extensively used to support and enhance the quality of decision-making and problem-solving in different industries. The promise of fast, accurate, repeatable, and low-cost decisions, with quality approaching human-like intelligence, has been an essential driver of the rapid developments in AI (Agrawal et al. 2019). AI is ushering in a new era of digital transformation through adoption by organizations in various industries such as healthcare, finance, retail, government, education, and so on, to enable digital capabilities that create business value (McKinsey 2018). A recent survey of executives shows that big companies as well as small and mid-scale businesses leverage AI to improve their business operations (Galvin 2018). Artificial intelligence may be defined as follows:

> "Defined as technologies that leverage machine-based intelligence and advanced computing capacity to mimic human "cognitive" functions, AI goes beyond conventional technologies by approximating human cognitive functions to search, analyze, and make decisions based on large-scale data" (Li et al. 2021, p. 1603).

Thus, AI differs from other ITs as AI learns on its own and is dynamic (Huang et al. 2019). As organizations have been using other ITs to improve the efficiency of business processes and solve business problems, they are also leveraging the revolutionary AI capabilities that imitate human behavior. For example, Google uses AI to paint pictures.[25]

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[24] https://www.forbes.com/sites/nicolemartin1/2019/06/27/13-greatest-quotes-about-the-future-of-artificial-intelligence/?sh=14c3d75f3bdf

[25] https://www.wsj.com/articles/BL-DGB-45048

The business value of IT (BVIT) literature provides insights into the impact of new IT investments (e.g., Mithas et al. 2012; Rai et al. 1997; Sabherwal et al. 2019; Steelman et al. 2019), but has not yet examined the effects of AI investments. AI-based algorithms are used across a myriad of professions to help in decision-making – human resource management (e.g., hiring decisions),[26] transportation (e.g., self-driving vehicles (Chen et al. 2015)), banking (e.g., credit risk predictions (Pacelli and Azzollini 2011)), public administration (e.g., immigration services (Chun 2007)), and psychological counseling (e.g., therapeutic conversational agent (Skjuve and Brandtzæg 2018)). AI helps in making quick and low-cost decisions by finding patterns in large datasets (Raisch and Krakowski 2021). Firms' investment in AI can be viewed as making judicious use of scarce resources or venturing into new business areas. Though mostly applied in IS literature in terms of organizational learning, firms could strategically invest in AI either to explore new areas of business growth enabled through AI (Ransbotham et al. 2018) or to exploit resources to gain cost savings and efficiency.

AI can empower firms to undertake a range of strategic actions to create differential value. For example, a firm could automate its business processes to improve efficiency and employ a workforce in creative tasks (e.g., Walmart employs robots for floor scrubbing and use its workforce in other creative tasks such as inventory management) thereby exploiting the opportunities enabled through AI. Another way is to use AI in close collaboration with humans to augment human intelligence and foster product innovation (e.g., Symrise's perfumers work with AI to get insights on customer demographics and generate personalized fragrances (Daugherty and Wilson 2018, p. 67)), thereby exploring new ways of product offerings. These

[26] https://www.nytimes.com/2015/06/26/upshot/can-an-algorithm-hire-better-than-a-human.html

examples suggest different strategic actions to create business value with the adoption of AI. Against this backdrop, our first research question is:

RQ1. How does a firm's strategic AI orientation affect its performance?

AI is regarded as more of a capability than mere technology as AI is the need for the firms in the third wave of business transformation to reap the benefits by using AI capabilities in adaptive processes (Daugherty and Wilson 2018, p. 5; Davenport and Ronanki 2018). AI capabilities could have different effects. They could help firms in various ways, including decision-making (Garbuio and Lin 2019), customer engagement (Davenport and Ronanki 2018), and knowledge transfer (Metcalf 2019). These capabilities may require firms to employ different strategies (Daveport and Ronanki 2018) for the realization of objectives. IT can be used to reduce costs or increase revenues (Mithas and Rust 2016). Cost-focused IT strategy involves improving productivity and efficiency. On the contrary, a revenue-focused IT strategy helps firms to take a path of exploring new business ventures, and finding, or creating new products/services. Although BVIT literature has stressed the importance of IT strategic emphasis on firm performance (Leidner et al. 2011), little is known about how the effect of overall IT strategy moderates the relationship between a firm's strategic action resulting from investment in a particular IT, in our case it is AI, and firm performance. Thus, our next research question is:

RQ2. How does a firm's IT strategy moderate the effect of the firm's strategic AI orientation on its performance?

A firm's industry environment creates both opportunities and obstacles for it. In an environment characterized by unpredictability, and extensive competition, firms face difficulty in allocating resources (March 1991). A firm's strategic investment in AI could help in such difficult environmental conditions by enabling the firm to quickly leverage new knowledge through the analysis of the copious amount of data to reveal hidden patterns and also improve or gain efficiency and productivity (Shrestha et al. 2019). However, if the firm's strategic investment in AI does not conform with its overall IT strategy, a firm may lose the competitive edge it could have gained or sustained through the judicious use of unprecedented technology, such as AI that provides both efficiency gains and enables new business opportunities. In light of this, our last research question investigates the interplay between a firm's AI strategic orientation through exploration or exploitation and overall IT strategy in a dynamic environment on its performance. Accordingly, our last research question is:

> RQ3. How does the environment dynamism moderate the moderate effect mentioned in RQ2?

This study uses the theoretical lenses of exploration and exploitation (March 1991, pp. 72) and dynamic capabilities (Teece et al. 1997). Exploration and exploitation literature sheds light on the strategic action a firm takes to create differential value, while dynamic capabilities theory provides insights into the reconfiguration of internal processes in changing environment. Despite the promise of AI, a firm's strategic action could have a detrimental impact if its AI strategic orientation does not align with its IT strategy. The effect could be much worse in a competitive environment. Thus, the symbiosis of exploration and exploitation strategy perspective and dynamic capabilities theory provides us a good theoretical base to understand the impact of actions a firm employs through investment in AI capabilities on its performance. Using a sample set of companies that have invested in AI in the period between 2010-2020 and employing text mining methodologies, this study investigates the above research questions and sheds light on the implications for the firms investing in AI. The study also offers directions for further theoretical and empirical work on the performance implications of AI.

The rest of this chapter is organized as follows. The next section provides the theoretical foundations for the chapter. The subsequent sections develop the theoretical model followed by the description of the data, including the sample and the measures. A description of the analyses and results follows. The chapter concludes with a discussion of the emergent findings and their implications for future research and practice.

Theoretical Foundations

Exploration and Exploitation Strategies

In the context of organizational learning, March (1991) defines exploration activities using terms such as search, variation, risk-taking, experimentation, play, flexibility, discovery, and innovation, and exploitation activities using terms such as refinement, choice, production, efficiency, selection, implementation, and execution. Researchers have argued that exploration and exploitation draw on different structures, processes, and resources, generating different performance outcomes (March 1991; Uotila et al. 2009; Sturm et al. 2021).

By reducing variety, increasing efficiency, and improving adaptation to current environments, exploitation activities can improve positive short-term performance. But such short-term performance improvements might be at the expense of long-term performance as the reduced variety and adaptation to the environment become liabilities when environments change over time. Firms that emphasize exploitation activities might lack the ability to adapt to significant environmental changes, and thus the recipe that makes such firms succeed in the short-term might endanger their success in the long run.

By contrast, exploration-oriented activities help the firm to develop new knowledge and create those capabilities necessary for survival and long-term prosperity. However, exploration activities are uncertain in their payoffs, and performance effects usually occur in the long run. In a competitive environment where all firms are trying to exploit the opportunities to increase their market share, the payoffs from the innovation resulting from exploration may be short-lived if the firms do not configure their internal processes to align with the exploration-oriented activities (Levinthal and March 1993). Next, we discuss the theoretical foundation for the importance of the prudent use of IT resources in changing environment to create differential value.

Dynamic Capabilities Theory (DCT)

Dynamic capability is the firm's ability to adapt, integrate, and reconfigure internal and external organizational skills, resources, and functional competencies to match the requirements of a changing environment (Teece et al. 1997). The capabilities perspective focuses on the internal dynamics of the organizations. If a firm lacks dynamic capabilities, it can achieve performance gains for a short period, but cannot sustain them in the long-term due to external changes. In the IS domain, embedding IT in organizational capabilities is the source of significant and sustained competitive returns (Kohli and Grover 2008; Rai et al. 2006). In this respect, IT serves as one the means through which new organizational capabilities can be created or existing ones can be improved (Mikalef et al. 2020). Firms may possess good organizational capabilities, but to make a meaningful difference in operational excellence and competitive response, these capabilities should be enhanced by IT (Rai et al. 2006; El Sawy et al. 2010). Building on this reasoning, we define IT capabilities as representing the firm's abilities to leverage its IT resources and IT competencies in order to address rapidly changing business environments (Bharadwaj 2000; Mikalef and Pateli 2017).

IT capabilities help firms in building and sustaining competitive advantage (Bharadwaj 2000), shaping firms' processes (Bharadwaj et al. 2007), creating agility (Sambamurthy et al. 2003), assimilating and applying new knowledge (Sabherwal and Becerra 2005), developing new products (Pavlou and Sawy 2005), creating customer satisfaction (Setia et al. 2013), and so forth. IT capabilities along these dimensions have been studied in IS research to highlight the importance of capability building in enabling efficient and effective processes. Using IT to build organizational capabilities is a complex and carefully orchestrated process (Sambamurthy et al. 2003). Grover and Kohli (2012) stressed the importance of IT-enabled capabilities that help firms improve performance. Overall, so far capabilities perspective has highlighted the importance of dynamic, improvisational, and operational capabilities and how they help firms to gain competitive advantage (see Pavlou and Sawy 2010; Setia and Patel 2013; Teece et al. 1997). Next, we examine how the alignment between the firm's strategic investment in AI and its overall IT strategy helps in dynamic environments.

Firm's Strategic AI Orientation

Venkatraman (1985) defines strategic orientation of business enterprises as means for achieving the business goals. Chan et al. (1997) extended Venkatraman strategic orientation into IS field to conceptualize IS orientation strategy as "strategy evident in IS investments and IS deployments" (Chan et al. 1997, p. 126). Following Venkatraman (1985) and Chan et al. (1997), we conceptualize a firm's strategic AI orientation as its strategic investment in AI capabilities to achieve business goals. By investing in AI, firms develop new AI capabilities that help them in various ways for the realization of objectives – decision making, efficiency in processes, cost savings, knowledge transfer, and new product development (Daugherty and Wilson 2018). Research has shown the benefits of AI (Dale 2016) and its applicability in areas such as human resources (Tambe et al. 2019) for hiring, marketing (Kumar et al. 2019), providing customized solutions, decision making (Shrestha et al. 2019) by evaluating a large amount of data in quick time, knowledge pooling (Metcalf et al. 2019), and usefulness to patients in healthcare and to consumers (Deng et al. 2019; Garbuio and Lin 2019; Wright and Schultz 2018).

Firms strategically invest in AI to either explore new business opportunities resulting in the creation of new jobs (Lindzon 2017; Wilson et al. 2017) or exploit the opportunities enabled by AI to help improve the productivity of workers (Wright and Schultz 2018) and knowledge (Li et al. 2009). AI is believed to help businesses in three types of jobs: process automation – automation of administrative activities, cognitive insights – detection of patterns from vast volumes of data, and cognitive engagement – interaction with employees and customers (Davenport and Ronanki 2018). For example, Allianz, the Munich-based insurance agent, increased fraud detection by 50 percent after deploying AI-based models in production. The company is scaling AI in other business areas as well. In a survey of 3076 executives, many are optimistic about the value AI will bring to the firms. Eighty-two percent believed that AI would help improve productivity and create new jobs (Ransbotham et al. 2018. AI is helping firms with new business prospects (Clifford 2017).

Research has argued the need of having an optimal balance between exploitation and exploration (see March 1991). Firms that engage in exploration to the exclusion of exploitation are likely to find that they suffer the costs of experimentation without gaining many of its benefits. They exhibit too many undeveloped new ideas and too little distinctive competence. Conversely, firms that engage in exploitation to the exclusion of exploration are likely to find themselves trapped in suboptimal stable equilibria. As a result, maintaining an appropriate balance between exploration and exploitation is a primary factor in system survival and prosperity. Although research has provided insights on the optimal balance between firms' strategic actions, what is missing is the fact that firms may choose one of the two strategic actions that AI capabilities help firms to embark on depending on their overall IT strategy to reap the maximum benefits. Thus, this study aims to shed light on the quintessential aspect of the alignment between strategic investment in AI and a firm's overall IT strategy in changing environment. The next section develops the theoretical model for the paper.

Theoretical Development

AI can enhance productivity, change work processe, and create jobs (Rao 2017). Firms invest in AI to create differential value. AI capabilities help firms in the automation of activities (e.g., robots), providing insights from data analysis (fraud detection system), and engagement with customers (chatbots). AI capabilities have been helping firms to automate routine tasks in operations and logistics. Recent advances in computational power, the exponential increase in data, and new machine-learning techniques now allow organizations to also use AI capabilities for managerial tasks (Brynjolfsson and McAfee 2017). AI capabilities play important roles in providing out of the box solutions that were once considered beyond any IT to perform, such as Unilever's talent-acquisition process (Marr 2018), Netflix's decisions regarding movie plots, directors, and actors (Westcott Grant 2018), and Pfizer's drug discovery and development (Fleming 2018). Needless to say, AI is engendering an era of economic prosperity through the exploitation of scarcity of resources and exploration of new products/services (Davenport and Kirby 2016; Daugherty and Wilson 2018; Manyika et al. 2017). Organizations strategically invest in IT as some prefer cost savings to gain efficiency whereas others make IT the core of their business processes and extensively invest in IT for innovation and as a source of revenue. Therefore to reap maximum benefits, a firm's strategic investment in AI needs to conform with its overall IT strategy and this becomes more important in a dynamic and competitive environment. Against this backdrop, Figure 1 depicts the overall research model to investigate the research questions, and Table 1 mentions key constructs used in the research model.

---Insert Figure 1 about here---

---Insert Table 1 about here---

IT facilitates human action and influences the shape and nature of the organization (Leavitt and Whisler 1958). AI capabilities help firms through improved productivity and innovation (Raisch and Krakowski 2021) and customers with personalized services (Kumar et al. 2019). The fast and low-cost processing capabilities of AI have engendered economic transformation at an unprecedented rate bestowing upon firms improved efficiency and increased innovation (Manyika et al. 2017; Raisch and Krakowski 2021). In a survey of 3,076 business executives, a study by Ransbotham et al. (2018) reveals that management feels the need and the pressure to act quickly on the adoption of AI at a wider scale to reap the business value and opportunities AI creates. Chevron CIO Bill Braun reports using AI in various areas – diagnosing machinery performance to predicting maintenance needs to strengthening cybersecurity within the energy giant that is creating ample business value.

AI capabilities enable the analyses of copious amount of data and provide real-time insights to make quick decisions. AI is already helping organizations reduce costs by enabling the proper use of the resources (see Ransbotham et al. 2018, pp. 4-5). Firms improving productivity through AI are witnessing an increase in customer satisfaction, a decline in time to resolve queries, and improvements in financial performance (see Davenport and Ronanki 2018). The exploitation of opportunities enabled through AI is helping firms boost economic growth, prevent fraud, and gain real-time insights improving operational efficiency and cost savings.[27] AI can help firms exploit the scarcity of resources by outsourcing some of the tasks that could be done quickly by the machines and thereby use their human workforce in other complex tasks. For example, many

[27] https://www.cio.com/article/303688/artificial-intelligence-increases-efficiency-and-accuracy-for-financial-organizations.html#:~:text=The%20right%20technology%20can%20magnify,Dell%20EMC%20OpenManage%20Enterprise%20globally.

companies these days are employing chatbots to solve routine queries and engaging their human workforce in other complex tasks thereby making most of the available resources.

A study by Huang et al. (2019) shows that AI also enables new business opportunities. For example, Amazon started business as an online marketplace for books, but with the advent of AI, Amazon has created a niche market segment by providing consumers with an AI-enabled product in the form of Alexa that could be queried about the weather, stream news, and music on demand, and serves as a robotic assistant that responds to voice commands to control home lighting and much more. Organizations are trying to scale AI to gain a competitive advantage. For example, Allianz, a Munich-based insurance agent, after reaping benefits from AI solutions, has started to build more AI capabilities. Similarly, in Symrise, analysts make decisions on the personalized perfumes for the customers by getting help from AI that provide insights on customer demographics. Therefore, AI is helping firms to be exploratory and create a novel product/service offerings for the end customers bringing in new sources of revenue.

IT investments benefits do not occur spontaneously and the realization of accrual gains from IT investments takes time (Weill and Broadbent 1998), which suggests a time lag in obtaining benefits from IT investments (e.g., Brynjolfsson and Hitt 1998; Mithas et al. 2012). Consistent with prior literature that includes one-year time lags in examining the effects resulting from IT investments (see Aral and Weill 2007; Sabherwal et al. 2019), we incorporate one-year lagged effects. Thus, we posit:

> H1a: A firm's strategic AI exploitation orientation in year *t-1* is associated with higher firm performance in year *t*.
> H1b: A firm's strategic AI exploration orientation in year *t-1* is associated with higher firm performance in year *t*.

Moderating Effects of IT Strategies

IT strategy is known to impact firm performance as firms with more focused IT goals tend to generate greater payoffs from IT (see Tallon et al. 2000). Oh and Pinsonneault (2007) in their study on the strategic value of IT investigate the deployment of IT applications for cost reduction and revenue growth. They find that firms following a contingency approach benefit more from cost-focused applications whereas firms following a resource-centered perspective benefit more from revenue-focused applications. Mithas and Rust (2016) empirically investigate the interplay between IT Strategy and IT investments on firm performance. Although their work provides useful insights on the important role of IT strategy, their work lacks how different firms pursuing different strategic use of IT could create differential value. Against this backdrop, following Mithas and Rust (2016) conceptualization of IT strategy in terms of revenue focus and cost focus, our work aims to understand the implications of revenue focus and cost focus facets of IT strategy on the relationship between different strategic investments in AI on firm performance.

A firm's IT strategy is crucial for investment in IT because strategic posture shapes its IT governance and management of IT projects to create business value. To create differential value and competitive advantage, a firm need to reconfigure its internal processes (Teece et al. 1997). These changes in business processes and reengineering efforts are often shaped by the firm's overarching IT strategy (Barua et al. 1996; Kohli and Grover 2008). Choosing a particular strategy implies making some trade-offs (Hindo 2007)[28] - that is, choosing some goals and functionalities in the hope that the overall combination ensures a better fit and that fit becomes less replicable for competitors (Porter 1996). Accordingly, a firm often chose between revenue expansion or cost reduction in its overall IT strategy.

[28] https://www.effectuation.org/wp-content/uploads/2016/06/3m-struggle-between-efficiency-and-creativity.pdf

Firms focusing on revenue growth aim to create diverse assets portfolios to realize accelerated cash flows. These firms' overarching goal is improved customer relationship management processes and new product development and offerings. Revenue-focused IT strategy is more geared toward customer satisfaction and is mostly customer-oriented. It often involves attracting new customers or repeat sales to existing customers (Saldanha et al. 2016). The processes are deeply intertwined with customer relationship software to better understand the demographics of the customers to provide customized offerings resulting into increase revenues (Raisch and Krakowski 2021). For example, UPS uses its integrated supply chain systems to better serve its customers, thus realizing revenue opportunities (Kohli 2007). Firms' strategic investment in AI for exploration activities is characterized by novel offerings for the customers, innovation, and improved customer satisfaction. For example, firms focusing on revenue generation benefits more by deploying AI for innovation purposes than for efficiency gains (see Ransbotham et al. 2018). In another example, Symrise was able to provide customized perfumes to its customers by using AI for innovation purposes. Therefore, echoing the voice of prior research that the alignment between IT strategy and deployment of IT applications is a precursor for maximizing the payoffs from IT investment. In light of this, we posit:

> H2a: A firm's revenue-focused IT strategy in year *t-1* weakens the positive relationship between the firm's strategic AI exploitation orientation in year *t-1* and firm performance in year *t*.
> H2b: A firm's revenue-focused IT strategy in year *t-1* strengthens the positive relationship between the firm's strategic AI exploration orientation in year *t-1* and firm performance in year *t*.

Firms focusing on cost reduction aim to improve productivity and efficiency. Firms pursuing such a strategy tend to invest in ITs that could bring cost savings. For example, these firms use IT in their supply chain to reduce procurement costs and automate the business processes with an overall goal to reduce the search costs (Kohli 2007). Their IT strategy hinges on streamlining internal processes and getting rid of legacy applications that are costly to maintain. These firms do not believe in expanding the horizons and creating diverse avenues of revenue as managing heterogeneous sources would involve investment in new skills and hiring of additional managers and workforce. Firms pursuing cost-focused IT strategies restrain from managing diverse IT assets and investing in IT to lower costs. Firms strategic investments in AI for exploitation are mostly done to automate repetitive and replication tasks. Such investments are mostly helpful in gaining efficiency and resulting in low-cost solutions for organizations. This enables firms to exploit the scarcity of resources and divert the existing workforce to other complex tasks resulting in tasks with improved efficiency and productivity growth. On the contrary, firms with a cost-focused IT strategy investing in AI for exploration would create disharmony as exploration often requires further investments in IT, and firms incur additional expenses to create innovative offerings. Cost-focused IT strategy firms do not have a strategic goal of innovation and their main goal is to bring costs down. As previously noted, a firm's IT strategy needs to conform with its choices concerning the strategic investment in IT to reap maximum payoffs. Against this backdrop, we posit:

> H3a: A firm's cost-focused IT strategy in year *t-1* strengthens the positive relationship between the firm's strategic AI exploitation orientation in year *t-1* and firm performance in year *t*.
> H3b: A firm's cost-focused IT strategy in year *t-1* weakens the positive relationship between the firm's strategic AI exploration orientation in year *t-1* and firm performance in year *t*.

Moderating Effects of Environment Dynamism

IS research has stressed the importance of environmental dynamism as firms need to adapt to the changing environment to sustain competitive advantage and improve performance (Pavlou and El Sawy 2010). Environment dynamism is defined as "the rate and unpredictability of environmental change" (Newkirk and Lederer 2006, p. 394). It poses a challenge for the firm to adopt new tactics and policies quickly (Yayla and Hu 2012). Environmental dynamism requires firms to make quicker decisions. Firms could strategically invest in AI for exploration to engage in innovation, discovery, and creation of new knowledge. Exploration helps the firm with new knowledge and capabilities for survival in the changing environment. AI can be strategically invested in exploring new business avenues (Brock and Von Wangenheim 2019). For example, Allianz and Clariant scaling of AI operations in new business opportunities enabled through AI (see Ransbotham et al. 2018). AI investment for exploration purposes leads to the creation of new jobs and fostering of creativity (Wilson et al. 2017).

By contrast, exploitation activities include using resources wisely and refining existing processes by reducing variety and improving adaptation to the environment. Exploitation helps by reducing variety and enabling the firm to adapt to the changing environment. AI capabilities help firms in exploiting scarce resources, such as by using chatbots to engage with customers and using the human workforce in other key activities. For example, Walmart uses robots for floor scrubbing and employs its in-store employees for inventory management. Thus, firms can benefit from AI by either using it for cost savings through utilizing efficient use of existing resources or for revenue generation by exploring new opportunities through it (Ransbotham et al. 2018; Manyika et al. 2017). AI strategic orientation that is better aligned with the firm's overall IT strategy will help to more quickly firms respond to unpredictability. Firms would better use AI investment to deal with the dynamic environment and create new revenue sources through AI for exploration or save costs through AI for exploitation. Thus, we posit:

> H4a: Greater environment dynamism in year *t-1* enhances the weakening effect of the firm's revenue-focused IT strategy in year *t-1* on the positive relationship between the firm's strategic AI exploitation orientation in year *t-1* and firm performance in year *t*.
>
> H4b: Greater environment dynamism in year *t-1* enhances the strengthening effect of the firm's revenue-focused IT strategy in year *t-1* on the positive

relationship between the firm's strategic AI exploration orientation in year *t-1* and firm performance in year *t*.

H4c: Greater environment dynamism in year *t-1* enhances the strengthening effect of the firm's cost-focused IT strategy in year *t-1* on the positive relationship between the firm's strategic AI exploitation orientation in year *t-1* and firm performance in year *t*.

H4d: Greater environment dynamism in year *t-1* enhances the weakening effect of the firm's cost-focused IT strategy in year *t-1* on the positive relationship between the firm's strategic AI exploration orientation in year *t-1* and firm performance in year *t*.

Methods

Data

The study uses data on announcements by the U.S. publicly-traded firms on AI during 2010-2020, obtained from Lexis-Nexis. Appendix 1 provides the search string used for pulling the announcements from the PR Newswire and Business Wire sections of Lexis-Nexis. The search string was developed in a 4-step process: (1) the initial search string was developed using keywords related to AI; (2) a senior faculty and a junior faculty reviewed, and provided minor suggestions on the search string; (3) we revised the search string accordingly; (4) the same senior faculty and the junior faculty reviewed the revised search string again, and approved it. We then used the approved search string to extract AI investment announcements from Lexis-Nexis. This produced an initial set of 778 announcements. After text mining the announcement text using LIWC 2022 (v 1.0.0)[29] to identify the other ITs (Appendix 2 provides the list of keywords used for other ITs),[30] we excluded 141 announcements that mentioned another IT (e.g., cloud computing) in addition to AI in the same text. This is because the other ITs' strategic orientation for either exploration or exploitation would confound the effects of AI strategic orientation. This exclusion led to a sample of 637 firms who have only announced IT investments related to AI.

[29] https://www.liwc.app/

[30] This list was taken from https://www.kaggle.com/tahahavakhor/search-keywords-for-each-information-technology. Blockchain, Virtual Reality, and Augmented Reality ITs were added to the list.

Since IT investments take a longer time to reap benefits, we used one-year lagged effects to test hypotheses. To avoid confounding effects on the lagged firm performance from AI announcements that happen in consecutive years by the same firm, we removed such announcements from our sample. This resulted in the removal of 66 further announcements, providing with a final sample size of 571 AI investment announcements by 326 unique firms. Out of these 326 firms, 107 made multiple AI investment announcements in the same year, which we aggregated due to our focus on firm-year observations. This led to a total 464 firm-year observations related to AI investment belonging to 326 unique firms for the years 2010-2020. The next section discusses the measurement of study variables.

Measurement

Measures of the Firm Performance

We measure firm performance using Tobin's q ratio, which has been used to measure firm performance in studies on IT impacts (Bharadwaj et al. 1999; Mithas and Rust 2016; Sabherwal et al. 2019). Tobin's q incorporates a market-based measure of firm value, which is forward-looking, risk adjusted, and less vulnerable to changes in accounting practices, and is considered suitable for measuring the performance impact of IT investments (Chari et al. 2008). A Tobin's q value above one indicates that the long-run equilibrium market value of the firm is greater than the replacement value of its assets signifying an unmeasured source of value (Bharadwaj et al. 1999). We use the well-known Chung and Pruitt (1994) measure of Tobin's q ratio.[31]

Measures of Strategic AI Orientation

We measure the strategic AI exploitation and exploration orientation using LIWC 2022 (v 1.0.0). We created custom dictionaries for AI strategic orientation (exploitation and exploration),

[31] This ratio is computed as q = (Market value of equity + book value of inventories + liquidating value of preferred stock + long-term debt + net short-term debt)/Total assets.

and used them to text mine each entire AI announcement to measure exploitation and exploration. Each dictionary was developed in a 4-step process: (1) we developed the initial dictionaries based on prior literature (March 1991; Stettner and Lavie 2013; Sturm et al. 2021; Uotila et al. 2009); (2) a senior faculty reviewed, and provided minor suggestions on, the dictionaries; (3) we revised the dictionaries accordingly; (4) the same senior faculty reviewed the revised dictionaries (see Appendix 3), and after his approval, we used them to text mine the entire AI announcement made by the firm. We also manually coded the entire announcements to verify the reliability of the LIWC software. Two individuals – a doctoral candidate and a senior faculty – independently coded 10 randomly-selected announcements. The results of their coding were in complete agreement, and consistent with the LIWC measures in all cases, thus showing the reliability of the LIWC coding. Therefore, we proceeded to use the measures based on LIWC (shown in Table 2) for strategic AI orientation (exploitation and exploration).

Exploitation and exploration strategies for each entire AI announcement by the firm are computed as the ratio of the number of sentences in the entire AI announcement mentioning exploration and exploitation keywords (shown in Appendix 3), respectively, to the number of sentences in the entire AI announcement. Appendix 4 provides further details on the measurement of AI strategic orientation variables (exploitation and exploration). As mentioned above, we have 107 cases where a firm made multiple AI investment announcement in the same year. In such situations, the firm's exploration and exploitation strategy scores are computed as the weighted average (weighted by the length of each entire AI announcement in sentences) of the exploration and exploitation scores for each entire AI announcement that year by that firm, respectively.

Measures of IT Strategy

We measure the firm's IT strategy – revenue-focused and cost-focused using LIWC 2022 (v 1.0.0). We created custom dictionaries for (a) the keywords for revenue and cost (shown in Appendix 5); and (b) the keywords for ITs (including AI (Appendix 6) and other ITs (Appendix 2)). We then measured revenue-focused and cost-focused IT strategies by using the pairwise combinations of IT keywords and the keywords for the focal strategy (e.g., we used pairwise combinations of all keywords for ITs with all keywords for cost in searching for "cost-focused IT strategy") to text mine the entire firm's annual reports (i.e., Forms 10-K and 10-KSB). Each dictionary was developed using the 4-step process noted above for coding AI announcements, starting with initial dictionaries based on prior literature: for revenue and cost related keywords – Mithas and Rust 2016; Mittal et al. 2005; Rust et al. 2002; for AI related keywords – Alekseeva et al. 2020; Brynjolfsson and Mcafee 2017; Daugherty and Wilson 2018; Davenport and Kirby 2016; Lacity and Willcocks 2018; and for other ITs (Havakhor et al. 2022).[32]

We then measured IT strategy variables (revenue-focused and cost-focused) as shown in Table 2. Revenue-focused and cost-focused IT strategy scores for a firm are computed as the ratios of the number of sentences in the entire annual report mentioning revenue-focused IT strategy (i.e., pairwise combinations of revenue keywords and all IT keywords) and cost-focused IT (i.e., pairwise combinations of cost keywords and all IT keywords), respectively, to the number of sentences in the entire annual report mentioning all ITs (including AI keywords as

[32] This list was taken from https://www.kaggle.com/tahahavakhor/search-keywords-for-each-information-technology. Blockchain, Virtual Reality, and Augmented Reality ITs were added to the list. We add "information technolog*," "telecommunication," "computer system*," "digital," "web," and "online" (from Steelman et al. 2019, p. 210), and "information system*," "computer*," and "internet" to the list of other ITs (shown in Appendix 2) before creating pairwise combinations with revenue and cost focused keywords.

shown in Appendix 6 and keywords as mentioned in the footnote #35). Appendix 7 provides further details on the measurement of IT strategy variables (revenue-focused and cost-focused).

Measures of Environment Dynamism

Following prior literature (Keats and Hitt 1988; Xue et al. 2011), we measure environment dynamism by quantifying the volatility of industry sales using COMPUSTAT. For each firm, we regress the natural log of total sales of the four-digit SIC industry code to which a firm belongs against an index variable of years, for a period of five years (t-1, t-5), where *t* is the year of examining the firm performance. We then use the antilog of the standard error of the regression coefficient to measure sales volatility as a proxy for a firm's environment dynamism.

Measures of Control Variables

We control for environment complexity and environment hostility. We measure environment complexity as the reciprocal of industry concentration. Following Xue et al. (2011), we use the log value of the reciprocal of the industry Herfindahl index (i.e., the sum of the squares of the market shares of the four firms with the highest sales in the industry) to measure complexity. We measure environment hostility based on the growth in industry's sales (Keats and Hitt 1988; Xue et al. 2011). To do so, we regress the natural log of total sales of the four-digit SIC industry code to which the firm belongs against an index variable of years, for a period of five years (t-1, t-4), where *t* is the year of examining the firm performance. We then use the reciprocal of the antilog of the regression coefficient to measure hostility.

We control for investment in other ITs for exploitation and exploration (refer Appendix 2) by the firms in our sample set for the year *t-1* and year *t*, where *t* is the year of examining firm performance. We use LIWC 2022 (v 1.0.0), with custom dictionaries for exploitation and exploration (summarized in Appendix 3) based on the relevant literature (March 1991; Uotila et al. 2009). We use these custom dictionaries to text mine the entire announcement text to measure exploitation and exploration using LIWC. Exploitation and exploration strategy scores for each other ITs announcement made by the firm are computed as the ratio of the number of sentences in the entire other ITs announcement mentioning exploration and exploitation keywords (shown in Appendix 3), respectively, to the number of sentences in the entire other ITs announcement. In our sample set, all the firms made multiple other ITs announcements over the year. Thus, the firm's exploration and exploitation strategy scores for other ITs are computed as the weighted average (weighted by the length of each entire other ITs announcement in sentences) of the exploration and exploitation scores for each entire other ITs announcement that year by that firm, respectively.

We also control for emphasis on AI and emphasis on other ITs. We measure these using LIWC 2022 (v 1.0.0). We use custom dictionaries for – (1) AI-related keywords (shown in Appendix 6) based on the relevant literature (Alekseeva et al. 2020; Brynjolfsson and Mcafee 2017; Daugherty and Wilson 2018; Davenport and Kirby 2016; Lacity and Willcocks 2018), and (2) Other ITs (shown in Appendix 2) and developed using the same 4-step procedure as discussed above for strategic AI orientation. We use these custom dictionaries to text mine the entire annual reports to measure emphasis on AI and emphasis on Other ITs scores. Emphasis on AI for the year for the firm is computed as the ratio of the number of sentences in the entire annual report mentioning AI keywords (shown in Appendix 6) to the total number of sentences in the entire annual report. Emphasis on other ITs for the year for the firm is computed as the ratio of the number of sentences in the entire annual report mentioning other ITs keywords (shown in Appendix 2) to the total number of sentences in the entire annual report.

We also control for industry performance (Sabherwal et al. 2019), industry capital intensity (Mithas et al. 2012), firm size (Faleye 2007), firm age (Fama and French 2004; Shumway 2001), firm R&D intensity (Uotila et al. 2009), organization slack (Iyer and Miller 2008), operating expenditure (Mithas et al. 2012), and profitability for the year *t-1*, where *t* is the year of examining firm performance. Table 2 summarizes all the variables along with their measures.

---Insert Table 2 about here---

Analyses and Results

We reduce the potential threat of artificial multicollinearity by standardizing all the variables in the model before creating the interactions (Aiken et al. 1991; Cohen et al. 2014). For firms announcing an AI investment mean Tobin's q is significantly ($t = 23.57$, $p < 0.05$) above zero. Table 3 presents the means, standard deviations, and correlations of the study variables.

---Insert Table 3 about here---

To test hypotheses H1-H4, we conduct regression analyses. We estimate robust standard errors to correct for potential bias in standard errors due to heteroskedasticity. We also check for variance inflation factor (VIF) and all the values were below 10 (Hair et al. 1998; Mathieson et al. 2001), suggesting multicollinearity is not a major concern in our models. Table 4 presents the results. We find support for H1a, H1b, H2b, H3a, H4a, and H4b. We find that both exploitation and exploration strategic AI orientations result in a positive impact on Tobin's q (H1a and H1b). We find that firms pursuing revenue-focused IT strategy gain more from strategic AI exploration orientation (H2b) whereas firms pursuing cost-focused IT strategy gain more from strategic AI exploitation orientation (H3a). We also find that in a dynamic environment, the effect of exploitation on Tobin's q is weakened for firms pursuing revenue-focused IT strategy as the environment dynamism increases lending support for H4a. On the contrary, the effect of exploration on Tobin's q is more for firms pursuing revenue-focused IT strategy as the environment dynamism increases, (supporting H4b). Table 4 presents the results, while Table 5 summarizes the findings in the context of the hypotheses. Figure 2 depicts the two-way interaction plots, and Figure 3 and Figure 4 depicts three-way interaction plots.

---Insert Table 4 about here---

---Insert Table 5 about here---

---Insert Figure 2 about here---

---Insert Figure 3 about here---

---Insert Figure 4 about here---

From Figure 2 (two-way interaction plots), we observe that at higher strategic AI exploitation orientation, the effect is higher on Tobin's q for firms pursuing higher levels of cost-focused IT strategy. Similarly, at higher strategic AI exploration orientation, the effect is higher on Tobin's q for firms pursuing a more revenue-focused IT strategy. From Figure 3, we observe that when the environment dynamism is low, firms pursuing a more revenue-focused IT strategy tend to gain greater benefits from increasing their strategic AI exploitation orientation. By contrast, at higher environment dynamism, firms pursuing a more revenue-focused IT strategy tend to lose more from increasing their strategic AI exploitation orientation.

From Figure 4, we observe that when the environment dynamism is low, firms pursuing a *less* revenue-focused IT strategy tend to gain greater benefits from increasing their strategic AI exploration orientation. By contrast, at higher environment dynamism, firms pursuing a *more* revenue-focused strategy tend to gain greater benefits from increasing their strategic AI exploration orientation. The next subsection discusses various robustness tests performed to check the generalizability of our findings using alternate measures of variables.

Supplemental Analyses

We conduct a series of robustness tests, as summarized in Table 6. The supplemental analyses include nine robustness tests to address potential concerns regarding our estimation and inclusion of variables within the main model. Table 7 provides the results of robustness tests. All nine robustness tests provide results consistent with the main result.

---Insert Table 6 about here---

---Insert Table 7 about here---

To address the generalizability of our findings across the different measures of firm performance, we use return on assets as an alternative measure of dependent variable (R1) from COMPUSTAT. We find results consistent with the main results (Model M4, Table 4). To address potential concerns related to the measures of various variables used in our study, we used alternative measures of firm size – natural log of sales (R2), alternative measure of organization slack – debt to assets ratio (R3); alternate measure of strategic AI orientation, using binary measures of exploration and exploitation (R4); alternate measure of revenue focused IT strategy – ratio of the total number of revenue focused IT strategy keywords to the total number of all ITs related keywords in the annual report (R5); alternate measure of cost focused IT strategy – ratio of the total number of cost focused IT strategy keywords to the total number of all ITs related keywords in the annual report (R6); an alternative measure of environment dynamism – industry's operational income volatility (R7); an alternative measure of environment complexity - log value of the reciprocal of the Herfindahl index of the market shares of all firms in the industry (R8); and an alternative measure of environment hostility – industry's operating income growth (R9). We find results to be consistent with our main model (Model M4, Table 4). Next subsection, we discuss how we address potential endogeneity concerns.

Test for Endogeneity

Our focal independent variables (strategic AI exploration and exploitation orientation) may not be purely exogenous. Firms tend to follow their peer firms when making policies and investments (Almazan et al. 2005; Bustamante and Frésard 2021; Leary and Roberts 2014). Thus, strategic AI orientations (exploitation and exploration) by the sample firms may be affected by strategic investments in exploitation and exploitation by their peer firms, and may thereby suffer from the issue of endogeneity in our model.

We use instrumental variables to address such endogeneity concerns. More specifically, we instrument exploitation and exploration by the focal firm using the weighted average of investment in exploration and exploitation, respectively, by all the peer firms belonging to the same industry as the focal firm in our sample set, with the peer firms being identified based on their product proximity scores. This process involves the following steps – (1) For each firm in our sample set for the year of AI investment announcement, we first identified all the peer firms that are similar in the product using Hoberg and Phillips dataset.[33] Hoberg and Phillips dataset provides the proximity score of each pair of firms based on product similarity as a continuous measure (Hoberg and Phillips 2018; Kim et al. 2016). We believe that the choice of peer firms based on product similarity is strategically relevant in the context of our study because firms' strategic investment in AI may be governed by how the peer firms have invested in IT before. (2) We text mine the annual reports of all the peer firms for the year prior to the announcement year of AI investment by the focal firm to measure exploration and exploitation scores using a custom dictionary having keywords (shown in Appendix 3) in LIWC. (3) Hoberg and Phillips product similarity score provides information about how close the firms are in terms of products they use

[33] https://hobergphillips.tuck.dartmouth.edu/industryclass.htm

or market. In light of this, we believe a simple average of the exploitation and exploration scores of all the peer firms belonging to the focal firm as obtained in step 2 may not accurately reflect the true effect resulting from more close peer firms. Therefore, we use the weighted — by product similarity score provided by the Hoberg and Phillips dataset — average scores of exploitation and exploration for the peer firms.

We perform 2SLS using the *ivreg2* command in Stata 17.0 for the endogeneity test. First, we perform an underidentification test to check whether our choice of instrument variables is correlated with endogenous variables (see Qi et al. 2021; Windmeijer 2021). The underidentification test checks whether the equation is identified, i.e., that the excluded instruments are relevant, meaning correlated with the endogenous regressors. In other words, the test examines the null hypothesis that the instruments have insufficient explanatory power to predict the endogenous variable(s) in the model for identification of the parameters. For the underidentifcation test, Kleibergen-Paap rk LM statistic obtained from 2SLS results was significant at 5.43 ($p < 0.05$), implying that our choice of instrument variables have sufficient explanatory power to predict endogenous variables and there is no underidentification. Next, we test whether our endogenous regressors can be treated as exogenous. To test that, we use the *endog* option in the 2SLS ivreg2 command in Stata. The endogeneity test of endogenous regressors statistic ($\chi^2 = 2.01$, $p > 0.05$) was non-significant. Thus, we fail to reject the null hypothesis that 2SLS and OLS estimates are the same. This indicates that our specified endogenous regressors can be treated as exogenous. We find 2SLS results (R10) consistent with our main model (Model M4, Table 4). The next section throws light on key findings, limitations of our study, and implications to both research and practice.

Discussion

AI is revolutionizing nearly every aspect of human existence, including the ways that firms market products and provide services to end consumers. Along with innovations in computational power, the technological advances in the field of AI are exerting profound effects across myriad of operations in the industry. It comes as no surprise that firms across nearly every business sector (e.g., retailing, manufacturing, healthcare, financial) keep steadily increasing their AI spending, driven to reach various objectives. For example, many manufacturing firms seek cost savings through mechanized and robotic production processes, which both limit labor costs and increase production efficiencies. Retailers and service firms devote more spending to better understand customer behavior in attempts to connect with customers and provide customized offerings, thereby increasing their revenues. Prior research and anecdotal evidence suggest that in the next decade, AI is going to revolutionize the entire operational processes, decision-making, and governance policies of the firms resulting in new jobs and requiring new skills and talents. Economic productivity is expected to increase by 0.8 percent in the next 10 years (Manyika et al. 2017). In order to create differential value, firms need to strategically invest in AI that would provide maximum payoffs from AI investment otherwise failing to do so will entrench firms into vicious cycles providing short-term benefits yet long-term losses. Against this backdrop, the study explores how firms pursuing different overall IT strategy creates differential value from the strategic AI orientation – exploitation and exploration, and how such payoffs differ in a dynamic environment.

Using a sample of 464 AI investment announcements, we theorize and empirically test the strategic AI orientation - exploitation and exploration on firm performance (H1). Exploitation relates to efficiency, growth productivity, and cost savings; whereas exploration activities provide firms an opportunity for new knowledge search and lead firms on an innovation path resulting in new sources of business opportunities. We find that both the exploitation and exploration strategic AI orientations help firms generate differential value. The significant lagged effect from our study also emboldens prior IT investment payoff findings that IT investment (e.g., AI in this case) takes time to create value. Although AI is expected to bring prosperity and new business opportunities, such payoff may be short-lived if the firm's overall IT strategy do not conform with deployment of AI capabilities. Firms invest in IT for cost savings or generation of revenue. Since exploitation helps firms in cost reduction and exploration provides new sources of revenue, it is quintessential for the firms pursuing revenue-focused IT strategy to strategically invest in AI for exploration and firms pursuing cost-focused IT strategy to invest in AI for exploitation to avoid falling into a vicious cycle of short-term gains yet long-term losses. Our results lend credibility to the importance of such conformance of IT strategy with strategic AI orientation (H2b and H3a). Such conformance becomes even more critical when the environment is turbulent and unstable creating a lot of unpredictability in the market. In a stable environment, firms could create a competitive advantage with the alignment of overall IT strategy with the strategic AI orientation. Such competitive advantage may become short-lived as environment turbulence increases. Uncertainty in the environment forces management to act swiftly. We find support that firms pursuing revenue-focused IT strategy notice a decline in performance in a dynamic environment when strategic AI orientation is for exploitation purposes (H4a). On the contrary, revenue-focused IT strategy firms benefit more in a dynamic environment when strategic AI orientation is for exploration purposes (H4b).

Limitations

The above results should be viewed in light of the study's limitations. First, our sample set consists of U.S. publicly-traded companies only as we did not have access to data for the private companies. Second, firms that did not make their AI investment announcements public were not considered in our sample set of firms. Third, we used a text-mining approach to measure the strategic AI orientation - exploitation and exploration, and IT strategy by using a corpus of words related to exploitation, exploration, revenue-focused, and cost-focused because we do not have data on these aspects. While acknowledging these limitations, we believe our findings, which are robust to several alternative specifications, would be useful for the field.

Implications for Research

This study contributes to the emerging literature on AI. Prior AI research provides useful insights into the development of AI algorithms related to image processing, data analysis, autonomous cars, the use of drones, conversational agents, and so on. Much of the prior research on the behavioral aspects of AI is theoretical and discusses the ethical issues related to AI. To the best of our knowledge, this study is the first to investigate the impact of strategic investment in AI on firm performance. The study makes some key theoretical contributions. First, it extends the literature on exploitation and exploration uses of IT by examining the strategic AI orientation - exploitation and exploration purposes. Our results consistently indicate that firms benefit from both exploitation and exploration.

Second, our study complements IT investment productivity literature to show performance gains from IT investment (e.g., AI in this case). Benefits realization from IT investment is a long-term process (Mithas et al. 2012). Our study finds a significant effect of the lagged effect (one year) of the strategic investments in AI on firm performance (i.e., Tobin's *q*).

Tobin's *q* is forward-looking, risk adjusted, and is considered suitable for measuring the performance impact of IT investments (Chari et al. 2008). In light of this, we contribute to the literature on lagged performance benefits accrued from IT investments.

Third, we contribute to the strategy literature by underscoring the benefits of overall IT strategy alignment with the strategic AI orientation. Gains from investments in AI could be short-lived if the firm's overall IT strategy does not conform with the strategic deployment of AI capabilities. Our findings are consistent with prior IS research that emphasizes the importance of aligning IT strategy with the use of IT assets. For instance, a firm's revenue-focused IT strategy would provide benefits if the firm's deployment of IT assets is used for exploration purposes as seen in our findings.

Fourth, this study contributes to dynamic capabilities theory by highlighting the fact that strategic investment in AI provides firms the maximum payoff in a turbulent environment. Our study indicates that the effects of dynamic environment, found in prior studies on IT investments in general, play a pivotal role for firms pursuing revenue-focused IT strategy and such effects become more profound at high dynamic environment when the strategic AI orientation for exploration purposes aligns with revenue-focused IT strategy.

Last, the study provides methodological rigor by using a text-mining algorithm with custom-built dictionaries to measure the strategic AI orientation – exploitation and exploration from the announcement text; and to measure IT strategy – revenue-focused and cost-focused using the firm's annual reports. Future research could benefit from the use of this custom-built dictionary in studying the strategic AI orientation and the IT strategy in various contexts.

Implications for Practice

This study also has potential implications for practice. First, it shows that strategic AI orientation have *positive impacts on firm performance*. The performance gains attributed to firms making AI investments should instill greater confidence among those allocating organizational resources to AI regarding its potential impacts. Management needs to be patient with the actual benefits realization of AI investments as findings from our one-year lagged model indicate the performance gains from both strategic AI orientations – exploitation and exploration.

Second, the study shows the importance of making *appropriate* AI investments, i.e., investments that are aligned with the firm's overall IT strategy. Thus, executives should pursue AI investments that are aligned with the firm's IT strategy in terms of revenue generation or cost reduction. Despite the benefits accrued with the alignment of overall IT strategy with the strategic AI orientation, AI investments that are not aligned with IT strategy would hurt performance. For instance, using AI for exploitation activities when the firm's strategic goals are to use IT for revenue generation would hurt innovation, while deploying AI for exploration when the firm's strategic goals are to use IT for cost reduction would amplify the costs and entrenched firms in a vicious cycle of no gains but indefinite search resulting in inefficiency. The study wants to bring to management's attention our findings that how firms could leverage different strategic investments in AI for the realization of objectives. Different firms pursue different IT strategies, and one-size-fits-all does not work in the context of AI investments. Firms need to look at their goals and make a strategic decision to invest in AI that aligns with their objectives to reap the maximum benefits from AI. Failing to do so would result in losses, as happened in the case of IBM when IBM Watson, AI product, failed to demonstrate its success in the drug discovery process and IBM put on hold more than $62 million ‘Watson for Oncology’ AI product after the system started to provide incorrect recommendations to patients.[34]

Finally, the study highlights the need for managers to consider their *industry environment* when deploying AI assets. Aligning the AI investments with the firm’s IT strategy is useful in general and it becomes even more important in a dynamic environment. Benefits would become short-term gains and firms may lose competitive advantage in a dynamic environment if failing to strategically align their IT goals with investment in AI capabilities.

[34] https://www.forbes.com/sites/matthewherper/2017/02/19/md-anderson-benches-ibm-watson-in-setback-for-artificial-intelligence-in-medicine/?sh=7f586e433774.

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Figures of Chapter 3

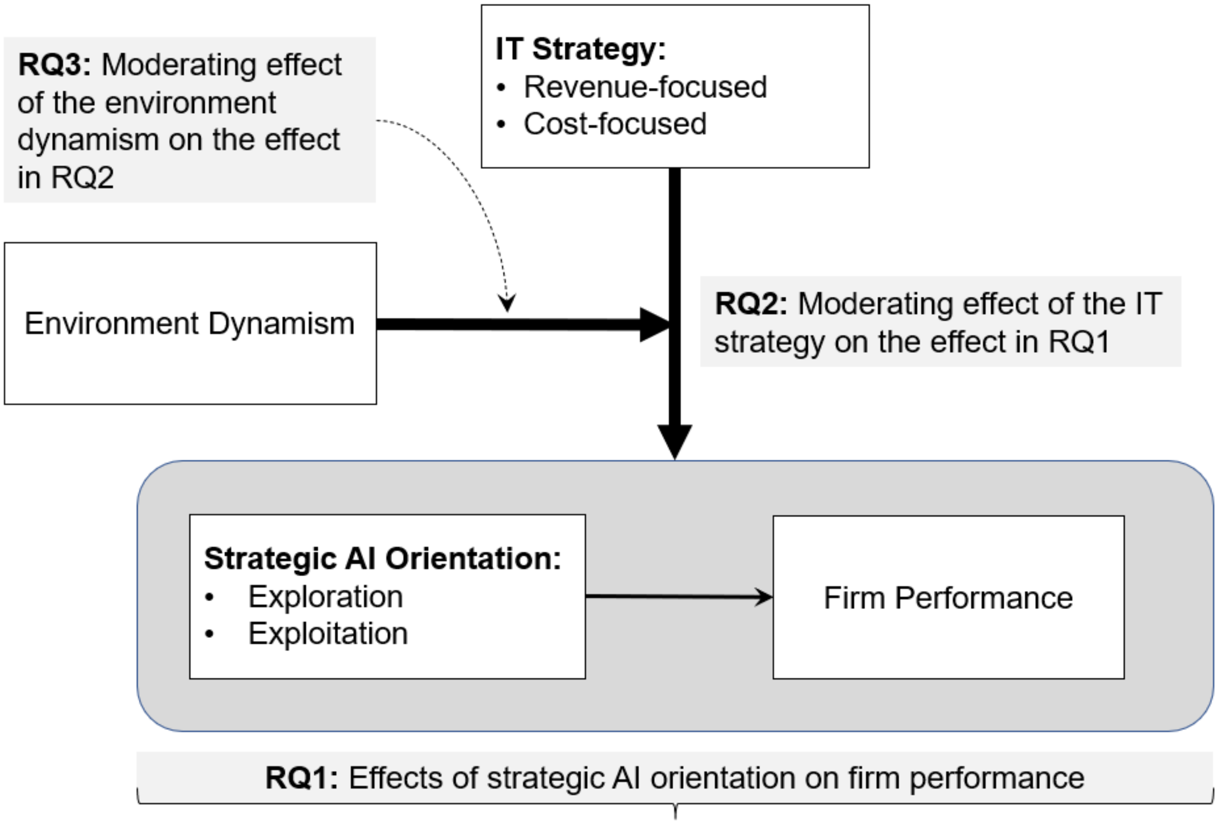

Figure 1. Research model

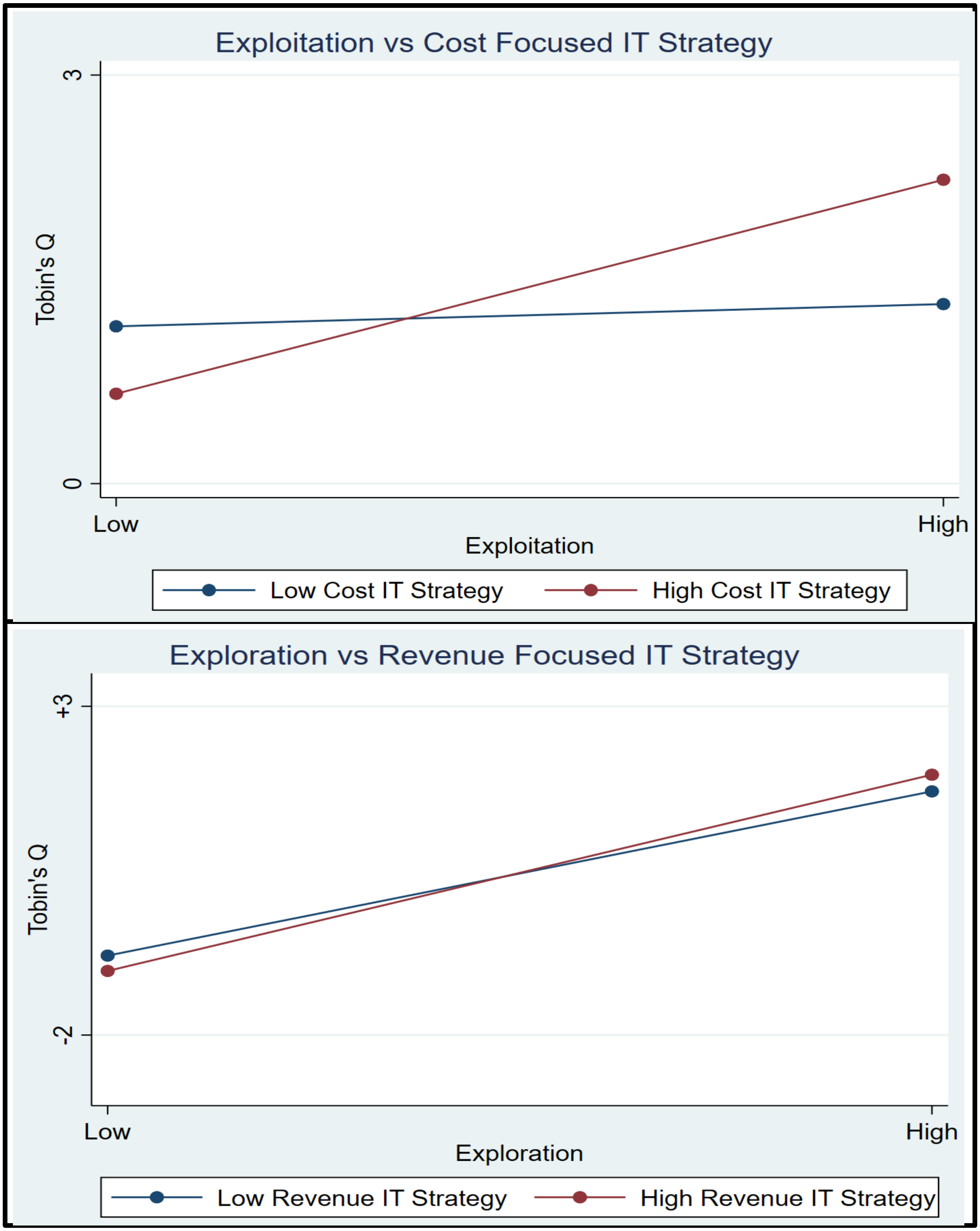

Figure 2. Two-way interaction plots

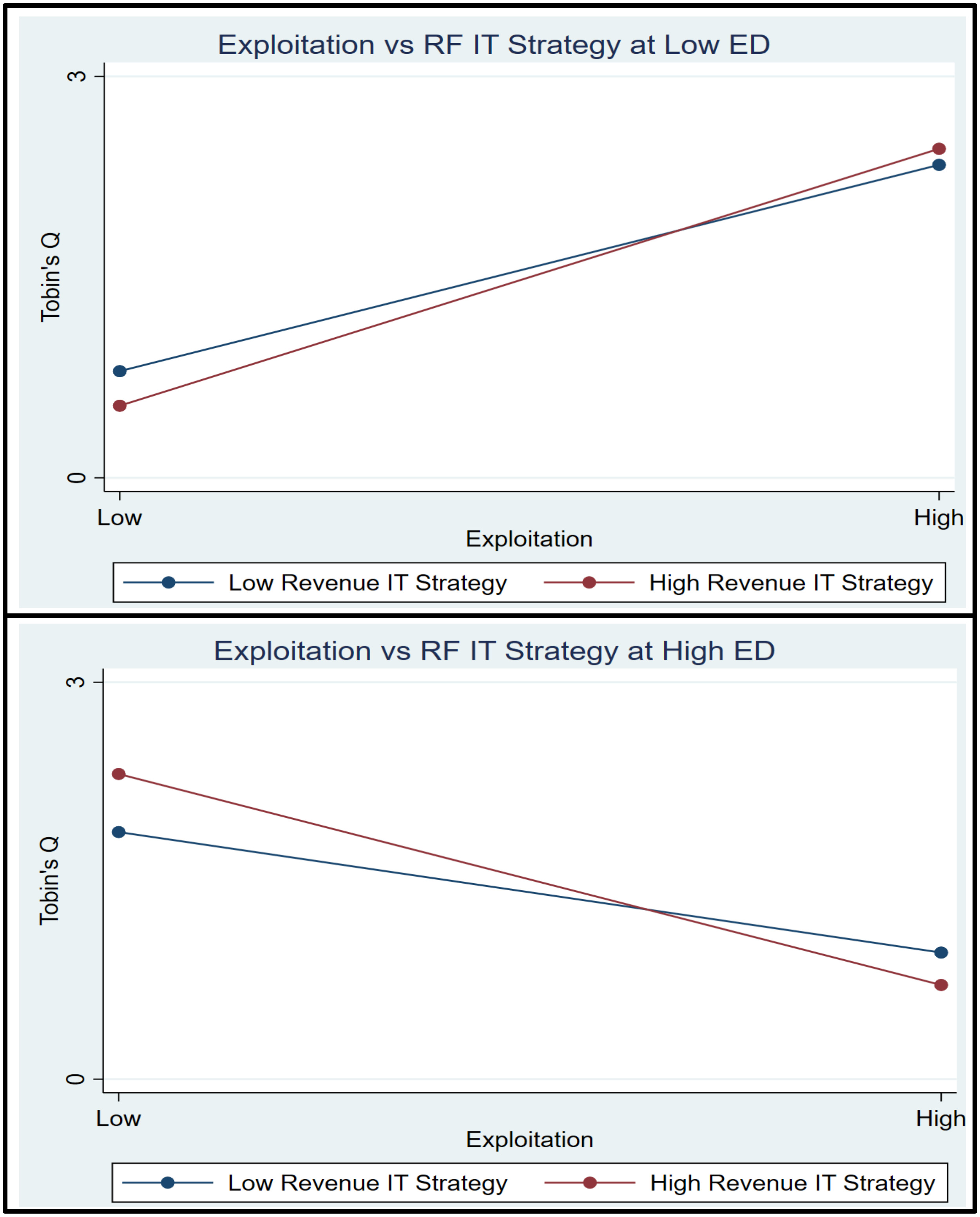

Figure 3. Three-way interaction plots for exploitation vs revenue-focused (RF) IT strategy at low and high environment dynamism (ED)

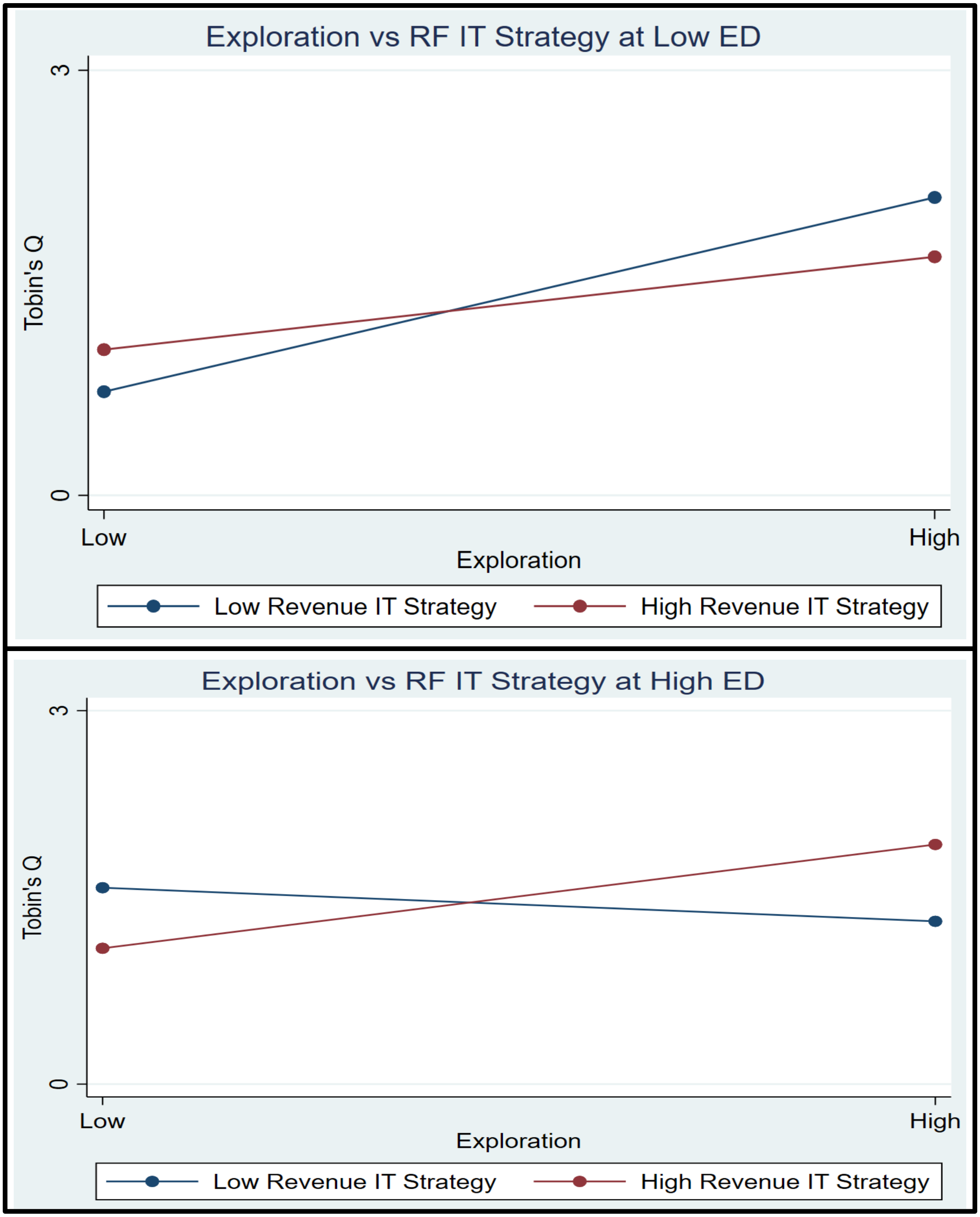

Figure 4. Three-way interaction plots for exploration vs revenue-focused (RF) IT strategy at low and high environment dynamism (ED)

Tables of Chapter 3

Table 1. Key constructs and definitions

Construct	Definition
Strategic AI orientation	Firm's strategic investment in AI capabilities to achieve business goals (adapted from Chan et al. 1997, p. 126).[35]
Exploration	Exploration is characterized by activities including terms such as "search, variation, risk taking, experimentation, play, flexibility, discovery, innovation" (March 1991, p. 71).
Exploitation	Exploitation is characterized by activities including terms such as "refinement, choice, production, efficiency, selection, implementation, execution" (March 1991, p. 71).
IT strategy	"An expression of the dominant strategic objective that the firm chooses to emphasize, which can be revenue expansion or cost reduction" (Mithas and Rust 2016, p. 223).
Revenue-focused	IT strategy focusing on revenue growth (adapted from Mithas as Rust 2016, p. 225)
Cost-focused	IT strategy focusing on cost reduction (adapted from Mithas as Rust 2016, p. 225)
Firm performance	A market-based measure of firm value measuring the impact of AI investments (adapted from Steelman et al. 2019).[36]

Table 2. List of variables and measures used in the study

Variable	Measure	Sources
Main		
Firm Performance (Tobin's *q*)	(Market value of equity + book value of inventories + liquidating value of preferred stock + long-term debt + net short-term debt)/Total assets.	Chung and Pruitt (1994)
Exploitation_AI	Weighted average (weighted by the length of each announcement in sentences) of the exploitation scores for each entire announcement in a year by the firm	
Exploration_AI	Weighted average (weighted by the length of each announcement in sentences) of the exploration scores for each entire announcement in a year by the firm	
Revenue-focused IT Strategy	Ratio of the number of sentences in the entire annual report mentioning revenue-focused IT strategy keywords to the number of sentences in the entire annual report mentioning all ITs[37]	
Cost-focused IT Strategy	Ratio of the number of sentences in the entire annual report mentioning cost-focused IT strategy keywords to the number of sentences in the entire annual report mentioning all ITs	
Environment Dynamism	Volatility of industry sales	Xue et al. (2011)
Control		

[35] Chan et al. (1997, p. 126) refers IS orientation strategy to "strategy evident in IS investments and IS deployments"

[36] "Firm performance is measured using Tobin's q, a market-based measure of firm value. Tobin's q is a forward-looking and risk-adjusted measure of firm performance that has been found to be less vulnerable to differing accounting practices and suitable for measuring the impact of IT investments (Chari et al. 2008)." (p. 209)

[37] All ITs include keywords related to Other ITs (shown in Appendix 3) and AI (shown in Appendix 5).

Table 2. (Cont.)

Variable	Measure	Sources
Control		
Industry Performance	Median of the Tobin's q ratios of the firms in that industry	Sabherwal et al. (2019)
Industry Capital Intensity	Ratio of physical capital/value added.	Mithas et al. (2012)
Firm Size	Natural log of employees.	Faleye (2007)
Firm Age	Natural log of the difference between the year under investigation and the year firm appears first on COMPUSTAT	Fama and French (2004)
Firm R&D Intensity	Natural log of the firm R&D expense divided by its sales	Uotila et al. (2009)
Organization Slack	Debt to equity ratio	Iyer and Miller (2008)
Operating Expenditure (OPEX)	Sales - costs of goods sold - operating income	Mithas et al. (2012)
Profitability (t-1)	Return on assets	Hitt and Brynjolfsson (1996)
Exploitation_OtherIT	Weighted average (weighted by the length of each announcement in sentences) of the exploitation scores for each entire announcement on other ITs in a year by the firm	See Appendix 2 for list of other ITs
Exploration_OtherIT	Weighted average (weighted by the length of each announcement in sentences) of the exploration scores for each entire announcement on other ITs in a year by the firm	See Appendix 2 for list of other ITs
AI_Emphasis	Ratio of the number of sentences mentioning AI words (see Appendix 6) to the total number of sentences in the entire annual report	Alekseeva et al. (2020); Brynjolfsson and Mcafee (2017); Daugherty and Wilson (2018); Davenport and Kirby (2016); Lacity and Willcocks (2018)
OtherIT_Emphasis	Ratio of the number of sentences mentioning other ITs (see Appendix 2) to the total number of sentences in the entire annual report	See Appendix 2 for list of other ITs
Environment Complexity	Natural log of the reciprocal of the industry Herfindahl index	Xue et al. (2011)
Environment Hostility	Opposition to growth in industry sales	Xue et al. (2011)

Table 3. Summary statistics and correlations[a]

Variables	Mean	S.D.	1	2	3	4	5
1. Exploitation_AI	0.37	0.14					
2. Exploration_AI	1.97	0.68	0.03				
3. Revenue-focused IT Strategy	0.03	0.02	0.02	0.24**			
4. Cost-focused IT Strategy	0.01	0.01	0.28*	0.01	0.01		
5. Environment Dynamism	1.11	0.24	0.04	0.03	0.09	0.03	
6. Tobin's Q	2.38	0.76	0.10*	0.36***	0.25**	0.14*	0.01

[a] Correlations are reported as: ***p < 0.001; *p < 0.05; n = 464.

Table 4. Results of regressions for H1-H4[a]

	DV = Tobin's q							
Variables	**M1**		**M2**		**M3**		**M4**	
Industry Performance	0.060*	(0.607)	0.040*	(0.627)	0.062*	(0.681)	0.086+	(1.149)
Industry Capital Intensity	-0.158**	(0.644)	-0.089*	(0.523)	-0.087*	(0.513)	-0.085*	(0.495)
Firm Size	0.087	(0.084)	0.069	(0.079)	0.060	(0.082)	0.046	(0.089)
Firm Age	-0.108+	(0.172)	-0.085	(0.169)	-0.100+	(0.181)	-0.100	(0.190)
Firm R&D Intensity	0.266*	(1.954)	0.192*	(1.691)	0.211*	(1.742)	0.228*	(1.924)
Organization Slack	-0.006	(0.002)	-0.005	(0.002)	-0.000	(0.002)	-0.007	(0.002)
Operating Expenditure (OPEX)	0.073	(0.000)	0.042	(0.000)	0.035	(0.000)	0.033	(0.000)
Profitability (*t-1*)	0.181*	(1.387)	0.172*	(1.272)	0.173*	(1.316)	0.174+	(1.349)
Exploitation_OtherIT	0.071*	(1.223)	0.049+	(1.057)	0.043	(1.141)	0.054+	(1.151)
Exploration_OtherIT	0.091*	(1.508)	0.087*	(1.357)	0.065+	(1.335)	0.054	(1.435)
AI_Emphasis	0.314**	(0.127)	0.231*	(0.112)	0.290*	(0.113)	0.178*	(0.142)
OtherIT_Emphasis	0.040	(0.414)	0.048	(0.402)	0.051	(0.424)	0.045	(0.447)
Environment Complexity	-0.075	(1.097)	-0.078	(1.597)	-0.077	(1.660)	-0.086	(1.120)
Environment Hostility	-0.100	(1.252)	-0.049	(1.139)	-0.042	(1.191)	-0.045	(1.161)
Exploitation_AI			0.193*	(0.317)	0.199*	(0.313)	0.142*	(0.333)
Exploration_AI			0.246***	(0.216)	0.292***	(0.233)	0.255***	(0.237)
Revenue-focused IT Strategy (RF IT Str)					0.124**	(0.005)	0.016*	(0.005)
Cost-focused IT Strategy (CF IT Str)					0.092**	(0.029)	0.096*	(0.046)
Exploitation_AI X RF IT Str					-0.053	(0.019)	-0.025	(0.019)
Exploitation_AI X CF IT Str					0.065*	(0.051)	0.097***	(0.064)
Exploration_AI X RF IT Str					0.079*	(0.008)	0.049***	(0.008)
Exploration_AI X CF IT Str					0.019	(0.041)	0.064	(0.063)
Environment Dynamism (ED)							-0.035	(0.136)
Exploitation_AI X ED							-0.080*	(0.206)
Exploration_AI X ED							-0.032	(0.232)
RF IT Str X ED							0.114**	(0.006)
CF IT Str X ED							0.057	(0.061)
Exploitation_AI X RF IT Str X ED							-0.080*	(0.019)
Exploitation_AI X CF IT Str X ED							0.051	(0.133)
Exploration_AI X RF IT Str X ED							0.110**	(0.009)
Exploration_AI X CF IT Str X ED							0.073	(0.084)
R^2 (%)	33.69		38.24		45.29		47.64	
F-value	11.21***		10.44***		9.25***		9.31***	

[a] Standardized regression coefficients are reported with robust standard errors. Robust standard errors are reported within parentheses. Significance levels reported are two-tailed and are indicated as: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+} < 0.10$; $n = 464$ for all models.

Table 5. Summary of results

Hypothesis	Result
H1a: A firm's strategic AI exploitation orientation in year *t-1* is associated with higher firm performance in year *t*.	Supported
H1b: A firm's strategic AI exploration orientation in year *t-1* is associated with higher firm performance in year *t*.	Supported
H2a: A firm's revenue-focused IT strategy in year *t-1* weakens the positive relationship between the firm's strategic AI exploitation orientation in year *t-1* and firm performance in year *t*.	Not Supported
H2b: A firm's revenue-focused IT strategy in year *t-1* strengthens the positive relationship between the firm's strategic AI exploration orientation in year *t-1* and firm performance in year *t*.	Supported
H3a: A firm's cost-focused IT strategy in year *t-1* strengthens the positive relationship between the firm's strategic AI exploitation orientation in year *t-1* and firm performance in year *t*.	Supported
H3b: A firm's cost-focused IT strategy in year *t-1* weakens the positive relationship between the firm's strategic AI exploration orientation in year *t-1* and firm performance in year *t*.	Not Supported
H4a: Greater environment dynamism in year *t-1* enhances the weakening effect of the firm's revenue-focused IT strategy in year *t-1* on the positive relationship between the firm's strategic AI exploitation orientation in year *t-1* and firm performance in year *t*.	Supported
H4b: Greater environment dynamism in year *t-1* enhances the strengthening effect of the firm's revenue-focused IT strategy in year *t-1* on the positive relationship between the firm's strategic AI exploration orientation in year *t-1* and firm performance in year *t*.	Supported
H4c: Greater environment dynamism in year *t-1* enhances the strengthening effect of the firm's cost-focused IT strategy in year *t-1* on the positive relationship between the firm's strategic AI exploitation orientation in year *t-1* and firm performance in year *t*.	Not Supported
H4d: Greater environment dynamism in year *t-1* enhances the weakening effect of the firm's cost-focused IT strategy in year *t-1* on the positive relationship between the firm's strategic AI exploration orientation in year *t-1* and firm performance in year *t*.	Not Supported

Table 6. Summary of robustness tests

Model	Potential biases and alternative arguments	Alternate measure for Robustness test	Results compared to main model
R1	Are the results generalizable to alternative dependent variable?	▪ Return on assets	Consistent
R2	Are the results generalizable to alternative measure of firm size?	▪ Natural log of sales.	Consistent
R3	Are the results generalizable to alternative measure of organization slack?	▪ Debt to assets ratio	Consistent
R4	Are the results generalizable to alternative measure of strategic AI orientation?	▪ Use of binary measures for exploration and exploitation	Consistent
R5	Are the results generalizable to alternative measure of revenue focused IT strategy	▪ Ratio of the total number of revenue focused IT strategy keywords to the total number of all ITs related keywords in the annual report	Consistent
R6	Are the results generalizable to alternative measure of cost focused IT strategy	▪ Ratio of the total number of cost focused IT strategy keywords to the total number of all ITs related keywords in the annual report	Consistent
R7	Are the results contingent on the estimation of dynamism?	▪ Industry's operational income volatility.	Consistent
R8	Are the results contingent on the estimation of complexity?	▪ Natural log value of the reciprocal of the Herfindahl index of the market shares of all firms in the industry.	Consistent
R9	Are the results contingent on the estimation of hostility ?	▪ Industry's operational income growth.	Consistent
R10	Are the independent variables endogenous?	▪ Test for endogeneity	Consistent

Table 7. Robustness tests[a]

Variables	M4	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
IP	0.086+ (1.149)	0.010 (1.191)	0.239** (1.622)	0.086+ (1.168)	0.084+ (1.139)	0.077 (1.162)	0.084+ (1.142)	0.081+ (1.009)	0.071 (1.006)	0.072 (1.011)	0.078 (1.174)
ICI	-0.085* (0.495)	-0.050 (0.852)	-0.049 (0.780)	-0.111** (0.552)	-0.084* (0.495)	-0.084* (0.483)	-0.088* (0.499)	-0.086* (0.478)	-0.080* (0.460)	-0.097* (0.489)	-0.109** (0.538)
FS	0.046 (0.089)	0.171 (0.139)	0.083 (0.181)	0.372* (0.172)	0.048 (0.089)	0.033 (0.087)	0.010 (0.092)	0.008 (0.100)	0.032 (0.093)	0.253* (0.134)	0.358** (0.163)
FA	-0.100 (0.190)	-0.144+ (0.255)	-0.186* (0.252)	-0.109+ (0.185)	-0.097 (0.194)	-0.098 (0.193)	-0.103 (0.189)	-0.139* (0.184)	-0.132* (0.188)	-0.139* (0.185)	-0.107+ (0.187)
FR&DI	0.228* (1.924)	0.261** (1.779)	0.216* (2.046)	0.277** (1.98)	0.116 (1.148)	0.244* (1.83)	0.240* (1.893)	0.267** (1.715)	0.271** (1.669)	0.311** (1.739)	0.301** (1.89)
OS	-0.007 (0.002)	-0.018 (0.003)	-0.025+ (0.002)	-0.007 (0.002)	-0.008 (0.002)	-0.046 (0.743)	-0.049* (0.051)	-0.054 (0.069)	-0.060 (0.712)	-0.054 (0.699)	-0.037 (0.718)
OPEX	0.033 (0.000)	0.028 (0.000)	0.036 (0.000)	0.019 (0.000)	0.032 (0.000)	0.033 (0.000)	0.031 (0.000)	0.037 (0.000)	0.039 (0.000)	0.029 (0.000)	0.020 (0.000)
Profitability (*t-1*)	0.174+ (1.349)	0.323* (1.763)	0.271* (1.735)	0.145+ (1.197)	0.062 (2.986)	0.177+ (1.362)	0.173+ (1.332)	0.168+ (1.225)	0.172+ (1.250)	0.152+ (1.194)	0.148+ (1.214)
Explt_oIT	0.054+ (1.151)	0.025 (1.538)	0.039 (1.624)	0.046 (1.213)	0.045* (1.154)	0.055 (1.128)	0.054 (1.139)	0.037 (1.104)	0.038 (1.092)	0.032 (1.103)	0.047 (1.182)
Explr_oIT	0.054 (1.435)	0.024 (1.609)	0.041 (1.773)	0.057 (1.432)	0.043 (1.435)	0.051 (1.469)	0.054 (1.429)	0.043 (1.240)	0.039 (1.307)	0.041 (1.312)	0.054 (1.463)
AI_Emp	0.178* (0.142)	0.242* (0.190)	0.095* (0.277)	0.473* (0.230)	0.187* (0.150)	0.167* (0.133)	0.138* (1.422)	0.118* (0.100)	0.146+ (0.094)	0.345** (0.140)	0.458* (0.217)
oIT_Emp	0.045 (0.447)	0.057 (0.441)	0.122 (0.728)	0.049 (0.450)	0.046 (0.448)	0.046 (0.443)	0.045 (0.445)	0.028 (0.352)	0.028 (0.353)	0.031 (0.351)	0.049 (0.445)
EC	-0.086 (1.120)	-0.034 (1.265)	-0.071+ (1.918)	-0.085* (1.117)	-0.090* (1.100)	-0.089** (1.969)	-0.087* (1.083)	-0.079* (1.025)	-0.081* (1.924)	-0.081* (1.907)	-0.087* (1.983)
EH	-0.045 (1.161)	-0.078 (1.606)	-0.041 (1.520)	-0.047 (1.161)	-0.038 (1.156)	-0.049 (1.129)	-0.048 (1.147)	-0.039 (1.084)	-0.041 (1.092)	-0.041 (1.091)	-0.050 (1.127)
Explt_AI	0.142* (0.333)	0.123* (0.283)	0.085+ (0.314)	0.148** (0.336)	0.144* (0.337)	0.142** (0.337)	0.142* (0.334)	0.121** (0.243)	0.122** (0.247)	0.126** (0.247)	0.148** (0.339)
Explr_AI	0.255*** (0.237)	0.258** (0.336)	0.168* (0.394)	0.258*** (0.238)	0.252* (0.236)	0.256*** (0.234)	0.257*** (0.237)	0.296*** (0.205)	0.296*** (0.203)	0.296*** (0.201)	0.259*** (0.235)
RF IT Str	0.016* (0.005)	0.016* (0.007)	0.014* (0.010)	0.014 (0.005)	0.018 (0.005)	0.018 (0.005)	0.018 (0.005)	0.022 (0.004)	0.023 (0.004)	0.022 (0.004)	0.015 (0.005)
CF IT Str	0.096* (0.046)	0.074* (0.079)	0.054* (0.097)	0.094+ (0.048)	0.099* (0.047)	0.090** (0.047)	0.096+ (0.046)	0.112* (0.042)	0.105 (0.041)	0.104* (0.042)	0.089+ (0.049)

Table 7. (Cont.)

Variables	M4	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Explt_AI X RF IT Str	-0.025 (0.019)	-0.041 (0.021)	-0.079 (0.028)	-0.017 (0.018)	-0.023 (0.019)	-0.027 (0.018)	-0.023 (0.019)	-0.027 (0.016)	-0.032 (0.016)	-0.025 (0.016)	-0.019 (0.018)
Explt_AI X CF IT Str	0.097*** (0.064)	0.154* (0.058)	0.178^{+} (0.075)	0.095** (0.064)	0.098* (0.064)	0.101 (0.062)	0.098** (0.064)	0.100** (0.052)	0.104** (0.052)	0.101** (0.051)	0.099** (0.062)
Explr_AI X RF IT Str	0.049*** (0.008)	0.078^{+} (0.011)	0.038* (0.014)	0.036 (0.008)	0.046 (0.008)	0.048 (0.008)	0.040 (0.008)	0.034 (0.008)	0.043 (0.007)	0.034 (0.007)	0.036 (0.008)
Explr_AI X CF IT Str	0.064 (0.063)	0.050 (0.133)	0.099 (0.149)	0.068 (0.066)	0.058 (0.064)	0.065 (0.063)	0.067 (0.064)	0.025 (0.063)	0.023 (0.063)	0.027 (0.063)	0.068 (0.065)
ED	-0.035 (0.136)	-0.081 (0.203)	-0.002 (0.183)	-0.008 (0.129)	-0.037 (0.142)	-0.038 (0.137)	-0.035 (0.136)	-0.074 (0.151)	-0.077 (0.152)	-0.058 (0.149)	-0.011 (0.130)
Explt_AI X ED	-0.080* (0.206)	-0.096* (0.282)	-0.141** (0.336)	-0.091* (0.217)	-0.081* (0.207)	-0.079* (0.201)	-0.082* (0.204)	-0.074* (0.190)	-0.071* (0.187)	-0.079* (0.190)	-0.091* (0.211)
Explr_AI X ED	-0.032 (0.232)	-0.006 (0.357)	-0.003 (0.374)	-0.062 (0.255)	-0.029 (0.222)	-0.031 (0.226)	-0.035 (0.232)	-0.055 (0.243)	-0.051 (0.235)	-0.071 (0.238)	-0.059 (0.248)
RF IT Str X ED	0.114** (0.006)	0.078 (0.010)	0.110* (0.012)	0.115** (0.006)	0.109* (0.006)	0.112** (0.006)	0.114** (0.006)	0.099* (0.007)	0.096* (0.006)	0.096* (0.006)	0.112** (0.006)
CF IT Str X ED	0.057 (0.061)	0.028 (0.069)	-0.012 (0.072)	0.061 (0.062)	0.058 (0.061)	0.051 (0.062)	0.055 (0.061)	0.028 (0.059)	0.023 (0.059)	0.027 (0.060)	0.056 (0.063)
Explt_AI X RF IT Str X ED	-0.080* (0.019)	-0.060* (0.016)	-0.080* (0.028)	-0.078* (0.019)	-0.084* (0.019)	-0.085* (0.018)	-0.083* (0.018)	-0.079* (0.016)	-0.083* (0.016)	-0.081* (0.016)	-0.082* (0.018)
Explt_AI X CF IT Str X ED	0.051 (0.133)	0.071^{+} (0.115)	0.152^{+} (0.175)	0.046 (0.134)	0.052 (0.135)	0.054 (0.130)	0.053 (0.133)	0.073^{+} (0.114)	0.076^{+} (0.114)	0.072^{+} (0.113)	0.049 (0.130)
Explr_AI X RF IT Str X ED	0.110** (0.009)	0.150** (0.009)	0.139* (0.023)	0.113** (0.009)	0.110* (0.009)	0.105** (0.009)	0.109** (0.009)	0.107** (0.009)	0.102** (0.009)	0.105** (0.009)	0.109** (0.009)
Explr_AI X CF IT Str X ED	0.073 (0.084)	0.024 (0.077)	0.085 (0.157)	0.074 (0.086)	0.067 (0.086)	0.073 (0.084)	0.074 (0.084)	0.031 (0.077)	0.029 (0.078)	0.030 (0.078)	0.074 (0.087)
R^2 (%)	47.64	42.00	40.02	33.96	27.55	31.00	30.91	32.03	32.12	33.94	28.60
F-value	9.31***	7.84***	7.48***	7.62***	10.01***	6.80***	6.58***	6.84***	6.98***	7.73***	7.9***

[a] Standardized regression coefficients are reported with robust standard errors. For endogeneity test (R10), we use *betacoeff* module in stata to get standardized coefficients and centered R square is reported. Significance levels reported are two-tailed and are indicated as: ***p < 0.001; **p < 0.01; *p < 0.05; $^{+}$ < 0.10; n = 464 for all models. *IP* refers to Industry Performance; *ICI* refers to Industry Capital Intensity; *FS* refers to Firm Size; *OS* refers to Organization Slack; *Explt_oIT* refers to Exploitation_OtherIT; *Explr_oIT* refers to Exploration_OtherIT; *EC* refers to Environment Complexity; *EH* refers to Environment Hostility; *Explt_AI* refers to Exploitation_AI; *Explr_oIT* refers to Exploration_AI; *RF IT Str* refers to Revenue-focused IT Strategy; *CF IT Str* refers to Cost-focused IT Strategy; *ED* refers to Environment Dynamism.

Appendices

Appendix 1. Search String for AI Announcements on Lexis Nexis

(“artificial intelligence” or “deep learning” or “machine learning” or “cognitive systems” or “cognitive computing” or “intelligent systems” or “chatbots” or “virtual assistants” or “recommender systems” or “pattern recognition”) or hlead(“algorithms” or “image processing” or “image recognition” or “speech recognition” or “object recognition” or “object tracking” or “face recognition” or “facial recognition” or “ biometric*” or “robot” or “computer vision” or “driverless” or “autonomous vehicles”) and hlead((“invest” or “purchase” or “buy” or “acquire” or “implement” or “install” or “adopt” or “alliance” or “partner” or “collaborat*” or “develop” or “build*” or “create” or “launch” or “merge*” or “acquisition”)) and (“NASDAQ” OR “NYSE” or “AMEX”) and not (“Comtex SmarTrend® Alert” or “conference” OR “exhibit” or “exhibitor” or “exhibition” or “annual reports” or “q* earnings” or “industry report” or “research” or “divest” or “university”) and not hlead (“news commentary” or “stocks update”) and not title(“initial public offering” or “stock option”)

Appendix 2. Keywords for Blockchain and Virtual and Augmented Reality added to Other ITs List[38]

Blockchain[39]: AlphaPoint, Axcore, Axoni, B2Broker, Bankchain, BigChainDB, bitcoin, Blockchain, Blockchain Evidence Locker, Blocko, Blockstream, Brainbot, Bubichain, Chain Core, Chainalysis KYT, Corda, cryptocurrency, Digital Asset Platform, Domus Tower Blockchain, Ethereum, Factom Harmony, GemOS, Hydrachain, Hyperledger, Hyperledger Fabric, Hyperledger Indy, Hyperledger Iroha, Hyperledger Sawtooth, IBM Blockchain, Kaleido, Microsoft Azure Blockchain, Monax, MultiChain, NEM, NEO, Nexledger, Nxt Platform, Omni, Onchain, OpenCSD, Oracle Blockchain Cloud Service, ParallelChain, pNetwork, Polkadot, Quorum, Ripple, RSK, SettleMint, Signchain Signature, Stellar, StreamCore, Swirlds, Symbiont Assembly, Tangle, Tendermint, VeChain ToolChain, Velas, Waves, Zeeve, Zilliqa

Virtual and Augmented Reality[40]: 1trip2, 3D Anatomy Viewer 4 Artists, 3-in-1 Ruler, 4D Sight, 6D.AI, 8th Wall, Absco , Absco Sheds, Admix, Adobe Aero, Adobe Lightroom 4.3, After Ice, Aglet, AI Scry, Air Museum, AirMeasure, AKUNA-TX EARBUD, ALAIRA, Alipay AR Red Envelopes (Hong Bao), Ameyt World, Ammazza, ANI, AnimateYou, Appfity, AR, Augment* reality, AR Alphabets, AR Chess by BrainyChess, AR Chief Trump, AR Distance, AR Docs, AR Educational Toys, AR Experiments, AR FaceFighter, AR fart app, AR Fly Ruler, AR Grimoire, AR History, AR Hockey Ultra, AR LOKA, AR Lyrics, AR MeasureKit, AR Planes, AR Pong, AR Search, AR Social, AR Stickers, AR Studio Player, AR Translator, AR Warriors, AR Zyion Invasion, AR.fx, AR.js, AR/VR Today, Arbi , ARBOOX, Archeology,

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38 This list was taken from https://www.kaggle.com/tahahavakhor/search-keywords-for-each-information-technology. Blockchain, Virtual Reality, and Augmented Reality ITs were added to the list. Keywords include ITs and product names of respective ITs.

39 Blockchain IT words are based using Lacity (2020) and https://www.gartner.com/reviews/market/blockchain-platforms.

40 Virtual Reality and Augment Reality words are based using https://www.producthunt.com/topics/augmented-reality

ARChess, ARcraft.me, Arcus, Aremi, Aremo, AREmoji , AR-GO, ARiddle, arjoy, Arkerobox, ARKit2, ARKit-Emperor, ARKitty, ARMA APP, ARMeasureApp, ARQ Editor, ARscape, Art.com, Arthouse, Articcio, Artios, ARToolkit, ARTX, ARWAY, AR-XR, Aryel, Aryzon AR/MR, ARZombi 2, ASH, Assemblr, Asteroid, Asteroid 2, Astral, Astrophilia, Augment Desktop, Augmented AR Jungle Adventure, Augmented Halloween, Augmented Human, Augray, Augspace, Avvnue, Bacydar, Bad Screenprints Dot Com, Balloon Invaders: Pop Balloons in AR, Banuba Face Filters SDK, Barty App, Bazar, BBC Civilisations AR, Beard Live - Beard Cam Live, Beatsy, Beem, BeyondPass AR, bicoco, BioHazard AR Escape Room, Biometrics Input Kit for XR, Bitcoin AR, Blackbox, BlindGuide Maps / KLIC, Blippar, Blocker, BlocSide Sports, Bloxels Build Your Own Video Games, BlueScore, Bold Poker, Bookful, boomApp, BOSE Audio AR platform, Bose Frames, Bridge, BRIO, Bubbles, Bubo - AR Social Network, Bunny Run AR, Butterfly Story, Byond, CalculatAR Beta, Camera IQ, Cannabis Viewer AR, CAPTUR3D, Capture, Carafes Letter, Carbon 0, Cardlet, Carloudy, Cat Tiny Homes, Catchar, Changes, Cheapshot, Cheddar Live News on Magic Leap, chem3D, Chroma, Cibo, CifiPowa, CINEMOOD 360, Citizen, Clean Hero AR!, Client Finda Commercial, Clik Shop, Climb Designer, ClipDrop, Clothes Filters, Coachy, Coachy 2.0, Coin Hunter, ColdSpotting, Conekton, Convergence, Cosmos Creator, Crafter: AR Build Battle, Craftle, Creator Cam, CrittARs, Crypto Lingo, CUBE, Cubiques AR, Customized Videos!, CVRNT Podcast, CYBER, Da Vinci Eye, Dance Nation, DAQRI Smart Glasses, DecorMatters, DEVAR, DictionARy, DigiBets, Digital Art, dilium, Dimension - Explore AR Worlds, display.land, Dog Identifier, domFire, DominanceAR, doodlar, DoodleLens, DopeBalls, Doppler, Dot Go, DottyAR App, DRAFT, Dragon Federation, Draki Hero, DrawmaticAR - Writing Magic, DrillRoom, Echotags, Eclipse Ares, Edgybees, EeziShop, ElementClip (App Clip), Embla

Candles, Entrance Architect, Envision Glasses, Escape The Room: AR, eurecaStudio™, Everything VR & AR, exaQuark, Exploratu, Explore Nearby, Fabric - Social AR, Fabrik, Face in the Hole, Face Maker, Facebook AR Studio, FacefARt, FaceMock, Fantasmo, fARtjacker, Fascroll, Figment AR, Filtroo.com, FitaDo, FitaDo AR, Fitly.ai, Fitness AR, Flame, Flappy Box, Flashcards + AR, FlippAR, Flotogram, FocalHub, Focals Showroom, FoodNoms, Foodvisor, For All Mankind: Time Capsule, Forbes' The Premise - Designing Future Things, FORM Swim Goggles, Fractoz, frankie, Frimousse, FringeFM Podcast, Fritz AI for Snap Lens Studio, Fulldive VR, FunAR, fuse.it, Galaxy Explorer Project, GallARy, Gallery AR, Game Face, Gameboard-1, Gantri AR View, GEENEE, Geenee AR, Geoga, GeoGeek AR, Geography quiz in , Geopogo, GHeight, Ghost, Ghost Seeker, GIPHY World, Glimpse AR, Glitché NFT Tool, Glowing Gloves, Gold Coast Motorcycles, GoodVision Video Insights, Google ARCore, Google Lookout, Gorillaz, Graphmented, Grapic, Guess The Person CEO Quiz, Guidance Internal, Gyroscope v3.5, hakus, HandX, Happy Snap, HAPTICAL, Hawkeye Access, HearHere, HeartsBridges, Heijar, HelloAR, Help Me Read This, heymesh, Hidden Secrets: Mobile Treasure Hunt, HideNHunt, Hiface: Explore Your Style, HIGHTYPE, HillaryDonald Go, hire.AR, Holo, HoloCam, HolodeckVR, Hologo, Holographica, Hololamp, Hololens 2, Holon, Holosports, Holotoolkit, Home AR, Hootsy, Horizon Explorer, HorrorMasks, Hotdog face snapchat lens, House Shfiting Service, Housecraft, Hoverlay, Hybri, Hyper Online, ICON, Ideal Reality, ifcXR, Imagina Books: The Human Body, ImmerseAR, IMMY Mark 1, In Wonder ~Prologue~, InAssist, Iron HUD, Is this place good?, iTagged, IUnknown, JackOxr, Jarit, Jevar, JFK Moonshot, Jig Pro by JigSpace, JigSpace, Jobs in XR, Kalkul [proto]Type 1, KAMP, Kavtek, Ketogram, King Children, Kivisense AR Sneaker, Klub, Klues, Knockout Boxing VR: Ring Fight, Kodama 3DGo, Koka v1.0, KUBE, Kustom AR, Lalinga, Lampix, Layar, Legal Graffiti, LEGO AR Studio, LEGO Hidden Side, Leo Video Camera, Lexting: Hands- 3D Rapid Text Entry, Lifecast, Lifeliqe, Lightform LF2, Lightship ARDK, Little Engineer, Little Rebels, Live Home 3D for iOS, Live Link Face, LivePaper, LivePics, Loly, LoopLeap, Lucyd Loud 2020 Smartglasses, Lumo, LUNAR, MAD Gaze, Made With ARKit, MagePrints, Magic Chess AR, Magic Leap Creator Portal, Magic Leap One, Magic Photos, Magic Sudoku , Magicplan, Maguss, Makebox AR, makeSEA, Makeup Genius, Marketing New Realities, Marsbot for AirPods, Mask Fashions, MASSIVE, Measure, MeasureKit 2.0 with LiDAR Scanner, MechFightAR, Medici, Meet Diana Danko, Megastores.com, Mem Place, Memeois World, MemoAR, Memojis, Merge Cube, Meta 2 Dev Kit, Metal 2, Metaverse, Micro Breaker, Microsoft Hololens, mimesys, Minecraft Earth, Minsar Studio, Mint and List your NFT, MIX, Moatboat, MoCap, Modelified 3D Scanner, Modiface, Mokosh Simple Gallery, moonmoons AR, MR Builder, Mudra Inspire, Muglife, Music Kit V.3, MY DARE BOX, My Virtual Girlfriend AR, myHouseby, n3xt, Neatsy, Nerdeo, New School VR - The Five E's of VR Learning, Nexto, NFTs 2.0, Nodesk, NOMone AR/VR desktop on the GO, nosedive BETA, Notable Me, noteit AR, NoteStorm, Observer Analytics, Octi 2.0, Open Villas, Opuscope, ORA-X, Orbit-Ed, Orboot, Orbu, Osmo Pizza Co., Paint the City, Paint3r - Coloring in 3D, Paint-AR, PairPlay Audio Adventures, Panda, Paperframe, Paperplane, Pastie, PeakFinder AR, PeakVisor, Periodic Table Chemistry 4 app, Personal Sticker Maker for WhatsApp, Phantom Augmented Robotality, Photo Find, PhotoCatch, PianoVision, PicAlive, Pictarize, Pictofit, PictureThat, Pikmin Bloom, Pin Club, Pinmyspot, Placie, Plane Finder AR, Planet Attack AR, PlayCanvas, PlayCrowd, Playmoji: Childish Gambino, PlayTable, PlayVisit, PLNAR, PlugXR, Pokemon Go, POLARIS, Pong AR, POP AR, Portalble, Possessions., Pretia, Primepads, Primer, Prism, Product Hunt Collection of Media Tech, Project Clear, Prompto, Properly, Proximie, PubFighters, Qhanu, Qibla Finder, Qlone, Quartz Brief, WRain It!, Rainbrow, REAL cARds™, Reality Filters, Reality Tasks, Reality Tasks macOS, Really Make, Recyclinator, Reliance MET Industrial Plots, RemoteMac.io, Render People, Research VR Podcast, ResearchVR 006 - Drones, , HMD's and ZUI, resources.AR, Respond, REWILD, RideOn, Rini, Roav, RocketXR, RoCo, Rovr, RP-FX, rumii, Run an Empire 3.0, SAFARI CENTRAL, SatelliteSkill5, Scavengar, SceneShot, SearchCam, Seat360, Sebela, Seek, SeeSignal, Selfie Fixer, Sellar Listing Tool, Sephora Virtual Artist, Shazam Codes, Shepard Fairey AR exhibition, Sherpa Tours, ShiShi TryOn, ShowMe Assist, Shuffle Cups AR, SIMO AR, sippBOX , SiteScape, SketchAR, Sketchfab, Skip, Skrite, Sky Guide RA, Skyway, Slidrs, Smart AR Home, SmartLens, Smash Tanks!, SmileFun, Snatch, SNOW, Social Bee Adventures, Society, Solar3D glasses, Soundmaze, Space Era, Spatial, Spatial Computing Platform, Speak To Anything, Spellbound, Spheroid Universe, Spiff 3D, Spotlight, Squavel, Stack AR, Stambol VR, Stellart, Sticker It!, StickLing, SticStac, Stories AR View, Suggestic, Sun Locator Lite, Sun Seeker, SureMDM, Surreal Words, Talkie OCR, Tangar, TekRevol, TeleStory, Terace 2.0, tethr, The Don, The Fidj, The Fourth Transformation, The Future Wave Newsletter, The Ghost Howls, The Legend of Jack-o'-Lantern, The Lookout, The Machines By Directive Games, The Mona Lisa, Augmented, THE RAW SPACE EXPERIENCE, TheParallaxView, TikTok, Tilt Five, TIME Immersive, Timelense, TinkerNote, TomToons, Tooder, toolbox, Torch, Touristerguide Wand, Trail of Treasures, Tribe XR DJ School, Trickshot League, Triffic, TRIPP, TRY BUY, TryAR, TurboHire, TV Size AR, TweetReality, UBeBot, Ultraman Kaiju Kombat, UniteAR, Unity AR+GPS Location, Unity3D, Universal AR, Unomi 3D , unspun, VAIR, VAM/R, VIBZ, Victorise, Vigilante, Virtlo, Virtual Reality, VR, Virtual Travel Experience, Virtual Try On, Virtuhunt, Virus Hunters, Visao, Visual Money, Visual Shazam, Visualist, Vived Learning, Vossle, voxelizeAR, VR Maker, Vrumble

2.0, Vuzix Blade, Wacky Face, Waggle Words, Walk the Property Lines, Walker of Aldenor, WallaMe, Wallary, Wallr, Wand, War of the AI, Warby Parker Virtual Try-On, warpAR, watAR, Wayfarer Stories, WEbXR Experiments by Google, WebXR Viewer, Weird Cuts, WiDAR, Wildeverse, WiTag, Woah AR, Wonderscope, WooCommerce AR, Worldopo, WrldCraft, WYD Pride, Xiaomi Smart Glasses, Xibit, Xmas Card AR, XO, XR Loaded, XR Typography Guidelines 1.0, YAS, Yaw2, Yeehaw Wand, YoPuppet, You Gun Die AR, ZapBox, ZapWorks, ZapWorks Studio 6, ZINE LOOP, Zumbio

Appendix 3. Keywords for the Strategic AI Orientation

Exploitation: capitalize, deploy, deployment, draw upon, efficiency, efficient, efficiently, executable, execute, executes, execution, executions, executor, exploit, exploitation, exploiter, implement, implementation, implementations, implemented, implementing, implements, leverage, leveraged, leveraging, production, refine*, refinement, refining, use

Exploration: discover, discovered, discovery, examination, examine, experiment, experimentation, experimenting, exploration, exploratory, explore, explored, flexibility, flexible, forage, innovat*, innovation, innovative, inquest, inquiry, inquisition, inspect, inspection, interrogate, interrogation, investigate, investigation, investigative, play, probation, probe, probing, query, quest, question, research, researched, researching, risk, risky, search, searched, searches, searching, study, variation, variations

Appendix 4. Measures of Exploitation and Exploration using AI Announcements

Below, we provide as an example a snippet of an AI investment announcement by H&R Block, Inc. listed in New York Stock Exchange under the ticker symbol HRB.[41]

> *‘‘We are introducing something this tax season that is totally new, and is in fact, a first in the tax preparation category," said Bill Cobb, H&R Block's president and chief executive officer. "By combining the human expertise, knowledge and judgment of our tax professionals with the cutting-edge cognitive computing power of Watson, we are creating a future where our clients will benefit from an enhanced experience and our tax pros will have the latest technology to help them ensure every deduction and credit is found. <u>This partnership with Watson means we can leverage the best technology available to help our clients get their taxes won</u>.’’*

We use LIWC to measure AI strategic orientation (exploitation and exploration). In the above snippet of an AI announcement, total number of sentences are 3 and we see only one word “leverage” belonging to exploitation list of keywords (see Appendix 3) in the highlighted sentence. There is no word in the snippet of an announcement shown that belongs to exploration list of keywords (shown in Appendix 3). Thus, the measure of AI strategic exploitation orientation computed by LIWC is: *1/3 = 0.33*, and the measure of AI strategic exploration orientation computed by LIWC is: 0/3 = 0 in this part of the announcement.

[41] For space limitations, we provide a snippet of an AI investment announcement made by H&R Block in February 2017 as mentioned in Lexis-Nexis. Text mining was done on the entire announcement.

Appendix 5. Keywords for the Revenue-focused and Cost-focused

Revenue Focused: custom*, diversif*, earning*, expand*, expansion, explor*, growth, income, leader*, market*, proceeds, return*, revenue*, sale*

Cost Focused: cost*, economical, efficien*, exploit*, frugal, homogeniz*, inexpensive, low-budget, optimiz*, parsimon*, productivity, prudent, refin*, saving, standardiz*, streamlin*, thrifty

Appendix 6. AI related Keywords[42]

AI ChatBot, AI KIBIT, AI marketplaces, AI governance, AI cloud services, AI-assisted system, AI-related C&SI services, AI developer toolkits, AI Paas, Aida, Alexa, algorithm, AlphaGo, Amazon Web Service, Amelia, ANTLR, Apertium, Artificial Intelligence, Artificial Narrow Intelligence, Artificial General Intelligence, Artificial Super Intelligence, ANI, AGI, ASI, ASR, Audio recognition, Audio Signal Processing, Augmentation, Augmented AI, AutoML, Automatic Speech Recognition, automation, autonomous, autonomous driving, autonomous system, autonomous vehicle, AWS, biometric, Bot, Caffe Deep Learning Framework, Chatbot, Cobot, cognitive computing, cognitive insight, cognitive system, cognitive technology, Collaborative robot, Collaborative robotic, Computational Linguistics, Computer Vision, conversational agent, conversational assistant, conversational user interfaces, Data labeling and annotation services, Decision intelligence, Decision Trees, Deep Learning, Deeplearning4j, Deep neural network ASICs, Digital ethics, Distinguo, DL, Driverless AI, driverless technologies, Echo, Echo Voyager, Edge AI, Einstein, Expert Systems, Extended Reality, Explainable AI, face recognition, facial recognition, FPGA accelerators, Gesture recognition, Google Cloud Machine Learning Platform, Google Now, Gradient boosting, Graph analytics, GPU accelerators, H2O , IBM Watson, ID recognition, Image Analysis, Image analytics, image classification, Image Processing, Image Recognition, Insight engines, intelligence software, Intelligent Agent, Intelligent applications, Intelligent automation, Intelligent product, Intelligent system, Intelligent Virtual Agent, Interactive agent, Interactive system, Ithink, Knowledge graphics, Keras, Kik, Latent Dirichlet Allocation, Latent Semantic Analysis, Lexalytics, Lexical Acquisition, Lexical Semantic, Libsvm, Lowebot, Machine

[42] Keywords include AI and product names of AI.

Learning, machine learning algorithms, Machine Translation, Machine Vision, Madlib, Mahout, MARF, Mayhem, micro-expression recognition, Microsoft Cognitive Toolkit, ML, MLPACK, Mlpy, Modular Audio Recognition Framework, MoSes, MT, MXNet, natural language, Natural Language Processing, Natural Language Toolkit, ND4J, Nearest Neighbor Algorithm, neural network, Neuromorphic hardware, NLTK, Object Recognition, Object Tracking, OpenCV, OpenNLP, Opinion Mining, Pattern Recognition, Personalization, Predictive System, Predix, Pybrain, Quantum computing, Random Forests, recognition, recommendation, Recommendation agent, Recommendation system, recommendations algorithm, Recommender agent, Recommender System, Reinforcement learning, robot, robotic, RPA, Robotic process automation, Robotic process automation software, Roomba, S Voice, SDSCM, Semantic Driven Subtractive Clustering Method, Semi-Supervised Learning, Sentiment Analysis, Sentiment Classification, Shallow learning, Siri, Smart algorithms, Smart systems, Smart robotics, Speech analytics, Speech Recognition, Speech to Text, Supervised Learning, Support Vector Machines, SVM, Tay, TensorFlow, Text analytics, Text Mining, Text to Speech, Tokenization, Torch, TTS, Unsupervised learning, VPA-enabled wireless speakers, Video analytics, Virtual Agent, Virtual Assistant, virtual bartender, vision processing, Voice recognition, Vowpal, Wabbit, Watson, Watson Ads, Word2Vec, Xgboost, XiaoIce

Appendix 7. Measures of IT Strategy – Revenue-focused and Cost-focused using 10-K Report

Below, we provide as an example a snippet of Adobe 10-K report filed with Security and Exchange Commission in 2019.[43]

> *"Adobe continues to redefine the creative process with Adobe Creative Cloud so that our customers can obtain everything they need to create, collaborate and be inspired. One part of our strategy is Adobe Sensei, a proprietary framework and set of intelligent services for dramatically improving the design and delivery of digital experiences. Adobe Sensei leverages Adobe's massive content and data assets, as well as its deep domain expertise in the creative, marketing and document segments, within a unified artificial intelligence ("AI") and machine learning framework to help customers discover hidden opportunities, reduce tedious processes and offer relevant experiences to every customer."*

We use LIWC to measure IT strategy (revenue-focused and cost-focused). In the above snippet of an annual report, there are 3 sentences. First and the third sentence speak about helping customers through the Adobe Creative Cloud and machine learning framework. Second sentence mention the technology but no keywords are present belonging to corpus of revenue-focused or cost-focused words (shown in Appendix 5). First and third sentence mention IT strategy words in the bucket of revenue-focused IT strategy as they are customer oriented sentences. Therefore, measure of revenue-focused IT strategy computed using LIWC is: 2/3= 0.66 and measure of cost-focused IT strategy computed using LIWC is 0/3 = 0 in this snippet of an annual report.

[43] For space limitations, we provide a snippet of annual report filed by Adobe in the year 2019. Text mining was done on the entire annual report.

Chapter 4: A Study of the Adoption and Use of Recommender Systems

> "A lot of times, people don't know what they want until you show it to them."
> (Steve Jobs, 1997)

Introduction

The explosive growth in information on the World Wide Web (WWW) has provided people with the ability to access a massive amount of information, including descriptions, advertisements, comments, and reviews of most products and services, from a variety of sources (Batmaz et al. 2019). However, this almost instant access to such information leads to the information overload problem (Batmaz et al. 2019; Lu et al. 2015).

One way to address this plethora of data is through a recommender system (RS), which uses machine learning and deep learning algorithms (Jannach and Jugovac 2019; Ricci et al. 2011) to filter information and provide users with personalized content (Schafer et al. 2001) in the form of recommendations. Recommender systems take information about a user's preference (e.g., about movies) as an input and provide suggestions (e.g., new movies available) to her. The term "recommender system" was first mentioned in the early 1980s when Salton (1986) presented a word-vector algorithm for searching amongst textual documents. Over the past several years, RSs have integrated various artificial intelligence (AI) techniques to cater to users' needs. Thus, technological advancements in the field of AI and improvement in computational power provide opportunities to enhance the user's experience and satisfaction in the use and adoption of RSs.

Netflix credits RSs with creating a business value of up to 1 billion US dollars per year, while YouTube attributes an increase of 60 percent of the clicks on the home screen to RSs (Jannach and Jugovac 2019). Designed initially for e-commerce, RSs have been used in various other areas over the past few years, including healthcare (Bouayad et al. 2020), and entertainment (Hosanagar et al. 2014), creating value for both consumers and providers (Abdollahpouri et al. 2017).

A RS collects and acts on users' data, thereby shaping users' experiences and interactions. The various features of RS could have a varied impact on the user's beliefs about the system. For instance, a RS with anthropomorphic characteristics could enhance the overall user experience by creating a social environment (Qiu and Benbasat 2009). By contrast, a RS could also engender oppression on the users by exerting control over the types of recommendations (Kane et al. 2021). Thus, RS features could attenuate or enhance the users' perception of the quality of the RS. Against this backdrop, we address the following research question:

RQ1. How do the features of a RS affect its success?

Literature on human psychology has examined that needs of humans relate to their well-being and effective functioning (Deci and Ryan 2000). Individuals use technology for improved performance (Davis 1989), and users' psychological needs influence the use of various technology features (Karahanna et al. 2018). The features of technology provide action possibilities to users to satisfy their psychological needs in the form of affordances (Gaver 1991; Karahanna et al. 2018). Although research has stressed RS's usefulness and ubiquitous nature, it has also highlighted the ethical issues and risks arising from RS (Adomavicius et al. 2018; Koene et al. 2015). In this context, we draw upon the needs-affordances-features (NAF) perspective, which Karahanna et al. (2018) proposed in a study on social media applications. RS affordances that help fulfill users' needs would increase the users' perceived usefulness and satisfaction level of the RS. For example, users seeking relatedness would perceive RS to be of much greater use if users could impact others from their reviews on recommendations through affordances provided by RS. Thus, this study develops a taxonomy of affordances in the context of RS by addressing the following research question:

> RQ2: What affordances does a RS provide, and how do they satisfy user's psychological needs?

Karahanna et al. (2018) argue that individuals' psychological needs motivate their use of technology, and their psychological well-being depends on fulfilling those needs through the affordances provided by the technology. We interact with RS regularly when we use digital services, products, and apps in various contexts, from entertainment to shopping to healthcare. Amazon, Netflix, and Garmin Connect recommend the type of movie that would interest us, products that would suit our needs, to go for a walk after sitting for a few hours on a chair. NAF perspective provides a proper theoretical foundation to examine the use of RS, especially when the use is personal and voluntary. RS reduces information overload and cognitive load by providing content that may be of value (Li et al. 2020). Users would be inclined to use RS if they perceive it helpful. This perceived usefulness will be greater if the RS fulfills their psychological needs through affordances enabled by their features.

Additionally, IS success model (DeLone and McLean 1997; Rai et al. 2002; Sabherwal et al. 2006) has stressed the importance of system quality and perceived usefulness in the success of the IS system. System quality and perceived usefulness are beliefs that affect the use of the system or the consumption of the system's output (Rai et al. 2002; Wixom and Todd 2005). In the context of RS, the NAF perspective and IS success model complement each other to provide a holistic theoretical framework and help us examine how users' psychological needs drive the use of RS and the consumption of recommendations generated from RS that fulfill their needs. Therefore, our third research question is:

> RQ3. How does the alignment between the user's psychological needs and affordances provided by a RS affect its success?

This study makes use of the theoretical lenses of the Needs-Affordances-Features (NAF) perspective (Karahanna et al. 2018) and IS Success Model (Sabherwal et al. 2006). NAF perspective sheds light on users' psychological needs motivating the use of information systems (e.g., RS in this study), and the extent of use depends on the action possibilities in the form of affordances that these information systems provide to satisfy users' needs. IS Success model provides a framework for understanding the antecedents of the system's use. NAF perspective and IS Success model complement each other as NAF provides a theoretical foundation to understand how the congruence between the system's affordances and users' needs impacts the perceived usefulness of the system and further drives its use. Although RSs affect consumer choice and generally lead to an increase in sales volume, there is little discussion of how different RS features influence the RS's effectiveness.

RSs affect consumer search and learning and help resolve product uncertainty, such as reviews and product descriptions. However, RSs sometimes suffer from content diversity (Fleder & Hosanagar 2008), personalization (Zhou et al. 2012), data sparseness (Grčar et al. 2006), and cold start problem (Lika et al. 2014), lack of explainability (Rai 2020), and many more. Given that users' psychological needs drive the use of the system, users vary in preferences over the features in the system. They tend to favor those affordances enabled through features that align with their needs. Against this backdrop, we investigate different dimensions of affordances that users make use of in RS that help satisfy their needs. We conduct longitudinal survey-based study using a sample of 355 full-time working individuals recruited from a third party, Prolific. We employ an advanced clustering method in the form of k-means clustering using python to classify participants into different groups based on their use of affordances of RSs. Using a novel measure of alignment between users' psychological needs and affordances following the approach by Sabherwal and Kirsch (1994), this study investigates the research questions. It sheds light on the implications for the firms investing in RSs. The study also offers directions for further theoretical and empirical work on the performance implications of RSs.

The rest of the chapter is organized as follows. The next section provides the theoretical foundations for the paper. The subsequent sections develop the theoretical model, followed by the data description, including the sample and the measures. A description of the analyses and results follows. The chapter concludes by discussing the emergent findings and their implications for future research and practice.

Prior Work on Recommender Systems

Over the last few years, the application of RSs can be seen in various areas – e-commerce, transportation, healthcare, agriculture, and media (see Fayyaz et al. 2020). Contemporary RS development involves the confluence of the IS fields of artificial intelligence and big data (Ricci et al. 2011). Adopting Li and Karahanna's (2015) conceptualization, we define RS as a web-based technology that explicitly or implicitly collects user preferences and recommends options that may be useful to individuals. A RS assists users by presenting services or products that are most likely of their interest, and recommendations help users of the RS in decision-making and dealing with information overload problems (Ricci et al. 2011). A RS uses different information sources such as users' past information transactions and browsing behavior, analyzes the data, and provides recommendations that may be of interest to users and that users might consume or purchase (Resnick and Varian 1997).

Research on RSs examines technical and economic aspects providing details on the evolution of design and development of algorithms, the architecture of RS, and the impact of RS on firm performance in sales, churn rate, and customer retention (Hosanagar et al. 2014; Smith and Linden 2017). Moreover, research also investigates the application of RS in various sectors –

healthcare, agriculture, transport, and media, to name a few. Researchers have studied the business value of RS across the following dimensions – click-through rates (CTR) (Davidson et al. 2010), conversion flow from viewing to purchasing (Chen and Canny 2011), sales and revenue (Lee and Hosnagar 2014), and sales distribution (Lawrence et al. 2001). Work in the technical context has primarily focused on the design and improvement of the algorithms for better prediction accuracy (Adomavicius and Tuzhilin 2005; Okura et al. 2017). For example, Domingues et al. (2013) and Kirshenbaum et al. (2012) find that using both collaborative filtering and content-based approaches results in better recommendations accuracy. Although Xiao and Benbasast (2007) argue the importance of user's input in the recommendations generation process and display of recommendations on RSs adoption, most of the work in RS literature focuses on technical details surrounding the algorithm design and accuracy in the prediction of recommendations and the impacts of RS (see Table 1). Moreover, RSs are generally categorized into three types based on their recommendations (Adomavicius and Tuzhilin 2005). Table 2 lists various types of RSs.

---Insert Table 1 about here---

---Insert Table 2 about here---

Although some studies (Greer and Murtaza 2003; Komiak and Benbasat 2006; Lee and Benbasat 2011; Qiu and Benbasat 2011; Wang and Benbasat 2005; Xu 2006) investigate the use of RS, they examine the effect of RS design on use. To the best of our knowledge, prior literature lacks an overarching framework that studies the interplay between the user’s psychological needs and the affordances of RS on the use of recommendations. This study aims to bridge the gap in RS literature to provide a holistic overview of the factors that impact RS success.

Theoretical Foundations

Needs-Affordances-Features Perspective

Individuals' needs are the impetus for energizing human behaviors (Deci and Ryan 1987). People engage in activities that would satisfy their psychological needs. NAF perspective posits that these needs motivate people to use technology with affordances through which users could fulfill their needs and attain satisfaction (Karahanna et al. 2018). For example, RS from Amazon offers the affordance to seek additional information on the recommendations, enabled by features such as ratings and reviews from others. Using these features could help users acquire knowledge on the recommendations and fulfill their psychological need for competence. Thus, needs motivate individuals to use RS features that provide affordance to fulfill their needs. Figure 1 shows the NAF perspective in the context of RS.

---Insert Figure 1 about here---

User's Psychological Needs

Karahanna et al. (2018), in their study of NAF, provided five broad categories of psychological needs using self-determination (Deci and Ryan 2000) and psychological ownership theory (Pierce et al. 2001). Based on a literature review of RS (see Table 2), the needs mentioned in the NAF perspective also provide a valuable starting point in the context of RS (see Table 3), which generates online content in the form of recommendations. Individuals use recommendations for self-identity, learning about new things for competence, and much more.

---Insert Table 3 about here---

Features of Recommender Systems

Prior work on RS has provided us insights into the functionalities of various RS used in different contexts. Very few studies explicitly mentioned the attributes of RS (Li et al. 2020;

Schafer et al. 2001), yet these studies have talked only about a handful of RS features. For instance, Schafer et al. (2001) studied e-commerce RS and developed a taxonomy of RS based on functional I/O, recommendation method used, and design issues. Xiao and Benbasat (2007) provide a good overview of RS characteristics. However, RSs have evolved since, and their applications are seen not only in e-commerce but in other contexts, such as music to listen to, news to read, and movies to watch. Thus we need a revisit to understand in detail the various features that provide action opportunities through affordances that could satisfy the user's psychological needs. We could not identify a study that examines the various features of RS by taking a holistic view of potential contexts. We identify a comprehensive set of 25 *a priori* features of RS (as mentioned in Table 4) based on the literature review of scholarly articles from 2000 to 2020.

---Insert Table 4 about here---

Affordances of Recommender Systems

Affordances are actionable possibilities offered by technology to users. In other words, affordances are what a user can potentially do through using the technology to fulfill their needs (Karahanna et al. 2018). Karahanna et al. (2018) developed the needs-affordance-features (NAF) framework to study social media applications. We adopt their framework in the context of RS, as shown in Figure 1. We identify a comprehensive set of *a priori* RS affordances (see Table 5) based on the literature review of scholarly articles on RS from 2000 to 2020 that prior literature has either investigated or suggested as potentially affecting users' attitudes toward the RS.

---Insert Table 5 about here---

IS Success Model

Users play an essential role in the eventual success of an information system (IS) (DeLone and McLean 1992; Rai et al. 2002; Sabherwal et al. 2006). IS success is generally viewed in terms of four aspects: perceived usefulness, user satisfaction, system quality, and usage (Sabherwal et al. 2006). IS success theoretical lens benefits this study by providing insights into the success factors that should be considered when examining the use and adoption of RS. RSs generate content as recommendations for specific users that could be potentially valuable to them. Therefore, we examine recommendation quality and recommendation use instead of RS quality and RS use, which prior studies have done (see Sabherwal et al. 2006). Users may feel differently about the recommendation use as some may feel apprehensive due to ethical concerns (Adomavicius et al. 2018). Some users may feel excited about encountering new information (Grange et al. 2019). NAF perspective complements IS success literature in understanding how users' needs get fulfilled by RS affordances that subsequently influence the users' attitudes toward RS, continuing to use recommendations generated by RS. Thus, we draw upon NAF and IS success model (DeLone and McLean 1992; Rai et al. 2002; Sabherwal et al. 2006) as theoretical foundations to understand the factors affecting RS success.

Theoretical Development

RSs assist individuals in making choices by providing alternatives that may be of value. They may suggest exciting content in addition to those that are based on personal preferences. RSs have become part of our lives as we interact with streaming devices to watch movies (e.g., Netflix) or listen to music (e.g., Spotify) or monitor our fitness level (e.g., Strava). From e-commerce (suggest to buyers articles that could interest them) to online advertisement (suggest to users the suitable contents, matching their preferences), RSs are today unavoidable.

Organizations invest in RS to offer personalized services that help customers in decision-making, enhance user experience, and benefit the organizations (Jannach and Jugovac 2019). This study aims to provide an overarching framework of the features of RS and users' psychological needs that either encourage or discourage RS use. Figures 2 to 5 show our theoretical models, and Table 6 lists the key constructs of our study. Figure 2 provides a broad overview of our research model. Figure 3 shows the IS success model (Sabherwal et al. 2006) in the context of RS. Figures 4a and 4b show the RS success framework at times T1 and T2, respectively. Figure 5 shows the RS success framework over time.

---Insert Table 6 about here---

---Insert Figure 2 about here---

---Insert Figure 3 about here---

---Insert Figure 4a about here---

---Insert Figure 4b about here---

---Insert Figure 5 about here---

If Web 3.0 technologies provide a framework for users to engage with each other online and generate content in both structured and unstructured formats (e.g., the use of Instagram to post pictures and use of online communities to provide reviews), they also create a plethora of information. Users have gained access to a massive amount of information resulting in cognitive overload (Li et al. 2020). The improved computational power enables firms to harness massive data, and AI-enabled RS act on the data to gain insights into users' likes and dislikes. These RS help users by filtering out unwanted content and providing content that could be of value to users. However, the use of RS also raises concerns among the adopters of RS. For example, RS act on users' personal information, raising privacy issues,[44] and could help users acquire new knowledge by providing novel recommendations that users have not seen before or new information on prior recommendations. Therefore, features of RS may impact users' perception of recommendation quality. Thus, we posit H1a while planning to explore the possibility that some RS features might positively affect quality and others might negatively affect it. Moreover, affordances are action opportunities enabled by the features of the system. So we posit:

> H1a: RS features affect recommendation quality.
> H1b: RS features affect RS affordances.

Users differ in their psychological needs, which motivate them to engage in actions that would provide growth and well-being (Deci and Ryan 2000). From the lens of NAF, users could fulfill their needs through the use of affordances provided by the technology. In the era of web 3.0 technologies, information is abundant, and users confront too many choices. In the context of RS, these systems help solve the problem of information overload by acting as information filtering tools and could help fulfill their psychological needs with the relevant information. For example, if in buying a product, RS could provide the rating of the product accompanied by descriptive information about the product and a short video providing helpful information about the product, it would fulfill users' psychological need for competence by providing new information. It would help reduce uncertainty among the users (Daft and Lengel 1986). By contrast, if the affordances of RS do not help users filter out recommendations that do not align with their self-identity, it would reduce their perceived usefulness of RS. Therefore, we posit H2:

> H2: The alignment between the user's psychological needs and affordances provided by RS positively affects the perceived usefulness of RS.

[44] https://towardsdatascience.com/the-ethical-and-privacy-issues-of-recommendation-engines-on-media-platforms-9bea7bcb0abc

IS success model (DeLone and McLean 1992; Rai et al. 2002; Sabherwal et al. 2006) suggests that system quality leads to satisfaction; perceived usefulness leads to satisfaction, satisfaction, and usefulness leads to use, and use leads to perceived usefulness. In the context of RS, the quality of recommendations and the perceived usefulness would impact the satisfaction level of the users. The more satisfied the users are with the RS, the more intent they would express in using RS and consuming recommendations. Similarly, the more useful the users perceive the RS to be, the more they will use it. Also, the use will affect the perceived usefulness of the system (Sabherwal et al. 2006).[45] The more use of the RS depicts the higher levels of perceived usefulness. Thus, prior use of RS will impact the perceived usefulness of the RS at a later time. Behavioral intention is a vital determinant of the use of the system (Venkatesh et al. 2003). Thus, the level of satisfaction with the RS and the perceived usefulness of the RS affect the continued intention to use recommendations. So, based on the IS success model, we posit:

> H3: Recommendation quality positively affects user satisfaction.
> H4a: Perceived usefulness positively affects user satisfaction.
> H4b: Perceived usefulness positively affects the subsequent extent of use of recommendations.
> H4c: Perceived usefulness positively affects the subsequent continued use intention of recommendations.
> H5a: User satisfaction positively affects the subsequent extent of use of recommendations.
> H5b: User satisfaction positively affects the subsequent continued use intention of recommendations.

Prior literature has examined that the use of the technology impacts the perceived usefulness of the system (DeLone and McLean 1992; Rai et al. 2002; Sabherwal et al. 2006). Although IS literature has examined the use of the system in terms of frequency and for work-related outcomes, such as task accomplishments and job performance, it is essential to understand the

[45] Rai et al. (2002) and Sabherwal et al. (2006), posit and empirically find perceived usefulness and use to be correlated. However, since we measure use at a later point in time than perceived usefulness, we hypothesize perceived usefulness to affect the subsequent extent of use.

use of the system from a needs-based, especially when the use becomes personal and voluntary as in the case of RS. NAF perspective provides a theoretical lens to investigate the nature of the use of RS by examining the fulfillment of needs through affordances provided by RS. Theories of cognition argue that the use of a system leads to an improved understanding of the system. In the context of RS, users would better understand the recommendations generated from RS if they have used the system before. Through the prior use, users would be better able to judge whether and how affordances provided by RS would fulfill their psychological needs. Users would be able to recognize better the affordances offered by the RS if the prior use of RS has resulted in satisfactory outcomes through which users feel their needs are met. Hence, we posit:

> H6a: Extent of use of recommendations from a RS positively affects the subsequent perceived usefulness of the RS.
> H6b: Extent of use of recommendations by a RS leads to the subsequent greater recognition of affordances provided by the RS.

Methods

This research conducts interviews and surveys. We obtained approval letter (as mentioned in Appendix 1) from Institutional Review Board (IRB) before conducting the surveys. The following subsection discusses our study design.

Study Design and Participants

Interviews

Since the study uses newly developed items for features and affordances, we first conduct interviews with assistant professors, industry experts, and PhD students to understand their use of recommender systems. The purpose of the interview is to help refine the items, specifically items related to features and affordance, as they were newly developed based on prior literature. We interview 11 participants online separately using Zoom or Microsoft Teams, depending on the choice of the participants. Each participant was given survey items for the constructs of time

T1 and T2 (as mentioned in Figure 4a and Figure 4b) through email. Participants completed the surveys and returned the completed surveys in an email to the researchers before the scheduled interview with them. We asked open-ended questions to the participants in the interview about the type and description of the recommender systems they use the most, their experiences with the surveys, and any suggestions they have for us related to the positioning of the items in the survey, any rewording on the items. Interview times varied from 15 min to 25 min. We identified the time of completion for each survey – surveys at times T1 and T2 through this stage pool of participants. We believe that our pool of diverse participants for the interview differing in work experience, educational background, ethnicity, and profession, provided valuable insights to refine our survey items. Table 7 lists the demographics of the participants for the interviews. The following subsection details the surveys conducted at various stages by recruiting participants online through a third-party provider – *Prolific*.[46]

---Insert Table 7 about here---

Stages of Survey in Prolific

This research is based surveys with each informant at two different times – T1 and T2 (as mentioned in Figure 4a and Figure 4b). We recruited survey participants through prolific in three rounds, and in each round, only the participants who completed survey 1 were given survey 2 with a gap of one week between the two surveys. We ensured that no participant was part of more than one round. We recruited full-time working professionals residing in the U.S.A., having minimum education qualifications of a bachelor’s degree, and whose first language is English. We asked questions related to the RS participants use the most. We administered survey 1 at time T1 and survey 2 at time T2. We used several attention check questions in both surveys

[46] https://www.prolific.co/

to ensure the responses we receive from the participants are devoid of errors. Table 8 lists the constructs measured at time T1 and time T2 along with their scale items for surveys conducted in Prolific. The following subsections provide details about each round.

---Insert Table 8 about here---

Round 1

We first conducted round 1 of surveys with 50 participants to test the reliability of the measures and check the completion time of each survey. In survey 1, 49 out of 50 participants passed the validation check, and only they were given survey 2. All 49 participants completed survey 2 without failing any validation checks. Based on the insights from the pilot interviews, we had set the expected survey completion times for surveys 1 and 2 at 30 minutes each, but they took a mean of 28 and 25 minutes, respectively, to complete in Round 1.

Round 2

Next, we conducted round 2 of surveys with a large pool of participants. We used the above mean completion times for surveys 1 (28 minutes) and 2 (25 minutes) from Round 1 to specify the expected completion times. We administered survey 1 to 290 participants in round 2. Seven of them failed the validation check. We administered survey 2 to the remaining 283 participants one week after survey 1. Five of the 283 participants failed the validation check in survey 2, and 10 refused to participate. Therefore, in round 2, we have a final sample of 268 participants who participated in both surveys and passed the validation checks.

Round 3

Since we had lost 22 potential respondents in Round 2, we conducted a round 3 with 42 participants. We used the same estimation times of completion for surveys 1 (28 minutes) and 2 (25 minutes) as in Round 2. All 42 participants completed survey 1 and passed validation checks.

We then administered survey 2 to them one week after survey 1. Of the 42 participants from survey 1, 38 completed survey 2 and passed validation checks.

Since we had reduced the expected completion times from 30 minutes each for surveys 1 and 2 in round 1 to 28 and 25 minutes for surveys 1 and 2, respectively, in rounds 2 and 3, we conduct a one-way ANOVA test to check the difference in the completion time of each survey across the three rounds. However, homogeneity of variance assumption is violated in both surveys, so we perform one-way ANOVA assuming unequal variances.[47] We do not find any significant difference across the three rounds in the completion times for survey 1 (*Welch statistic* $= 1.08$ at $p > 0.05$; *Brown-Forsythe statistic* $= 1.45$; $p > 0.05$) or survey 2 (*Welch statistic* $= .76$ at $p > 0.05$; *Brown-Forsythe statistic* $= .97$; $p > 0.05$) based on this analysis or Bonferroni and Tukey's post hoc test. In the light of these results, we combine all the three rounds of participants for subsequent analyses. The overall sample includes 355 participants from all three rounds who passed validation checks and completed both surveys 1 and 2.

Table 9 provides the demographic characteristics of the final set of participants (n=355). Table 10 lists the names of the RSs final set of participants use the most. Of the 355 participants, 11 participants did not provide the name of the RS they use the most.

---Insert Table 9 about here---

---Insert Table 10 about here---

Measures

The study aims to understand the antecedents of the use of recommendations. Literature has primarily studied the use of systems (see Sabherwal et al. 2006). We study the use of recommender systems in terms of the use of recommendations because we wish to study whether

[47] ANOVA assuming homogenous variances also does not indicate a significant difference in the completion time across the three rounds for survey 1 ($F = 1.50$; $p > 0.05$) or survey 2 ($F = 1.21$; $p > 0.05$).

the millions of dollars spent by companies in designing their RS to generate recommendations for the end-users are resulting in the consumption of recommendations or not.

All constructs except RS features, RS affordances, Age, and RS experience in this study are operationalized with published scales (Table 8) that have demonstrated good psychometric properties in prior research. The items are adapted in the context of RS and we measure them using Likert-type 7-point scales ranging from 1 = “completely disagree” to 7 = “completely agree”. For recommendation use, we use Likert-type 7-point frequency scale (Table 8). *Age* and *RS experience* are measured as reported by the participants. Based on the literature review on *RS features* (Table 4) and *RS affordances* (Table 5), we develop scale items for both RS features and RS affordances, and we measure them using Likert-type 7-point scale. In this study, we control for age, RS experience, the expertise of the RS provider firm, and trust in the RS provider firm.

Before proceeding on combine the samples across the three rounds, we measure the standardized Cronbach alphas (reliability) of the constructs in each round. The reliabilities of all the constructs are above the threshold of 0.7 in each round.[48] We combine all the three rounds of participants to perform the factor analysis on the full list of items for RS features and RS affordances (as mentioned in Table 8) to get first-order dimensions because we find consistency in the reliability values of the constructs across rounds and non-significant difference in the completion time of both the surveys across rounds. Table 11 lists the reliability values of the items from each round.[49] We did not need to compare early vs. late responses because all

[48] We do not measure the reliability of dimensions RS features and RS affordances at this stage because we do not have *a priori* dimensions and need to first perform the exploratory factor analyses to identify the inherent factors.

[49] One of the items (“I intend to use the recommendations from my recommendation system more for other purposes”) for continued use intention of recommendation (CUIR) does not load with its other items in all three rounds. It was dropped in the analysis. Reported Cronbach alpha value for CUIR in Table 11 excludes that item. Cronbach alpha value including this item for CUIR for rounds 1, 2, and 3 were 0.65, 0.63, and 0.66, respectively.

responses for both the surveys of all rounds were collected during a single day, and we did not send out reminders (see Hair et al. 1998).

---Insert Table 11 about here---

Factor Analyses of RS Features and RS Affordances

We use the sample size of 355 participants to perform exploratory factor analysis with varimax rotation on the items of RS features and RS affordances (shown in Table 8). We conduct a series of factor analyses in Stata (v 17.0), which is used for all analyses in this paper. We drop items with multiple loadings and single-item factors (see Appendix 2 for the list of dropped items). We continue this iterative process of evaluating the results of factor analysis, dropping items, and repeating the analysis on the remaining items until we find the set of items having no multiple-loadings or single-item factor. Appendix 2 provides the list of items of RS features and RS affordances that were dropped after factor analysis. Table 12 lists the final factors of RS features and RS affordances from exploratory factor analysis along with their respective items.

---Insert Table 12 about here---

The final factor solution for RS features includes 17 items loading on four factors. The first factor, *informative*, includes items 3, 15, 16, and 22. These features focus on providing additional information on the recommendations, and generates new recommendations that may interest users. The second factor, *contextual*, includes items 4, 5, and 7. These features consider the location and time before generating recommendations, and extend the recommendations across different contexts. For instance, providing recommendations on books based on the movie preference of the user. The third factor, *interactive*, includes items 10, 12, 13, and 25. These features engage with users to explain the process of generating recommendations and understand the attributes required by the users before generating recommendations. The fourth factor, *considerate*, includes items 6, 17, 19, 20, 23, and 24. These features incorporate users' feedback and consider their ratings on products before providing them recommendations. These features generate recommendations based on users' needs and actions.

The final factor solution for affordances includes 13 items loading on three factors. Each item loaded onto its respective constructs, supporting convergent validity and unidimensionality of the constructs. The first factor, *information acquisition*, includes items 2, 5, 6, 8, and 12. These affordances allow users to compare recommendations and get additional information and explanation on the recommendations. They help users to acquire information about others' purchases and opinions, and are highly information intensive. The second factor, *preference elicitation*, includes items 3, 4, 9, 10, and 17. These affordances enable users to do trade-offs among various product attributes before getting recommendations. They also enable users to provide feedback to the RS. The third factor, *recommendations filtering*, includes items 7, 14, and 15. These affordances provide an authoritarian role to the users, enabling them to control the number of recommendations and filter unwanted content or information. They also provide users an opportunity to search for relevant recommendations. The following subsections provide details on the various measurement model tests.

Measurement Model Tests

We test three measurement models due to the large number of items across the two surveys. The first measurement model includes the emergent factors of RS features and RS affordances. The results for thus measurement model supports a four-factor solution for RS features and three-factor solution for RS affordances. The measurement model fits the data well, with a Root Mean Square Error of Approximation (RMSEA) of 0.06, Standardized Root Mean Square Residual (SRMR) of 0.05, Comparative Fit Index (CFI) of 0.91, and a χ^2 to degrees of freedom ratio of 3.67. Table 13 lists the emergent factors of RS features and RS affordances along with their items and standardized loading coefficients (lambdas) in the final measurement model. Table 14 lists the descriptive statistics, inter-factor correlations, and square root of the average variance extracted (AVE) for the factors of RS features and RS affordances.

---Insert Table 13 about here---

---Insert Table 14 about here---

As shown in Table 14, the square root of each factor's average variance extracted exceeds its correlations with all other factors, indicating *discriminant validity* among constructs (Fornell and Larcker 1981). Further, the average variance extracted of each construct exceeds 0.5, supporting *convergent validity* of the measures of all factors (Fornell and Larcker 1981). Table 15 lists the standardized Cronbach alphas, composite reliabilities, and rho_A coefficient values of all the constructs in the study. Cronbach alphas (Cronbach 1951), composite reliabilities (Zhang et al. 2022), and rho_A (Dijkstra and Henseler 2015) examines the internal consistency of the scale items. The Cronbach alphas of all the constructs (including those measured at both T1 and T2) range from 0.68 - 0.70; Composite reliability all the constructs in the overall structural model are at or above 0.82; and rho_A reliability indices are at or above 0.70 for all the constructs in the overall structural model. Composite reliabilities were computed using *avecr*[50] command in Stata and rho_A coefficient values were computed using *plssem* command in Stata. Thus, our scale items indicate *convergent validity* of the measures.

---Insert Table 15 about here---

The second measurement model focuses on constructs measured at time T1. It includes recommendation quality (RQ); first order constructs of user's psychological needs – autonomy,

[50] https://github.com/franksun319/AVECR

relatedness, competence, having a place, coming to know the self, expressing self-identity, and maintaining continuity of self-identity; perceived usefulness; user satisfaction. The measurement model fits the data well, with a RMSEA of 0.06, SRMR of 0.03, CFI of 0.93, and a χ^2 to degrees of freedom ratio of 2.65. Table 16 lists the descriptive statistics, square roots of AVEs, and intervariable correlations for the study variables measured at time T1. As Table 16 shows, the square root of each variable's AVE exceeds its correlations with all other variables, indicating *discriminant validity* among constructs. Further, each construct's AVE exceeds 0.5, supporting *convergent validity* of all the measures. Table 17 lists the constructs measured at T1 along with their items and standardized loading coefficients (lambdas) in the measurement model.

---Insert Table 16 about here---

---Insert Table 17 about here---

The measurement model for constructs measured at time T2 includes recommendation quality, factors of RS features and RS affordances (see Table 12), perceived usefulness, user satisfaction, and recommendation use between time T1 and time T2, continued use intention of recommendation. The measurement model fits the data well, with a RMSEA of 0.04, SRMR of 0.02, CFI of 0.96, and a χ^2 to degrees of freedom ratio of 1.74. Table 18 lists the descriptive statistics, square roots of AVEs, and intervariable correlations for the study variables measured at time T2. As shown in Table 18, the square root of each variable's AVE exceeds its correlations with all other variables, indicating *discriminant validity* among constructs. Further, the average variance extracted of each construct exceeds 0.5, supporting *convergent validity* of the measures of all factors. Table 19 lists the constructs measured at T2 along with their items and standardized loading coefficients (lambdas) in the measurement model.

---Insert Table 18 about here---

---Insert Table 19 about here---

Tests for Common Method Bias

We conduct two different approaches to test for common method bias. We first perform the Harman's one-factor test (Harman 1960) and find that the total variance extracted by one factor is 28.64 percent. Harman one-factor test shows that our data does not suffer from common method bias (Podsakoff et al. 2003) and the total variance extracted is less than the recommended threshold of 50 percent.

We also follow the approach suggested by Williams et al. (2010) to test for common method bias for our structural model. We employ CFA marker variable technique to test for common method bias, and researchers have acknowledged the technique as one of the robust approaches to test for common method bias (see Richardson et al. 2009, p. 796; Schmitz et al. 2016). Lindell and Whitney (2001, p. 118) advise using "one or more multiple marker variables that are more similar to the criterion in terms of semantic content, proximity, a small number of items, and narrowness of definition". The marker variable has to be theoretically unrelated to the study variables. Spector et al. (2019) stress the importance of selecting the marker variable that belongs to the same class as study constructs (see Table 4, p. 873). Our study uses behavioral constructs, and thus, in light of all this, we believe social desirability as the choice of marker variable is relevant to our study. We use Stata (v 17.0) to run a series of covariance-based CFA models.

The *initial CFA* model includes all our study variables and marker variable along with their items. The *baseline CFA* model adds the constraints as zero to the correlations between the marker variable and other variables in the initial CFA model. We then add item paths between the marker latent factor and all manifest variables. We constrain these paths to be constant in the model. We name this model *Method-C*. Thus, in model Method-C each non-marker item loads on to its theoretical construct and the marker construct. We constrain the path from marker latent factor to its manifest variable to a common value in both baseline and Method-C model.

We conduct a multivariate normality test on the variables before comparing the χ^2 statistics as an assumption of multivariate normality in empirical research need not be taken for granted (Cain et al. 2017). We test for multivariate normality using *the mvtest* command in *Stata*. We observe that both Henze-Zirkler (Henze and Zirkler 1990) and Doornik-Hansen (Doornik and Hansen 2008) statistics are significant ($p \leq 0.05$). Therefore, we use *the Satorra-Bentler* correction factor to check the differences between chi-square statistics obtained from baseline and Method-C models. Satorra-Bentler statistic controls non-normality in the data (Pavlov et al. 2020). We find the difference in χ^2 statistics between the baseline and Method-C model non-significant (Satorra-Bentler $\Delta\chi2 = 2.51$, $\Delta df = 1$). Thus, we conclude the absence of common method bias from our data.

Tests for Measurement Invariance

Our study is longitudinal study involving measuring constructs at two time periods – T1 and T2. It is important to examine measurement invariance when the same construct is measured at different points in time (Chan 1998; Ployhart and Vandenberg, 2010). Measurement invariance test attempts to verify that the estimated factors are measuring the same underlying latent construct within each time period. We test for measurement invariance by comparing two models - configural and metric invariance models. We measure recommendations quality, perceived usefulness, and user satisfaction in both the time periods (T1, T2).

For configural invariance model, we set all the parameters free for the constructs used in measurement invariance test. This allows to get an idea of the best fit for the measurement model that we can obtain with these data. For model identification purposes, we fix the loading for the first item at one and the item one intercepts at zero for constructs used in measurement invariance test. We fix the item one intercepts at zero so that we can estimate the factor means. For metric invariance model, we constrain the factor loadings to be equal across time periods for each construct. We then test the significance of the difference in chi-square statistics obtained from configural and metric invariance model for each of the construct used in measurement invariance test. If the constrained model does not fit the data significantly worse than the base model of configural invariance, metric invariance is established. We obtain the statistics for the constructs: recommendations quality ($\Delta\chi2 = 0.45$, $\Delta df = 5$, $p > 0.05$); perceived usefulness ($\Delta\chi2 = 3.54$, $\Delta df = 5$, $p > 0.05$); and user satisfaction ($\Delta\chi2 = 0.89$, $\Delta df = 3$, $p > 0.05$). The extremely small change in chi-square statistics ($p > 0.05$ for all the constructs) tells us that the model in which the factor loadings are constrained to be equal fits equally as well as the model with all parameters free to vary. Thus, it concludes the presence of measurement invariance in our study.

Analyses

The analytic process consists of three steps. First, we classify the participants based on the affordances they use in the recommender systems by performing cluster analysis on the factors of affordances (as mentioned in Table 10). Second, we compute the alignment between affordances and users' psychological needs following Sabherwal and Kirs (1994). Last, we test research hypotheses using structural equation modeling. The following subsections provide details on these three steps.

Classification of Participants

We perform cluster analysis to classify participants using the factors of affordances (as mentioned in Table 10) – information acquisition, preference elicitation, and recommendations filtering. Cluster analysis is considered a useful technique for developing empirical taxonomy

(Ulrich and McKelvey 1990). Cluster analysis refers to grouping data points together that have common characteristics. Some of the most common clustering techniques are – single linkage (nearest neighbor), complete linkage (farthest neighbor), group average linkage, and Ward's method. We employ K-means clustering, which is regarded as one of the powerful clustering techniques (Coates and Ng 2012). We perform K-means clustering using python to get the required number of clusters. K-means clustering is one of the most popular unsupervised machine learning algorithms that identify *k* number of centroids (center of the cluster) and then allocate every data point to the nearest cluster while keeping the centroids as small as possible. The allocation of data points to each cluster happens by reducing the in-cluster sum of squares. To find the correct number of clusters (*k*), we perform a series of steps: (1) we first generate within the sum of squares (WSS) values for various values of *k*, ranging from one to 11. Table 20 provides the WSS values for different values of *k*. We find that there is not much significant improvement in WSS values as *k* is increased from three to four and onwards. We then plot the *elbow plot* to check at what value of *k* the graph starts to show kink. Figure 6 shows the *elbow plot*. We observe that after *k*=3, the *elbow plot* starts to become flat.

---Insert Table 20 about here---

---Insert Figure 6 about here---

We then examine the Silhouette index (SI) scores to evaluate the clustering performance. The score evaluates the quality of the clusters. It measures how close each point in one cluster is to points in the neighboring clusters and thus provides a way to assess the number of clusters. The silhouette index technique for cluster validation is one of the well-known and best-performing techniques (Burney and Tariq 2014; Vendramin et al. 2010). Silhouette index score ranges from [-1, 1]. The value of +1 signifies that data points of one cluster are far from the neighboring clusters, and the value of 0 signifies points that are very close to the neighboring clusters. The value of -1 signifies that data points may have been assigned to the wrong cluster. Table 20 lists the silhouette index scores for various values of k, and Figure 7 shows the silhouette plot for different values of k. We observe that the SI values tend to decrease as we increase the number of clusters, i.e., the value of k. Table 21 shows that the silhouette score for k=3 is the highest, and Figure 7 shows that for k=3, the cluster sizes seem uniform. Therefore, we choose the number of clusters as 3.

---Insert Table 21 about here---

---Insert Figure 7 about here---

We validate the number of clusters using different clustering techniques to assess the robustness of our findings. We use hierarchical clustering with the group average linkage method (Ulrich and McKelvey 1990) and find that our choice of the number of clusters as three is consistent with both k-means and hierarchical clustering methods. Figure 8 shows the dendrogram for hierarchical clustering with the group average linkage method.

---Insert Figure 8 about here---

We also conduct ANOVA to examine the difference among three clusters across three dimensions of affordances used for cluster analysis – *information acquisition, preference elicitation, and recommendations filtering*. We find significant difference among clusters across information acquisition ($F=290.90$, *p-value* < 0.001), preference elicitation ($F=528.55$, *p-value* < 0.001), and recommendations filtering ($F=466.88$, *p-value* < 0.001).

We examine the three clusters to understand the characteristics of each cluster. Figure 9 shows the characteristics of each cluster differing across information acquisition, preference elicitation, and recommendations filtering.

---Insert Figure 9 about here---

We observe that cluster 1 (*n* = 125) participants are neutral regarding their use of affordances related to information acquisition, preference elicitation, and recommendations filtering. The participants in this cluster do not have a high demand for information access, trade-offs among features of recommendations, and filter of unwanted recommendations as compared to cluster 2 participants. However, they are more demanding across these three factors of affordances than cluster 3 participants. They do have equal preference for all types of affordances. We name cluster 1 as *basic pitchers*.

Cluster 2 participants (*n* = 128) have high demand for affordances related to information acquisition, preference elicitation, and recommendations filtering. These participants make maximum use of all the dimensions of affordances. They use RS affordances to access additional information on recommendations. They use RS affordances to specify trade-offs among various features of recommendations before RS provides recommendations. They also make use of search and filter to be able to control unwanted recommendations. The participants in this cluster need everything. We name cluster 2 as *gold diggers*.

Cluster 3 participants (*n* = 102) are low-maintenance users. They are less demanding in terms of all the three factors of affordances and rank lowest on the use of all types of affordances when looking for recommendations. They seem to be easily gratified with the recommendations provided. We name cluster 3 as *relaxing rhinos*. The following section discusses the computation of alignment between affordances and the user's psychological needs.

Computation of Alignment between Affordances and User's Psychological Needs

Following Sabherwal and Kirs (1994), we use profile deviation to measure the alignment. This process of measurement reflects the extent to which a user's psychological needs resemble an “ideal” profile of psychological needs that is suitable for the three factors of affordances identified earlier – information acquisition, preference elicitation, and recommendations filtering. Participants whose psychological needs profile is close to the ideal psychological needs profile for the three factors of affordances would be said to have a high degree of alignment. We perform four major steps using the profile deviation approach: (1) the development of an ideal user’s psychological needs profile, (2) the identification of a study sample, (3) the use of differential weights for various dimensions of the user’s psychological needs – autonomy, competence, relatedness, having a place, coming to know the self, expressing self-identity, and maintaining continuity of self-identity, and (4) comparison with the baseline measure to assess the predictive power of profile deviation measure.

First, we develop the ideal profile of psychological needs for each cluster, which serves as a benchmark for the psychological needs of participants within that cluster. To the best of our knowledge, prior literature does not identify such ideal profiles exists for user’s psychological needs. We use the highest-performing participants to represent the ideal profile (see Sabherwal and Kirs 1994; Venkatraman and Prescott 1990). Specifically, we use a calibration sample with participants in the top 10 percent on the perceived usefulness scale within each cluster. We use perceived usefulness measured at time T2 since we measure dimensions of affordances at time T2 in our study. We compute the ideal profile for each cluster as the mean values of the user’s psychological needs’ dimensions for the participants in the calibration sample.

Second, we identify the sample within each cluster to test the hypotheses. Since we use the top 10 percent of participants within each cluster (in terms of perceived usefulness of RS), we remove the bottom 10 percent (in perceived usefulness of RS) to have an unbiased sample. Thus, the final sample within each cluster consists of all the participants less than the top 10 percent (the calibration sample) and the bottom 10 percent (removed to offset the downward shift in perceived usefulness). This results in a final sample size of 285 participants for testing our hypotheses. We name it a hypotheses sample to avoid any confusion.

Third, we compute proximity to the ideal psychological needs' profile for each participant within each cluster in the hypotheses sample. We use differential weights for dimensions of psychological needs as we believe users may have a different preference for each of their needs when using RS. We first regress perceived usefulness at time T2 on dimensions of user's psychological needs within each cluster using the hypotheses sample of 285 participants. We normalize the standardized beta weights of regressions in each cluster by dividing their sum in that cluster. We consider beta weights of only those dimensions of the user's psychological needs that were significantly ($p \leq 0.05$) related to perceived usefulness at time T2 within each cluster. Thus, we obtain differential weights by normalizing the standardized beta weights of regressions of perceived usefulness at time T2 on dimensions of the user's psychological needs. We calculate the alignment between affordances and the user's psychological needs as one less the weighted Euclidean distance of psychological needs' dimensions from the ideal profile for the cluster to which the participant belongs. For the i^{th} participant in the test sample,

$$\text{Alignment}_i = 1 - \sqrt{\sum_{j=1}^{j=N} w_j\left(x_{ij} - c_j\right)^2}, \text{ where}$$

$w_j = b_j / \Sigma b_j$); b_j = standardized beta weight of j^{th} variable in the regression for perceived usefulness at time T2 in the given cluster; x_{ij} = score of i^{th} participant in the hypotheses sample for the j^{th} variable; c_j is the mean of the scores of the j^{th} variable for the participants in the calibration sample; and j = 1, N where N is the number of user's psychological needs dimensions that are significantly related to perceived usefulness at time T2 in that cluster. Table 22 presents the ideal profiles of the user's psychological needs in the three clusters. Table 22 also presents the standardized beta coefficients (b_j) for the psychological needs variables in the regressions for perceived usefulness at time T2 in each cluster. We find that: autonomy is significantly associated with gold diggers (cluster 2) and relaxing rhinos (cluster 3); relatedness is significantly associated with basic pitchers (cluster 1), gold diggers, and relaxing rhinos; competence and having a place are significantly associated with gold diggers; coming to know the self is significantly associated with basic pitchers and relaxing rhinos; expressing self-identity is significantly associated with basic pitchers, gold diggers, and relaxing rhinos; and maintaining continuity of self-identity is significantly associated with gold diggers.

---Insert Table 22 about here---

Fourth, we examine the predictive power of this alignment measure. We compare that with the baseline measure based on the distance from the mean psychological needs using the entire sample of 355 participants. Specifically, we compare the correlations of perceived usefulness at time T2 with alignment and the baseline measure for each cluster. We find that correlation of perceived usefulness with alignment (0.22) is significantly (t-statistic = 2.89 at p-value < 0.01) greater than its correlation with baseline measure (-0.08). This shows that the alignment measure performs better than the baseline measure.

Hypotheses Testing

We test our research model using hypotheses sample size of 285 participants (we explain this hypotheses sample in step 2 of computation of alignment section earlier). We use *sem* command to conduct structural equation modeling (SEM) (Jöreskog and Sörbom 1993) in Stata (v 17.0). Considering a large number of indicators, we use the summated measures (the means of items comprising each scale) (Babin and Boles 1998). To adjust for measurement errors, we set the path from each latent variable to its measure equal to the square root of the scale reliability.

We set the error variances equal to the variance of the scale multiplied by one minus scale reliability (Jöreskog and Sörbom 1993). We also set the variance-covariance matrix of latent exogenous variables to unstructured. For the single-item measure of each control variable, we set reliability at 0.90 (Davy and Shipper 1993; Sabherwal and Becerra-Fernandez 2005). Next, we discuss the results from SEM and descriptive statistics of the study variables.

Results

Table 23 reports descriptive statistics, square root of the average variance extracted (AVE), and intervariable correlations for the study variables. It is based on the middle 80 percent of the sample (i.e., after excluding the top 10 percent and bottom 10 percent on the perceived usefulness scale within each cluster).

---Insert Table 23 about here---

The initial structural model includes the two latent exogenous variables (recommendations quality measured at time T1 and recommendations systems' features measured at time T2), eight latent endogenous variables (perceived usefulness measured at T1 and T2, user satisfaction measured at T1 and T2, recommender systems affordances measured at T2, alignment computed at T2, use of recommendations measured at T2, and continued intention to use of recommendations measured at T2), the hypothesized direct paths (Hypotheses 1-6), and paths from each control variables to each latent endogenous variable. Table 24 lists the SEM results.

---Insert Table 24 about here---

H1 is more exploratory in nature as we first find the factors of RS features and RS affordances through factor analysis, explained earlier in the paper. We find that users in our sample set have better experience with informative and considerate RS features as these features positively affect recommendation quality. Interestingly, we notice that interactive features of RS creates bad perception on quality of recommendation as the effect is found to be significantly negative on the recommendation quality. It could be because RS still lacks in having a good engaging experience with the users resulting in user's dissatisfaction with the quality of recommendation. We also find that: informative, contextual, and interactive features of RS provide actionable opportunities to users to acquire information; contextual, interactive, and considerate features of RS provides actionable opportunities to users to do tradeoff in the product or elicit their preferences during the recommendation generation process; and contextual and interactive features of RS helps users to filter out unwanted recommendation. Overall, we find RS features impacts recommendation quality and different RS features enable different action opportunities for the users of RS during the use of recommendation. Thus, we find support for H1 by examining the impact of four dimensions of RS features on recommendation quality and three dimensions of RS affordances.

We find that alignment between RS affordances and the users' psychological needs positive affects perceived usefulness of RS. Therefore, H2 is supported. All the hypothesized paths in the initial structural model were significant ($p < 0.05$), except the path from user satisfaction measured at time T1 to the extent of use of recommendations between time T1 and T2 measured at time T2 ($z = 1.22$, $p > 0.05$), and user satisfaction measured at time T2 to continued use intention of recommendation ($z = -0.41$, $p > 0.05$). Thus, H3, H4(a, b, c), and H6(a, b) are supported; and H5(a, b) are not supported. We do not find support for hypotheses H5a and H5b regarding the effect of user satisfaction on use. These non-supported paths are consistent with the results from Sabherwal et al. (2006).

We then evaluate the structural model by examining the modification indices of each constrained path. Modification index indicates the predicted decrease in chi-square if the constrained path is relaxed (Jöreskog 1978). It helps identification of an excluded relationship that might have both practical and theoretical significance (McAllister 1995). Based on theoretical considerations and modification indices of 10.0 or more (Denison et al. 1996), we include the following paths: (1) perceived usefulness at time T1 to RS features at time T2 – informative (*MI = 47.59*), contextual (*MI = 35.07*), interactive (*MI = 34.50*), and considerate (*MI* = 24.03); and (2) extent of use of recommendations between time T1 and T2 to RS features at time T2 - informative (*MI =27.22*), contextual (*MI =20.64*), interactive (*MI = 29.44*), and considerate (*MI = 25.92*). We test our structural model with these new paths. We find that perceived usefulness of RS leads to more recognition of informative, contextual, interactive, and considerate features of RS. We also find that prior use of the RS leads to greater recognition of informative, contextual, and interactive features of RS. Figure 10 shows a revised structural model with new emergent paths. We exclude the paths from control variables from Figure 10 to avoid further complicating it.

We argue theoretically for these new emergent paths. Users will explore RS features if they perceive RS to be of value to them. Similarly, more use of the recommendations will motivate users to explore additional features of RS to be able to receive new recommendations that they may find useful. Also, users will spend time recognizing more RS features if they perceive RS to be useful. Therefore, we find these new emergent paths theoretically logical and justify the inclusion of these new paths in the revised structural model (as shown in Figure 10) both theoretically and statistically. The revised structural model has a good overall fit (*CFI* = 0.92, χ^2 to degrees of freedom ratio of 2.82, *RMSEA* = 0.065, and *SRMR* = 0.04).

Table 25 summarizes the hypothesized and emergent paths. We next conduct supplemental analysis to check the differences across different types of recommender systems.

---Insert Table 25 about here---

Supplemental Analyses

We categorize recommender systems most used by the participants in our sample into hedonic and utilitarian (see Table 26). We then conduct *t-tests* of the differences in the means of constructs between hedonic and utilitarian recommender systems. Table 27 provides the results. We find significant differences between hedonic and utilitarian types of recommender systems in the means of perceived usefulness (measured at time T1), use of recommendations between time T1 and time T2, RS features – contextual and interactive, RS affordances – information acquisition, recommendations filtering, and preference elicitation, alignment, perceived usefulness (measured at time T2), and continued intention to use recommendations. Thus, compared to the participants using recommender systems for hedonic purposes, the participants using recommender systems for utilitarian purposes perceive RS as more useful, find RS features (contextual and interactive) and RS affordances (information acquisition, recommendations filtering, and preference elicitation) to be more appealing, and show greater intention to continue to use recommendations. However, participants using recommender systems for utilitarian purposes and hedonic purposes do not differ in their perceptions of recommendations quality, extent of use of recommendations between time T1 and time T2, alignment of psychological needs with RS affordances, satisfaction, and one of the RS features (informative). We next highlight the study's key findings, limitations, and implications for research and practice.

---Insert Table 26 about here---

---Insert Table 27 about here---

Discussion

RSs are applications of Artificial Intelligence and Machine Learning technology in practice. Nowadays, such systems accompany us through our daily online lives — for example, on e-commerce sites, on media streaming platforms, or on social networks. They influence the choices we make every day — what book to read next, which song to download, and which person to date. They help us by suggesting things assumed to be of interest to us and which we are likely to inspect, consume, or purchase. Consumers save the time and effort of wading through the vast possibilities of the digital marketplace, and businesses build loyalty and drive sales through differentiated experiences. RSs have a wider impact on users and society more broadly. However, as with many other new technologies, digital recommendations are also a source of unintended consequences. RSs can manipulate preferences in ways consumers do not realize. After all, the details underlying recommendation algorithms are far from transparent (Rai 2020). Faulty RSs that inaccurately estimate consumers' true preferences could leave consumers disappointed from unmet expectations. The fact that these systems are of utmost importance cannot be argued. However, critics of RSs have pointed out that these systems can fragment users into specific information consumption bubbles (see Pariser 2011; Sunstein 2009).

After all, they shape user preferences and guide individual and social choices. This impact is significant and deserves an investigation into the needs of the consumers that drive the adoption of RS, which RS literature has so far overlooked. Therefore, a holistic understanding is needed to evaluate the RS's design and use and the trade-offs between the different interests at stake. A failure to do so may lead to opportunity costs and problems that, in turn, lead to public distrust and backlash against using RS in general (Koene et al. 2015). Our findings highlight the importance of the features of RS and the alignment between affordances provided by RS and the user's psychological needs that impact the perceived usefulness of RS and, eventually, the consumption of recommendations generated by RS.

Our research design comprises of interviews with experts and longitudinal surveys using a sample of 355 respondents. We find that our pool of participants favors features of RS that help them acquire information about the recommendations generation process and peers' opinions. Users like to have an interactive engagement with RS by providing their preferences before RS generates recommendations. We also find that users favor RS that incorporates their feedback before providing users recommendations. Users have different needs that further drive their behavior in the social ecosystem, ranging from buying books to listening to music to exploring new knowledge, specifically using the recommendations generated by RS in this study. We find three different groups of users in our sample size. Group 1, which we call basic pitchers, has an equal preference for information acquisition, preference elicitation, and recommendations filtering. Though they have an equal preference for these affordances that users use in RS, they do not have a high demand for these compared to group 2 users. Users in group 2, whom we call gold diggers, use RS to acquire information, feed their preferences to RS before RS provides recommendations, and look to filter out unwanted recommendations. Users in group 3 that we call relaxing rhinos do not make much use of affordances in RS, and instead, they let RS handle the recommendations for them.

We find that alignment between the action opportunities enabled by the RS and users' psychological needs plays a pivotal role in shaping users' attitudes toward the consumption of recommendations generated by RS. Unlike previous studies on system use, our longitudinal study design provides valuable insights into the connection between system use and antecedents of use at different times. We observe that prior use of the recommendations leads to more use of the affordances of RS. We also find through our non-hypothesized relationships that prior perceived usefulness and prior use of the RS leads to recognition of new features of RS.

Limitations

The above results should be viewed in light of the study's limitations. First, our cluster analysis using the dimensions of affordances comes from the sample size of 355 respondents. Future work could use the larger sample size and unravel new affordances clusters. Second, we administer survey 2 one week after survey 1. Thus, the extent of use of recommendations studied between survey 1 and survey 2 is about the use in one week. Future studies could increase the time between survey 1 and survey 2. Third, we identify the comprehensive set of features and affordances through a literature review on RS from 1990 to 2020. Future work could extend our list of features and affordances of RS by exploring new work on RS. Fourth, we did not specifically study one type of RS. Future work could test our model by examining a particular RS. While acknowledging these limitations, we believe our findings, robust to several alternative specifications, would be helpful to the field.

Implications for Research

This study makes key contributions to RS, IS success, and technology adoption literature. Prior research on RS provides valuable insights into the technical details of different types of algorithms that generate recommendations. Our study is the first to investigate holistically various facets of RS that drive the use of recommendations. First, this study extends the literature on NAF in the context of RS to underline the importance of alignment between the user's psychological needs and the affordances enabled through the features of RS. Users differ in terms of their needs. RS is a social form of information system that shapes the behavior of the users by influencing their lifestyle and thus have societal implications. RS adoption depends on the extent to which the user's needs are gratified. In light of this, our study applies the NAF perspective to investigate the interplay between the user's psychological needs and the affordances provided by RS and is the first to the best of our knowledge to compute alignment between affordances and needs. Additionally, we investigate the various features of RS that impact the use of RS.

Second, we extend the literature on IS success by applying IS success theoretical model in the context of RS. We contribute to this stream of literature in many folds. We examine the use of the information generated by the system as we believe in the context of our study, the use of recommendations is more relevant to the study than the use of the system. We conduct a longitudinal study to understand the impact of prior use of the recommendations generated by RS on their subsequent use. Longitudinal design to test IS success model in the context of RS complements the NAF perspective as we find that prior use not only impacts the perceived usefulness of the system in the future but also leads to recognition of features of the system and more use of the affordances at a later time.

Third, our study is more generic in nature as we did not study one particular type of RS. Using prior literature, we identify the comprehensive set of features and affordances from all forms of RSs. We conceptualize the second-order constructs of RS features and RS affordances by developing scale items of RS features and RS affordances and their respective first-order constructs. The validity and reliability of the scale items were tested in three rounds of surveys (as mentioned in Table 9). We contribute to the IS survey-based literature by providing scale items of RS features and affordances that future work can use. Future work could use our developed items to test against a particular RS.

Fourth, we contribute to the IS design literature by examining the various dimensions of features and affordances through confirmatory factor analysis and how these dimensions impact the use of RS. Our analytical procedure using cluster analysis to classify participants and various dimensions of RS features and affordance sheds useful insights on the successful design elements of RS that shape their adoption.

Our work also adds rigor to the methodology. Fifth, we use the profile deviation approach to first derive an ideal profile for each type of need. Prior research has used the profile deviation approach in the context of organizations. Our work is the first of its kind, to the best of our knowledge, to use the profile deviation approach to develop an ideal profile based on the needs of the users. We provide a novel measure of alignment between affordances and the user's psychological needs that plays a pivotal role in the use of recommendations and their usefulness. Last, we employ advanced clustering techniques to classify participants using various dimensions of affordances.

Implications for Practice

This study also has potential practical implications. First, using our findings, firms could implement the necessary features that enable affordances fulfilling the needs of the target population. RS providers should first try to understand their customer base before generating recommendations for them. Designers of RS could implement features that first ask users to specify their psychological needs before providing recommendations. That way, firms would get to know about their consumer's needs and could shape their overall experience by having a provision built in the RS to provide only the requisite set of RS features and affordances that align with their needs. This would result in customer satisfaction and increased use of the recommendations. Understanding the needs of the target population could help firms address the ethical issues surrounding the RS.

Second, our analysis of the impact of types of features on recommendations use reveals that users of RS prefer RS to be interactive, informative, and considerate. RS providers should design RS in such a way that RS provides an explanation on the process of generating recommendations; allows visibility to others' opinions on recommendations and their likings and ratings on the recommendations; allows users to explicitly state their preferences before generating recommendations; and has features that consider the user's changing needs.

Finally, our cluster analysis process that classifies participants reveals that certain segments of users have high demands for information acquisition, preference elicitation, and recommendations filtering. Thus, firms should have RS features built in such a way that provides action opportunities to users in the form of affordances through which users of RS could seek additional information on generated recommendations, explore novel recommendations, and explicitly elicit their preferences on the attributes of recommendations, and able to control the number and content of recommendations.

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Figures of Chapter 4

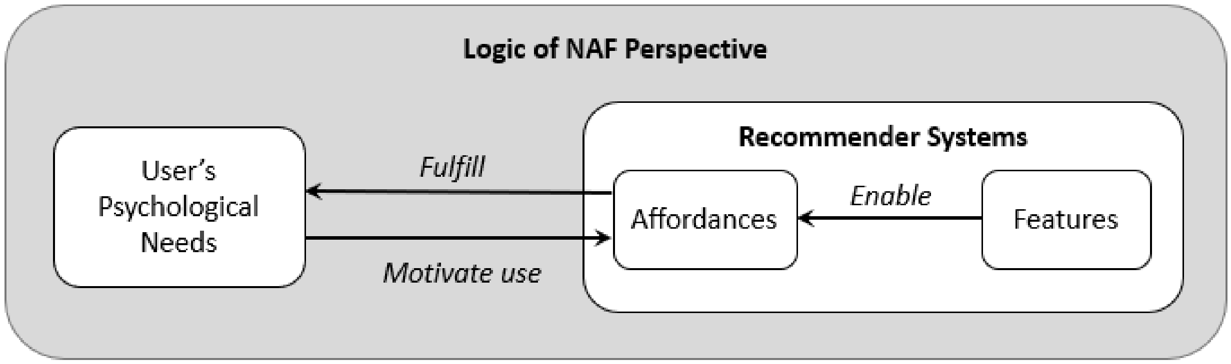


Figure 1. Needs-Affordances-Features (NAF) perspective in RS context[51]

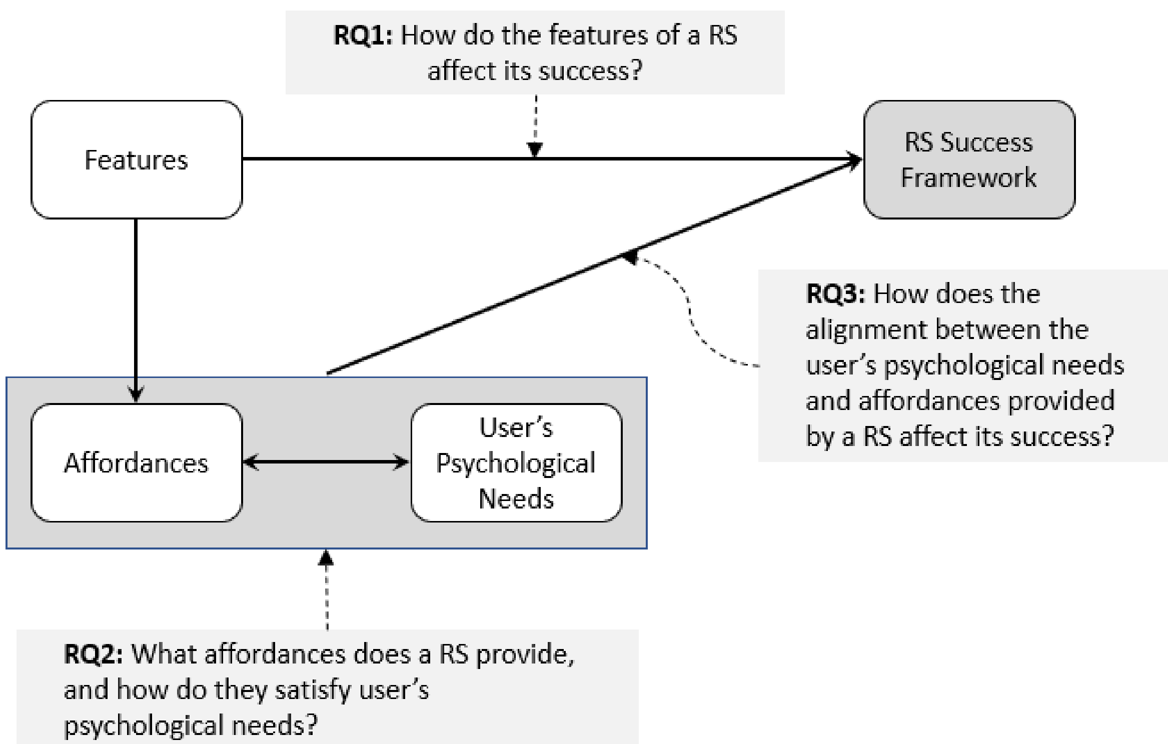


Figure 2. Research model

[51] NAF perspective adapted from Karahanna et al. (2018)

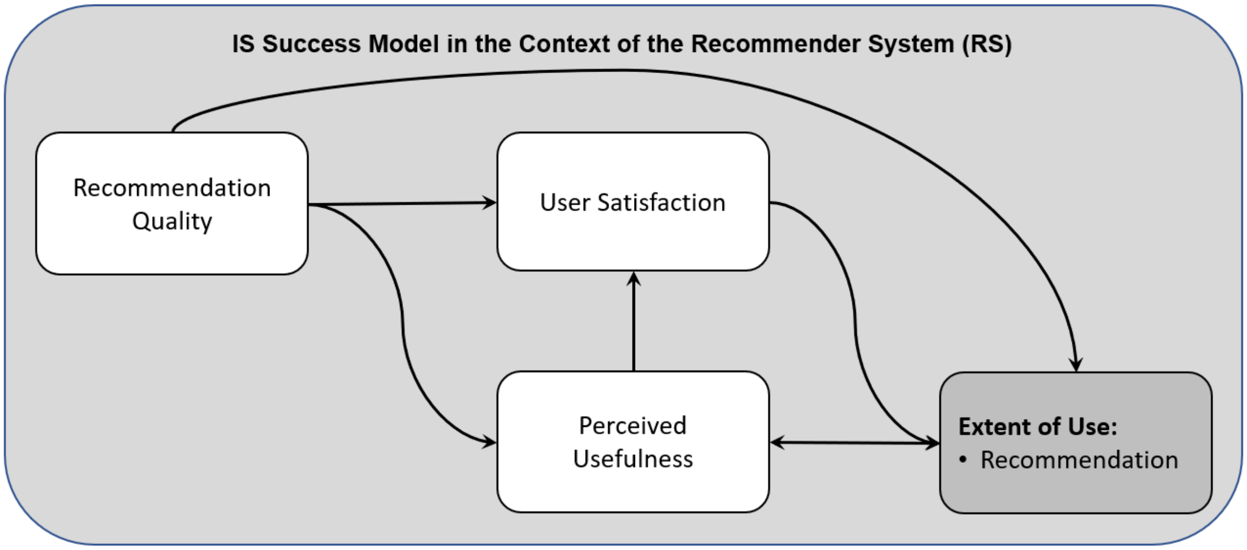
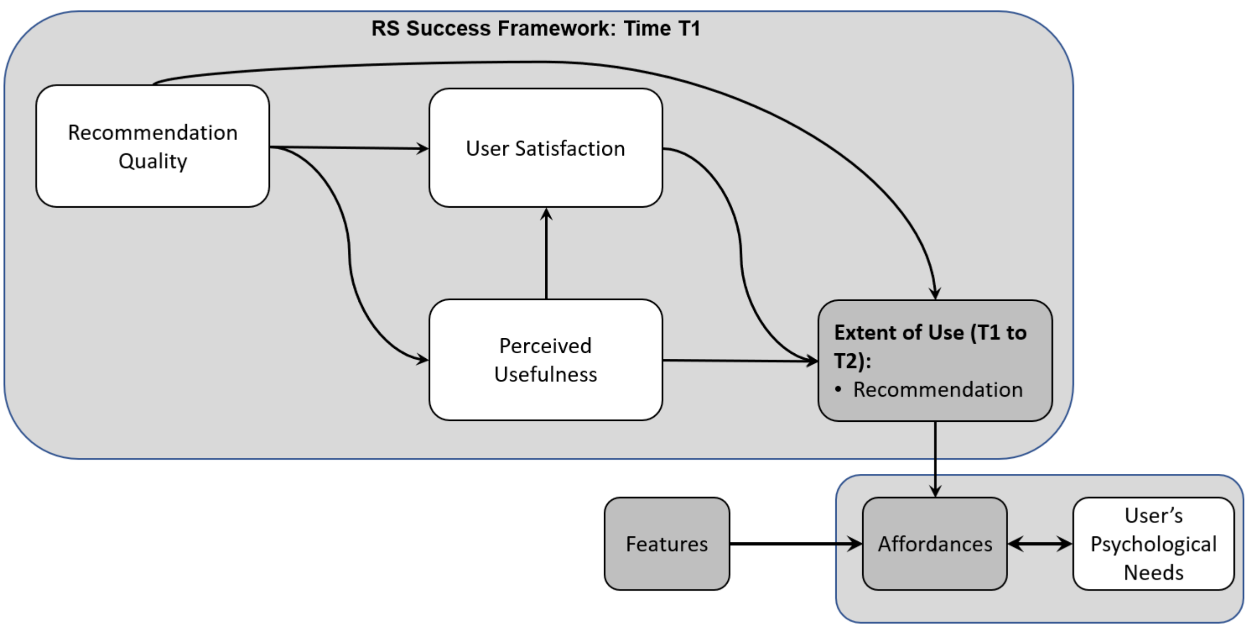
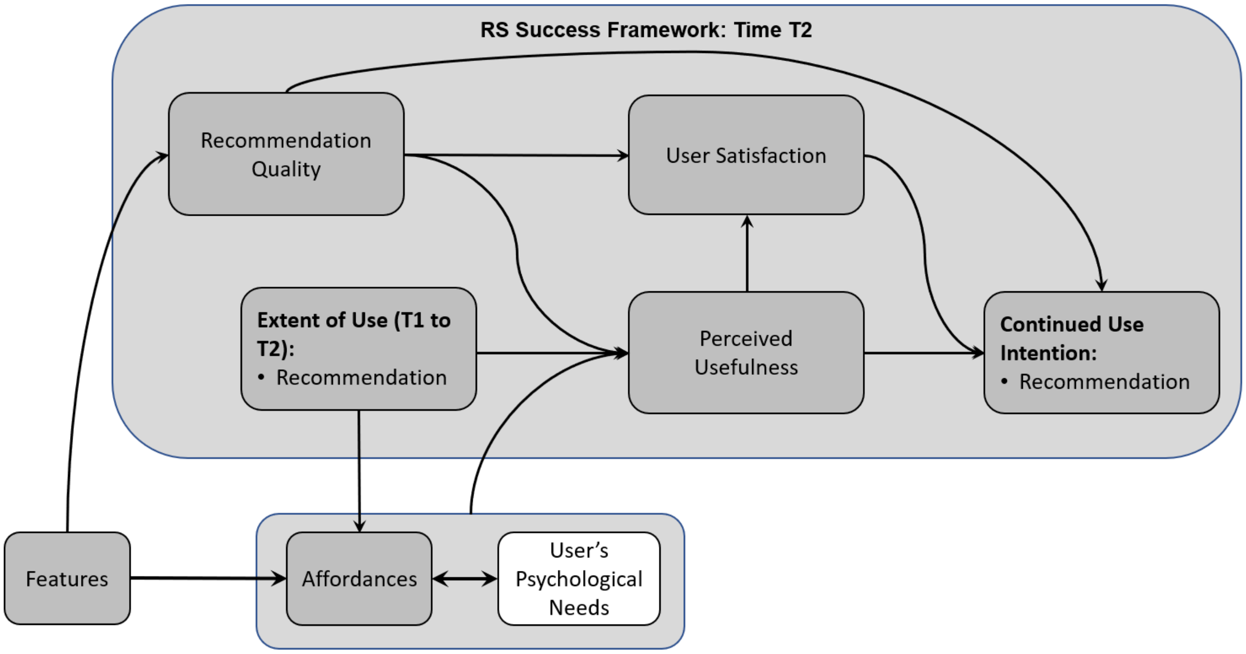


Figure 3. RS success framework



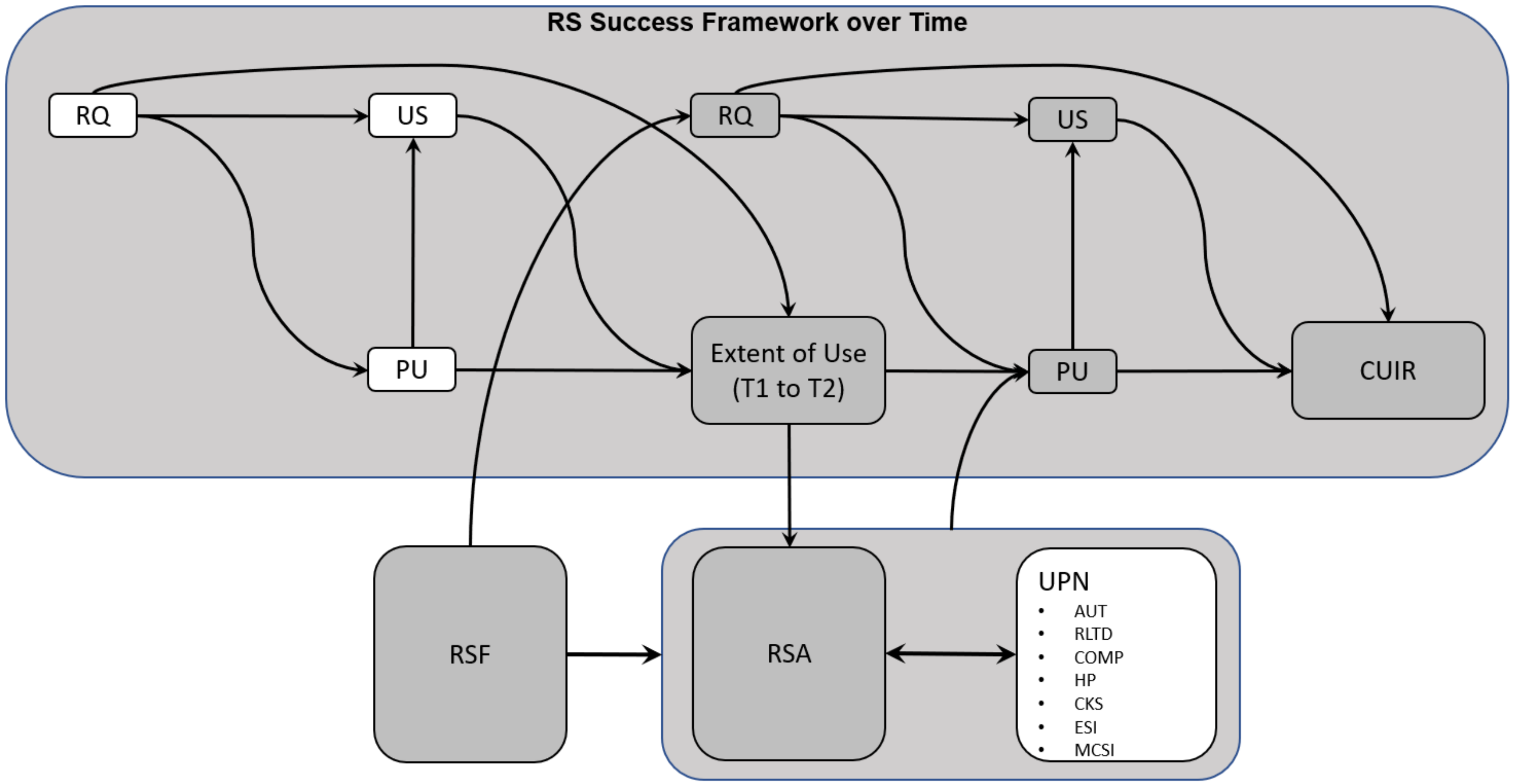
Constructs in unshaded boxes are measured at time T1, while those in shaded boxes are measured at time T2.

Figure 4a. RS success framework at time T1



Constructs in shaded boxes are measured at time T2, while those in unshaded boxes are measured at time T1.

Figure 4b. RS success framework at time T2



Constructs in unshaded boxes are measured at time T1, while those in shaded boxes are measured at time T2.

Figure 5. RS success framework over time[a]

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[a] *RQ*: recommendations quality; *US*: user satisfaction; *PU*: perceived usefulness; *RSF*: recommender system features; *RSA*: recommender system affordances; *UPN*: user's psychological needs; *CUIR*: continued use intention of recommendations; *AUT*: autonomy, *RLTD*: relatedness, *COMP*: competence, *HP*: having a place, *CKS*: coming to know the self, *ESI*: expressing self-identity, and *MCSI*: maintaining continuity of self-identity are dimensions of user's psychological needs.

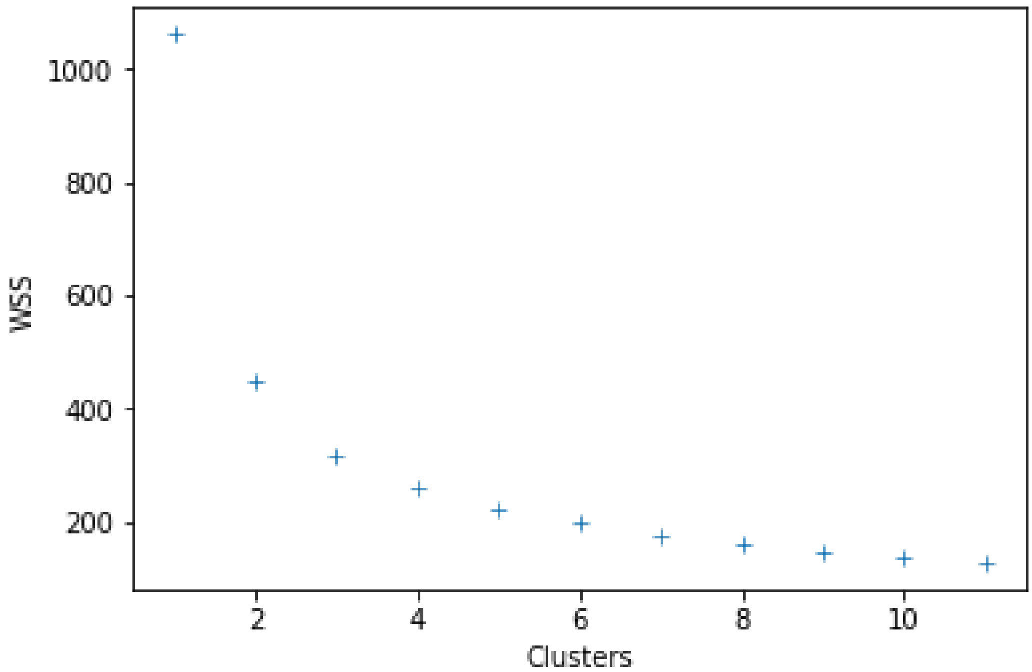

Figure 6. Elbow plot – WSS vs. *k* (number of clusters)

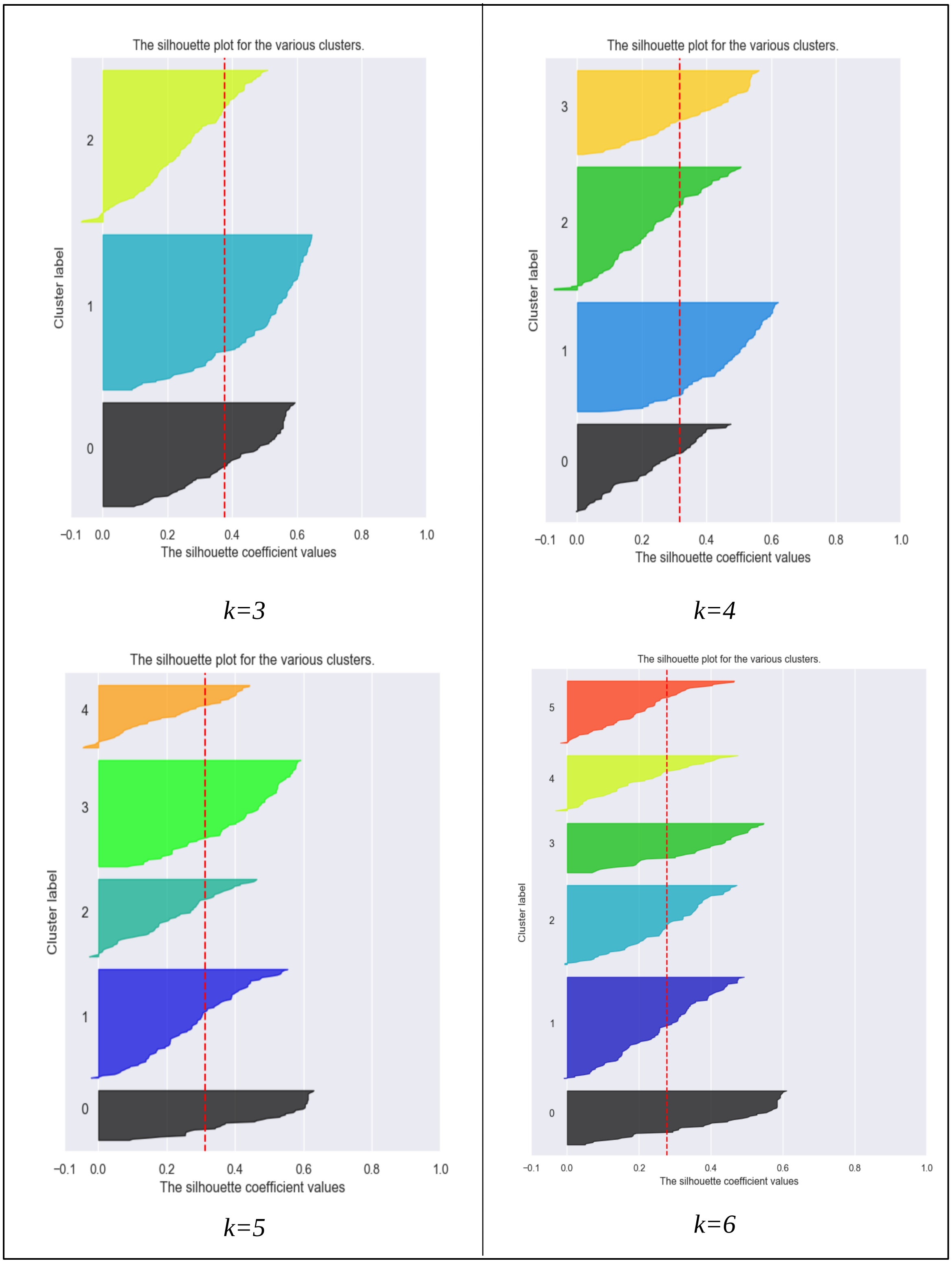

Figure 7. Silhouette index (SI) scores vs. *k* (number of clusters)

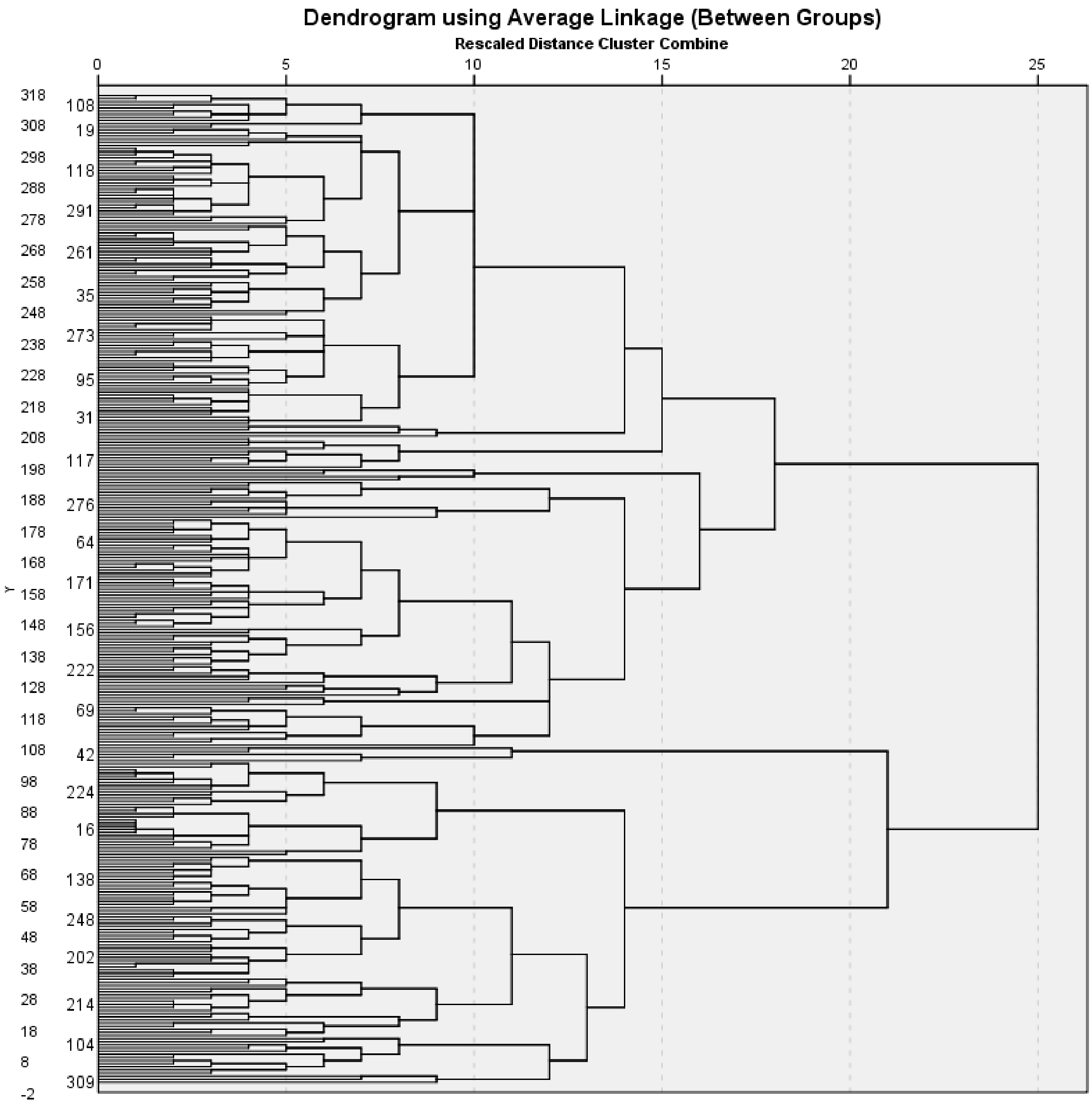

Figure 8. Hierarchical clustering with within group average linkage method

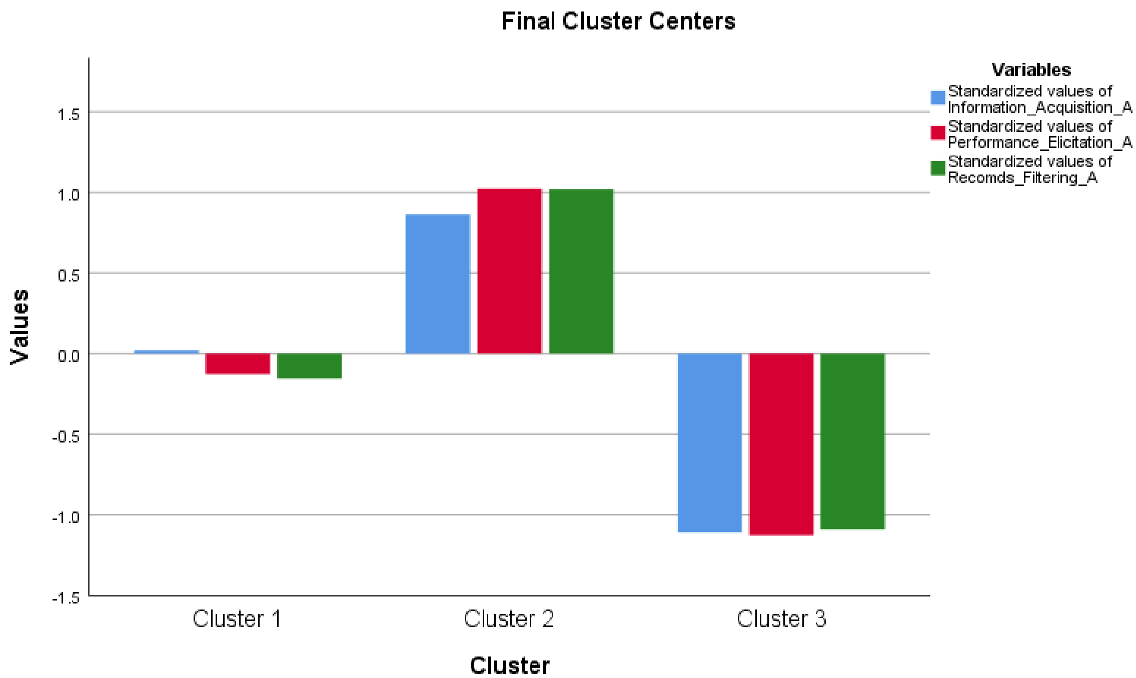

Figure 9. Characteristics of clusters across factors of affordances[52]

[52] Blue color bar refers to information acquisition factor of affordances; red color refers to preference elicitation factor of affordances; and green color refers to recommendations filtering factor of affordances.

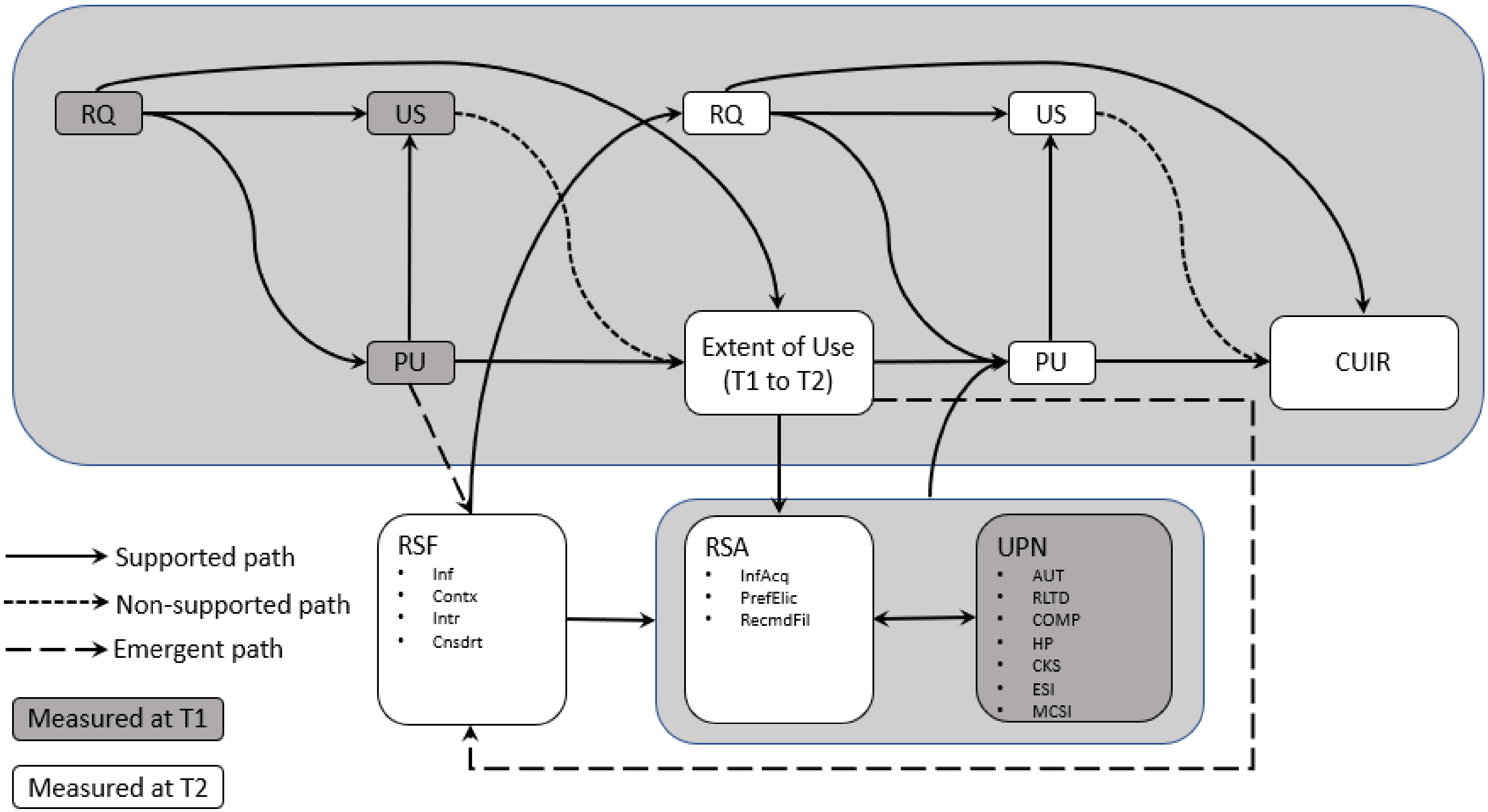

Figure 10. Emergent model[a]

[a] *RQ*: recommendations quality; *US*: user satisfaction; *PU*: perceived usefulness; *RSF*: recommender system features; *RSA*: recommender system affordances; *UPN*: user's psychological needs; *Inf*: informative, *Contx*: contextual, *Intr*: interactive, and *Cnsdrt*: considerate are dimensions of RS features. *InfAcq*:

information acquisition, *PrefElic*: preference elicitation, and *RecmdFil*: recommendation filtering are dimensions of RS affordances. *CUIR*: continued use intention of recommendations; *AUT*: autonomy, *RLTD*: relatedness, *COMP*: competence, *HP*: having a place, *CKS*: coming to know the self, *ESI*: expressing self-identity, and *MCSI*: maintaining continuity of self-identity are dimensions of user's psychological needs.

Tables of Chapter 4

Table 1. Summary of literature on recommender systems

Source	IVs	DVs	Theoretical Lens
Al-Natour et al. (2006)	Recommendation agent's (RA's) suggestive guidance, directives, and decision rules	Perceived personality; perceived similarity (personality and behavioral)	Similarity-attraction theories
Chau and Lai (2003)	Presence of personalization, perceived ease of use	Perceived usefulness; consumer's attitude	Technology acceptance model
Grange et al. 2019	Design, review sampling, product sampling, risk aversion	Serendipity	Expectation disconfirmation theory
Greer and Murtaza (2003)	Perceived innovation characteristics of personalization (e.g., relative advantage, etc.)	Intention to use and future use	Technology acceptance model, innovation diffusion theory
Hess et al. 2009	RA's extraversion, interface vividness, computer playfulness	Social presence, trusting beliefs	Social presence theories, trust theories
Ho et al. (2011)	Recommendation approach (adaptive or static), time of recommendation (early or late)	Consumer satisfaction, quality of recommendations (i.e., accuracy)	Consumer search theory, stopping rule model
Komiak and Benbasat (2006)	Perceived personalization	Cognitive trust, emotional trust, intention to adopt	Theory of reasoned action; trust theory
Lee and Benbasat (2011)	Implicit and explicit methods of preference elicitation	Trade-off difficulty, perceived control and recommendation accuracy, intention to use RS.	Concepts related to cognitive trade-off and perceived control.
Li and Karahanna (2012)	Recommendation approach (social network-based vs. collaborative), product category	Recommendation accuracy	Social influence theories; homophily theory
Liang et al. (2006)	Explicit vs. Implicit methods of generating user profile, individual motivation.	Recommendation accuracy, user satisfaction	Effort-based, motivation-based, and process-oriented theories
Qiu and Benbasat (2009)	Humanoid embodiment and output modality (human voice vs. text)	Social presence, trusting beliefs, perceived usefulness and enjoyment, use intention	Social agency and trust theories, technology acceptance model
Sheng et al. (2008)	Personalization	Intention to adopt, privacy concern	Ubiquitous commerce, privacy calculus
Wang and Benbasat (2005)	Types of explanation facilities (how, why, and guidance), perceived ease of use of a RA	Perceived usefulness, trust, intention to use	Technology acceptance model, trust theory
Wang and Benbasat (2007)	Explanation facilities (how, why, and trade-off)	Competence trust belief, Benevolence trust belief, Integrity trust belief	Trust theories
Wang and Benbasat (2008)	Types of explanation facilities (how, why, and guidance), reasons for using a RA	Trust in recommendation agent	Trust theories, trust reason literature
Wang and Benbasat (2009)	Explanation facilities: decision strategy (different methods of explicitly collecting consumer preferences)	Perceived advice quality; perceived cognitive effort	Decision-related theories
Xu (2006)	Personalization, entertainment, Informativeness, Irritation, Creditability	Attitude, intention to use	Technology acceptance model

Table 1. (Cont.)

Source	IVs	DVs	Theoretical Lens
Xu et al. (2011)	Overt vs. covert personalization	Perceived benefits of information disclosure; perceived risks of information disclosure.	Privacy calculus

Table 2. Types of recommender systems

Types	Recommender systems
Content-based	Users are provided recommendations based on what he/she preferred in the past by analyzing the content or the attributes of the item.
Collaborative	Users are provided recommendations based on what people with similar tastes and preferences have liked in the past.
Hybrid	Uses the approach of both content and collaborative types.

Table 3. User's psychological needs in the context of recommender systems

<table>
<tr><th colspan="2">Psychological needs</th><th>Definition</th><th>Example</th></tr>
<tr><td colspan="2">Autonomy</td><td>An individual need to be autonomous in their actions and act according to their desires and preferences (Deci and Ryan 2000).</td><td>RS provisions users to choose recommendations based on their past preferences or likes.</td></tr>
<tr><td colspan="2">Competence</td><td>An individual need to be able to control the environment and have a personal impact on self by acquiring knowledge and competencies (Deci and Ryan 2000).</td><td>RS provisions users to personalize the amount and the type of recommendations.</td></tr>
<tr><td colspan="2">Relatedness</td><td>An individual need to feel connected with others (Deci and Ryan 2000).</td><td>RS provisions users to help others through reviews and interaction.</td></tr>
<tr><td colspan="2">Having a place</td><td>An individual need to have their own space or territory (Pierce et al. 2001).</td><td>RS provisions users to create their own profile and have recommendations based on their identity.</td></tr>
<tr><td rowspan="3">Self-identity</td><td>Coming to know the self</td><td>An individual need to explore the environment and learn about one's preferences (Festinger 1954).</td><td>RS provisions users to see what others own and able to compare one's preferences with others.</td></tr>
<tr><td>Expressing self-identity</td><td>An individual need to convey his/her identity to others (Goffman 1959).</td><td>RS provisions users to convey his/her ownership to others.</td></tr>
<tr><td>Maintaining continuity of self-identity</td><td>An individual need to maintain connection between self-identity and his/her past (Pierce et al. 2001).</td><td>RS provisions users to be able to view their past likes and preferences.</td></tr>
</table>

Table 4. Features of recommender systems

Feature	Source	Description
Aesthetic	Guntuku et al. (2016)	RS emphasize on "how to recommend" to enhance the quality of experience. They provide the information that users really want to see in the first attempt.
Anthropomorphic	Hess et al. (2009), Qiu and Benbasat (2009)	RS pose as avatars that use animation and human voice to provide recommendations. Such RS exert social influence on users.
Balanced	Xia and Benbasat (2007)	Balance of both familiar and novel.
Context-aware/proactive	Adomavicius and Tuzhilin (2005)	RS provide recommendation by considering the contextual information, such as location and time.
Covert versus Overt	Xu et al. (2011)	Covert – Users getting access to recommendations based on their location by tracking their mobile phone; Overt – Users could provide their preferences to get recommendations.
Cross-domain	Lu et al. (2015)	RS help extend recommendation across various domains.
Discriminatory	Ekstrand et al. (2018)	RS provide recommendations that are biased against certain races or gender. This discrimination could affect user satisfaction.
Ease of generating new/additional recommendations	Xiao and Benbasat (2007)	Ease for user to generate new/additional recommendations.
Explainable	Kane et al. (2021)	RS help mitigate the problem of opacity by addressing problems associated with limited feedback and lack of transparency through explanations.
Familiar	Xia and Benbasat (2007)	Whether recommendations contain familiar products.
Features-based or needs-based	Xiao and Benbasat (2007)	Recommendation is provided by asking consumer the features required in a product (features-based). In needs-based, recommendation is provided by knowing the information about a consumer and how she plans to use the recommendation.
Information bundling	Pathak et al. (2019)	RS recommend bundle of products.
Information richness	Alba et al. (1997); Xiao and Benbasat (2007)	RS provide additional information that increase the attractiveness of the systems. This helps resolve uncertainty. For example, providing average ratings on the products.
Informative	Tam and Ho (2006)	RS inform users about products which they may not be aware. This role could fulfil the motives of the users who seek new knowledge and have desire to experience new things.
Interactive	Kane et al. (2021)	RS that incorporate feedback from real time dataset help solve the problem of undesirable behavior as they are built on training dataset and refine themselves when encountered new datasets.
Oppressive	Kane et al. (2021); Young et al. (2021)	RS tend to exert control over the users by showing more than what user is willing to accept by controlling the type of recommendations.
Reactive	Ricci et al. (2011)	RS provide recommendation in response to user action.
Responsive	Xiao and Benbasat (2007)	Recommendations are generated timely. Response time is less to received recommendations.
Session-based recommendation	Zhang et al. (2017)	RS enables users to get recommendations without having to login to the system thereby allaying fears among users about exposure of their identity.
Stage-wise	Smith and Linden (2017)	Stage-wise complement the current recommendation with additional recommendations that may be useful to users based on the past purchase behavior.

Table 4. (Cont.)

Feature	Source	Description
Time-aware	Campos et al. (2014)	RS consider changing user needs and in providing recommendation put more weight on the users' recent browsing behavior
Timer	Adomavicius et al. (2013)	RS forces users to watch a video for certain time before asking their ratings to better understand their preferences. Mostly suitable for video RS.
Trade-off	Aloysius et al. (2006); Xiao and Benbasat (2007)	Built on preference elicitation method, RS compel users to make tradeoffs before providing recommendations.

Table 5. Affordances of recommender systems

Affordance	Source	Description
Anthropomorphic interaction	Qiu and Benbasat (2009)	An extension of personalized and interaction affordance in which users could engage in anthropomorphic interaction based on their needs to feel more socially connected. For example, some users may prefer interacting with just a voice and an image of an avatar while some users may prefer recommendation presented by an agent in the form of human.
Asynchronous offline discussion (AOD)	Eryilmaz et al. (2019)	Allowing users to search for additional information from others' posts and engage in a discussion resulting into knowledge building and novelty.
Cut-off	Lee and Benbasat (2011)	An extension of the PEM in which allowing users to state minimum cut-off on the attributes.
Diagnosticity	Grange et al. (2019)	Allowing users to get interpretable meaning for the recommendations and a provision to compare recommendations.
Diversity	Grange et al. (2019)	Access to heterogeneity of peer opinions and recommendations.
Ethics-awareness by design	Paraschakis (2018)	An extension of the perceived control enabling users to control the sensitive aspects of the recommendations.
Explanation	Milano et al. (2020)	Allowing users to get explanation on the recommendations.
Explicit user preferences	Liang et al. (2006)	Allowing users to explicitly state their preferences about the recommendation's types and presentation.
Feedback	Arazy et al. (2010); Wang and Benbasat (2008)	Allowing users for feedback on the recommendations, such as rating and liking of the recommendations, and reconfiguring the preferences.
Group discussion	Marquez and Ziegler (2016)	Allowing users to collaborate during the preference process before generating recommendations catering to the needs to the group as a whole.
Information richness	Alba et al. (1997)	Allowing users to get additional information on the recommendations, such as ratings and images.
Interaction	Komiak and Benbasat (2006)	An extension of personalized affordance in which users could engage in an interaction stating their expertise level thus enabling RS to provide recommendations for basic purpose or advanced purpose or mix of both.
Perceived control	Ariely (2000)	Allowing users to control the number of recommendations in the result list.
Preference elicitation method (PEM)	Lee and Benbasat (2011)	Allowing users a trade-off among various features of a product before generating recommendations.
Recommendations filtering	Wang and Benbasat (2005)	Allowing users a search bar that could filter out the suggested recommendations further based on attributes in order to expedite the search process and make it easier to the end user.
Session-based	Zhang et al. (2017)	Allowing users to get recommendations without having to login.
Timer	Adomavicius et al. (2013)	Allowing users to watch a content for a specified time before eliciting their preferences. Mostly suitable for video RS.
Weighted	Lee and Benbasat (2011)	An extension of the PEM in which allowing users to state weighted importance of the attributes.

Table 6. Key constructs and definitions

Construct	Definition
Recommendation quality	The quality of the content of the recommender system (adapted from Wang et al. 2007)
User's psychological needs	Energizing psychological states acting as an impetus to action (Deci and Ryan 1985; Karahanna et al. 2018).
Perceived usefulness	The degree to which the user believes that using the recommender system would enhance his or her performance (adapted from Davis 1989, pp. 320).[53]
User satisfaction	The extent to which user believes recommender system meet his or her information requirements (adapted from Sabherwal et al. 2006, pp. 1851).[54]
Use	The individual's behavior of, or effort put into, using the recommendations from the recommender system (adapted from Sabherwal et al. 2006).[55]
Continued use intention of recommendations	The likelihood that a person will continue using the recommendations from the recommender system (adapted from Cho et al. 2009).[56]
Features	Attributes of recommender system.
Affordances	Action possibilities provided by the features of recommender system (adapted from Karahanna et al. 2018)
Alignment between user's psychological needs and affordances	Extent to which users' needs are fulfilled by the affordances provided by recommender system (adapted from Sabherwal and Kirs 1994).[57]

Table 7. Demographics of interview participants[a]

Designation	Education qualifications	Ethnicity
Assistant Professor (1)	PhD in Accounting	Caucasian
Assistant Professor (1)	PhD in Supply Chain	Caucasian
Assistant Professor (2)	PhD in Information Systems	Caucasian
Assistant Professor (1)	PhD in Finance	Asian
Senior Marketing Manager in Fortune 500 company (1)	PhD in Marketing	Caucasian
PhD Student (1)	Information Systems	Caucasian
PhD Student (4)	Information Systems	Asian

[a] Number in parenthesis against designation denotes the number of participants.

[53] "The degree to which a person believes that using a particular system would enhance his or her job performance".
[54] "The extent to which the user believes that the system meets his or her information requirements".
[55] "The individual's behavior of, or effort put into, using the system".
[56] "The likelihood that a person will continue using a technology or a system (Ajzen and Fishbein 1980)".
[57] "The extent to which IT capability meets information processing requirements" (p. 304).

Table 8. Constructs and scale items[a]

Constructs	Items	Source	Surveys
Recommendation quality (RQ)	1) My recommender system provides recommendations that is exactly what I need. 2) My recommender system provides recommendations I need at the right time. 3) My recommender system provides recommendations that is relevant to me. 4) My recommender system provides sufficient recommendations. 5) My recommender system provides recommendations that are easy to understand. 6) My recommender system provides up-to-date recommendations.	Wang et al. (2007)	T1, T2
Autonomy (AUT)	1) I need to be able to decide for myself how to live my life. 2) I need to be able to freely voice my ideas and opinions. 3) In my daily life, I have the need to act freely.	Karahanna et al. (2018)	T1
Relatedness (RLTD)	1) I feel the need to socially interact with people. 2) I feel the need to have a lot of social contacts. 3) I feel the need to develop friendships with people I regularly interact with. 4) I feel the need to be close to many people.	Karahanna et al. (2018)	T1
Competence (COMP)	1) I need to feel competent. 2) I need to feel capable in what I do. 3) I need to have opportunities to show how capable I am.	Karahanna et al. (2018)	T1
Having a Place (HP)	1) I need to have a safe and secure place like home. 2) I need places that feel like home to me.	Karahanna et al. (2018)	T1
Coming to know the self (CKS)	1) I feel a need to develop a sense of self-identity. 2) I feel a need to discover what kind of person I am. 3) I feel a need to learn about myself.	Karahanna et al. (2018)	T1
Expressing self-identity (ESI)	1) I feel a need to express who I am. 2) I feel a need to express my personality. 3) I feel a need to express my self-identity.	Karahanna et al. (2018)	T1
Maintaining continuity of self-identity (MCSI)	1) I have a need that who I am today also incorporates my past. 2) I have a need that my past be an important part of my self-identity. 3) I feel a need that who I am today does not ignore my past.	Karahanna et al. (2018)	T1
Perceived usefulness (PU)	1) My recommender system would enable me to accomplish tasks more quickly. 2) My recommender system would improve my performance. 3) My recommender system would increase my productivity. 4) My recommender system would enhance effectiveness. 5) My recommender system would help me do my task. 6) I find my recommender system useful.	Venkatesh et al. (2003)	T1, T2

Table 8. (Cont.)

Constructs	Items	Source	Surveys
User satisfaction (US)	1) I am satisfied with my recommender system. 2) My recommender system has met my expectations. 3) My experience with my recommender system is very pleasing. 4) My recommender system does a satisfactory job of fulfilling my needs.	Wang et al. (2019)	T1, T2
Recommendation use measured at time T1 (RU)	Please indicate the frequency using the following scale about how often you use the recommendations from the recommender system you use the most: *Note*: Scale ranging from 1 to 7, where 1 = never; 2 = rarely (less than once a month); 3 = a few times a month; 4 = weekly; 5 = daily; 6 = a few times a day; 7 = hourly or more. Frequency of the use of the recommendations ________		T1
Recommendation use measured at time T2 (RU)	Please indicate the frequency using the following scale about how often you have used the recommendations from the recommender system that you use the most in the past 1 week: *Note*: Scale ranging from 1 to 7, where 1 = never; 2 = once a week; 3 = a few times a week; 4 = daily; 5 = A few times a day; 6 = hourly; 7 = few times an hour. Frequency of the use of the recommendations ________		T2
Continued use intention of recommendations(CUIR)	1) I will use the recommendations from my recommender system in the future. 2) I intend to use the recommendations from my recommender system more in work. 3) I intend to use the recommendations from my recommender system more for other purposes. 4) I intend to increase use of the recommendations from my recommender system.	Cho et al. (2009)	T2
RS Features (RSF)	1) My recommender system values aesthetics to enhance the quality of experience in the recommender system. 2) My recommender system poses as avatar that use animation and human voice to provide recommendations. 3) My recommender system provides both familiar and novel recommendations. 4) My recommender system provides recommendations by considering the contextual information, such as location and time. 5) My recommender system provides recommendations based on my location by tracking my location. 6) My recommender system considers my preferences before providing recommendations. 7) My recommender system extends recommendations across various domains such as, music, movies, books, products, etc. 8) My recommender system provides recommendations that are biased against races or gender l. 9) My recommender system considers ease for me to generate new/additional recommendations.		T2

Table 8. (Cont.)

Constructs	Items	Source	Surveys
RS Features (RSF)	10) My recommender system explains the process in generating recommendations. 11) My recommender system provides recommendations containing familiar products. 12) My recommender system asks me the features required in a product before provides recommendations. 13) My recommender system asks how I plan to use the recommendations before provides recommendations. 14) My recommender system provides recommendation in a bundle. 15) My recommender system provides additional information on the recommendations. 16) My recommender system provides new recommendations that I am not aware of. 17) My recommender system incorporates my feedback on the recommendations. 18) My recommender system shows more recommendations than I want. 19) My recommender system generates recommendations in response to my action. 20) My recommender system generates recommendations in a timely manner. 21) My recommender system generates recommendations without requiring me to login to the system. 22) My recommender system complements the current recommendation with additional recommendations that may be useful to me based on the past purchase behavior. 23) My recommender system considers my changing needs. 24) My recommender system provides information on products and asks me to rate products to understand my preferences. 25) My recommender system asks me to make trade-offs on product features before provides recommendations.		T2
RS Affordances (RSA)	1) My recommender system allows me to engage with recommender system using image of an avatar or interacting with voice. 2) My recommender system allows me to search for additional information from others' purchases. 3) My recommender system allows me for trade-off among various features of a product before generating recommendations. 4) My recommender system allows me to specify minimum requirement on various features of a product before generating recommendations. 5) My recommender system allows me to compare recommendations. 6) My recommender system allows me to access heterogeneity of peer opinions and recommendations.		T2

Table 8. (Cont.)

Constructs	Items	Source	Surveys
RS Affordances (RSA)	7) My recommender system allows me to control the sensitive aspects of the recommendations. 8) My recommender system allows me to get explanation on how the recommendations are generated. 9) My recommender system allows me to explicitly state my preferences about the recommendation types and presentation. 10) My recommender system allows me for feedback on the recommendations, such as rating and liking of the recommendations, and reconfiguring the preferences. 11) My recommender system allows me to collaborate with others during the preference process catering to the needs of the group as a whole. 12) My recommender system allows me to get additional information on the recommendations, such as ratings and images. 13) My recommender system allows me to state basic or advanced use of recommendations to recommender system before getting recommendations. 14) My recommender system allows me to control the number of recommendations. 15) My recommender system allows me to filter out the suggested recommendations further. 16) My recommender system allows me to get information on various products for a specified time before eliciting my preferences. 17) My recommender system allows me to state weighted importance on the attributes of product.		T2
Age	Please state your age: _____Years _____Months		T1
RS experience	Please state your experience with recommender systems (in months): ________		T1
RS provider company trust	1) I trust my recommender system provider company. 2) My recommender system provider company makes truthful claims. 3) My recommender system provider company is honest. I do not believe my recommender system provider company. (R)	Newell and Goldsmith (2001)	T1
RS provider company expertise	1) My recommender system provider company has a great amount of expertise. 2) My recommender system provider company is skilled in what they do. 3) My recommender system provider company has great expertise. My recommender system provider company does not have much experience. (R)	Newell and Goldsmith (2001)	T1
Social desirability[b]	1) I smile at people every time I meet them. 2) I always practice what I preach to people. 3) If I say to people I will do something, I always keep my promise no matter how inconvenient it might be. 4) I never lie to people. 5) I laugh at a joke people may make.	Haghighat (2007)	T1

[a] Autonomy, Relatedness, Competence, Having a Place, Coming to know the self, Expressing self-identity, and Maintaining continuity of self-identity are dimensions of user's psychological needs. Items marked in (R) are reverse coded. All scale items were measured using Likert seven point scale ranging from 1 to 7, where 1 = strongly disagree; 2 = disagree; 3 = somewhat disagree; 4 = neutral; 5 = somewhat agree; 6 = agree; 7 = strongly agree. Survey stages denote the time at which the constructs were measured. Please refer to Table 12 for the revised list of items for features and affordances, and their respective factors.

[b] Social desirability is used as marker variable to test for common method bias.

Table 9. Demographic characteristics of the participants from rounds 1, 2, and 3

Characteristics		**Frequency (n=355)**
Gender	Female	159
	Male	193
	Non binary	3
Age (years)	>=20 and < 30	65
	>=30 and < 40	135
	>=40 and < 50	87
	>=50 and < 60	53
	>=60 and < 70	15
Ethnicity	African-American	18
	Asian/Pacific Islander	31
	Caucasian	279
	Hispanic/Latino	18
	Native American/ Alaskan Native	1
	Others	8
Annual Income	<40000	62
	>=40000 and < 80000	174
	>=80000 and <120000	75
	>=120000 and < 160000	26
	>=160000	18
RS use context	Personal	324
	Work	31
Designation	Senior Executive	3
	Professor	17
	Manager	64
	Engineer	19
	Director	14
	Developer	7
	Analyst	18
	Assistants	16
	Others	191
Work industry	Accommodation and Food Services	7
	Agriculture, Forestry, Fishing and HR	3
	Arts, Entertainment, and Recreation	20
	Construction	5
	Educational Services	71
	Finance and Insurance	42
	Health Care and Social Assistance	41
	Information Technology	29
	Manufacturing	32
	Mining, Quarrying, and Oil and Gas	3

Table 9. (Cont.)

Characteristics		Frequency (n=355)
	Professional, Scientific, and Technical Services	67
	Public Administration	17
	Trade	9
	Transportation and Warehousing	7
	Utilities	2

Table 10. Name of the recommender system participants use the most

Name of recommender system	Frequency (n = 355)
Netflix	119
Amazon	104
YouTube	36
Spotify	11
Google	10
Hulu	9
Apple	8
Grammarly	5
Facebook, HBO, and Instagram	3 each
Discovery, Disney+, eBay, LinkedIn, Pinterest, Shein, Steam, and Twitter	2 each
ASOS, Castle Learning, Criterion, Goodreads, Ibotta, Indeed, Kickstarter, Lukx, Microsoft Outlook, NVidia, Optimizely, Pandora, Peerius, Reddit, Samsung, Storygraph, and Tik Tok	1 each
Missing	11

Table 11. Reliabilities of constructs in various rounds[a]

Construct	R1S1	R2S1	R3S1	R1S2	R2S2	R3S2
Recommendation quality (T1)	0.85	0.93	0.92			
Autonomy (T1)	0.89	0.88	0.89			
Relatedness (T1)	0.93	0.92	0.93			
Competence (T1)	0.77	0.80	0.78			
Having a Place (T1)	0.88	0.87	0.81			
Coming to know the self (T1)	0.93	0.89	0.94			
Expressing self-identity (T1)	0.96	0.94	0.96			
Maintaining continuity of self-identity (T1)	0.97	0.93	0.98			
Perceived usefulness (T1)	0.95	0.95	0.93			
User satisfaction (T1)	0.94	0.95	0.94			
RS provider company trust (T1)	0.88	0.84	0.82			
RS provider company expertise (T1)	0.76	0.74	0.78			
Recommendation quality (T2)				0.82	0.92	0.93
Perceived usefulness (T2)				0.94	0.96	0.95
User satisfaction (T2)				0.92	0.96	0.96
Continued use intention of recommendations (T2)				0.85	0.91	0.98
n	49	268	38	49	268	38

[a] Values represents the alpha (reliabilities of the scale items). T1 represents the measure of the construct at time T1 and T2 represents the measure of the construct at time T2. R1S1= Round 1- Survey 1; R2S1 = Round 2- Survey 1; R3S1 = Round 3- Survey 1; R1S2 = Round 1- Survey 2; R2S2 = Round 2- Survey 2; R3S2 = Round 3- Survey 2;

Survey 1 was administered at time T1, and Survey 2 was administered at time T2. Shaded boxes refers to construct not being measured. *n* denotes the sample size for the respective stage of the rounds.

Table 12. Factors of RS features and RS affordances from factor analysis[a]

Factor	Item (Each item starts with "My recommender system …")
RSF-Informative (RSF-Inf)	
RSF-Inf1	… provides both familiar and novel recommendations.
RSF-Inf2	… provides additional information on the recommendations.
RSF-Inf3	… provides new recommendations that I am not aware of.
RSF-Inf4	… complements the current recommendation with additional recommendations that may be useful to me based on the past purchase behavior.
RSF-Contextual (RSF-Contx)	
RSF-Contx1	… provides recommendations by considering the contextual information, such as location and time.
RSF-Contx2	... provides recommendations based on my location by tracking my location.
RSF-Contx3	... extends recommendations across various domains such as, music, movies, books, products, etc.
RSF-Interactive (RSF-Intr)	
RSF-Intr1	... explains the process in generating recommendations.
RSF-Intr2	... asks me the features required in a product before providing recommendations.
RSF-Intr3	... asks how I plan to use the recommendations before providing recommendations.
RSF-Intr4	... asks me to make trade-offs on product features before providing recommendations.
*RSF-Considerate (RSF-*Cnsdrt*)*	
RSF-Cnsdrt1	... considers my preferences before providing recommendations.
RSF-Cnsdrt2	... incorporates my feedback on the recommendations.
RSF-Cnsdrt3	... generates recommendations in response to my action.
RSF-Cnsdrt4	... generates recommendations in a timely manner.
RSF-Cnsdrt5	... considers my changing needs.
RSF-Cnsdrt6	... provides information on products and asks me to rate products to understand my preferences.
RSA-Information_Acquisition (RSA-InfAcq)	
RSA-InfAcq1	... allows me to search for additional information from others' purchases.
RSA-InfAcq2	... allows me to compare recommendations.
RSA-InfAcq3	... allows me to access heterogeneity of peer opinions and recommendations.
RSA-InfAcq4	... allows me to get explanation on how the recommendations are generated.
RSA-InfAcq5	... allows me to get additional information on the recommendations, such as ratings and images.
RSA-Preference_Elicitation (RSA-PrefElc)	
RSA-PrefElc1	... allows me for trade-off among various features of a product before generating recommendations.
RSA-PrefElc2	... allows me to specify minimum requirement on various features of a product before generating recommendations.
RSA-PrefElc3	... allows me to explicitly state my preferences about the recommendation types and presentation.
RSA-PrefElc4	... allows me for feedback on the recommendations, such as rating and liking of the recommendations, and reconfiguring the preferences.
RSA-PrefElc5	... allows me to state weighted importance on the attributes of product.

Table 12. (Cont.)

Factor	Item (Each item starts with “My recommender system …”)
RSA-Recommendation_Filtering (RSA-RcmdFil)	
RSA-RcmdFil1	... allows me to control the sensitive aspects of the recommendations.
RSA-RcmdFil2	... allows me to control the number of recommendations.
RSA-RcmdFil3	... allows me to filter out the suggested recommendations further.

[a] *n* = 355. RSF and RSA refers to RS features and affordances, respectively.

Table 13. Measurement model for features and affordances[a]

Factor	Item (Each item starts with “My recommender system …”)	λ
RSF-Informative (RSF-Inf)		
RSF-Inf1	… provides both familiar and novel recommendations.	0.71
RSF-Inf2	… provides additional information on the recommendations.	0.78
RSF-Inf3	… provides new recommendations that I am not aware of.	0.62
RSF-Inf4	… complements the current recommendation with additional recommendations that may be useful to me based on the past purchase behavior.	0.68
RSF-Contextual (RSF-Contx)		
RSF-Contx1	… provides recommendations by considering the contextual information, such as location and time.	0.85
RSF-Contx2	... provides recommendations based on my location by tracking my location.	0.81
RSF-Contx3	... extends recommendations across various domains such as, music, movies, books, products, etc.	0.68
RSF-Interactive (RSF-Intr)		
RSF-Intr1	... explains the process in generating recommendations.	0.62
RSF-Intr2	... asks me the features required in a product before providing recommendations.	0.86
RSF-Intr3	... asks how I plan to use the recommendations before providing recommendations.	0.87
RSF-Intr4	... asks me to make trade-offs on product features before providing recommendations.	0.73
*RSF-Considerate (RSF-*Cnsdrt*)*		
RSF-Cnsdrt1	... considers my preferences before providing recommendations.	0.74
RSF-Cnsdrt2	... incorporates my feedback on the recommendations.	0.72
RSF-Cnsdrt3	... generates recommendations in response to my action.	0.73
RSF-Cnsdrt4	... generates recommendations in a timely manner.	0.73
RSF-Cnsdrt5	... considers my changing needs.	0.65
RSF-Cnsdrt6	... provides information on products and asks me to rate products to understand my preferences.	0.67
RSA-Information_Acquisition (RSA-InfAcq)		
RSA-InfAcq1	... allows me to search for additional information from others' purchases.	0.67
RSA-InfAcq2	... allows me to compare recommendations.	0.76
RSA-InfAcq3	... allows me to access heterogeneity of peer opinions and recommendations.	0.70
RSA-InfAcq4	... allows me to get explanation on how the recommendations are generated.	0.73
RSA-InfAcq5	... allows me to get additional information on the recommendations, such as ratings and images.	0.67
RSA-Preference_Elicitation (RSA-PrefElc)		
RSA-PrefElc1	... allows me for trade-off among various features of a product before generating recommendations.	0.79

Table 13. (Cont.)

Factor	Item (Each item starts with "My recommender system …")	λ
RSA-Preference_Elicitation (RSA-PrefElc)		
RSA-PrefElc2	... allows me to specify minimum requirement on various features of a product before generating recommendations.	0.83
RSA-PrefElc3	... allows me to explicitly state my preferences about the recommendation types and presentation.	0.76
RSA-PrefElc4	... allows me for feedback on the recommendations, such as rating and liking of the recommendations, and reconfiguring the preferences.	0.70
RSA-PrefElc5	... allows me to state weighted importance on the attributes of product.	0.78
RSA-Recommendation_Filtering (RSA-RcmdFil)		
RSA-RcmdFil1	... allows me to control the sensitive aspects of the recommendations.	0.78
RSA-RcmdFil2	... allows me to control the number of recommendations.	0.77
RSA-RcmdFil3	... allows me to filter out the suggested recommendations further.	0.73

[a] $n = 355$. RSF and RSA refers to RS features and affordances, respectively. Standardized loading coefficients (λ) are given in the last column.

Table 14. Descriptives and correlations for the factors of RS features and RS affordances[a]

Factor	Mean	S.D.	RSF-Inf	RSF-Contx	RSF-Intr	RSF-Cnsdrt	RSA-InfAcq	RSA-PrefElc	RSA-RcmdFil
RSF-Inf	5.02	1.08	**0.78**						
RSF-Contx	3.93	1.58	0.34	**0.87**					
RSF-Intr	3.36	1.27	0.34	0.53	**0.98**				
RSF-Cnsdrt	5.05	1.04	0.45	0.31	0.47	**0.87**			
RSA-InfAcq	4.02	1.40	0.51	0.55	0.51	0.48	**0.85**		
RSA-PrefElc	3.57	1.51	0.38	0.55	0.56	0.49	0.37	**0.84**	
RSA-RcmdFil	3.68	1.60	0.32	0.56	0.57	0.42	0.35	0.41	**0.89**

[a] $n = 355$. Square roots of average variances extracted (AVEs) are reported along the diagonal.

Table 15. Reliability values (Cronbach alphas) for the study constructs[ab]

Construct	Cronbach alpha	Composite reliability	rho_A
RQ (T1)	0.92	0.87	0.89
AUT (T1)	0.88		
RLTD (T1)	0.93		
COMP (T1)	0.80		
HP (T1)	0.87		
CKS (T1)	0.90		
ESI (T1)	0.95		
MCSI (T1)	0.94		
PU (T1)	0.95	0.95	0.96
US (T1)	0.95	0.95	0.95
RSF-Inf (T2)	0.68	0.82	0.70
RSF-Contx (T2)	0.76	0.87	0.78

Table 15. (Cont.)

Construct	Cronbach alpha	Composite reliability	rho_A
RSF-Intr (T2)	0.72	0.88	0.86
RSF-Cnsdrt (T2)	0.80	0.89	0.82
RSA-InfAcq (T2)	0.77	0.88	0.78
RSA-PrefElc (T2)	0.85	0.92	0.87
RSA-RcmdFil (T2)	0.77	0.88	0.78
RQ (T2)	0.92	0.90	0.90
PU (T2)	0.95	0.96	0.96
US (T2)	0.95	0.95	0.95
CUIR (T2)	0.91	0.91	0.91

[a] n = 355. T1 represents the measure of the construct at time T1 and T2 represents the measure of the construct at time T2. RQ: recommendation quality; AUT: autonomy, RLTD: relatedness, COMP: competence, HP: having a place, CKS: coming to know the self, ESI: expressing self-identity, and MCSI: maintaining continuity of self-identity are the dimensions of user's psychological needs; PU: perceived usefulness; US: user satisfaction; RSF-Inf, RSF-Contx, RSF-Intr, and RSF-Cnsdrt are the factors of RS features; RSA-InfAcq, RSA-PrefElic, and RSA-RcmdFil are the factors of RS affordances. Please refer to Table 12 for the factors of RS features and RS affordances. CUIR: continued use intention of recommendations.

[b] Latent constructs of user's psychological needs were not in the structural paths in the final measurement model as these constructs were used to compute alignment. Therefore their composite reliability and rho_A coefficient values are not reported.

Table 16. Descriptives and correlations for the constructs measured at time T1[a]

Construct	Mean	S.D.	RQ	AUT	RLTD	COMP	HP	CKTS	ESI	MCSI	PU	US
RQ	5.55	0.98	**0.81**									
AUT	6.15	0.88	0.19	**0.91**								
RLTD	4.28	1.60	0.05	0.12	**0.87**							
COMP	5.99	0.89	0.18	0.50	0.34	**0.85**						
HP	6.41	0.85	0.22	0.50	0.17	0.50	**0.81**					
CKS	5.58	1.31	0.22	0.37	0.17	0.38	0.37	**0.87**				
ESI	5.54	1.23	0.20	0.43	0.36	0.45	0.35	0.61	**0.88**			
MCSI	5.11	1.45	0.13	0.36	0.23	0.35	0.33	0.38	0.42	**0.88**		
PU	4.63	1.49	0.66	0.18	0.16	0.26	0.17	0.31	0.27	0.09	**0.91**	
US	5.54	1.16	0.46	0.14	0.18	0.20	0.08	0.30	0.28	0.25	0.53	**0.93**

[a] n = 355. Square roots of average variances extracted (AVEs) are reported along the diagonal. RQ: recommendation quality; AUT: autonomy, RLTD: relatedness, COMP: competence, HP: having a place, CKS: coming to know the self, ESI: expressing self-identity, and MCSI: maintaining continuity of self-identity are the dimensions of user's psychological needs; PU: perceived usefulness; US: user satisfaction.

Table 17. Measurement model for constructs measured at time T1[a]

Factor	Item	λ
Recommendation quality (RQ)		
RQ1	My recommender system provides recommendations that is exactly what I need.	0.68
RQ2	My recommender system provides recommendations I need at the right time.	0.77
RQ3	My recommender system provides recommendations that is relevant to me.	0.78
RQ4	My recommender system provides sufficient recommendations.	0.61
RQ5	My recommender system provides recommendations that are easy to understand.	0.60
RQ6	My recommender system provides up-to-date recommendations.	0.74
Autonomy (AUT)		
AUT1	I need to be able to decide for myself how to live my life.	0.84
AUT2	I need to be able to freely voice my ideas and opinions.	0.81
AUT3	In my daily life, I have the need to act freely.	0.89
Relatedness (RLTD)		
RLTD1	I feel the need to socially interact with people.	0.86
RLTD2	I feel the need to have a lot of social contacts.	0.90
RLTD3	I feel the need to develop friendships with people I regularly interact with.	0.85
RLTD4	I feel the need to be close to many people.	0.87
Competence (COMP)		
COMP1	I need to feel competent.	0.88
COMP2	I need to feel capable in what I do.	0.92
COMP3	I need to have opportunities to show how capable I am.	0.59
Having a Place (HP)		
HP1	I need to have a safe and secure place like home.	0.86
HP2	I need places that feel like home to me.	0.90
Coming to know the self (CKS)		
CKS1	I feel a need to develop a sense of self-identity.	0.81
CKS2	I feel a need to discover what kind of person I am.	0.94
CKS3	I feel a need to learn about myself.	0.89
Expressing self-identity (ESI)		
ESI1	I feel a need to express who I am.	0.89
ESI2	I feel a need to express my personality.	0.94
ESI3	I feel a need to express my self-identity.	0.95
Maintaining continuity of self-identity (MCSI)		
MCSI1	I have a need that who I am today also incorporates my past.	0.90
MCSI2	I have a need that my past be an important part of my self-identity.	0.94
MCSI3	I feel a need that who I am today does not ignore my past.	0.90
Perceived usefulness (PU)		
PU1	My recommender system would enable me to accomplish tasks more quickly.	0.81
PU2	My recommender system would improve my performance.	0.90
PU3	My recommender system would increase my productivity.	0.91
PU4	My recommender system would enhance effectiveness.	0.94
PU5	My recommender system would help me do my task.	0.92
PU6	I find my recommender system useful.	0.68
User satisfaction (US)		
US1	I am satisfied with my recommender system.	0.94
US2	My recommender system has met my expectations.	0.93
US3	My experience with my recommender system is very pleasing.	0.86
US4	My recommender system does a satisfactory job of fulfilling my needs.	0.91

[a] n = 355. Standardized loading coefficients (λ) are given in the last column. AUT: autonomy, RLTD: relatedness, COMP: competence, HP: having a place, CKS: coming to know the self, ESI: expressing self-identity, and MCSI: maintaining continuity of self-identity are the dimensions of user's psychological needs.

Table 18. Descriptives and correlations for the constructs measured at time T2[a]

Construct	Mean	S.D.	Use	Inf	Contx	Intr	Cnsdrt	InfAcq	PrefElc	RcmdFil	RQ	PU	US	CUIR
RU	4.09	1.13	**0.95**											
Inf	5.01	1.08	0.17	**0.84**										
Contx	3.94	1.58	0.30	0.34	**0.93**									
Intr	3.36	1.27	0.32	0.34	0.33	**0.92**								
Cnsdrt	5.05	1.04	0.22	0.35	0.31	0.27	**0.95**							
InfAcq	4.02	1.41	0.20	0.51	0.55	0.61	0.48	**0.94**						
PrefElc	3.57	1.51	0.33	0.38	0.55	0.56	0.50	0.31	**0.96**					
RcmdFil	3.68	1.60	0.37	0.32	0.56	0.57	0.41	0.34	0.41	**0.94**				
RQ	5.42	1.01	0.10	0.45	0.14	0.10	0.49	0.18	0.09	0.07	**0.90**			
PU	4.62	1.53	0.40	0.40	0.50	0.51	0.41	0.51	0.51	0.44	0.30	**0.91**		
US	5.50	1.16	0.36	0.52	0.27	0.34	0.33	0.40	0.35	0.35	0.62	0.51	**0.92**	
CUIR	3.65	1.45	0.44	0.11	0.48	0.50	0.11	0.36	0.50	0.47	0.62	0.57	0.46	**0.92**

[a] *n* = 355. Square roots of average variances extracted (AVEs) are reported along the diagonal. RU: recommendation use; Inf: informative, Contx: contextual, Intr: interactive, and Cnsdrt: considerate are the dimensions of RS features; InfAcq: information acquisition, PrefElic: preference elicitation, and RcmdFil: recommendation filtering are the dimensions of RS affordances; RQ: recommendation quality; PU: perceived usefulness; US: user satisfaction; CUIR: continued use intention of recommendations.

Table 19. Measurement model for constructs measured at time T2[a]

Factor	Item	λ
Recommendation quality (RQ)		
RQ1	My recommender system provides recommendations that is exactly what I need.	0.86
RQ2	My recommender system provides recommendations I need at the right time.	0.81
RQ3	My recommender system provides recommendations that is relevant to me.	0.87
RQ4	My recommender system provides sufficient recommendations.	0.82
RQ5	My recommender system provides recommendations that are easy to understand.	0.74
RQ6	My recommender system provides up-to-date recommendations.	0.75
Perceived usefulness (PU)		
PU1	My recommender system would enable me to accomplish tasks more quickly.	0.86
PU2	My recommender system would improve my performance.	0.93
PU3	My recommender system would increase my productivity.	0.93
PU4	My recommender system would enhance effectiveness.	0.93
PU5	My recommender system would help me do my task.	0.91
PU6	I find my recommender system useful.	0.69
User satisfaction (US)		
US1	I am satisfied with my recommender system.	0.94
US2	My recommender system has met my expectations.	0.94
US3	My experience with my recommender system is very pleasing.	0.87
US4	My recommender system does a satisfactory job of fulfilling my needs.	0.91
Recommendation use (RU)		
RU1	Please indicate the frequency using the following scale about how often you have used the recommendations from the recommender system that you use the most in the past 1 week: *Note*: Scale ranging from 1 to 7, where 1 = never; 2 = once a week; 3 = a few times a week; 4 = daily; 5 = A few times a day; 6 = hourly; 7 = few times an hour. Frequency of the use of the recommendations ________	0.91
Continued use intention of recommendations(CUIR)		
CUIR1	I will use the recommendations from my recommender system in the future.	0.90
CUIR2	I intend to use the recommendations from my recommender system more in work.	0.62
CUIR4	I intend to increase use of the recommendations from my recommender system.	0.91
	Item (Each item for RSF and RSA starts with “My recommender system …”)	
RSF-Informative (RSF-Inf)		
RSF-Inf1	… provides both familiar and novel recommendations.	0.76
RSF-Inf2	… provides additional information on the recommendations.	0.78
RSF-Inf3	… provides new recommendations that I am not aware of.	0.62
RSF-Inf4	… complements the current recommendation with additional recommendations that may be useful to me based on the past purchase behavior.	0.66
RSF-Contextual (RSF-Contx)		
RSF-Contx1	… provides recommendations by considering the contextual information, such as location and time.	0.84
RSF-Contx2	... provides recommendations based on my location by tracking my location.	0.80
RSF-Contx3	... extends recommendations across various domains such as, music, movies, books, products, etc.	0.73
RSF-Interactive (RSF-Intr)		
RSF-Intr1	... explains the process in generating recommendations.	0.62
RSF-Intr2	... asks me the features required in a product before providing recommendations.	0.85
RSF-Intr3	... asks how I plan to use the recommendations before providing recommendations.	0.87
RSF-Intr4	... asks me to make trade-offs on product features before providing recommendations.	0.74

Table 19. (Cont.)

Factor	Item (Each item for RSF and RSA starts with "My recommender system …")	λ
*RSF-Considerate (RSF-*Cnsdrt*)*		
RSF-Cnsdrt1	... considers my preferences before providing recommendations.	0.75
RSF-Cnsdrt2	... incorporates my feedback on the recommendations.	0.71
RSF-Cnsdrt3	... generates recommendations in response to my action.	0.74
RSF-Cnsdrt4	... generates recommendations in a timely manner.	0.73
RSF-Cnsdrt5	... considers my changing needs.	0.67
RSF-Cnsdrt6	... provides information on products and asks me to rate products to understand my preferences.	0.69
RSA-Information_Acquisition (RSA-InfAcq)		
RSA-InfAcq1	... allows me to search for additional information from others' purchases.	0.67
RSA-InfAcq2	... allows me to compare recommendations.	0.77
RSA-InfAcq3	... allows me to access heterogeneity of peer opinions and recommendations.	0.70
RSA-InfAcq4	... allows me to get explanation on how the recommendations are generated.	0.73
RSA-InfAcq5	... allows me to get additional information on the recommendations, such as ratings and images.	0.69
RSA-Preference_Elicitation (RSA-PrefElc)		
RSA-PrefElc1	... allows me for trade-off among various features of a product before generating recommendations.	0.79
RSA-PrefElc2	... allows me to specify minimum requirement on various features of a product before generating recommendations.	0.82
RSA-PrefElc3	... allows me to explicitly state my preferences about the recommendation types and presentation.	0.76
RSA-PrefElc4	... allows me for feedback on the recommendations, such as rating and liking of the recommendations, and reconfiguring the preferences.	0.65
RSA-PrefElc5	... allows me to state weighted importance on the attributes of product.	0.78
RSA-Recommendation_Filtering (RSA-RcmdFil)		
RSA-RcmdFil1	... allows me to control the sensitive aspects of the recommendations.	0.76
RSA-RcmdFil2	... allows me to control the number of recommendations.	0.73
RSA-RcmdFil3	... allows me to filter out the suggested recommendations further.	0.68

[a] $n = 355$. RSF and RSA refers to RS features and affordances, respectively. Standardized loading coefficients (λ) are given in the last column. One of the items of CUIR was not considered for analysis as inter-item reliability was low. Details are provided in the footnote during the discussion of Table 11 earlier.

Table 20. Within sum of squares (WSS) values for different *k*'s

k	WSS score
1	1062.000041
2	450.415955
3	318.579383
4	262.354372
5	224.597473
6	198.341081
7	177.105583
8	161.434704
9	147.143107
10	135.807262
11	128.757659

Table 21. Silhouette index (SI) values for different *k*'s

k	Silhouette index score
3	0.3709600977339997
4	0.31842701866658574
5	0.3116024739068727
6	0.27903121267357345
7	0.27522471251844066
8	0.27548286215812284
9	0.27780252745717504
10	0.2761688033287823
11	0.27731088340934373

Table 22. Ideal profiles of user's psychological needs

	Regression coefficients (betas)[a]			Ideal profiles[b,c]		
User's psychological needs:	Basic Pitchers	Gold Diggers	Relaxing Rhinos	Basic Pitchers	Gold Diggers	Relaxing Rhinos
Autonomy (AUT)		0.26*	0.21*		5.33	6.51
Relatedness (RLTD)	0.22*	0.28**	0.24*	4.53	5.41	5.02
Competence (COMP)		0.29*			6.88	
Having a Place (HP)		0.16**			7	
Coming to know the self (CKS)	0.27*		0.29*	6.44		5.92
Expressing self-identity (ESI)	0.28*	0.39***	0.33*	6.11	6.59	6.26
Maintaining continuity of self-identity (MCSI)		0.25*			6.35	
R^2	0.15	0.19	0.16			
F-statistics	2.95**	3.19**	2.45*			
N[d]	98	102	75	12	13	10

[a] Betas are reported only for those dimensions of psychological needs that are significantly (* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$) associated with perceived usefulness.

[b] The ideal profiles are based on calibration sample comprising the top 10 percent (in perceived usefulness) participants in each cluster.

[c] For each cluster, the ideal profiles are the means, within the calibration sample, of those psychological needs' dimensions that are significantly associated with perceived usefulness.

[d] N denotes the number of participants in the cluster. For regressions, we use exclude the calibration sample (top 10 percent) and bottom 10 percent on perceived usefulness.

Table 23. Descriptive statistics and correlations[a,b,c]

Construct	Mean	S.D.	RQ	PU	US	RU	Inf	Contx	Intr	Cnsdrt	InfAcq	PrefElic	RecmdFil	Align	RQ	PU	US
RQ	6.30	0.78															
PU	4.48	1.35	0.13														
US	5.55	1.07	0.47	0.41													
RU	3.47	1.30	0.08	0.34	0.19												
Inf	5.03	0.95	0.26	0.26	0.36	0.19											
Contx	3.95	1.47	0.31	0.40	0.12	0.28	0.28										
Intr	3.46	1.21	0.42	0.49	0.26	0.35	0.30	0.32									
Cnsdrt	5.06	0.92	0.38	0.30	0.47	0.15	0.61	0.22	0.29								
InfAcq	4.04	1.34	0.30	0.47	0.26	0.17	0.45	0.53	0.58	0.37							
PrefElic	3.61	1.45	0.40	0.45	0.23	0.34	0.35	0.55	0.67	0.44	0.28						
RecmdFil	3.66	1.54	0.15	0.44	0.23	0.40	0.29	0.58	0.71	0.32	0.20	0.19					
Align	0.68	0.76	0.14	0.14	0.12	0.08	0.16	0.09	0.11	0.19	0.10	0.09	0.08				
RQ	6.22	0.81	0.58	0.14	0.39	0.16	0.39	0.29	0.31	0.41	0.19	0.21	0.38	0.46			
PU	4.46	1.27	0.28	0.64	0.27	0.38	0.27	0.52	0.65	0.33	0.58	0.60	0.56	0.25	0.22		
US	5.53	0.95	0.45	0.30	0.49	0.28	0.47	0.18	0.28	0.60	0.30	0.27	0.27	0.58	0.53	0.39	
CUIR	3.20	1.67	0.14	0.34	0.05	0.43	0.03	0.46	0.50	0.40	0.36	0.48	0.51	0.48	0.17	0.54	0.66

[a] n = 285. This sample is hypotheses test sample discussed in the alignment measure of the paper. It is based on the middle 80 percent of the sample (i.e., after excluding the top 10 percent and bottom 10 percent on the perceived usefulness scale within each cluster). Thus, means and S.D. are different from the values in Table 16 and Table 18.

[b] Shaded constructs are measured at time T1 and non-shaded constructs are measured at time T2.

[c] *RQ*: recommendation quality; *PU*: perceived usefulness; *US*: user satisfaction; *RU*: recommendation use; *Inf*: informative, *Contx*: contextual, *Intr*: interactive, and *Cnsdrt*: considerate are the dimensions of RS features; *InfAcq*: information acquisition, *PrefElic*: preference elicitation, and *RcmdFil*: recommendation filtering are the dimensions of RS affordances; *Align:* alignment between RS affordances and user's psychological needs; *CUIR*: continued use intention of recommendations.

Table 24. Path coefficients for the study variables from SEM[a,b]

Dependent variables	Independent variables	Coefficient[c]	S.E.[d]
Hypothesized Paths			
Perceived Usefulness (T1)	Recommendation Quality (T1)	0.14**	0.05
User Satisfaction (T1)	Perceived Usefulness (T1)	0.37***	0.03
	Recommendation Quality (T1)	0.50***	0.04
Recommendation Use (T2)[e]	User Satisfaction (T1)	0.02	0.08
	Perceived Usefulness (T1)	0.50***	0.08
	Recommendation Quality (T1)	0.65***	0.07
RSA-Information Acquisition (T2)	Recommendation Use (T2)	0.19***	0.06
	RSF-Informative (T2)	0.46***	0.06
	RSF-Contextual (T2)	0.27***	0.04
	RSF-Interactive (T2)	0.63***	0.05
	RSF-Considerate (T2)	-0.03	0.06
RSA-Preference Elicitation (T2)	Recommendation Use (T2)	-0.04	0.03
	RSF-Informative (T2)	0.05	0.06
	RSF-Contextual (T2)	0.17***	0.03
	RSF-Interactive (T2)	0.96***	0.03
	RSF-Considerate (T2)	0.16***	0.04
RSA-Recommendation Filtering *(T2)*	Recommendation Use (T2)	0.06**	0.04
	RSF-Informative (T2)	0.08	0.06
	RSF-Contextual (T2)	0.27***	0.04
	RSF-Interactive (T2)	0.94***	0.04
	RSF-Considerate (T2)	-0.06	0.05
Recommendation Quality (T2)	RSF-Informative (T2)	0.25***	0.04
	RSF-Contextual (T2)	-0.02	0.02
	RSF-Interactive (T2)	-0.19***	0.03
	RSF-Considerate (T2)	0.40***	0.04
Perceived Usefulness (T2)	Recommendation Use (T2)	0.31***	0.04
	Recommendation Quality (T2)	0.10*	0.05
	Alignment (T2)	0.06*	0.02
User Satisfaction (T2)	Perceived Usefulness (T2)	0.32***	0.03
	Recommendation Quality (T2)	0.68***	0.05
Continued Use Intention of Recommendations (CUIR) (T2)	Perceived Usefulness (T2)	1.08*	0.10
	Recommendation Quality (T2)	0.57***	0.12
	User Satisfaction (T2)	-0.04	0.10
Emergent Paths			
RSF-Informative (T2)	Perceived Usefulness (T1)	0.34***	0.05
	Recommendation Use (T2)	0.02***	0.00
RSF-Contextual (T2)	Perceived Usefulness (T1)	0.56***	0.08
	Recommendation Use (T2)	0.26***	0.07
RSF-Interactive (T2)	Perceived Usefulness (T1)	0.53***	0.07
	Recommendation Use (T2)	0.27***	0.05
RSF-Considerate (T2)	Perceived Usefulness (T1)	0.30***	0.05
	Recommendation Use (T2)	0.06	0.04

[a] n = 285. This sample is hypotheses test sample discussed in the alignment measure of the paper. It is based on the middle 80 percent of the sample (i.e., after excluding the top 10 percent and bottom 10 percent on the perceived usefulness scale within each cluster).

[b] We also test the model using PLS SEM and results were consistent with the only exception is path from User Satisfaction (T1) to Recommendation Use (T2) becomes significant at $p < 0.10$.

[c] Unstandardized coefficients are reported at significance level (* $p < 0.05$; **$p < 0.01$; *** $p < 0.001$).
[d] S.E. refers to standard error. We exclude the path from the control variables not to complicate the table.
[e] Recommendation use (T2) refers to use of recommendation between time T1 and time T2. T1 and T2 denote the time of measurement of constructs.

Table 25. Summary of results

Hypothesized Paths	**Result**
H1a: RS features affect recommendation quality.	Supported
H1b: RS features affect RS affordances.	Supported
H2: The alignment between the user's psychological needs and affordances provided by RS positively affects the perceived usefulness of RS.	Supported
H3: Recommendation quality positively affects user satisfaction.	Supported
H4a: Perceived usefulness positively affects user satisfaction.	Supported
H4b: Perceived usefulness positively affects the subsequent extent of use of recommendations.	Supported
H4c: Perceived usefulness positively affects the subsequent continued use intention of recommendations.	Supported
H5a: User satisfaction positively affects the subsequent extent of use of recommendations.	Not Supported
H5b: User satisfaction positively affects the subsequent continued use intention of recommendations.	Not supported
H6a: Extent of use of recommendations from a RS positively affects the subsequent perceived usefulness of the RS.	Supported
H6b: Extent of use of recommendations by a RS leads to the subsequent greater recognition of affordances provided by the RS.	Supported
Emergent Paths	**Result**
E1: Perceived usefulness leads to the greater recognition of RS features.	Supported
E2: Extent of use of recommendations leads to the greater recognition of RS features.	Supported

Table 26. Categorization of recommender systems[a]

Type of recommender system	Name of recommender system
Hedonic	Discovery, Disney+, Facebook, Goodreads, HBO, Hulu, Instagram, Netflix, Pandora, Pinterest, Spotify, Steam, Tik Tok, Twitter, YouTube
Utilitarian	ASOS, Amazon, Apple, Castle Learning, , Google, Grammarly, Ibotta, Indeed, Kickstarter, LinkedIn, Microsoft Outlook, NVidia, Optimizely, Peerius, Reddit, Samsung, Shein, Storygraph, eBay

[a] 11 participants did not provide the name of the recommender system they use the most.

Table 27. *t-test* for the difference in means of the study constructs[a,b,c,d]

Construct	Hedonic (N=196)		Utilitarian (N=148)		t-value
	Mean	S.D.	Mean	S.D.	
Recommendation Quality (T1)	5.58	1.05	5.55	0.85	0.36
Perceived Usefulness (T1)	4.37	1.51	4.99	1.39	3.92***
User Satisfaction (T1)	5.60	1.22	5.46	1.10	1.12
Recommendation Use (T2)	3.98	1.15	4.19	1.10	1.78
RSF-Informative (T2)	5.00	1.14	5.07	0.99	0.57
RSF-Contextual (T2)	3.56	1.53	4.43	1.51	5.27***
RSF-Interactive (T2)	3.21	1.28	3.54	1.23	2.47**
RSF-Considerate (T2)	5.13	1.07	4.97	0.95	1.38
RSA-Information Acquisition (T2)	3.69	1.44	4.45	1.22	5.26***
RSA-Preference Elicitation (T2)	3.23	1.44	3.84	1.53	3.14***
RSA-Recommendation Filtering (T2)	3.46	1.59	3.94	1.59	2.78**
Alignment (T2)	0.60	0.80	0.76	0.72	1.92
Recommendation Quality (T2)	5.43	1.06	5.44	0.92	0.11
Perceived Usefulness (T2)	4.42	1.61	4.89	1.38	2.88**
User Satisfaction (T2)	5.55	1.23	5.44	1.05	0.94
Continued Use Intention of Recommendations (CUIR) (T2)	2.85	1.77	3.56	1.78	3.64***

[a] Significance level is * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
[b] T1 represents the measure of the construct at time T1 and T2 represents the measure of the construct at time T2.
[c] N represents the sample size. 11 participants did not provide the name of the recommender systems they use the most and thus were excluded in *t-test*.
[d] We conduct unequal variance t-test due to non-normality in the data.

Appendices

Appendix 1. Approval Letter from Institutional Review Board (IRB)

UNIVERSITY OF ARKANSAS

To:	Ankur Arora
From:	Douglas J AdamsJustin R Chimka, Chair IRB Expedited Review
Date:	04/08/2022
Action:	**Exemption Granted**
Action Date:	04/08/2022
Protocol #:	2203393347
Study Title:	Study the Intent to Use Recommender System

The above-referenced protocol has been determined to be exempt.

If you wish to make any modifications in the approved protocol that may affect the level of risk to your participants, you must seek approval prior to implementing those changes. All modifications must provide sufficient detail to assess the impact of the change.

If you have any questions or need any assistance from the IRB, please contact the IRB Coordinator at 109 MLKG Building, 5-2208, or irb@uark.edu.

cc: Rajiv Sabherwal, Investigator

Appendix 2. Dropped Items of RS Features and RS Affordances from Factor Analysis

Table A1

Constructs	Items
RS Features (RSF)	1) My recommender system values aesthetics to enhance the quality of experience in the recommender system.
	2) My recommender system poses as avatar that use animation and human voice to provide recommendations.
	8) My recommender system provides recommendations that are biased against races or gender I.
	9) My recommender system considers ease for me to generate new/additional recommendations.
	11) My recommender system provides recommendations containing familiar products.
	14) My recommender system provides recommendation in a bundle.
	18) My recommender system shows more recommendations than I want.
	21) My recommender system generates recommendations without requiring me to login to the system.
RS Affordances (RSA)	1) My recommender system allows me to engage with recommender system using image of an avatar or interacting with voice.
	11) My recommender system allows me to collaborate with others during the preference process catering to the needs of the group as a whole.
	13) My recommender system allows me to state basic or advanced use of recommendations to recommender system before getting recommendations.
	16) My recommender system allows me to get information on various products for a specified time before eliciting my preferences.

Chapter 5: Conclusion

> "AI is in a 'golden age' and solving problems that were once in the realm of sci-fi." – Jeff Bezos

This dissertation was motivated by a desire to understand the dual role of AI. Although many organizations have reaped benefits from the use and deployment of AI – Starbucks' use of chatbots to notify customers when the orders are ready and Mastercard's use of chatbots to make it easy for customers to get information on their transactions, some AI projects have also encountered setbacks or failed, e.g., Facebook's chatbot[58] and IBM put on hold more than $62 million 'Watson for Oncology' AI product after the system started to provide an incorrect recommendation to patients.[59] If AI is producing benefits and causing economic growth and prosperity (Reuters 2018),[60] it is also posing fundamental and ethical challenges that have broader implications for society. For example, deaths resulting from self-driving cars of Tesla and Uber led to calls for a national moratorium on autonomous cars.[61]

Although BVIT research has studied the impact of new ITs on firm performance (e.g., Sabherwal et al. 2019; Steelman et al. 2019), literature on AI has mostly investigated the algorithm design and improvement (Androutsopoulou et al. 2019); and application of AI systems in various industrial sectors (Kumar et al. 2019; Tambe et al. 2019) thereby lacking in the thorough investigation of both growth and fundamental and ethical issues arising from the adoption of AI that has wider implications for both the users and the organizations. Furthermore, there is an ongoing tension related to the use of AI in organizations as top management of some

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[58] https://www.nzherald.co.nz/business/facebook-shuts-down-controversial-chatbot-experiment-after-ais-develop-their-own-language-to-talk-to-each-other/K2BVDVFEWVKWTT6LSUC22MUY7I/.

[59] https://www.forbes.com/sites/matthewherper/2017/02/19/md-anderson-benches-ibm-watson-in-setback-for-artificial-intelligence-in-medicine/?sh=7f586e433774.

[60] https://www.reuters.com/article/uk-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUKKCN1MK08K?edition-redirect=uk.

[61] https://www.theguardian.com/technology/2018/mar/19/uber-self-driving-car-kills-woman-arizona-tempe.

of the organizations believe that AI is more dangerous than a nuclear bomb (Clifford 2018) while some believe it will revolutionize the lives of humans and open new avenues for businesses to thrive (Clifford 2017). This disagreement in practice encourages us to seize an opportunity to investigate the duality role of AI in shaping firms and the user adoption of AI products. In the following, we explain the contributions of each essay.

Essay 1 has explored the application of WOM, signaling theory, and automation-augmentation perspective in understanding the nature of AI investment on firm's abnormal long-term stock returns and how the potential consequences resulting from the nature of AI investment in the form of – concerns about layoffs, optimism about hiring, and concerns about ethics attenuate or strengthen the effect of nature of AI investment on firm's long-term abnormal returns. The empirical study is based on secondary data on 169 AI announcements (by 142 unique U.S. publicly-traded companies) during years 2000-2019. We find that both kinds of AI investments – automation and augmentation – create a bullish market. Moreover, investors react positively to the AI-enabled automation when hiring is expected to occur as a result of the AI investment. However, concerns about layoffs and ethical issues arising from the AI investments attenuate the bullish sentiment of AI-enabled automation on the firm's long-term abnormal returns. In sharp contrast, the effect of AI-enabled augmentation on a firm's long-term abnormal returns is strengthened by concerns about layoffs following the AI investment. Thus, concerns about potential layoffs as a result of the AI investment hurt if the AI investment is expected to cause automation but help if the AI investment is expected to cause augmentation. These contrasting results highlight the needs for firms to align their planned AI investments and their potential societal implications to their core values. Firms also need to maintain, audit and update

AI systems with correct and new data to avoid bias and social inequalities resulting from insufficient or corrupt data.

Essay 2 has used dynamic capabilities theory to extend the literature on AI by examining the impact of a firm's strategic AI orientation on its performance. To create differential value, firms need to strategically invest in AI that would provide maximum payoffs from AI investment; failing to do so would entrench firms into vicious cycles providing short-term benefits yet long-term losses. This empirical study is based on secondary data on 464 firm-year observations related to AI investment belonging to 326 unique firms for the years 2010-2020. Our results lend credibility to the importance of conformance of IT strategy with strategic AI orientation. Such conformance becomes even more critical when the environment is turbulent and unstable, creating unpredictability in the market. We find that firms pursuing revenue-focused IT strategy notice a decline in performance in a dynamic environment when strategic AI orientation is for exploitation. By contrast, revenue-focused IT strategy firms benefit more in a dynamic environment when strategic AI orientation is for exploration. These results highlight how firms could leverage different strategic investments in AI to pursue their objectives. Firms pursue different IT strategies, and one-size-fits-all does not work for AI investments. Firms need to look at their goals and make a strategic decision to invest in AI that aligns with their objectives to reap the maximum benefits from AI. The study also highlights the need for managers to consider their industry environment when deploying AI assets. Aligning the AI investments with the firm's IT strategy is useful in general, but becomes even more critical in a dynamic environment. Also, managers need to be patient with the benefit realization of AI investments as findings from our one-year lagged model indicate the performance gains from both strategic AI orientations – exploitation and exploration.

Essay 3 focuses on the use of recommender systems (RSs), AI products that provide a personalized recommendation based on users' past preferences. Using NAF and IS success theoretical foundations, this study provides a generic theory of the RS success model. This empirical study is based on primary data collected through a longitudinal study (two survey responses, one week apart) of 355 full-time working individuals. The results provide insights to design science scholars about considering the user's psychological needs and designing RS features that enable affordances that would fulfil the user's needs, and thereby improve RS success. By understanding the needs propelling the use of RS, firms could proactively address the ethical issues that could arise during the design of the RS. Our results suggest that certain segments of users have high demands for information acquisition, preference elicitation, and recommendations filtering. Firms could design RS features that tap different customer segments. Practitioners could benefit from our research findings by emphasizing on the needs of the end-users during recommendations generation process and implementing RS features that could enable the required affordances in the RS design. It would help firms to be able to better engage with the customers resulting in customer satisfaction and increased returns.

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