Marketing Science Institute Working Paper Series 2025

Report No. 25-121

Marketing Employees with AI Expertise: Roles and Performance Implications

Suyun Mah, Chengxin Cao, Eunyoung Song and Ju-Yeon Lee

Marketing Employees with AI Expertise: Roles and Performance Implications

Suyun Mah
Assistant Professor of Marketing
Department of Marketing
Lee Kong Chian School of Business
Singapore Management University
Phone: +65-6828-9654
Email: symah@smu.edu.sg

Chengxin Cao
Assistant Professor of MIS
Paul H. Chook Department of Information Systems and Statistics
Zicklin School of Business
Baruch College
Phone: +1-646-312-3350
Email: chengxin.cao@baruch.cuny.edu

Eunyoung Song
PhD Student
Department of Marketing
Ivy College of Business
Iowa State University
Phone: +1-515-203-5403
Email: silvias@iastate.edu

Ju-Yeon Lee
Associate Professor of Marketing
Department of Marketing
John and Connie Stafford Professor in Business
Ivy College of Business
Iowa State University
Phone: +1-515-294-5402
Email: leejy@iastate.edu

Acknowledgement: The authors are grateful for the financial support received from the Ivy College of Business at Iowa State University.

Marketing Employees with AI Expertise: Roles and Performance Implications

ABSTRACT

Firms increasingly invest in artificial intelligence (AI), but it is ultimately human capital that oversees and operationalizes these technologies. Despite the growing importance of AI in marketing, practitioners lack clear guidance on how to effectively manage marketing employees with AI expertise. With two complementary multi-method studies, we investigate the roles and performance implications of such *marketing AI human capital*. In Study 1, our exploratory large-scale text analysis reveals that marketing AI human capital is involved in more responsible for externally-focused tasks that enhance customer understanding and engagement whereas non-marketing AI human capital emphasizes internally-focused tasks aimed at improving operational efficiency and model accuracy. In Study 2, analyzing multisource secondary panel data from 574 firms, we find that marketing AI human capital *inflow* (recruitment of individuals possessing AI-related expertise into marketing roles within the firm) is positively associated with stock returns, whereas *outflow* (departure of individuals possessing AI-related expertise from marketing roles within the firm) has a detrimental effect. Importantly, the negative impact of outflow exceeds the positive effect of inflow. We also find that these effects are moderated by seniority of inflowing/outflowing marketing AI human capital, a firm's market share, and its product market scope.

Keywords: Artificial intelligence, human capital, marketing positions, financial performance

Building "organizational readiness to adopt and effectively use AI-driven insights and create AI-driven solutions" becomes a key strategic priority (Marketing Science Institute 2024, p. 8). In response, an increasing number of firms not only invest heavily in developing artificial intelligence (AI) infrastructure but also focus on attracting skilled AI talent to improve their performance. For instance, Google's recent recruitment of a high-profile AI expert required $2.7 billion, demonstrating that firms are willing to secure top-tier AI professionals (Kruppa and Thomas 2024). In the financial sector, major banks such as JPMorgan Chase, Morgan Stanley, and Capital One have also been aggressively recruiting employees with AI talent (Bousquette 2024). Moreover, job postings for AI roles continue to grow, reflecting a 50% increase over the previous year even as positions in other technology sectors are facing cuts (Rattner and Dotan 2024). This focus on recruiting AI-skilled employees indicates that firms view human expertise as a critical asset in transforming AI potential into profitable applications.

This growing emphasis on AI talent has extended to marketing, with firms actively seeking *marketing AI human capital*—employees who not only hold marketing positions but also possess the advanced expertise to develop, apply, or manage AI technologies (e.g., proficiency in machine learning algorithms, predictive modeling, natural language processing). These marketing AI human capital leverages AI-driven insights to enhance customer experience and engagement, ultimately driving financial outcome (Boston Consulting Group 2024); this is a contrast to non-marketing AI human capital, who focuses on improving algorithmic precision, computational efficiency, and predictive accuracy (Babina et al. 2024; Wu, Lou, and Hitt 2025).

While marketing is one of the few functions that firms most often use AI (McKinsey&Company 2025), many firms struggle to fully realize the benefits of marketing AI human capital. For example, a leaked internal meeting of Apple revealed frustrations over

delayed AI feature launches, with substantial tensions arising between the Siri team and the marketing division, impacting Apple's performance (Gurman 2025). In addition, 60% of firms find it challenging to effectively integrate AI into their marketing efforts (BuzzBoard 2023), which highlights that AI and humans need to join forces to overcome the inability of AI to create personalized solutions (Forbes 2023). The challenge, therefore, is not whether firms should adopt AI, but how they implement these tools across diverse marketing activities to fully realize their potential while managing associated risks (Grewal et al. 2025). This "how" hinges on the marketing AI human capital; without such talent, firms may possess the tools but lack the interpretive and managerial capabilities required to integrate AI meaningfully into marketing workflows. Thus, our research questions are: *1) What roles does marketing AI human capital play within a firm?; 2) What are the effects of marketing AI human capital on financial performance?;* and *3) Under what conditions can firms best leverage their marketing AI human capital effectiveness?*

To address our research questions, we conduct two complementary multi-method studies. In Study 1, we perform an exploratory large-scale text analysis of 9,780 job descriptions related to marketing AI human capital in publicly traded firms in the US to better understand the organizational roles these individuals play. Specifically, we compare the content of marketing AI job descriptions with those of non-marketing AI roles to identify the distinct tasks and responsibilities that characterize marketing AI human capital. In Study 2, we provide empirical evidence of the performance effects of marketing AI human capital by analyzing a panel data set of 574 publicly traded U.S. firms during 2012–2021 from multiple secondary sources. Unlike prior research that relied primarily on surveys or cross-sectional designs to study organizational analytics or AI applications (Germann, Lilien, and Rangaswamy 2013; Mu and Zhang 2025), our

use of longitudinal secondary data enables a more comprehensive, dynamic perspective on how firms acquire and lose marketing AI professionals over time. Taken together, we offer new insight to the management of AI-skilled human capital within marketing functions, rather than studying a firm's overall focus on AI (Mishra, Ewing, and Cooper 2022). To the best of our knowledge, this is the first article to conceptualize and empirically document the distinct contributions of marketing AI human capital and its relevance to financial performance.

To develop a conceptual framework to understand the effects of marketing AI human capital on financial performance, we draw upon knowledge-based view (Grant 1996; Kogut and Zander 1992), which posits that knowledge is the key strategic asset, and human capital is central to knowledge generation, retention, and application. As shown in Figure 1, we examine the extents to which marketing AI human capital *inflow* (i.e., recruitment of individuals possessing AI-related expertise into marketing roles within the firm) and *outflow* (i.e., departure of individuals possessing AI-related expertise from marketing roles within the firm) affect financial performance. Rather than focusing on human capital stock, which offers only a static snapshot of available AI expertise at a given moment (Babina et al. 2024; Wu, Lou, and Hitt 2025), we emphasize how talent moves in and out of the firm to offer a more dynamic perspective (Eckert et al. 2022; Nyberg and Ployhart 2013). Studies on AI talent stock make the implicit assumption that acquiring and losing AI talents would manifest mirrored effects, and moderating conditions exhibit symmetrical effects. Yet, as the increase and decrease in such talent stock might impose different influences on the knowledge structure within the firm, it is likely that inflow and outflow impose distinct impacts on financial performance. We also explore how the effects of marketing AI human capital movement are affected by key firm-specific factors, such as marketing AI position seniority inflow/outflow, market share, and product market scope. These

represent structural, positional, and strategic conditions under which knowledge generated by marketing AI human capital is leveraged. Figure 2 illustrates our conceptual framework.

—Insert Figure 1 and Figure 2 about here—

This research makes three key contributions to the marketing literature, particularly at the intersection of marketing strategy, AI, and human capital. First, with Study 1, we advance understanding of what marketing AI human capital does by offering the first large-scale empirical delineation of its roles within organizations. Drawing on job description data and topic modeling in Study 1, we identify four core task domains that define AI human capital activities: CRM/database, strategic process, product/solution, and promotion. We reveal that while both marketing and non-marketing AI roles engage with the first three domains (promotion only appears among marketing AI human capital), their functional emphases diverge. Marketing AI human capital is more responsible for externally-focused tasks that enhance customer understanding and engagement; for instance, managing customer accounts or collaborating across teams to support product and service delivery (Boston Consulting Group 2024; Wedel and Kannan 2016). In contrast, non-marketing AI human capital is often responsible for internally-focused tasks aimed at improving operational efficiency and model accuracy, such as leveraging big data analytics to manage database systems. By highlighting these differences in their tasks, we offer new insight into the distinctive contributions of marketing AI human capital—an area largely overlooked in prior research on general AI talent (Babina et al. 2024; Wu, Lou, and Hitt 2025).

Second, with Study 2, we contribute to human capital research in marketing by focusing on the flow of marketing AI human capital—the inflow and outflow of AI-skilled employees across *all organizational levels*—rather than limiting our analysis to static measures or top

executives. While most marketing studies on human capital have concentrated on senior leaders and the upper echelons (Feng, Morgan, and Rego 2015; Whitler et al. 2021), our approach captures the movement of AI talent throughout the organization, from junior employees to top executives. This broader perspective offers a more comprehensive understanding of how marketing AI human capital shapes financial performance. Our findings reveal a significant asymmetry in the performance impact of marketing AI human capital movement; greater inflow of marketing AI talent enhances financial performance, but the negative effects of outflows are even more pronounced. That is, a 1% increase in inflow translates to a .38% increase in firm stock return, while a 1% increase in outflow translates to a .89% decrease in firm stock return; the negative effect of outflow is significantly stronger than the positive effect from the inflow. This asymmetry is particularly important as it suggests that marketing AI human capital is not easily replaceable; firms cannot simply recruit AI-skilled marketers to offset the damage caused by departures. AI-skilled marketers possess deep organizational knowledge and customer insights, which are difficult to replicate quickly. Their departure represents not just a loss of skills but also a disruption in AI-driven marketing initiatives (De Bruyn et al. 2020). Accordingly, our findings highlight the critical importance of talent retention, as firms that fail to keep their marketing AI employees risk significant financial setbacks that cannot be easily recovered through recruitment alone.

Third, we examine the heterogeneity of the performance effects of marketing AI human capital flow. Specifically, we examine the role of *seniority of marketing AI human capital inflow/outflow* in shaping the financial impact, providing insights into which types of employees that firms should prioritize for recruitment and retention. Our findings reveal that the effects of marketing AI human capital inflow and outflow vary depending on the seniority of such labor

force. Specifically, while the inflow of marketing AI human capital enhances performance on average, this positive effect diminishes when they are put into senior positions. Conversely, the negative impact of marketing AI outflow on financial performance is weakened when departures occur at senior levels. This contrasts with recent research suggesting that senior employees with shorter tenure tend to experience higher job satisfaction from AI adoption, as they face fewer concerns about job security and displacement (Chiong and Xie 2024). However, our findings highlight a different perspective: the inflow of senior marketing AI talent may not translate into strong stock market gains, emphasizing that firms might derive greater firm value from recruiting and retaining junior-level AI talent within the marketing functions.

Furthermore, we examine how a firm's market position—*market share* (competitive position within a market) and *product market scope* (degree of diversification across different markets)—moderates the performance impacts of marketing AI human capital inflow and outflow. A firm's market share amplifies the positive effect of marketing AI human capital inflow on financial performance while also buffering the negative effect of outflow. High-market-share firms not only integrate new AI talent more effectively due to their robust resources and organizational capabilities but also experience less disruption from outflows, as their deeper talent pools and institutionalized knowledge help sustain marketing performance despite departures. In contrast, firms with broader product market scope see weaker benefits from AI talent inflows, as AI expertise becomes more fragmented across diverse business segments, limiting its overall impact.

Understanding of AI and Human Capital

Human Capital with AI Expertise

AI is becoming deeply embedded in various marketing functions, from personalized

content delivery to relationship management (Davenport et al. 2020).While these tools offer new opportunities, it is ultimately human capital that determines whether such technologies translate into meaningful outcomes (Boston Consulting Group 2024). The value of AI human capital lies in employees' ability to convert specialized AI knowledge into business impact, by recombining existing knowledge or bridging ideas across domains to solve market problems (Wu, Hitt, and Lou 2020).

While many employees and firms use off-the-shelf AI tools like ChatGPT or HubSpot's AI-enabled CRM, these solutions prioritize broad accessibility and require little technical expertise. In turn, an increasing number of executives are recognizing the value of developing in-house AI capabilities. For instance, rather than relying on commercial tools, Morgan Stanley built its own proprietary AI system because, as its global head of technology and operations noted, off-the-shelf solutions often lack the flexibility and capabilities enterprises need: "building it ourselves gave us certain capabilities that we're not really seeing in some of the commercial products" (Wall Street Journal 2025). In line with this shift, our paper defines AI human capital as employees with *advanced* AI capabilities—those who can build, adapt, and optimize models beyond default settings. These individuals often bring the technical acumen to work with core algorithms or customize systems using firm-specific data. Without such in-house expertise, firms are confined to generic tools and miss the opportunity to fully leverage AI.

Literature Review

Human capital with AI expertise has been examined across several literature streams (Table 1), yet important gaps remain. First, much of the marketing literature treats AI primarily as a technological tool rather than a human resource challenge (see Panel A). A growing body of work has investigated AI applications—such as chatbots, recommendation systems, and

algorithmic decision aids—focusing largely on their effects on consumer behavior and operational efficiency (Garvey, Kim, and Duhachek 2023; Luo et al. 2021; Luo et al. 2019). While these studies have advanced understanding of AI adoption, they tend to conceptualize AI as a form of process innovation, largely overlooking the human infrastructure that enables its effective use. Early research in this area has focused narrowly on marketing analytics (e.g., Germann et al. 2014; Germann, Lilien, and Rangaswamy 2013), capturing only a subset of the broader capabilities that marketing AI human capital can offer. Specifically, there is limited insight into how firms attract, manage, and integrate employees with AI expertise into marketing operations. Our study addresses this gap by shifting the focus from the deployment of AI tools to the organizational systems and talent strategies that support AI integration within the marketing function (De Bruyn et al. 2020).

Second, when human capital is considered, it is typically measured at the firm level, without accounting for differences across functional areas (see Panel B). For instance, recent studies have documented the presence of AI-skilled talent across firms more broadly (Babina et al. 2024; Lou and Wu 2021; Wu, Lou, and Hitt 2025), but they do not differentiate between marketing and non-marketing roles. This aggregate approach fails to capture the functional heterogeneity in how AI is applied, and thus obscures the distinct value generated by marketers with AI expertise. By focusing specifically on marketing AI human capital, our study offers a more granular understanding of how functionally embedded talent contributes to performance.

Third, marketing research on human capital has traditionally focused on top or senior executives holding marketing positions (e.g., Feng, Morgan, and Rego 2015; Germann, Ebbes, and Grewal 2015; Srivastava, Kashmiri, and Mahajan 2023). However, this approach overlooks the broader organizational layers (e.g., mid- and lower-level employees) who interact directly

with AI tools and play a critical role in day-to-day marketing operations. Our study broadens this perspective by examining AI-skilled talent across all organizational levels, providing a more comprehensive view of how marketing AI human capital is distributed and utilized within firms.

Fourth, we move beyond the traditional, static view of human capital to adopt a dynamic perspective centered on the flow of marketing AI talent within firms. Prior research tends to conceptualize human capital as a stock (Babina et al. 2024; Wu, Hitt, and Lou 2020; Wu, Lou, and Hitt 2019), overlooking how the inflow and outflow of talent differentially influence performance. In contrast, we argue that the movement of talent, through recruitment (inflow) and departure (outflow), is a key mechanism shaping a firm's ability to leverage AI.

—Insert Table 1 about Here—

Study 1: Understanding the Role of Marketing AI Human Capital in Organizations

Given the limited research on the role that marketing AI human capital plays within organizations, we conduct an exploratory study to better understand the nature of tasks that define this emerging workforce. Specifically, we analyze a large-scale dataset of job descriptions to uncover the distinct responsibilities associated with marketing AI roles. The job descriptions were sourced from Revelio Labs, which compiles publicly available employment data from LinkedIn to provide insights into the current and historical workforce composition of various organizations (e.g., Law and Shen 2024). To extract underlying themes from these descriptions and identify the most prevalent task areas associated with marketing AI human capital, we employ the Latent Dirichlet Allocation (LDA) topic modeling (Blei, Ng, and Jordan 2003). This method identifies latent topics in a corpus by analyzing patterns in word co-occurrence, assuming that each document (in our case, each job description) reflects a mixture of topics, with each topic characterized by a specific distribution of words.

To contextualize these findings, we compare them to themes extracted from non-marketing AI job descriptions. This comparison enables us to examine how AI skills are deployed differently across functional domains. We focus on engineering as the primary comparison group because it accounts for approximately 73% of the general AI human capital in our dataset. In total, our dataset includes 9,780 job descriptions for marketing AI roles and 206,641 for engineering AI roles[1]. Using the Cv coherence score (Chen and Lee 2023; Röder, Both, and Hinneburg 2015) to guide topic selection, we identify seven distinct topics in marketing AI job descriptions and six in engineering AI descriptions. Additional details on algorithm specifications and coherence score evaluations are provided in Web Appendix A.

Table 2 shows the labels of 7 topics for marketing AI human capital and 6 topics for non-marketing AI human capital along with top relevant keywords for each topic. We label each topic based on the top keywords as well as probability of each topic across job descriptions.

To offer a more holistic understanding of the results, we categorize the topics into four overarching task domains that capture the functional scope of AI human capital across both role types: (1) *CRM/database* (managing customer or organizational data), (2) *strategic process* (shaping marketing or operational strategy), (3) *product/solution* (developing AI-enabled offerings or infrastructure), and (4) *promotion* (executing data-driven campaigns). These domains reflect how AI human capital is embedded within organizations (see Figure 3). We elaborate on these findings in the sections that follow.

—Insert Table 2 and Figure 3 about Here—

Marketing AI Human Capital's Core Responsibilities

CRM/Database. These roles focus on *managing customer accounts and providing*

[1] We limit the firms to those who appear in Study 2 to keep consistency across studies.

product or service support by collaborating with teams (Topic 1). Tasks include interpreting customer data, aligning marketing strategies with individual preferences and histories, and ensuring consistency across touchpoints. The following job description illustrates this emphasis:

> *I own the operational relationship with some of our highest-profile clients who demand high levels of satisfaction on a daily basis. I am the subject matter expert for my assigned clients that use our platform, which is a SaaS application. I provide a point of escalation for my clients for critical issues in funding/settlements and authorizations... (Topic 1, Fiserv Employee).*

This reflects how CRM/Database roles leverage SaaS platforms, client data, and internal collaboration to ensure seamless customer experience and support broader marketing goals.

Strategic process. Marketing AI human capital plays a key role in *developing and executing marketing strategies to achieve sales and revenue growth* (Topic 2). A job description of an Oracle employee illustrates this emphasis:

> *Led the marketing strategy and account-based efforts to drive cloud technology preference and demand across key industries and segments…. Responsibilities included working with my team and outside stakeholders to define and execute plans that deliver marketing-generated pipeline commitments in support of sales and business growth (Topic 2, Oracle Employee).*

This example reflects the strategic nature of marketing AI roles, where professionals coordinate across internal and external stakeholders to drive market-facing initiatives.

Product/Solution. In this domain, marketing AI human capital creates value through technological innovation. Tasks include *delivering cloud applications to solve customers' business needs* (Topic 3), *delivering solutions via big data analytics and cloud* (Topic 4), *leveraging Microsoft Azure, AI, and machine learning to enhance customer experience* (Topic 6), and *designing and visualizing products with 3D models* (Topic 7). These responsibilities position marketing AI human capital as translators between customer needs and technological capabilities. The following examples highlight how such marketing AI human capital apply advanced technologies to develop tailored solutions that meet the unique demands and challenges of different industries.

Responsible for building and growing the next generation of enterprise business services—Human Capital Management, Financial Management, and Payroll—and deliver the solutions on a true Software-as-a-Service [SaaS] model by establishing the company in the Nordic and Baltic market (Topic 3, Workday Employee).

Helped global financial services clients solve next generation data problems with unique solutions for real-time data analytics, hybrid/private cloud, machine & deep learning, GPU-accelerated applications, VMware, and database. More specifically, Pure delivers cloud and on-prem performance-at-scale solutions for requirements involving: OLTP database, VMware, VDI, containers, GPU-accelerated applications, Splunk, Vertica … (Topic 4, Pure Storage Employee).

Set up and led a cross-discipline growth team across PMs, data scientists, engineers, and UX to explore growth opportunities across M365 apps [like Office Mobile], leveraging data science, machine learning, and user research to drive insights. Drove product intervention and growth experiments to propel user growth for Office Mobile (Topic 6, Microsoft Employee).

Create, texture, animate, and render 3D art for F-18, F-15, and other aircraft/tiltrotor training lessons. Produce Flash animations, Illustrator and Photoshop art to support the development of curriculum for domestic and foreign military training programs. …Creation of computer-based presentations and training on various systems by use of various software such as: Adobe Photoshop, Adobe Illustrator, Bryce 3D, 3D Studio Max, Flash... (Topic 7, Boeing Employee).

This set of examples illustrates how marketing AI human capital serves as a vital link between customer expectations and technological innovation, ensuring that products and solutions are not only functional but also strategically aligned with business growth.

Promotion. Marketing AI human capital also *manages data-driven campaigns and content for online marketing* (Topic 5). These roles focus on engaging customers through personalized messaging and continuously optimizing campaign effectiveness through analytics. The job description of a Henry Schein employee illustrates this emphasis:

Website advertising, e-mail marketing, targeted print mailers [postcards, product sample mailings, self-mailers, letters], quarterly print sale flyer for the prosthodontic specialty, annual print catalog for the prosthodontic specialty, annual "what's new" flyer [featuring all new products for the year], search engine optimization pages [SEO], social media marketing, analytics: data mining to create customer target lists (Topic 5, Henry Schein Employee).

This example reflects how these roles leverage multichannel marketing tactics and customer data analytics to drive personalized engagement and continuously improve campaign performance. As shown below, this is a unique domain of responsibilities that only appears among marketing AI human capital.

Together, marketing AI human capital performs a diverse set of externally-focused tasks that translate AI capabilities into improved customer understanding. These roles range from managing customer accounts and service support to developing AI-enabled solutions such as cloud applications and predictive models (Mu and Zhang 2025). Through these activities, marketing AI professionals generate marketing knowledge by uncovering insights from customer data and disseminate it across the organization by collaborating with cross-functional teams to inform strategy, product design, and personalized communication. Such work is central to personalization, campaign optimization, and CRM; these are domains where marketing analytics enhance customer experience and engagement (Wedel and Kannan 2016). Thus, marketing AI human capital plays a key role in systematically embedding customer knowledge into firm decision-making (Grewal et al. 2024).

Non-Marketing AI Human Capital's Core Responsibilities

CRM/Database. Non-marketing AI human capital plays a role in designing and maintaining the digital infrastructure that supports organizational data management. These roles focus on ensuring that cloud-based platforms are integrated, scalable, and secure. Tasks include *managing solutions, product, and services strategies with cloud technologies* (Topic 1), *managing and securing virtual clouds and servers* (Topic 5), and *leveraging big data analytics to manage database warehouses using Hadoop, Spark, Hive, and SQL* (Topic 6). Unlike marketing roles that use customer data to personalize experiences, non-marketing teams ensure that the systems handling this data are efficient, reliable, and compliant—enabling internal teams to operate confidently at scale. The examples below highlight how non-marketing AI human capital supports core data infrastructure within organizations.

> *...map architecture and technical solutions to partner business outcomes... apply governance to identify, communicate, and minimize business and technical risks [e.g., Well-Architected Framework, Cloud Adoption Framework] ... build massive scale, high quality solutions with*

Microsoft Azure partners (Topic 1, Microsoft Employee).

...Deployed Azure IaaS virtual machines and PaaS role instances... Configured Azure Backup... Administered Azure networking components such as VNets, subnets, Network Security Groups [NSGs], and Azure Firewall ... performed monthly patching for production and non-production environments... (Topic 5, DXC Technology Employee).

Worked on analyzing Hadoop cluster and different Big Data analytic tools including HDFS, Hive, Sqoop, MapReduce, Spark... Develop Spark code using Scala and Spark-SQL... Performed advanced procedures like text analytics... Developed Scala scripts, UDFs using both DataFrames/SQL and RDD/MapReduce... (Topic 6, AbbVie Employee).

These roles show how non-marketing AI human capital enables data-driven operations at scale by ensuring backend systems remain efficient, secure and adaptable across the firm.

Strategic process. In this domain, non-marketing AI human capital is tasked with *developing and engineering software systems in project teams to support business process* (Topic 4). These roles involve process design, failure analysis, and cross-functional coordination to ensure robust, scalable solutions. A job description of a General Motors Powertrain Group employee captures this internal orientation:

Support daily manufacturing operations and United Auto Workers [UAW] skilled support personnel to meet and improve the plant's performance goals by providing technical input in problem resolution, as well as providing planning, preparation, and documentation for continuous improvement projects (Topic 4, General Motors Powertrain Group Employee).

This example underscores how engineering AI human capital contributes to the internal health of the organization, not by interfacing directly with customers, but by strengthening the systems and processes that support enterprise-scale operations.

Product/Solution. Non-marketing AI human capital focuses on the development and deployment of tools and models that enable advanced analytics and operational functionality. This includes *developing machine learning models and predictive AI to conduct data-driven research* (Topic 2), as well as *developing and deploying business applications using docker, Kubernetes, or Jenkin* (Topic 3). These tasks are internally oriented, aimed at enhancing system performance and delivering scalable, maintainable solutions that power various business

functions from the backend. The following examples illustrate how non-marketing AI human capital contribute to solve complex backend and infrastructure challenges.

> *Worked on supervised learning approach for forecasting taxi travel demand: dataset of 8GB, 15 million observations, 11 attributes. Made a supervised learning model which correctly predicted taxi travel demand at various locations in Bengaluru. Used time series, machine learning, and deep learning models to improve accuracy… (Topic 2, Cognizant Employee).*

> *Set up CI/CD pipelines with DevOps tools such as Git, AWS CodeCommit, AWS CodeBuild, Gradle Wrapper, AWS CodePipeline, Jenkins, Docker, and AWS CloudWatch for the automation of the software delivery lifecycle. Automated workflow for development teams to help engineer reliable, resilient, and scalable applications in AWS … Monitored performance and maintained systems according to requirements (Topic 3, DXC Technology Employee).*

These roles show how non-marketing AI human capital enables backend intelligence and infrastructure optimization through technical development and deployment expertise.

In sum, non-marketing AI human capital is primarily internally-focused and dedicated to building the technical backbone of the organization. These roles involve developing machine learning models, engineering software systems, and deploying business applications to support internal operations. They also manage cloud infrastructure and ensure data security and scalability, which are functions that enable operational efficiency and reliability.

Study 2: Performance Effects of Marketing AI Human Capital

Understanding Marketing AI Human Capital Flow: Knowledge-Based View

The knowledge-based view (KBV) provides a theoretical framework to understand how the inflow and outflow of marketing AI human capital affect firm performance. According to this view, competitive advantage arises from effectively integrating, disseminating, and applying specialized tacit knowledge, which is deeply embedded within individual expertise and organizational routines (Grant 1996; Kogut and Zander 1992). Much of this knowledge is tacit, residing within individuals and shaped by their experience and expertise. Ultimately, competitive advantage depends on the firm's ability to effectively integrate knowledge into organizational

practices rather than merely possessing it. As Grant (1996, p. 380) emphasizes, "the critical source of competitive advantage is knowledge integration rather than the knowledge itself."

Drawing on the KBV, we emphasize that the roles marketing AI human capital performs are central to the generation, integration, and dissemination of marketing knowledge (De Bruyn et al. 2020; Mu and Zhang 2025), which are mechanisms through which marketing AI talent inflow and outflow influence performance. Specifically, as illustrated in our Study 1, marketing AI human capital generates knowledge by extracting actionable insights from customer data and AI tools, and they disseminate this knowledge across the organization by collaborating with other functional teams (e.g., product development, IT) to align offerings with customer needs. Their involvement in tasks such as strategy development, campaign execution, and solution delivery facilitate the continuous flow of customer intelligence throughout the firm. Our hypotheses posit that the inflow of such human capital enhances financial performance by reinforcing the firm's knowledge-based capabilities. In contrast, the outflow of marketing AI human capital entails a loss of firm-specific tacit knowledge and disrupts established integration routines, weakening the firm's ability to leverage AI effectively. Recognizing that these effects are context-dependent, we identify boundary conditions under which marketing AI knowledge integration and dissemination most strongly affect financial performance: via inflowing/outflowing employee seniority, market share, and product market scope.

Positive Performance Effect of Marketing AI Human Capital Inflow

We argue that the inflow of marketing AI human capital enhances financial performance by strengthening the firm's ability to generate and disseminate marketing knowledge, thereby improving its responsiveness to customer needs. Findings from Study 1 support this view, showing that marketing AI human capital engages in externally-focused tasks such as developing

marketing strategies and managing data-driven campaigns. These roles serve as critical vehicles for generating new marketing knowledge and embedding it across the organization.

First, the inflow of marketing AI human capital enables firms to produce more actionable insights that improve strategic decision-making. These employees bring advanced AI expertise and novel perspectives that fuel innovation in areas such as real-time customer segmentation, predictive analytics, recommendation systems, and automated pricing algorithms (Davenport et al. 2020; Wu, Lou, and Hitt 2025). These capabilities allow firms to more effectively interpret customer data, anticipate market trends, and implement targeted solutions. Through such contributions, marketing AI professionals directly enhance the firm's marketing effectiveness.

Second, inflows of marketing AI human capital improve the firm's ability to disseminate AI-enabled marketing knowledge internally. Study 1 reveals that marketing AI roles frequently involve collaborative responsibilities—managing customer accounts, supporting cross-functional delivery teams, and aligning data insights with strategic marketing goals. These individuals act as knowledge bridges, integrating AI capabilities into existing workflows and fostering cross-departmental learning. Consistent with the KBV, such integration enhances the firm's absorptive capacity and facilitates the institutionalization of AI-driven decision-making (De Bruyn et al. 2020; Mishra, Ewing, and Cooper 2022). By strengthening the firm's capacity to both generate and disseminate marketing knowledge, the inflow of marketing AI human capital builds capabilities that translate into improved financial outcomes. Thus, we hypothesize:

H_1: The inflow of marketing AI human capital has a positive effect on financial performance.

Negative Performance Effect of Marketing AI Human Capital Outflow

Conversely, the outflow of marketing AI human capital can weaken financial performance by interrupting access to firm-specific tacit knowledge and disrupting the

established channels through which such knowledge is transferred (De Bruyn et al. 2020). First, when marketing AI professionals transition out of their roles, firms may face difficulty accessing the tacit knowledge these individuals developed over time. In marketing, tacit knowledge is critical for interpreting nuanced consumer behavior, shaping brand positioning, and applying data-driven tools within the firm's unique strategic and operational context—elements that are inherently difficult to codify or transfer. Marketing AI human capital often builds deep knowledge through iterative work with machine learning tools tailored to the firm's marketing objectives and customer base. When these employees move out of their roles, the organization loses direct access to this embedded know-how, impairing its ability to interpret complex market signals and refine predictive models. As a result, firms may experience reduced accuracy and diminished campaign relevance, ultimately leading to lower customer satisfaction and weakened performance (Mu and Zhang 2025). Because tacit knowledge cannot be fully captured in documents or formal systems, these transitions create persistent capability gaps that are difficult and costly to bridge.

Second, the outflow of marketing AI human capital disrupts informal networks and interpersonal routines that underpin effective knowledge transfer. In marketing organizations, the flow of tacit knowledge often depends on collaborative relationships and norms that enable teams to coordinate and learn (Homburg, Workman, and Jensen 2000; Moorman and Miner 1998). When key individuals exit these roles, the relational ties that support knowledge exchange often dissolve, weakening the mechanisms through which insights and technical expertise circulate across teams. This is particularly detrimental in AI-intensive marketing positions, where success depends on shared interpretations of customer data and continuous adaptation of AI tools to evolving strategic priorities (Davenport et al. 2020; Mishra, Ewing, and Cooper 2022).

Disruptions in these knowledge flows can result in slower execution cycles and reduced model precision. Over time, this breakdown in organizational learning impairs the firm's ability to scale and sustain its AI-enabled marketing capabilities, undermining its performance.

> **H_2**: The outflow of marketing AI human capital has a negative effect on financial performance.

Moderating Effects

We propose that the performance implications of marketing AI human capital inflow and outflow are contingent on firm-specific contextual factors that shape how marketing knowledge is accessed, integrated, and disseminated. Drawing on the KBV, we focus on three key moderators: the seniority of the marketing AI human capital inflow/outflow, the firm's market share, and its product market scope. Seniority reflects the distinction between junior-level operational roles and senior-level strategic roles. While senior hires can drive strategic renewal, they may face greater resistance from entrenched routines, reducing the visibility of short-term gains; conversely, their departures may be less disruptive due to the diffusion of strategic influence over time. Firms with greater market share tend to possess more organizational slack and established integration processes, enabling them to absorb and utilize incoming AI knowledge more effectively while mitigating the disruptive effects of talent loss. In contrast, a broader product market scope introduces strategic complexity and fragmentation of routines across markets, which can dilute the benefits of new AI talent and magnify the challenges of knowledge integration following employee departures. Together, these moderators capture the structural, positional, and strategic conditions that shape how firms leverage marketing AI human capital for competitive advantage.

Seniority of marketing AI human capital inflow/outflow. We propose that the seniority of inflowing/outflowing marketing AI human capital moderates the relationship between human

capital inflows/outflows and performance by influencing how organizational routines adapt and operate. Organizational routines serve as the foundation of a firm's knowledge-based capabilities, facilitating consistent decision-making, efficient problem-solving, and coordinated adaptation (Argote and Greve 2007). Yet, routines exhibit inertia, resisting radical alterations and making rapid changes costly and difficult.

Employees at different seniority levels influence these routines in distinct ways. Junior employees play operational roles, closely executing established routines, reinforcing consistency, and incrementally enhancing routine efficiency (Howard-Grenville 2005). As a result, when junior professionals with AI skills are put into a marketing position, their fresh operational knowledge of AI can quickly integrate into existing processes, promptly boosting routine effectiveness and firm performance. Conversely, departures of junior employees disrupt day-to-day routines, increasing job demands for remaining employees, thereby damaging operational performance (Reilly et al. 2014).

In contrast, senior marketing AI professionals predominantly influence routines through strategic rather than operational channels. Senior executives drive strategic renewal, shape high-level marketing directions, and manage significant changes in firm capabilities through decisions on adopting advanced AI tools and shifting strategies (Feng, Morgan, and Rego 2015; Whitler, Krause, and Lehmann 2018). Yet, senior-level inflows are less likely to produce immediate benefits compared to junior-level because their strategic initiatives typically encounter greater organizational inertia and require a longer time to alter the established routines effectively. Conversely, when senior executives leave, the short-term continuity of routines is less likely to be immediately disrupted, given their limited involvement in daily routine execution. The strategic adjustments previously influenced by these executives often persist in the short term

due to routine stickiness. Thus, senior-level outflows may be less immediately damaging than junior-level outflows, but potentially more consequential in the longer term.

> **H_{3a}**: The seniority of marketing AI human capital inflow suppresses the positive effect of the inflow of marketing AI human capital on financial performance.

> **H_{3b}**: The seniority of marketing AI human capital outflow alleviates the negative effect of the outflow of marketing AI human capital on financial performance.

Market share. We argue that a firm's market share enhances the positive effect of marketing AI human capital inflow on financial performance. Firms with greater market share are typically characterized by well-developed knowledge-integration capabilities; that is, they often possess deeply ingrained efficient routines shaped through accumulated experience and incremental improvement processes (Becker 2004; Rego, Morgan, and Fornell 2013). Such firms exhibit better internal coordination, enabling them to effectively integrate acquired AI expertise into their existing knowledge systems and operational routines. Consequently, when marketing AI talent joins these positions in the firm, the fresh knowledge can be more effectively leveraged through established organizational processes. Thus, higher market share acts as a strategic amplifier, enhancing the positive performance effects of marketing AI human capital inflows.

Similarly, market share alleviates the negative effect of marketing AI human capital outflow on financial performance. Firms with greater market share—demonstrating robust organizational routines and substantial collective know-how that foster greater resilience and inertia (Adler, Goldoftas, and Levine 1999; Nelson and Winter 1985)—can effectively buffer disruptions arising from talent losses by relying on embedded knowledge structures, stable operational models, and routine-based processes that sustain performance even when specific individuals exit. Their established frameworks, resulting from extensive past experience and learning, allow these firms to maintain operational continuity and avoid significant short-term

performance declines (Becker 2004). In contrast, firms with smaller market share typically lack these stable, resilient knowledge structures and thus face greater vulnerability to disruptions when marketing AI talent departs.

> **H_{4a}**: A firm's market share enhances the positive effect of the inflow of marketing AI human capital on financial performance.
>
> **H_{4b}**: A firm's market share alleviates the negative effect of the outflow of marketing AI human capital on financial performance.

Product market scope. Along the same logic, we argue that a firm's product market scope suppresses the positive effect of the inflow of marketing AI human capital on financial performance. Firms operating in multiple diverse product markets experience increased complexity, where greater organizational complexity can hinder effective knowledge integration and dissemination across the organization (Grant 1996; Tsai 2002). Greater product market scope disperses organizational routines, making them more fragmented, context-specific, and less adaptable across diverse market environments. As a result, when new marketing AI professionals join these diversified firms, their expertise must be tailored to fit multiple, differentiated operational routines rather than smoothly integrated into a cohesive organizational system. This complexity reduces the efficiency and speed with which new knowledge translates into enhanced performance, as benefits from incoming AI expertise become diluted across fragmented routines and coordination challenges intensify (Homburg, Workman, and Jensen 2000). Consequently, greater product market scope constrains a firm's ability to fully capitalize on the benefits of new marketing AI human capital inflow, thereby suppressing its potential positive financial impacts.

A firm's product market scope aggravates the negative effect of the outflow of marketing AI human capital on financial performance. Firms with high product market scope face greater strategic complexity, leading to more dispersed and context-specific routines across different

business units or product lines (Adler, Goldoftas, and Levine 1999; Cohen and Bacdayan 1994). Due to this increased complexity, these firms often rely heavily on specialized, context-specific tacit knowledge embedded within individual employees. The departure of marketing AI talent from these firms therefore disrupts highly specialized routines that are difficult to replicate or quickly replace. As a result, the loss of employees with critical marketing AI expertise disproportionately amplifies knowledge gaps, coordination difficulties, and operational disruptions across multiple product domains, thereby significantly undermining financial performance. Thus, high product market scope intensifies the negative performance consequences associated with the outflow of marketing AI human capital.

> **H_{5a}**: A firm's product market scope suppresses the positive effect of the inflow of marketing AI human capital on financial performance.
>
> **H_{5b}**: A firm's product market scope aggravates the negative effect of the outflow of marketing AI human capital on financial performance.

Methodology

Data

We aggregated data from multiple sources, including Revelio Labs, Compustat, CRSP, and Hoberg and Phillips Data Library. First, we obtained data on inflow and outflow of marketing AI human capital (hereafter, referred to as "inflow" and "outflow") and their characteristics from Revelio Labs. Revelio Labs is a data source that has been extensively used in recent research (e.g., Baker et al. 2024; Cai et al. 2024; He, Mostrom, and Sufi 2024). Revelio Labs standardizes all individual worker's public employment profiles from LinkedIn, presenting current and historical workforce composition and trends of companies. It allows researchers to track the position composition of any organization listed on LinkedIn over time. It contains detailed information on each employee, including skills, job titles, roles, O*NET occupation

codes, and employment duration. This is one of the most comprehensive firm workforce databases available to researchers, for example in 2019, Revelio Labs database covers over 35 million positions at publicly traded firms in the United States. As the Revelio Labs data is at the individual employee-position level, we track employees under the same firm using ticker and aggregate the inflow and outflow to the firm level. We collect data to calculate stock returns from CRSP and remaining control variables from Compustat. Our final sample consists of 574 publicly traded U.S. firms during 2012–2021.

Operationalizations

Financial performance. In line with extant research (e.g., Mishra and Modi 2016; Srinivasan and Hanssens 2009), we measure financial performance as unanticipated stock returns, based upon the Carhart four-factor model (Carhart 1997) as follows:

$$SR_{id} = \alpha_{id} + \beta_{iRM\_RF}RM\_RF_d + \beta_{iHML}HML_d + \beta_{iSMB}SMB_d + \beta_{iUMD}UMD_d + \varepsilon_{id} \quad (1),$$

where SR_{id} is stock return in excess of the U.S. Treasury bill risk-free rate for firm i in day d; RM_RF_d is value-weighted return on all stocks listed in the New York Stock Exchange, NYSE MKT (formerly the American Stock Exchange), and NASDAQ minus the U.S. Treasury bill rate for day d, thus representing the excess market returns; HML_d is book-to-market-based risk premium factor; SMB_d is size-based risk premium factor; UMD_d is returns momentum factor (i.e., the average returns on the two prior high-returns portfolios minus the average returns on the two prior low-returns portfolios in day d); and ε_{id} is residual for firm i in day d. This model allows to establish the expected stock returns (ESR_{id}) of firm i in day d. Following the extant literature (e.g., Bharadwaj, Tuli, and Bonfrer 2011), we employ the compounded daily unanticipated returns for the year in our stock response model. We calculate these as $STKRET_{it} = \log \prod_{d=1}^{d=260}(1 + r_{id})$, where r_{id} represents the daily unanticipated returns $(SR - ESR)_{id}$ and

$STKRET_{it}$ represents the annualized unanticipated returns $(SR - ESR)_{it}$ of firm i in year t.

Marketing AI inflow and outflow. Marketing AI inflow (INFLOW) is defined as the number of employees with AI skills joined the firm's marketing position each year[2]. Similarly, marketing AI outflow (OUTFLOW) is the number of employees with AI skills left the firm's marketing roles each year. First, following the human capital research in marketing (Feng, Morgan, and Rego 2015), we identify marketing roles by selecting those job titles agreed upon by three of the four coauthors as well as an independent research assistant. These include advertising specialist, brand manager, client relationship manager, communications specialist, consumer marketing, customer service, market research, marketing officer, and PR specialist (see Web Appendix B for the full list of marketing roles and details on how they are identified). Second, Revelio Labs collects individual worker's self-reported skills from LinkedIn. We recognize employees with AI skills using an AI skill list (see Web Appendix B for the full list of AI skills) adapted from prior research Lou and Wu (2021) and Babina et al. (2024). Specifically, Lou and Wu (2021) derived AI technology list from sources such as the United States Patent and Trademark Office (USPTO), Cockburn, Henderson, and Stern (2018)'s AI glossary for AI subfields, and the Association of Computing Machinery's Computing Classification System. Our list identifies AI skills as skills related to but are not limited to big data processing, neural networks, machine learning, robotics, natural language processing (NLP), and computer vision.

Seniority of marketing AI inflow and outflow. Revelio Labs also standardizes all the employment records and uses ensemble model to label the seniority of a position (Baker et al.

[2] To fully capture AI talent inflow into a firm's marketing function, we include both external hires and internal transitions. This reflects both theoretical and practical considerations. From a knowledge-based view, firms acquire knowledge through hiring and internal redeployment, especially tacit, firm-specific knowledge. Internal moves signal a firm's ability to reallocate existing AI expertise to marketing, combining technical and contextual knowledge for more effective application. Empirically, excluding such transitions would underestimate AI infusion, particularly in firms emphasizing cross-functional talent development.

2024), derived from factors such as individual's current title, company, job history, age, and duration and seniority of previous employment. The seniority score provided by Revelio Labs for each individual position has seven distinct levels (labelled from 1 to 7; for example, the highest levels 6 and 7 represent the executive level (e.g., Managing Director, Treasury; Director of Engineering) and senior executive level positions (e.g., Chief Executive Officer, Chief Operating Officer, Chief Finance Officer). Based on this seniority information, we define seniority of inflow (SENIORITYINFLOW) as the average seniority score of the positions the marketing employees with AI skills took up at the focal firm each year. Based on this seniority information, we define seniority of inflow (SENIORITYINFLOW) as the average seniority score of the positions the marketing employees with AI skills took up at the focal firm each year, while seniority of outflow (SENIORITYOUTFLOW) as the average seniority score of the positions those employees departed from the focal firm each year.

Market share and product market scope. Market share (MARKETSHARE) is measured by sales of the focal firm divided by the sum of sales of the industry in which focal firm is situated (Fang, Palmatier, and Steenkamp 2008). Product market scope (PRODMKTSCOPE) is measured by the number of industries that a firm belongs to in a given year, based on 10-K data. This measure was developed by Hoberg and Phillips (2025) using natural language processing and clustering techniques via the doc2vec embedding model. Greater product market scope represents that a given firm operates in a greater number of different product markets.

Control variables. Following extant marketing-finance interface literature, we included several firm-specific control variables. First, to account for the firm size, we control for the employee size (EMPSIZE; measured as the total number of employees) (Saboo et al. 2017), asset size (ASSET; measured as the total value of assets reported on the balance sheet) (Feng, Morgan,

and Rego 2015), and firm age (AGE; the number of years since the firm was listed on the stock market) (Saboo et al. 2017). Second, to capture the firm's accounting performance, we include financial leverage (LEVERAGE; the ratio of the firm's long-term debt to total assets; as highly leveraged firms may lack the financial flexibility to pursue strategic investments, influencing investor perceptions) (Kurt and Hulland 2013); liquidity (LIQUIDITY; total assets divided by current total liabilities) (Mishra, Ewing, and Cooper 2022), gross margin (GRSMARGIN; sales revenue in excess of the cost of goods sold) (Kim and McAlister 2011). Third, we account for firm strategies using several intensity measures: advertising intensity (ADVINT; advertising expenditure to total asset) (Kim and McAlister 2011), inventory intensity (INVTINT; inventory to sales ratio)(Sridhar, Narayanan, and Srinivasan 2014), capital investment intensity (CAPINVTINT; net capital expenditures made by a firm divided by its sales) (Berman et al. 1999), capital intensity (CAPINT; total firm assets divided by the number of employees for firm; to account for the effect of requirement of large amount of money or other financial resources for a firm to produce a good or service on investor perceptions about the firm's outlook) (Vomberg, Homburg, and Bornemann 2015). We also include a merger and acquisition dummy variable (MA), coded as 1 if the firm had an acquisition contributing to sales in the given year and 0 otherwise (Umashankar, Bahadir, and Bharadwaj 2022).

We also control for industry-specific control variables including industry growth (INDGROWTH; based on SIC 2-digit code) (Fang, Palmatier, and Steenkamp 2008) as well as dummy variables that indicate whether a focal firm belongs to a service (SERVICE), regulated (REGULATED), and utilities industry (UTILITIES), respectively (Lee et al. 2015). Table 3 summarizes the measures and sources, and Table 4 shows descriptive statistics and correlations.

—Insert Table 3 and Table 4 about Here—

Model Specification

Our analyses use a panel data that involve observations for multiple firms across multiple years. Thus, we consider a set of requirements needed for the analyses of such data as follows. First, we conducted a Wooldridge test for serial correlation; we could not reject the null hypothesis of no serial correlation in the errors ($p = .731$). Second, Breusch-Pagan test for heteroskedasticity showed that heteroskedasticity exists in our data ($p < .001$); to control for it, we estimate the model using robust standard errors. First-differenced models control for firm time-invariant unobservable and are widely used in marketing literature, especially when using unanticipated stock returns as a dependent variable (e.g., Mishra and Modi 2016) as the unanticipated stock returns only capture the unanticipated information. Thus, we first-differenced all continuous independent and control variables and included year-specific dummy variables as control variables. α_{1-36}; YEAR_y represents year dummy variables to capture unobserved factors that vary across years but are constant across firms. The first-differenced measures were constructed by regressing each firm's current year value on its prior-year value (Bharadwaj, Tuli, and Bonfrer 2011; Mishra and Modi 2016).

$$
\begin{aligned}
\text{STKRET}_{it} = {} & \alpha_0 + \alpha_1 \text{U}\Delta\text{INFLOW}_{it} + \alpha_2 \text{U}\Delta\text{OUTFLOW}_{it} \\
& + \alpha_3(\text{U}\Delta\text{INFLOW}_{it} \times \text{U}\Delta\text{SENIORITYINFLOW}_{it}) \\
& + \alpha_4(\text{U}\Delta\text{OUTFLOW}_{it} \times \text{U}\Delta\text{SENIORITYOUTFLOW}_{it}) \\
& + \alpha_5(\text{U}\Delta\text{INFLOW}_{it} \times \text{U}\Delta\text{MARKETSHARE}_{it}) \\
& + \alpha_6(\text{U}\Delta\text{OUTFLOW}_{it} \times \text{U}\Delta\text{MARKETSHARE}_{it}) \\
& + \alpha_7(\text{U}\Delta\text{INFLOW}_{it} \times \text{U}\Delta\text{PRODMKTSCOPE}_{it}) \\
& + \alpha_8(\text{U}\Delta\text{OUTFLOW}_{it} \times \text{U}\Delta\text{PRODMKTSCOPE}_{it}) \\
& + \alpha_9 \text{U}\Delta\text{EMPSIZE}_{it} + \alpha_{10} \text{U}\Delta\text{ASSET}_{it} + \alpha_{11} \text{U}\Delta\text{AGE}_{it} + \alpha_{12} \text{U}\Delta\text{LEVERAGE}_{it} \\
& + \alpha_{13} \text{U}\Delta\text{LIQUIDITY}_{it} + \alpha_{14} \text{U}\Delta\text{GRSMARGIN}_{it} + \alpha_{15} \text{U}\Delta\text{ADVINT}_{it} \\
& + \alpha_{16} \text{U}\Delta\text{INVTINT}_{it} + \alpha_{17} \text{U}\Delta\text{CAPINVTINT}_{it} + \alpha_{18} \text{U}\Delta\text{CAPINT}_{it} + \alpha_{19} \text{MA}_{it} \\
& + \alpha_{20} \text{U}\Delta\text{INDGROWTH}_{it} + \alpha_{21} \text{SERVICE}_{it} + \alpha_{22} \text{REGULATED}_{it} \\
& + \alpha_{23} \text{UTILITIES}_{it} + \sum_{y=24}^{36} \alpha_y \text{YEAR}_y + \varepsilon_{it}, \qquad (2)
\end{aligned}
$$

Addressing potential self-selection. The inflow and outflow are only realized if a shift exists in a firm's marketing AI labor force. Thus, accounting for the incidence of a shift in

marketing AI labor force, we address the selection issue associated with a firm's strategic decision of the recruitment and departure of marketing AI employees. Accordingly, we code a variable INOUT as taking a value of 1 if a firm had any shift in a given year in its marketing AI labor force and 0 otherwise. By endogenizing the decision to make such shifts, we account for the potential bias in the regression parameters for unanticipated stock returns, which is observable only for firms with shifts in marketing AI labor force. Using a two-stage Heckman estimation (Heckman 1979), the selection model accounts for the incidence of marketing AI employee being acquired or lost, conditional on which the post-stock returns outcome is observed. In the first stage, we use a Probit regression to estimate the probability of employees joining or leaving the marketing AI positions.

In the first stage, we include industry dummies (two-digit NAICS codes), geographical locations of the headquarters (measured by two-digit zip codes), and firm age to estimate the probability of labor shift. Heckman models perform well when at least one variable that works as an instrumental variable (IV), satisfying the exclusion restriction. Specifically, as each industry may have different recruitment trends, we include industry dummy variables. We include firm age because more established firms are more likely to add or lose workforce, demonstrating an active practice of shifting marketing AI labor. We use the location as an IV that satisfies the exclusion restriction. A firm's location is related to the decisions on hiring and losing its workforce as regional differences in the availability of human capital can influence the recruiting decisions, thereby satisfying the relevance criterion. Moreover, there is no conceptual reason to expect the location to directly influence the firm's stock returns, satisfying the exclusion restriction. In line with Wies, Moorman, and Chandy (2023), we compare the model fits between the model with geographic location and without it to support its selection as an IV. We find that

the fit of our selection model improves when geographic location is included (AIC=17158) than excluded (AIC=17249), which satisfies the relevance criteria. Yet, improvement in model fit is not depicted in the second stage estimation when geographic location is included (AIC=3861) compared to excluded (AIC=3789). We then calculate the inverse Mills ratio and include it in the second stage estimation to control for potential self-selection bias.

Addressing endogeneity concerns. A firm could set the inflow or outflow of marketing AI human capital to affect the stock returns, making them endogenous. Thus, we account for this potential endogeneity using a two-stage control function approach following previous research (e.g., Petrin and Train 2010). In the first stage, we regress the endogenous variables on a set of exogenous variables to estimate the correction terms.

As instruments, we use the average marketing AI human capital inflow (and outflow) of the peers-of-peers as exclusion variables, which are the peers of firm i's peers that are not in firm i's own peer group (Malshe, Colicev, and Mittal 2020; Shi, Grewal, and Sridhar 2021). Firms often operate across multiple strategic categories and compete with different competitors in each category, and the focal firm and its peers-of-peers will only be linked via the common peers. Therefore, peers-of-peers can influence focal firms only indirectly through their effect on the common peers, which ensures the peers-of-peers measures to satisfy the exclusion criterion. We refer to peers as firms operating in the same primary industry as the focal firm, and peers-of-peers as firms operating in the focal firm's peer firms' secondary industries. We collected four-digit primary and secondary standardized industry classification (SIC) codes of all segments of each firm from Compustat segment database to calculate the average inflow and outflow of peers-of-peers as the IVs. In the first stage, we estimate the focal firm's inflow and outflow using these IVs and the same control variables from our main regression model, obtaining the

estimated residuals. In the second stage, we add these residuals as additional control variables.

Results

We present the second stage results in Table 5 and first-stage results in Web Appendix C. Our results demonstrate that inflow has a positive and significant effect on stock returns (b = .991, p = .000) and outflow has a negative and significant effect on stock returns (b = -1.296, p = .000), supporting H_1 and H_2. This indicates recruiting marketing AI human capital increases stock returns while losing the existing marketing AI human capital reduces stock returns. The results indicate that the elasticity of inflow is approximately .38 (i.e., a 1% increase in inflow translates to a .38% increase in firm stock return), while the outflow shows more intensified effects, with an average elasticity of -.89—the F-test indicates that the negative effect of outflow is significantly stronger than the positive effect from the inflow. Thus, the results highlight that, on average, the adverse effect of losing marketing AI talent is greater than the positive effects from acquiring an equivalent amount of marketing AI human capital.

The results also show that the seniority of inflow weakens the positive effect of inflow on financial performance (b = -.002, p = .011), while the seniority of outflow mitigates the negative effect of outflow on financial performance (b = .002; p = .099). These findings provide support for H_{3a} and H_{3b}. Market share shows positive and significant moderating effects for the impacts of both inflow (b = .657, p = .002) and outflow (b = .227, p = .038) on financial performance, supporting both H_{4a} and H_{4b}. Finally, while the moderating effect of product market scope on the relationship between outflow and stock returns is not significant (b = .000, p = .250), failing to support H_{5b}, it is negative and significant for the relationship between inflow and financial performance (b = -.000, p = .053), supporting H_{5a}.

—Insert Table 5 about Here—

Robustness Analyses

Alternative model specifications. While our main findings are based on a simple fixed-effects model (using first differences) with endogeneity correction using peers-of-peers exclusion variables and with selection bias correction using inverse Mills ratio, we sought to check the robustness of our findings through different model specifications. First, we use a simple fixed-effects model without endogeneity correction and without selection bias correction and provide results in Web Appendix D. Our results demonstrate that all main findings associated with our hypotheses remain consistent in terms of both significance and direction. Second, we use a random-effects model with endogeneity correction and selection bias correction, and present results in Web Appendix E. Our findings provide robustness of our main results, as all hypothesized results show consistency in terms of significance and direction.

Alternative measure of stock returns. While we derive our measure for stock returns from the Carhart four-factor model, we use the market model to calculate the unanticipated stock returns to check the robustness of our findings. We adjust Equation 1 to calculate the market model-based stock returns. This type of stock returns has also been extensively used in previous research (Bhagwat et al. 2020; Warren and Sorescu 2017). Our results remain consistent in terms of significance and direction, except the moderating effect of seniority of outflow failing to show significance (b = .002, p = .121). The results are provided in Web Appendix F.

Post-hoc Analyses: Source of the AI Marketing Human Capital Inflow

Our main analyses involve the inflow of AI marketing human capital, regardless of the source, indicating both inflow from inside (i.e. transfers-in from non-marketing positions within the focal firm) and that from outside of the firm (i.e. newly hired marketing AI human capital from other firms). Despite both representing forms of marketing AI talent renewal, the two

groups differ in their ability to generate and disseminate marketing knowledge within the organization. Transfers-in arguably possess a significantly higher level of organization-specific knowledge than the newly hired. Thus, marketing AI human capital transferred in from other functional areas tend to have enhanced capabilities deeply rooted in firm-specific routines that help them work effectively with other team members, utilize pre-established networks, compared to the newly hired. Therefore, if the mechanism we proposed in the hypothesis section (knowledge creation and dissemination) is at work, we should expect transfers-in to have a more pronounced positive impact on the focal firm's financial performance, then the newly hired.

Building on this idea, we conduct post-hoc analyses to identify whether transfers-in manifest a stronger main effect than the newly hired. Specifically, we divide AI marketing human capital inflow into internal inflow and external inflow. First, our findings (in Appendix G) indicate that the effect of outflow stays consistent in both models with internal (b = -.819, p = .066) and external inflow (b = -.576, p = .000), reconfirming that outflow reduces stock returns. Second, both internal (b = 3.747, p = .089) and external inflow (b = 0.463, p = .000) are positively associated with stock returns. However, the magnitude of the effect is substantially larger for internal inflow, suggesting that the increase in stock returns is driven more by AI marketing employees transitioned internally than by those hired externally. This closely aligns with our theoretical arguments that emphasize generation and dissemination of knowledge, which can be most effectively achieved through internal inflow rather than external inflow.

Discussion

With two complementary studies, we examine the roles that marketing AI human capital play within a firm, and the performance implication of marketing AI human capital inflow and outflow. Our Study 1 draws on job description data and topic modeling, and indicates that marketing AI human capital is primarily associated with externally oriented tasks aimed at

enhancing customer understanding and engagement, whereas non-marketing AI human capital is focused on internal-facing backend operations. Given the dual role of marketing AI human capital in marketing and technical capabilities, Study 2 further investigates the impacts of the inflow and outflow of such talent on firm's financial performance and identifies the boundary conditions under which such effects are amplified.

Theoretical Implications

The study makes the following theoretical contributions. First, our study underscores the central premise of KBV and demonstrates that the integration of marketing and AI expertise is at the core of a firm's marketing capabilities. The tight coupling of such knowledge strengthens the firm's ability to assimilate, create and disseminate marketing knowledge across the organization. Consistent with the dynamic capability perspective, firms must continuously renew and expand their marketing AI knowledge base through the infusion of new talent to sustain strong financial performance. More importantly, we expand the KBV literature regarding knowledge loss. While the impact of knowledge acquisition in value creation is well documented in the KBV literature (e.g., Zahra and George 2002), studies on the effects of knowledge loss are sparse (Curado and Bontis 2006). Our study theoretically explains that the loss of marketing AI talent damages the firm's financial performance through disrupting the established channels of knowledge diffusion, underscoring the firm-specific and tacit nature of marketing AI knowledge. This is especially critical, as we are still in the early stages of transplanting AI technologies into marketing routines, understanding the mechanisms through which marketing AI talent becomes infused into or decoupled from marketing routines can reshape future marketing strategies.

Second, we theoretically explain the conditions under which marketing AI inflows and outflows impact firm financial performance. Specifically, when the acquired or departed

marketing AI positions are at junior level, the effects become more pronounced. Theoretically, we explain that existing organizational routines exhibit inertia, under which junior marketing AI professionals tend to focus on reinforcing routines and integrating new knowledge into current processes and enhance short-term financial performance of the firm. Seniors in contrast emphasize the strategic focus of the marketing organization, thus demonstrating less significant impacts on the firm's performance in the short term. This finding complements marketing literature on the significance of marketing upper echelons (Feng, Morgan, and Rego 2015; Whitler et al. 2021) and provides a more holistic view on the impact of marketing labor force.

In addition, we highlight that firms with dominant product market positions are better equipped to integrate newly acquired AI expertise into existing routines. Similarly, their established and stable processes help mitigate the impact of marketing AI talent loss. In contrast, firms with broader product market scope face complex and fragmented processes, which slow the translation of new knowledge into performance gains, as incoming AI expertise is dispersed across disjointed routines and heightened coordination challenges. These findings bolster organizational learning theories which suggest that firms in more stable and munificent environments should pursue efficiency improvement to achieve superior performance. Our study extends this notion and suggests that acquiring new marketing AI talent, particularly when the firm is a market leader with a specialized product focus, reinforces existing efficient routines and promotes effective knowledge integration and dissemination across the organization.

Managerial Implications

Our results have important implications for practice. First, our findings highlight the critical role of marketing AI human capital in shaping firm performance. Specifically, we show that the inflow of marketing AI talent positively influences financial performance, emphasizing

the value of acquiring individuals who can generate, translate, and apply AI-driven marketing knowledge. At the same time, the outflow of such talent has a detrimental effect, underscoring the need for effective retention strategies. To fully realize the benefits of marketing AI capabilities, firms must invest not only in hiring but also in building organizational processes that support knowledge integration and dissemination. This includes establishing cross-functional communication channels, codifying AI-related insights developed within marketing, and embedding those insights into firm-wide workflows. By institutionalizing AI expertise in this way, firms can convert individual knowledge into sustained competitive advantage while minimizing the risks associated with talent loss.

Second, we provide a strategic roadmap for balancing talent acquisition and retention. While marketing AI human capital inflow enhances firm performance on average, our findings suggest that this benefit diminishes at higher seniority levels, whereas the negative impact of outflow is alleviated when senior personnel depart. In addition, firms with greater market share not only gain more from acquiring marketing AI talent but are also better positioned to absorb the loss of such talent. Conversely, firms with broader product scopes see diminished returns from marketing AI inflows. These underscore the need for firms to tailor their AI talent strategies based on organizational characteristics such as seniority, market position, and product scope.

To contextualize the magnitude of these effects, we draw on our model estimates and summary statistics for marketing AI inflow, outflow, seniority, market share, and stock returns. Specifically, we find that seniority and market share significantly moderate these effects. A one SD increase in the seniority of inflow reduces its performance impact by 0.038, while seniority in outflow lessens the negative effect by 0.026—equivalent to 8.84% and 6.05% changes, respectively. Similarly, a one SD increase in market share amplifies the inflow effect by 12.35

and reduces the outflow impact by 2.94, translating to 2,873% and 684% changes relative to stock return variability. Collectively, these findings emphasize the critical importance of not only acquiring marketing AI talent but also integrating it effectively and retaining it strategically, with attention to firm-specific characteristics that shape the value such talent can generate.

Limitations and Future Research Directions

While our study offers important insights into the relationship between marketing AI human capital and firm performance, several avenues remain for future exploration. First, our sample is limited to large, publicly traded U.S. firms, which likely have greater resources to attract AI talent. Future research could extend this work to smaller firms or non-U.S. markets to explore how resource constraints, institutional environments, and cultural factors influence the value of marketing AI capabilities. Second, because our sample period ends in 2022, our findings primarily reflect the periods before largely accessible generative AI tools. As generative AI tools become more widespread and embedded in business processes, future studies should examine whether the drivers and outcomes of AI talent mobility shift. Third, although LinkedIn provides a rich, real-time source of skill-based talent data, self-reported AI expertise may vary in accuracy. Rather than treating this as a limitation, future work could explore how firms assess and validate AI skill claims, and whether signaling AI skills, accurately or otherwise, affects hiring outcomes and firm performance. More broadly, research could investigate how organizations build complementary capabilities (e.g., governance, training, or cross-functional integration) to fully leverage the potential of marketing AI talent.

References

Adler, Paul S, Barbara Goldoftas, and David I Levine (1999), "Flexibility Versus Efficiency? A Case Study of Model Changeovers in the Toyota Production System," *Organization Science*, 10 (1), 43-68.

Argote, Linda and Henrich R Greve (2007), "A Behavioral Theory of the Firm—40 Years and Counting: Introduction and Impact," *Organization Science*, 18 (3), 337-49.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson (2024), "Artificial Intelligence, Firm Growth, and Product Innovation," *Journal of Financial Economics*, 151, 103745.

Baker, Andrew C, David F Larcker, Charles G McClure, Durgesh Saraph, and Edward M Watts (2024), "Diversity Washing," *Journal of Accounting Research*, 62 (5), 1661-709.

Becker, Markus C (2004), "Organizational Routines: A Review of the Literature," *Industrial and corporate change*, 13 (4), 643-78.

Berman, Shawn L, Andrew C Wicks, Suresh Kotha, and Thomas M Jones (1999), "Does Stakeholder Orientation Matter? The Relationship between Stakeholder Management Models and Firm Financial Performance," *Academy of Management Journal*, 42 (5), 488-506.

Bhagwat, Yashoda, Nooshin L Warren, Joshua T Beck, and George F Watson Iv (2020), "Corporate Sociopolitical Activism and Firm Value," *Journal of Marketing*, 84 (5), 1-21.

Bharadwaj, Sundar G, Kapil R Tuli, and Andre Bonfrer (2011), "The Impact of Brand Quality on Shareholder Wealth," *Journal of Marketing*, 75 (5), 88-104.

Blei, David M, Andrew Y Ng, and Michael I Jordan (2003), "Latent Dirichlet Allocation," *Journal of Machine Learning Research*, 3 (Jan), 993-1022.

Boston Consulting Group (2024), "The Blueprint for Ai-Powered Marketing," (accessed May 12, 2025), [available at https://www.bcg.com/publications/2024/blueprint-for-ai-powered-marketing].

Bousquette, Isabelle (2024), "Why the Coolest Job in Tech Might Actually Be in a Bank," (accessed March 1, 2025), [available at https://www.wsj.com/articles/why-the-coolest-job-in-tech-might-actually-be-in-a-bank-274330c5].

BuzzBoard (2023), "Agency Talk: The Challenges of Ai in Marketing to Small Business," (accessed April 29, 2025), [available at https://www.buzzboard.ai/cracking-the-code-of-ai-marketing-challenges-faced-by-digital-agencies/#:~:text=According%20to%20a%20recent%20study%2C%2075%%20of,and%20develop%20a%20data%2Ddriven%20approach%20to%20marketing].

Cai, Wei, Yue Chen, Shiva Rajgopal, and Li Azinovic-Yang (2024), "Diversity Targets," *Review of Accounting Studies*, 29 (3), 2157-208.

Carhart, Mark M. (1997), "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52 (1), 57-82.

Chen, Yiwei and Stephanie Lee (2023), "User-Generated Physician Ratings and Their Effects on Patients' Physician Choices: Evidence from Yelp," *Journal of Marketing*, 88 (1), 77-96.

Chiong, Khai and Ying Xie (2024), "Ai and Job Satisfaction: Evidence from Glassdoor Employees' Reviews," *Available at SSRN 4976340*.

Cockburn, Iain M, Rebecca Henderson, and Scott Stern (2018), *The Impact of Artificial Intelligence on Innovation*: National bureau of economic research Cambridge, MA, USA.

Cohen, Michael D and Paul Bacdayan (1994), "Organizational Routines Are Stored as Procedural Memory: Evidence from a Laboratory Study," *Organization Science*, 5 (4), 554-68.

Curado, Carla and Nick Bontis (2006), "The Knowledge-Based View of the Firm and Its Theoretical Precursor," *International Journal of Learning and Intellectual Capital*, 3 (4), 367-81.

Davenport, Thomas, Abhijit Guha, Dhruv Grewal, and Timna Bressgott (2020), "How Artificial Intelligence Will Change the Future of Marketing," *Journal of the Academy of Marketing Science*, 48, 24-42.

De Bruyn, Arnaud, Vijay Viswanathan, Yean Shan Beh, Jürgen Kai-Uwe Brock, and Florian Von Wangenheim (2020), "Artificial Intelligence and Marketing: Pitfalls and Opportunities," *Journal of Interactive Marketing*, 51 (1), 91-105.

Eckert, Christine, Harald J van Heerde, Hauke A Wetzel, and Stefan Hattula (2022), "Spotlight Personnel: How Hiring and Turnover Drive Service Performance Versus Demand," *Journal of Marketing Research*, 59 (4), 797-820.

Fang, Eric, Robert W. Palmatier, and Jan-Benedict E. M. Steenkamp (2008), "Effect of Service Transition Strategies on Firm Value," *Journal of Marketing*, 72 (5), 1-14.

Feng, Hui, Neil A Morgan, and Lopo L Rego (2015), "Marketing Department Power and Firm Performance," *Journal of Marketing*, 79 (5), 1-20.

Forbes (2023), "10 Hurdles Companies Are Facing When Implementing Ai (and How to Overcome Them)," December 5), [available at https://www.forbes.com/councils/theyec/2023/10/25/10-hurdles-companies-are-facing-when-implementing-ai-and-how-to-overcome-them/].

Garvey, Aaron M, TaeWoo Kim, and Adam Duhachek (2023), "Bad News? Send an Ai. Good News? Send a Human," *Journal of Marketing*, 87 (1), 10-25.

Germann, Frank, Peter Ebbes, and Rajdeep Grewal (2015), "The Chief Marketing Officer Matters!," *Journal of Marketing*, 79 (3), 1-22.

Germann, Frank, Gary L Lilien, and Arvind Rangaswamy (2013), "Performance Implications of Deploying Marketing Analytics," *International Journal of Research in Marketing*, 30 (2), 114-28.

Germann, Frank, Gary L. Lilien, Lars Fiedler, and Matthias Kraus (2014), "Do Retailers Benefit from Deploying Customer Analytics?," *Journal of Retailing*, 90 (4), 587-93.

Grant, Robert M. (1996), "Toward a Knowledge-Based Theory of the Firm," *Strategic Management Journal*, 17, 109-22.

Grewal, Dhruv, Cinthia B Satornino, Thomas Davenport, and Abhijit Guha (2025), "How Should Gen Ai Fit into Your Marketing Strategy?," *Harvard Business Review*.

Grewal, Dhruv, Cinthia B. Satornino, Thomas Davenport, and Abhijit Guha (2024), "How Generative Ai Is Shaping the Future of Marketing," *Journal of the Academy of Marketing Science*.

Gurman, Mark (2025), "Apple's Siri Chief Calls Ai Delays Ugly and Embarrassing, Promises

Fixes," (accessed March 20, 2025), [available at https://www.bloomberg.com/news/articles/2025-03-14/apple-s-siri-chief-calls-ai-delays-ugly-and-embarrassing-promises-fixes].

He, Bianca, Lauren I Mostrom, and Amir Sufi (2024), "Investing in Customer Capital," *National Bureau of Economic Research*

Heckman, James J (1979), "Sample Selection Bias as a Specification Error," *Econometrica: Journal of the econometric society*, 153-61.

Hoberg, Gerard and Gordon M Phillips (2025), "Scope, Scale, and Concentration: The 21st-Century Firm," *The Journal of Finance*, 80 (1), 415-66.

Homburg, Christian, John P. Workman, Jr., and Ove Jensen (2000), "Fundamental Changes in Marketing Organization: The Movement toward a Customer-Focused Organizational Structure," *Journal of the Academy of Marketing Science*, 28 (4), 459-78.

Howard-Grenville, Jennifer A (2005), "The Persistence of Flexible Organizational Routines: The Role of Agency and Organizational Context," *Organization science*, 16 (6), 618-36.

Kim, MinChung and Leigh M. McAlister (2011), "Stock Market Reaction to Unexpected Growth in Marketing Expenditure: Negative for Sales Force, Contingent on Spending Level for Advertising," *Journal of Marketing*, 75 (4), 68-85.

Kogut, Bruce and Udo Zander (1992), "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology," *Organization Science*, 3 (3), 383-97.

Kruppa, Miles and Lauren Thomas (2024), "Google Paid $2.7 Billion to Bring Back an Ai Genius Who Quit in Frustration," (accessed November 7, 2024), [available at https://www.wsj.com/tech/ai/noam-shazeer-google-ai-deal-d3605697].

Kurt, Didem and John Hulland (2013), "Aggressive Marketing Strategy Following Equity Offerings and Firm Value: The Role of Relative Strategic Flexibility," *Journal of Marketing*, 77 (5), 57-74.

Law, Kelvin K. F. and Michael Shen (2024), "How Does Artificial Intelligence Shape Audit Firms?," *Management Science*, 71 (5), 3641-66.

Lee, Ju-Yeon, Shrihari Sridhar, Conor M. Henderson, and Robert W. Palmatier (2015), "Effect of Customer-Centric Structure on Long-Term Financial Performance," *Marketing Science*, 34 (2), 250-68.

Lou, Bowen and Lynn Wu (2021), "Ai on Drugs: Can Artificial Intelligence Accelerate Drug Development? Evidence from a Large-Scale Examination of Bio-Pharma Firms," *MIS Quarterly*, 45 (3), 1451-82.

Luo, Xueming, Marco Shaojun Qin, Zheng Fang, and Zhe Qu (2021), "Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions," *Journal of Marketing*, 85 (2), 14-32.

Luo, Xueming, Siliang Tong, Zheng Fang, and Zhe Qu (2019), "Frontiers: Machines Vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases," *Marketing Science*, 38 (6), 937-47.

Malshe, Ashwin, Anatoli Colicev, and Vikas Mittal (2020), "How Main Street Drives Wall Street: Customer (Dis) Satisfaction, Short Sellers, and Abnormal Returns," *Journal of Marketing Research*, 57 (6), 1055-75.

Marketing Science Institute (2024), "Research Priorities 2024," (accessed May 5, 2025),

[available at https://www.msi.org/article/msi-announces-2024-research-priorities/].

McKinsey&Company (2025), "The State of Ai: How Organizations Are Rewiring to Capture Value," (accessed March 15, 2025), [available at https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai].

Mishra, Sagarika, Michael T. Ewing, and Holly B. Cooper (2022), "Artificial Intelligence Focus and Firm Performance," *Journal of the Academy of Marketing Science*, 50 (6), 1176-97.

Mishra, Saurabh and Sachin B. Modi (2016), "Corporate Social Responsibility and Shareholder Wealth: The Role of Marketing Capability," *Journal of Marketing*, 80 (1), 26-46.

Moorman, Christine and Anne S. Miner (1998), "Organizational Improvisation and Organizational Memory," *The Academy of Management Review*, 23 (4), 698-723.

Mu, Jifeng and Jonathan Z Zhang (2025), "Artificial Intelligence Marketing Usage and Firm Performance," *Journal of the Academy of Marketing Science*, 1-54.

Nelson, Richard R and Sidney G Winter (1985), *An Evolutionary Theory of Economic Change*: Harvard University Press.

Nyberg, Anthony J and Robert E Ployhart (2013), "Context-Emergent Turnover (Cet) Theory: A Theory of Collective Turnover," *Academy of Management Review*, 38 (1), 109-31.

Petrin, Amil and Kenneth Train (2010), "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research*, 47 (1), 3-13.

Rattner, Nate and Tom Dotan (2024), "The Ai Spending Spree, in Charts," (accessed November 6, 2024), [available at https://www.wsj.com/tech/ai/artificial-intelligence-investing-charts-7b8e1a97].

Rego, Lopo L., Neil A. Morgan, and Claes Fornell (2013), "Reexamining the Market Share–Customer Satisfaction Relationship," *Journal of Marketing*, 77 (5), 1-20.

Reilly, Greg, Anthony J Nyberg, Mark Maltarich, and Ingo Weller (2014), "Human Capital Flows: Using Context-Emergent Turnover (Cet) Theory to Explore the Process by Which Turnover, Hiring, and Job Demands Affect Patient Satisfaction," *Academy of Management Journal*, 57 (3), 766-90.

Röder, Michael, Andreas Both, and Alexander Hinneburg (2015), "*Exploring the Space of Topic Coherence Measures*," in Proceedings of the eighth ACM international conference on Web search and data mining.

Saboo, Alok R, Amalesh Sharma, Anindita Chakravarty, and V Kumar (2017), "Influencing Acquisition Performance in High-Technology Industries: The Role of Innovation and Relational Overlap," *Journal of Marketing Research*, 54 (2), 219-38.

Shi, Huanhuan, Rajdeep Grewal, and Hari Sridhar (2021), "Organizational Herding in Advertising Spending Disclosures: Evidence and Mechanisms," *Journal of Marketing Research*, 58 (3), 515-38.

Sridhar, Shrihari, Sriram Narayanan, and Raji Srinivasan (2014), "Dynamic Relationships among R&D, Advertising, Inventory and Firm Performance," *Journal of the Academy of Marketing Science*, 42, 277-90.

Srinivasan, Shuba and Dominique M. Hanssens (2009), "Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions," *Journal of Marketing Research*, 46 (3), 293-312.

Srivastava, Chandra, Saim Kashmiri, and Vijay Mahajan (2023), "Customer Orientation and Financial Performance: Women in Top Management Teams Matter!," *Journal of Marketing*, 87 (2), 190-209.

Tsai, Wenpin (2002), "Social Structure of "Coopetition" within a Multiunit Organization: Coordination, Competition, and Intraorganizational Knowledge Sharing," *Organization Science*, 13 (2), 179-90.

Umashankar, Nita, S Cem Bahadir, and Sundar Bharadwaj (2022), "Despite Efficiencies, Mergers and Acquisitions Reduce Firm Value by Hurting Customer Satisfaction," *Journal of Marketing*, 86 (2), 66-86.

Vomberg, Arnd, Christian Homburg, and Torsten Bornemann (2015), "Talented People and Strong Brands: The Contribution of Human Capital and Brand Equity to Firm Value," *Strategic Management Journal*, 36 (13), 2122-31.

Wall Street Journal (2025), "How Morgan Stanley Tackled One of Coding's Toughest Problems," (accessed June 4, 2025), [available at https://www.wsj.com/articles/how-morgan-stanley-tackled-one-of-codings-toughest-problems-4f465959?st=nPLD7u].

Warren, Nooshin L and Alina Sorescu (2017), "Interpreting the Stock Returns to New Product Announcements: How the Past Shapes Investors' Expectations of the Future," *Journal of Marketing Research*, 54 (5), 799-815.

Wedel, Michel and PK Kannan (2016), "Marketing Analytics for Data-Rich Environments," *Journal of Marketing*, 80 (6), 97-121.

Whitler, Kimberly A, Ryan Krause, and Donald R Lehmann (2018), "When and How Board Members with Marketing Experience Facilitate Firm Growth," *Journal of Marketing*, 82 (5), 86-105.

Whitler, Kimberly A., Ben Lee, Ryan Krause, and Neil A. Morgan (2021), "Upper Echelons Research in Marketing," *Journal of the Academy of Marketing Science*, 49 (1), 198-219.

Wies, Simone, Christine Moorman, and Rajesh K Chandy (2023), "Innovation Imprinting: Why Some Firms Beat the Post-Ipo Innovation Slump," *Journal of Marketing*, 87 (2), 232-52.

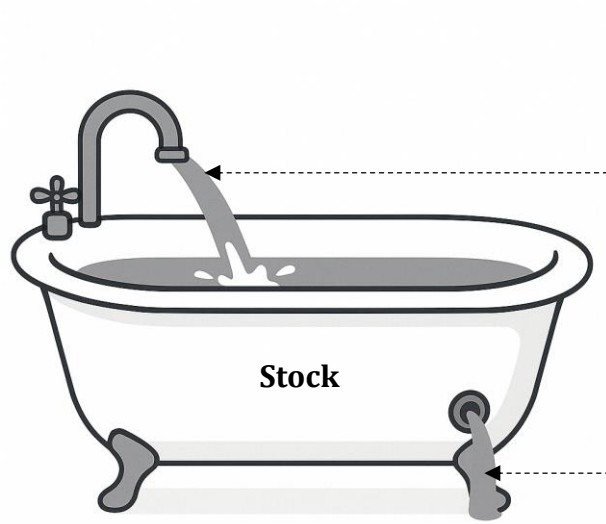
Wu, Lynn, Lorin Hitt, and Bowen Lou (2020), "Data Analytics, Innovation, and Firm Productivity," *Management Science*, 66 (5), 2017-39.

Wu, Lynn, Bowen Lou, and Lorin Hitt (2019), "Data Analytics Supports Decentralized Innovation," *Management Science*, 65 (10), 4863-77.

Wu, Lynn, Bowen Lou, and Lorin M Hitt (2025), "Innovation Strategy after Ipo: How Ai Analytics Spurs Innovation after Ipo," *Management Science*, 71 (3), 2360-89.

Zahra, Shaker A and Gerard George (2002), "Absorptive Capacity: A Review, Reconceptualization, and Extension," *Academy of Management Review*, 27 (2), 185-203.

FIGURE 1
Visualization of Marketing AI Human Capital Flow



Inflow of Marketing AI Human Capital
Recruitment of individuals possessing AI-related expertise into marketing roles in the firm

Outflow of Marketing AI Human Capital
Departure of individuals possessing AI-related expertise from marketing roles in the firm

FIGURE 2
Effects of Firm's Marketing AI Human Capital Flow on Financial Performance

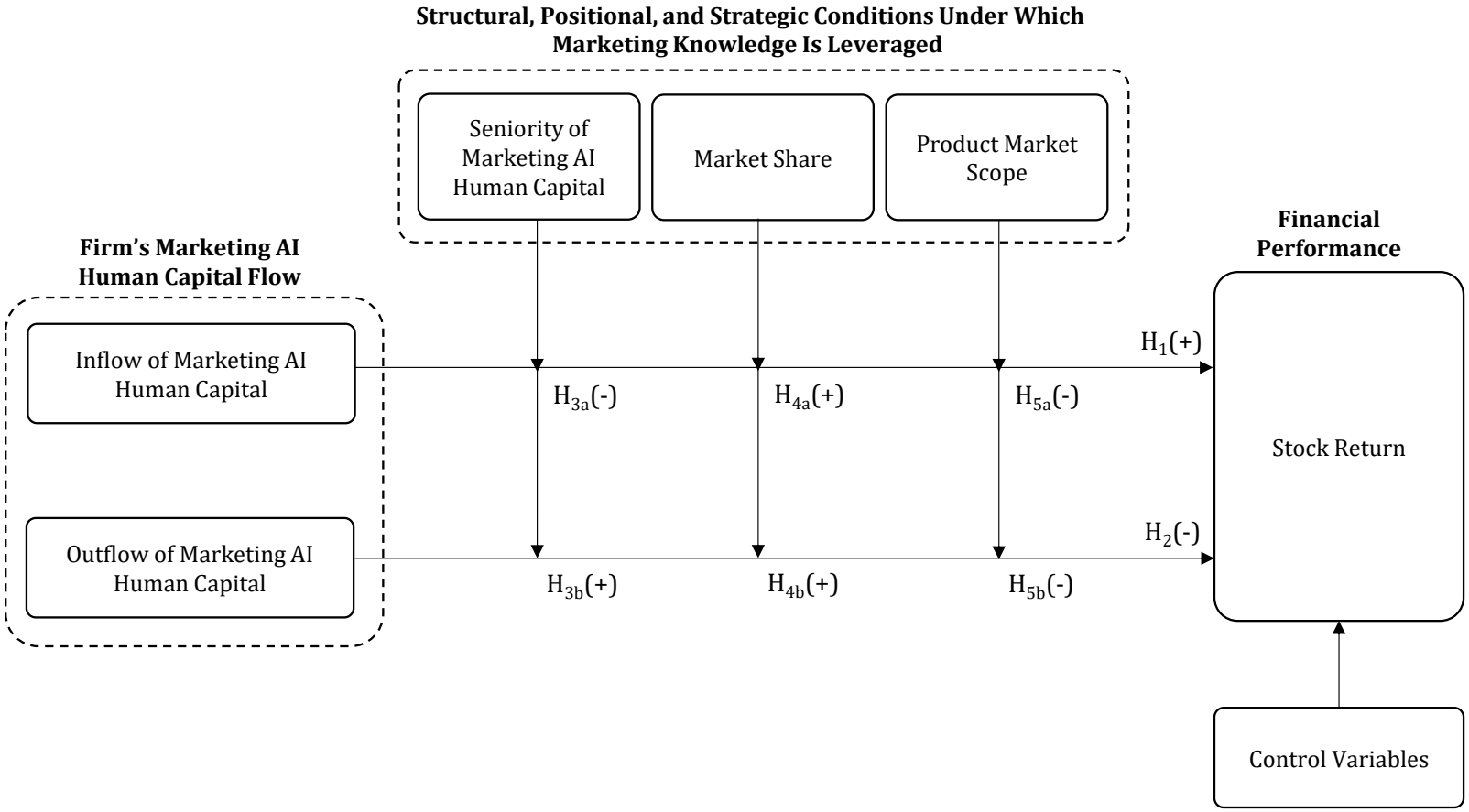


FIGURE 3
Roles of Marketing vs. Non-Marketing AI Human Capital: Text Analyses of Job Descriptions

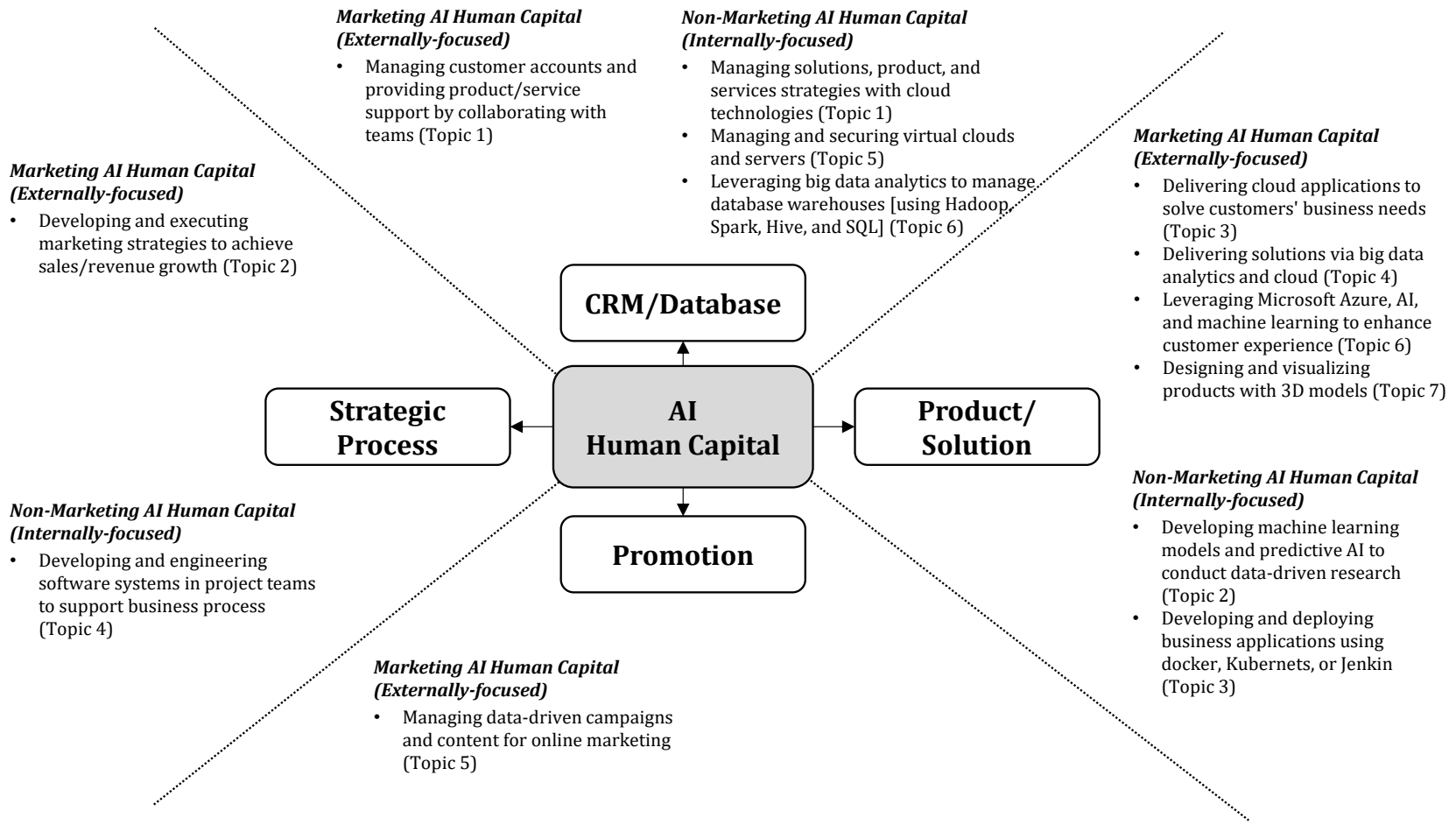


TABLE 1
Literature Review on AI and Human Capital

Authors	Context	Focus of the Study	Studied AI-Skilled Human Capital	Focused on Human Capital with Marketing Position	Organizational Scope of Human Capital	Human Capital Flow vs. Stock
This research	574 publicly traded US firms over 2012–2021	Marketing AI human capital	✓	✓	All organizational levels	Flow (Inflow and Outflow)
Panel A. Marketing Literature						
Feng, Morgan, and Rego (2015)	612 U.S. public firms over 1993–2008	Marketing power	×	✓	Top management team executives	Stock
Garvey, Kim, and Duhachek (2023)	Five experiments examining consumer responses to negative and positive offers from marketing AI agents versus human agents	Adoption of the technology (marketing AI agents)	×	×	Marketing agent	-
Germann, Ebbes, and Grewal (2015)	155 publicly traded US firms over 2000–2011	Chief marketing officers	×	✓	Chief marketing officers	Stock
Germann, Lilien, and Rangaswamy (2013)	Cross-sectional survey of 212 senior executives of Fortune 1000 firms	Marketing analytics	×	×*	-	Stock
Germann et al. (2014)	Cross-sectional survey of 418 senior executives based in the Americas, Europe Middle East and Africa (EMEA) and Asia	Customer analytics	×	×*	-	Stock
Luo et al. (2019)	6,255 attempted customers who are called by service agents	Adoption of the technology (AI chatbot)	×	×	Service agents	-
Luo et al. (2021)	429 sales agents receiving on-the-job training feedback	Adoption of the technology (AI coaches)	×	×	Sales agents	-
Mishra, Ewing, and Cooper (2022)	19,000 firm-year observations from publicly traded U.S. firms (2005–2019), based on 10-K filings and COMPUSTAT data	Firm's overall emphasis on AI	×	×	-	-
Mu and Zhang (2025)	6,859 Chinese high-tech firms (2016–2019) and survey of four managers at each firm annually	AI marketing usage (application of artifcial intelligence tools to manage marketing tasks in a firm)	×	×	-	-
Srivastava, Kashmiri, and Mahajan (2023)	389 publicly traded Fortune 500 firms over 2007–2015	Female influence in the top management team	×	×	Top management team executives	Stock
Panel B. AI Human Capital Literature Outside Marketing						
Babina et al. (2024)	120 million individual employment profiles (2007–2018), and 42 million job postings in the US (2007 and 2010–2018)	AI-skilled human capital across all functions	✓	×	All organizational levels	Stock
Lou and Wu (2021)	644 global bio-pharma firms from 2010–2019	AI innovation capability (firm's ability to develop, manage, and utilize AI resources for scientific discovery and research and development, reflected in patents and job postings)	✓	×	All organizational levels	Stock
Ployhart, Van Iddekinge, and MacKenzie Jr (2011)	238 franchises from a large US based quick service restaurant organization	Human capital resources	×	×	All organizational levels	Flow (Inflow and Outflow)
Wu, Hitt, and Lou (2020)	Over 2,000 publicly traded firms that were issued a patent over 1988–2013	Data analytics	×	×	All organizational levels	Stock
Wu, Lou, and Hitt (2019)	1,864 publicly traded firms over 1988–2013	Data analytics	×	×	All organizational levels	Stock
Wu, Lou, and Hitt (2025)	1,471 publically traded firms over 1988-2013	AI analytics capability (employees who possess relevant AI analytics skills)	✓	×	All organizational levels	Stock

*Note: Respondents of the survey were asked to evaluate their SBUs or their firm as a whole instead of their marketing human capitals.

TABLE 2
Topics and Keywords of Job Description

Domain	Topics	Top Keywords	Probability
Panel A. Marketing AI Human Capital			
CRM/ Database	Managing customer accounts and providing product/service support by collaborating with teams (Topic 1)	customer, management, client, team, support, success, product, ensure, account, service	27%
Strategic Process	Developing and executing marketing strategies to achieve sales/revenue growth (Topic 2)	sales, marketing, partnership, revenue, strategy, business, executive, development, global, growth	20%
Product/ Solution	Delivering cloud applications to solve customers' business needs (Topic 3)	Oracle, cloud, customer, solution, business, SaaS, service, PaaS, enterprise, application	15%
	Delivering solutions via big data analytics and cloud (Topic 4)	data, analytics, security, service, IBM, cloud, big data, solution, business, platform	13%
	Leveraging Microsoft Azure, AI, and machine learning to enhance customer experience (Topic 6)	Microsoft, Azure, AI, learning, team, customer, digital, machine, development, experience	10%
	Designing and visualizing products with 3D models (Topic 7)	design, 3D, modeling, printing, graphic, project, work, animation, store, visual	4%
Promotion	Managing data-driven campaigns and content for online marketing (Topic 5)	marketing, content, campaign, product, media, data, web, social, email, management	11%
Panel B. Non-Marketing AI Human Capital			
CRM/ Database	Managing solutions, product, and services strategies with cloud technologies (Topic 1)	business, solution, management, customer, team, cloud, service, product, technology, strategy	27%
	Managing and securing virtual clouds and servers (Topic 5)	security, management, server, Azure, configuration, network, cloud, infrastructure, virtual, environment	14%
	Leveraging big data analytics to manage database warehouses [using Hadoop, Spark, Hive, and SQL] (Topic 6)	data, Hadoop, big, analytics, Spark, SQL, reporting, database, Hive, warehouse	11%
Strategic Process	Developing and engineering software systems in project teams to support business process (Topic 4)	system, development, software, testing, team, project, product, design, process, engineering	15%
Product/ Solution	Developing machine learning models and predictive AI to conduct data-driven research (Topic 2)	learning, machine, modeling, AI, ML, data, prediction, science, algorithm, research	19%
	Developing and deploying business applications using docker, Kubernets, or Jenkin (Topic 3)	AWS, Docker, deploy, Kubernetes, service, development, application, Jenkins, automation, DevOps	16%

TABLE 3
Summary of Measures and Sources

Variable	Definition	Measure	Source
Financial performance (STKRET)	Firm's performance in financial markets	Unanticipated stock returns based on Carhart four-factor model (Carhart 1997).	CRSP
Marketing AI human capital inflow (INFLOW)	Recruitment of individuals possessing AI-related expertise into marketing roles within the firm.	The number of employees with AI skills joined the focal firm's marketing position each year (Babina et al. 2024; Feng, Morgan, and Rego 2015; Lou and Wu 2021).	Revelio
Marketing AI human capital outflow (OUTFLOW)	Departure of individuals possessing AI-related expertise from marketing roles within the firm.	The number of employees with AI skills left from the focal firm's marketing position each year (Babina et al. 2024; Feng, Morgan, and Rego 2015; Lou and Wu 2021).	Revelio
Seniority of marketing AI human capital inflow (SENIORITYINFLOW)	Average seniority level of marketing AI inflow of a firm.	Average seniority score of the positions the marketing employees with AI skills took up at the focal firm each year. Seniority score provided by Revelio Labs for each individual position has seven distinct levels (labelled from 1 to 7; the highest levels 6 and 7 represent executive level and senior executive level positions) (Baker et al. 2024).	Revelio
Seniority of marketing AI human capital outflow (SENIORITYOUTFLOW)	Average seniority level of marketing AI outflow of a firm.	Average seniority score of the positions the marketing employees with AI skills departed from the focal firm each year. Seniority score provided by Revelio Labs for each individual position has seven distinct levels (labelled from 1 to 7; the highest levels 6 and 7 represent executive level and senior executive level positions) (Baker et al. 2024).	Revelio
Market share (MARKETSHARE)	Firm's competitive position within a market.	Sales of firm divided by the sum of sales of the industry in which focal firm is situated in each year (Fang, Palmatier, and Steenkamp 2008).	Compustat
Product market scope (PRODMKTSCOPE)	Degree of a firm's diversification across different markets.	Total count of industries a firm in each year belongs to. This variables is computed using doc2vec and K-means clustering along with a procedure to map each firm to each of the centroid clusters (Hoberg and Phillips 2024).	Hoberg and Phillips Data Library
Employee size (EMPSIZE)	Firm size in terms of number of employees.	Total number of employees (Saboo et al. 2017).	Revelio
Asset size (ASSET)	Firm size in terms of total assets.	Total value of assets reported on the balance sheet (Feng, Morgan, and Rego 2015).	Compustat
Firm age (AGE)	Age of the firm.	Age of the firm since it was listed on the stock market (Saboo et al. 2017).	Compustat
Financial leverage (LEVERAGE)	The extent to which the firm lacks financial flexibility to make strategic investments.	Ratio of the firm's long-term debt to total assets (Kurt and Hulland 2013).	Compustat
Liquidity (LIQUIDITY)	Firm's ability to convert assets into cash.	The ratio of current asset to liability (Mishra, Ewing, and Cooper 2022).	Compustat
Gross margin (GRSMARGIN)	Firm's ability to generate a price premium over the cost of goods sold.	Sales revenue minus costs of goods sold (Kim and McAlister 2011).	Compustat
Advertising intensity (ADVINT)	The extent to which the firm invests in advertising activities.	Advertising expenditure to total asset (set to zero if advertising expenditure measure is missing) (Kim and McAlister 2011).	Compustat
Inventory intensity (INVTINT)	The amount of capital tied up in work in progress and unsold product.	Inventory to sales ratio. This measure reflects the amount of capital tied up in work in progress and unsold product (Sridhar et al. 2014).	Compustat
Capital investment intensity (CAPINVTINT)	Availability of investment opportunities.	Net capital expenditures divided by its sales revenue (Berman et al. 1999).	Compustat
Capital intensity (CAPINT)	Asset intensity per employee	Total firm assets divided by the number of employees (Vomberg et al. 2015).	Compustat
Merger and acquisition (MA)	Merger and acquisition identifier.	Dummy variable for merger and acquisition where 1 if the firm had an acquisition that contributed to sales (Umashankar et al. 2022).	Compustat
Industry growth (INDGROWTH)	Rate of sales growth within an industry.	Five-year growth of industry sales. Regressing industry sales for each year t on time t, the antilog of the resulting regression slope coefficient is used as industry growth in year t in each industry. The industry growth measure is based on the firms' two-digit SIC codes (Fang, Palmatier, and Steenkamp 2008).	Compustat
Service industry (SERVICE)	Whether a firm is a service business.	Dummy variable where 1 if a firm is in a service industry (a firm's SIC code begins with 4-9) and 0 otherwise (e.g., Fang, Palmatier, and Steenkamp 2008).	Compustat
Regulated industry (REGULATED)	Whether a firm is in a regulated industry.	Dummy variable where 1 if a firm is in a regulated industry (a firm's SIC code begins with 4 (transportation and communication companies and utilities), 6 (financial companies), and 9 (public administration companies) and 0 otherwise (Lee et al. 2015).	Compustat
Utilities industry (UTILITIES)	Whether a firm is in a utilities industry.	Dummy variable where 1 if a firm is in a utilities industry (a firm's SIC code begins with 49) and 0 otherwise (Lee et al. 2015).	Compustat

Notes: Measures indicated in Equation 2 are shown in parentheses next to variable names.

TABLE 4
Correlation Matrix and Descriptive Statistics

Variable	Mean	Std. dev.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1 Financial performance	.03	.43	-.92	7.55	1																					
2 Δ Marketing AI inflow	.38	18.8	-484.3	422.45	.05*	1																				
3 Δ Marketing AI outflow	.69	12.97	-175.6	212.68	-.02	.37*	1																			
4 Δ Seniority of marketing AI inflow	-.00	.99	-2.27	4.25	.04	.05*	.07*	1																		
5 ΔSeniority of marketing AI outflow	.01	.94	-2.52	3.39	.01	.04*	.06*	.49*	1																	
6 Δ Market share	-.00	.00	-.05	.06	.06*	.03	-.02	.05*	.03	1																
7 Δ Product market scope	-.07	3.20	-24.71	29.79	-.01	.04*	.02	.06*	.05*	.06*	1															
8 Δ Employee size	114.77	1517.34	-12740.80	23842.23	.11*	.21*	.11*	.03	.02	.19*	.03	1														
9 Δ Asset size	206.03	5550.70	-124846.90	108240.30	.05*	.02	.05*	.04*	.03	.27*	.07*	.19*	1													
10 Firm age	28.14	20.18	0	71	-.10*	-.05*	-.08*	-.20*	-.18*	-.09*	-.11*	-.13*	-.04*	1												
11 Δ Financial leverage	.01	.12	-.35	1.69	-.01	-.03	-.02	-.06*	-.07*	-.04*	.03	-.02	-.01	.01	1											
12 Δ Liquidity	-28275.62	81366.77	-2086592	-396.46	.01	.00	-.01	.03	.03	-.11*	.04*	-.18*	-.09*	-.21*	-.01	1										
13 Δ Gross margin	-20.79	1977.35	-24811.20	42381.52	.07*	.03	.02	.04*	.03	.36*	.05*	.31*	.37*	-.10*	-.05*	-.30*	1									
14 Δ Advertising intensity	.00	.03	-.18	.79	.07*	-.00	-.00	-.06*	-.07*	.02	-.03	.01	-.03	-.05*	.02	.03	.01	1								
15 Δ Inventory intensity	-.05	.08	-.19	1.13	-.05*	-.04*	-.07*	-.20*	-.22*	-.05*	-.04*	-.09*	-.01	.27*	.01	-.06*	-.09*	-.00	1							
16 Δ Capital investment intensity	-.15	.04	-.30	1.01	-.00	.01	-.00	-.01	-.04*	-.04	.03	.06*	.04*	.02	.07*	-.05*	-.02	-.04	.01	1						
17 Δ Capital intensity	-1718.61	346.38	-3545.93	1805.36	.02	.00	-.00	.05*	.05*	.04	-.01	.03	.13*	.06*	.07*	-.25*	-.02	-.08*	-.03	.24*	1					
18 Merger and acquisition	.94	.24	0	1	-.01	.03	-.01	.03	.03	.05*	.01	.00	.05*	-.03	.01	.02	.01	-.01	-.09*	-.05*	-.04*	1				
19 Δ Industry growth	-.00	.03	-.18	.10	.09*	.01	.04*	.10*	.12*	.10*	.03	.11*	.01	-.14*	-.04*	.02	.12*	.02	-.14*	-.02	-.03	.02	1			
20 Service industry	.64	.48	0	1	.06*	.03	.06*	.10*	.10*	.06*	.00	.03	.04*	-.34*	.02	.16*	.04*	.01	-.48*	.01	-.04*	.02	.17*	1		
21 Regulated industry	.10	.29	0	1	-.03	-.03	-.04*	-.07*	-.06*	.03	.03	-.05*	.08*	.05*	.10*	-.00	-.00	-.03	-.17*	.27*	.23*	-.03	-.07*	.25*	1	
22 Utilities industry	.01	.09	0	1	-.02	-.01	-.01	-.04	-.04*	.01	-.02	-.01	.04*	.12*	.02	-.00	.00	-.03	-.00	.33*	.28*	.01	-.04*	.07*	.29*	1

Notes: *p < .05.

TABLE 5
Effects of Marketing AI Inflow and Outflow on Financial Performance

Variable		Model 1 Control variables		Model 2 Main effects added		Model 3 Moderation effects added	
		Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Δ Marketing AI inflow	H_1			.991	.000	1.010	.000
				(.125)		(.118)	
Δ Marketing AI outflow	H_2			-1.296	.000	-1.317	.000
				(.158)		(.150)	
Δ Marketing AI inflow × Δ Seniority of marketing inflow	H_{3a}					-.002	.011
						(.001)	
Δ Marketing AI outflow × Δ Seniority of marketing AI outflow	H_{3b}					.002	.099
						(.001)	
Δ Marketing AI inflow × Δ Market share	H_{4a}					.657	.002
						(.216)	
Δ Marketing AI outflow × Δ Market share	H_{4b}					.227	.038
						(.109)	
Δ Marketing AI inflow × Δ Product market scope	H_{5a}					-.000	.053
						(.000)	
Δ Marketing AI outflow × Δ Product market scope	H_{5b}					.000	.250
						(.000)	
Δ Seniority of marketing AI inflow				.006	.508	.002	.797
				(.009)		(.009)	
Δ Seniority of marketing AI outflow				-.013	.159	-.010	.266
				(.009)		(.009)	
Δ Market share				5.644	.041	8.215	.001
				(2.754)		(2.478)	
Δ Product market scope				-.004	.186	-.003	.197
				(.003)		(.003)	
Δ Employee size		.000	.001	-.001	.000	-.001	.000
		(.000)		(.000)		(.000)	
Δ Asset size		.000	.479	.000	.000	.000	.000
		(.000)		(.000)		(.000)	
Firm age		-.002	.000	-.027	.000	-.028	.000
		(.000)		(.003)		(.003)	
Δ Financial leverage		-.027	.738	1.629	.000	1.658	.000
		(.080)		(.229)		(.217)	
Δ Liquidity		.000	.054	-.000	.000	-.000	.000
		(.000)		(.000)		(.000)	
Δ Gross margin		.000	.000	-.000	.000	-.000	.000
		(.000)		(.000)		(.000)	
Δ Advertising intensity		1.052	.443	3.420	.023	3.485	.021
		(1.371)		(1.509)		(1.510)	
Δ Inventory intensity		-.040	.684	-6.459	.000	-6.560	.000
		(.097)		(.788)		(.748)	
Δ Capital investment intensity		.005	.983	-.901	.001	-.923	.000
		(.220)		(.264)		(.259)	
Δ Capital intensity		.000	.022	-.001	.000	-.001	.000
		(.000)		(.000)		(.000)	
Merger and acquisition		-.017	.593	-3.999	.000	-4.064	.000
		(.032)		(.497)		(.470)	
Δ Industry growth		.726	.019	27.982	.000	28.383	.000
		(.310)		(3.405)		(3.216)	
Service industry		-.008	.711	.204	.000	.203	.000
		(.021)		(.031)		(.031)	
Regulated industry		-.030	.262	-1.176	.000	-1.189	.000
		(.027)		(.136)		(.130)	
Utilities industry		-.076	.168	2.740	.000	2.789	.000
		(.055)		(.351)		(.332)	
Inverse Mills ratio		-.091	.002	-.087	.003	-.086	.003
		(.030)		(.029)		(.029)	
Control function residual for marketing AI inflow				-.990	.000	-1.007	.000
				(.125)		(.118)	
Control function residual for marketing AI outflow				1.294	.000	1.314	.000
				(.158)		(.150)	
Constant		.193	.005	.682	.000	.693	.000
		(.069)		(.094)		(.093)	
Year fixed effects		Yes		Yes		Yes	
Prob > F		.000		.000		.000	
R-squared		.057		.064		.069	

Notes : n = 2,929. Robust standard errors in parentheses.

WEB APPENDICES

Marketing Employees with AI Expertise: Roles and Performance Implications

Table of Contents

These materials have been supplied by the authors to aid in the understanding of their paper.

WEB APPENDIX A: Procedure for LDA Text Analysis of Job Descriptions

To examine the underlying tasks associated with marketing and engineering AI human capital, we conduct a large-scale topic modeling analysis using Latent Dirichlet Allocation (LDA), a widely applied unsupervised machine learning technique for discovering latent thematic structures in text corpora (Blei et al. 2003). This section outlines the detailed preprocessing procedures and modeling strategy, following methodological of text analysis from Chen and Lee (2023).

Data Preprocessing

Prior to applying LDA, we perform a series of six preprocessing steps to reduce noise, standardize the text, and enhance the quality of the input data.

1. Normalization: We convert all job descriptions to lowercase and normalize them using the Unicode NFKD standard to ensure consistent character representation across documents.

2. Noise removal: We remove non-ASCII characters and replace all non-alphanumeric symbols (e.g., punctuation marks, special characters) with spaces. Tokens composed entirely of whitespace or formatting characters (e.g., underscores) are eliminated.

3. Tokenization: Using the Natural Language Toolkit (NLTK) tokenizer, we segment each job description into tokens, preserving the word-level granularity necessary for topic modeling.

4. Stop-word filtering: We remove commonly used but semantically uninformative words (e.g., "the," "and," "is") based on the MALLET default stop-word list (McCallum 2002). We also identify and exclude additional domain-specific stop-words (e.g., “www,” “http,” “iii”) to further refine the corpus.

5. Numeric filtering: We exclude standalone numeric tokens unless they form meaningful alphanumeric terms relevant to the domain (e.g., “3d,” “b2b,” “b2c,” “e2e”).

6. Stemming: We reduce tokens to their root forms using the Porter stemming algorithm, consolidating different morphological variants into a single base form (e.g., "designing," "designed," and "designer" are all reduced to "design").

Topic Modeling with LDA

We apply the LDA model using the gensim.models.ldamodel package. The model is trained separately for marketing AI and engineering AI job descriptions, allowing for 100 passes to enhance convergence. Based on model selection procedures described below, we identify 7 topics for marketing AI and 6 topics for engineering AI.

LDA assumes that each document (i.e., job description) is a mixture of multiple latent topics, where each topic is characterized by a distribution over words (Blei et al. 2003). For a given job description i, the model draws a topic distribution θ_i. Each topic k is associated with a word distribution ψ_k. Each word w in a document is generated by first selecting a topic z according to θ_i and then selecting a word from ψ_k. After observing all words across documents, the model uses Bayesian inference to estimate the posterior distributions of θ_i and ψ_k.

Rank Topics and Keywords

To determine the relative importance of each topic, we calculate the average topic probability across all job descriptions and sort the topics in descending order of their overall prevalence. To rank keywords within each topic, we adopt the relevance-weighted ranking method proposed by (Sievert and Shirley 2014), following the procedure outlined by Chen and Lee (2023). Specifically, the relevance score $r(w, k)$ for a keyword w within topic k is computed to balance two factors: (1) the probability of the word within the topic ϕ_{kw}, and (2) the

distinctiveness of the word relative to its frequency across the entire corpus P_w. The relevance score is calculated as:

$$r(w,k) = \exp\left[\lambda \log(\phi_{kw}) + (1-\lambda)\log\left(\frac{\phi_{kw}}{P_w}\right)\right]$$

where λ controls the weight between within-topic probability and distinctiveness and is set to $\lambda = 2/3$. This approach prioritizes keywords that are both common within a topic and relatively uncommon elsewhere, thus enhancing the interpretability of topic labels.

Model Selection: Determining the Optimal Number of Topics

To identify the optimal number of topics for each dataset, we estimate a series of LDA models with the number of topics (k) ranging from one to ten. Following established practices (Chen and Lee 2023; Röder et al. 2015), we evaluate each model using the Cv coherence score, which measures the degree of semantic similarity among the top-ranked keywords within each topic. We then plot the coherence scores against the number of topics and select the optimal k based on the point where the coherence score reaches a local maximum or shows diminishing improvements.

For the marketing AI human capital dataset, the coherence score reaches a maximum (Cv = 0.405) at seven topics (Figure WA1). For the engineering AI human capital dataset, although the coherence score reaches its highest value at ten topics, the most substantial improvement occurs at four topics. To balance parsimony with the need for greater granularity in capturing engineering AI tasks, we selected six topics (Cv = 0.458) as the optimal number, as it exhibits a comparable coherence improvement to four topics while offering more detailed topic differentiation (Figure WA2).

Figure WA1: Coherence score of Marketing AI human capital

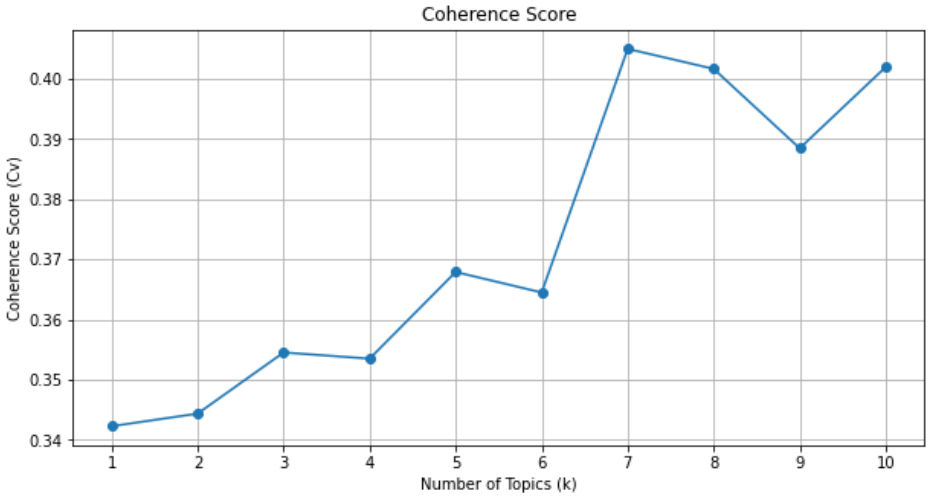
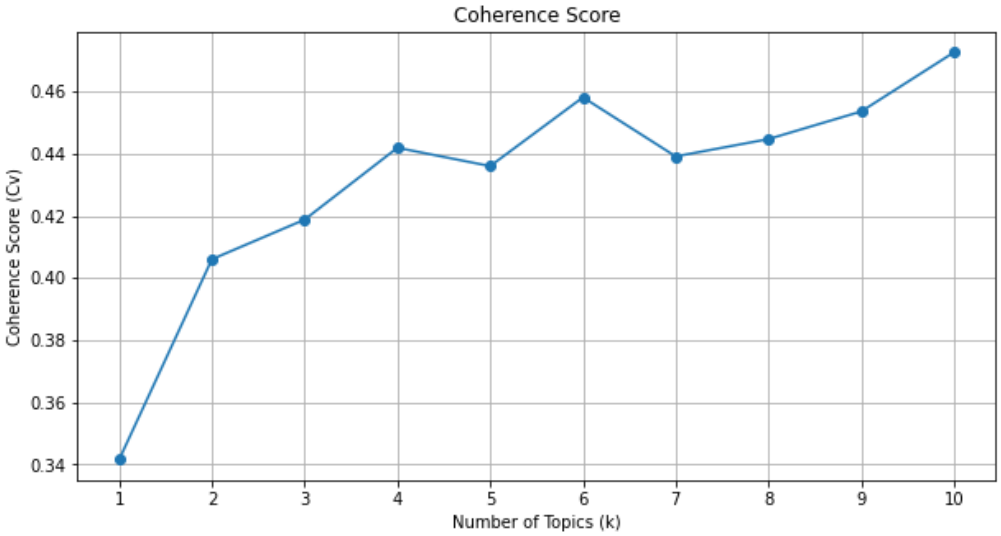


Figure WA2: Coherence score of Engineering AI human capital



WEB APPENDIX B: Identified Marketing Roles and AI Skills from Revelio Labs

First, building on Feng et al. (2015), three out of four authors of this paper and an independent research assistant read the descriptions on marketing roles in Appendix B of Feng et al. (2015). Focusing on the 1250-level role classification from Revelio Labs, which is sufficiently granular to identify whether a job falls under marketing, we include only those roles that were unanimously classified as marketing-related. The full list of the marketing jobs that we identified are as follows:

> *Advertising specialist, alliance manager, brand ambassador, brand manager, brand representative, business relationship manager, client account manager, client relations, client relationship manager, client service professional, client service representative, client services, client solutions, client specialist, client support specialist, communication specialist, communications consultant, communications specialist, consumer marketing, content analyst, content creator, content specialist, copywriter, corporate affairs, customer service, CS, CSA, CSE, CSR, customer account specialist, customer advocate, customer care, customer care representative, customer consultant, customer development, customer engagement manager, customer engineer, customer experience specialist, customer marketing, customer operations specialist, customer project manager, customer relations, customer relationship manager, customer representative, customer sales associate, customer service, customer service agent, customer service analyst, customer service consultant, customer service coordinator, customer service officer, customer service representative, customer service sales associate, customer services, customer services agent, customer solutions specialist, customer success specialist, customer support, customer support representative, design consultant, design manager, designer, digital account manager, digital designer, digital marketing specialist, digital media intern, digital product manager, digital project manager, digital specialist, ecommerce specialist, editor, editorial assistant, engagement manager, event specialist, graphic artist, graphic designer, market access manager, market analyst, market research, marketing, marketing analyst, marketing communications specialist, marketing consultant, marketing coordinator, marketing officer, marketing operations, marketing project manager, marketing representative, marketing services manager, media manager, media planner, media relations manager, merchandise manager, merchandise planner, merchandiser, merchandising specialist, online marketing manager, online specialist, PR specialist.*

Second, we determine AI skills based on prior research (Babina et al. 2024; Lou and Wu 2021) which derives AI skill list from multiple sources that include United States Patent and Trademark Office (USPTO), Cockburn et al. (2018)' AI glossary for AI subfields, and the

Association of Computing Machinery's Computing Classification System. Based on these prior works, we identify AI skills related to machine learning, NLP, cloud computing, computer vision, and robotics. The full list of AI skills that we identified are as follows:

> *3d modeling, predictive analytics, cloud computing, devops, software as a service, 3d printing, predictive modeling, docker, computer vision, 3d studio max, cloud computing, elasticsearch, unity3d, 3d visualization, amazon web services, Hadoop, natural language processing, computer animation, apache hive, plc programming, computer graphics, apache pig, mapreduce, robotics, artificial intelligence, apache spark, microsoft azure, data mining, big data analytics, openstack, machine learning, Cassandra, paas, pandas, cloud applications, saas*

WEB APPENDIX C: First-Stage Control Function Approach Results

Variable	Model 1		Model 2	
	Dependent variable: Δ Marketing AI inflow		Dependent variable: Δ Marketing AI outflow	
	Coeff.	p-value	Coeff.	p-value
Δ Peers-of-peers marketing AI inflow	-4.635	.081		
	(2.660)			
Δ Peers-of-peers marketing AI outflow			-4.360	.055
			(2.275)	
Δ Employee size	.003	.002	.001	.043
	(.001)		(.000)	
Δ Asset size	-.000	.820	.000	.213
	(.000)		(.000)	
Firm age	-.009	.448	-.027	.003
	(.011)		(.009)	
Δ Financial leverage	-2.614	.251	-.725	.658
	(2.277)		(1.636)	
Δ Liquidity	.000	.582	-.000	.615
	(.000)		(.000)	
Δ Gross margin	-.000	.357	-.000	.033
	(.000)		(.000)	
Δ Advertising intensity	-7.720	.133	-4.058	.326
	(5.141)		(4.132)	
Δ Inventory intensity	-1.972	.602	-6.451	.004
	(3.778)		(2.254)	
Δ Capital investment intensity	-.138	.982	-.809	.839
	(6.111)		(3.980)	
Δ Capital intensity	.001	.147	-.000	.757
	(.001)		(.001)	
Merger and acquisition	2.366	.001	-1.263	.050
	(.697)		(.645)	
Δ Industry growth	-14.481	.196	9.974	.350
	(11.199)		(10.662)	
Service industry	1.173	.094	1.065	.039
	(.700)		(.515)	
Regulated industry	-1.652	.079	-2.148	.004
	(.940)		(.751)	
Utilities industry	-.444	.721	1.839	.029
	(1.244)		(.842)	
Constant	.921	.654	1.075	.486
	(2.052)		(1.541)	
Year fixed effects	Yes		Yes	
Prob > F	.000		.000	
R-squared	.067		.032	

Notes: Robust standard errors in parentheses.

WEB APPENDIX D: Alternative Model Specification: Fixed-Effects Model without Endogeneity Correction and Selection Bias Correction

Variable	Model 1 Main effects		Model 2 Moderation effects	
	Coeff.	p-value	Coeff.	p-value
Δ Marketing AI inflow	.001	.003	.003	.000
	(.000)		(.001)	
Δ Marketing AI outflow	-.002	.007	-.003	.007
	(.001)		(.001)	
Δ Marketing AI inflow × Δ Seniority of marketing inflow			-.002	.011
			(.001)	
Δ Marketing AI outflow × Δ Seniority of marketing AI outflow			.002	.096
			(.001)	
Δ Marketing AI inflow × Δ Market share			.695	.001
			(.217)	
Δ Marketing AI outflow × Δ Market share			.219	.048
			(.111)	
Δ Marketing AI inflow × Δ Product market scope			-.000	.059
			(.000)	
Δ Marketing AI outflow × Δ Product market scope			.000	.284
			(.000)	
Δ Seniority of marketing AI inflow	.010	.244	.007	.448
	(.009)		(.009)	
Δ Seniority of marketing AI outflow	-.009	.338	-.006	.505
	(.009)		(.009)	
Δ Market share	6.123	.030	8.671	.000
	(2.819)		(2.487)	
Δ Product market scope	-.003	.193	-.003	.206
	(.003)		(.003)	
Δ Employee size	.000	.003	.000	.003
	(.000)		(.000)	
Δ Asset size	.000	.419	.000	.810
	(.000)		(.000)	
Firm age	-.001	.008	-.001	.005
	(.000)		(.000)	
Δ Financial leverage	-.032	.688	-.035	.657
	(.079)		(.079)	
Δ Liquidity	.000	.087	.000	.094
	(.000)		(.000)	
Δ Gross margin	.000	.001	.000	.001
	(.000)		(.000)	
Δ Advertising intensity	1.050	.448	1.059	.446
	(1.384)		(1.387)	
Δ Inventory intensity	-.076	.438	-.087	.375
	(.098)		(.098)	
Δ Capital investment intensity	-.011	.959	-.019	.930
	(.225)		(.222)	
Δ Capital intensity	.000	.028	.000	.029
	(.000)		(.000)	
Merger and acquisition	-.024	.457	-.024	.458
	(.032)		(.032)	
Δ Industry growth	.822	.008	.782	.013
	(.312)		(.313)	
Service industry	.024	.175	.023	.201
	(.018)		(.018)	
Regulated industry	-.051	.050	-.051	.046
	(.026)		(.026)	
Utilities industry	-.094	.092	-.088	.113
	(.056)		(.055)	
Constant	.125	.041	.131	.033
	(.061)		(.061)	
Year fixed effects	Yes		Yes	
Prob > F	.000		.000	
R-squared	.059		.064	

Notes: n = 2,929. Robust standard errors in parentheses.

WEB APPENDIX E: Alternative Model Specification: Random-Effects Model with Endogeneity Correction and Selection Bias Correction

Variable	Model 1		Model 2	
	Main effects		Moderation effects added	
	Coeff.	p-value	Coeff.	p-value
Δ Marketing AI inflow	.921	.000	.945	.000
	(.124)		(.104)	
Δ Marketing AI outflow	-1.206	.000	-1.234	.000
	(.155)		(.131)	
Δ Marketing AI inflow × Δ Seniority of marketing inflow			-.001	.072
			(.001)	
Δ Marketing AI outflow × Δ Seniority of marketing AI outflow			.003	.008
			(.001)	
Δ Marketing AI inflow × Δ Market share			.668	.000
			(.162)	
Δ Marketing AI outflow × Δ Market share			.231	.026
			(.104)	
Δ Marketing AI inflow × Δ Product market scope			-.000	.044
			(.000)	
Δ Marketing AI outflow × Δ Product market scope			.000	.252
			(.000)	
Δ Seniority of marketing AI inflow	.003	.757	-.000	.996
	(.009)		(.010)	
Δ Seniority of marketing AI outflow	-.017	.090	-.014	.161
	(.010)		(.010)	
Δ Market share	3.354	.194	6.173	.017
	(2.583)		(2.585)	
Δ Product market scope	-.004	.081	-.004	.089
	(.003)		(.003)	
Δ Employee size	-.001	.000	-.001	.000
	(.000)		(.000)	
Δ Asset size	.000	.000	.000	.000
	(.000)		(.000)	
Firm age	-.026	.000	-.026	.000
	(.003)		(.003)	
Δ Financial leverage	1.513	.000	1.553	.000
	(.243)		(.214)	
Δ Liquidity	-.000	.000	-.000	.000
	(.000)		(.000)	
Δ Gross margin	-.000	.000	-.000	.000
	(.000)		(.000)	
Δ Advertising intensity	3.025	.000	3.124	.000
	(.865)		(.841)	
Δ Inventory intensity	-6.178	.000	-6.299	.000
	(.776)		(.665)	
Δ Capital investment intensity	-1.077	.000	-1.109	.000
	(.258)		(.255)	
Δ Capital intensity	-.001	.000	-.001	.000
	(.000)		(.000)	
Merger and acquisition	-3.728	.000	-3.814	.000
	(.494)		(.417)	
Δ Industry growth	26.044	.000	26.597	.000
	(3.357)		(2.828)	
Service industry	.184	.000	.184	.000
	(.036)		(.034)	
Regulated industry	-1.110	.000	-1.129	.000
	(.134)		(.115)	
Utilities industry	2.599	.000	2.663	.000
	(.344)		(.292)	
Inverse Mills ratio	-.101	.011	-.099	.013
	(.040)		(.040)	
Control function residual for marketing AI inflow	-.920	.000	-.943	.000
	(.124)		(.104)	
Control function residual for marketing AI outflow	1.205	.000	1.230	.000
	(.155)		(.131)	
Constant	.642	.000	.655	.000
	(.113)		(.109)	
Year fixed effects	Yes		Yes	
Prob > Chi2	.000		.000	
R-squared	.061		.066	

Notes: n = 2,929. Robust standard errors in parentheses.

WEB APPENDIX F: Alternative Stock Returns Measure based on Market Model

Variable	Model 1 Main effects		Model 2 Moderation effects added	
	Coeff.	p-value	Coeff.	p-value
Δ Marketing AI inflow	.971	.000	.990	.000
	(.122)		(.116)	
Δ Marketing AI outflow	-1.268	.000	-1.289	.000
	(.154)		(.147)	
Δ Marketing AI inflow × Δ Seniority of marketing inflow			-.002	.007
			(.001)	
Δ Marketing AI outflow × Δ Seniority of marketing AI outflow			.002	.121
			(.001)	
Δ Marketing AI inflow × Δ Market share			.638	.003
			(.217)	
Δ Marketing AI outflow × Δ Market share			.238	.035
			(.113)	
Δ Marketing AI inflow × Δ Product market scope			-.000	.053
			(.000)	
Δ Marketing AI outflow × Δ Product market scope			.000	.314
			(.000)	
Δ Seniority of marketing AI inflow	.006	.489	.002	.788
	(.009)		(.009)	
Δ Seniority of marketing AI outflow	-.016	.082	-.013	.150
	(.009)		(.009)	
Δ Market share	5.255	.066	7.852	.002
	(2.855)		(2.506)	
Δ Product market scope	-.003	.272	-.003	.289
	(.003)		(.003)	
Δ Employee size	-.001	.000	-.001	.000
	(.000)		(.000)	
Δ Asset size	.000	.000	.000	.000
	(.000)		(.000)	
Firm age	-.027	.000	-.027	.000
	(.003)		(.003)	
Δ Financial leverage	1.593	.000	1.621	.000
	(.226)		(.216	
Δ Liquidity	-.000	.000	-.000	.000
	(.000)		(.000)	
Δ Gross margin	-.000	.000	-.000	.000
	(.000)		(.000)	
Δ Advertising intensity	3.303	.024	3.367	.022
	(1.462)		(1.464)	
Δ Inventory intensity	-6.325	.000	-6.430	.000
	(.770)		(.736)	
Δ Capital investment intensity	-.895	.001	-.918	.000
	(.261)		(.256)	
Δ Capital intensity	-.001	.000	-.001	.000
	(.000)		(.000)	
Merger and acquisition	-3.916	.000	-3.983	.000
	(.485)		(.461)	
Δ Industry growth	27.445	.000	27.853	.000
	(3.326)		(3.164)	
Service industry	.195	.000	.195	.000
	(.031)		(.031)	
Regulated industry	-1.149	.000	-1.163	.000
	(.133)		(.128)	
Utilities industry	2.686	.000	2.736	.000
	(.342)		(.326)	
Inverse Mills ratio	-.091	.002	-.089	.002
	(.029)		(.029)	
Control function residual for marketing AI inflow	-.969	.000	-.987	.000
	(.122)		(.116)	
Control function residual for marketing AI outflow	1.266	.000	1.286	.000
	(.154)		(.147)	
Constant	.664	.000	.674	.000
	(.094)		(.093)	
Year fixed effects	Yes		Yes	
Prob > F	.000		.000	
R-squared	.055		.059	

Notes: n = 2,929. Robust standard errors in parentheses.

WEB APPENDIX G: Effects of Internal and External Marketing AI Inflow on Financial Performance

Variable	Model 1		Model 2	
	Financial Performance: Internal Inflow		Financial Performance: External Inflow	
	Coeff.	p-value	Coeff.	p-value
Δ Internal marketing AI inflow	3.747	.089		
	(2.198)			
Δ External marketing AI inflow			.463	.000
			(.086)	
Δ Marketing AI outflow	-.819	.066	-.576	.000
	(.446)		(.099)	
Δ Seniority of internal marketing AI inflow	-.009	.481		
	(.012)			
Δ Seniority of external marketing AI inflow			.006	.465
			(.009)	
Δ Seniority of marketing AI outflow	-.011	.601	-.014	.146
	(.020)		(.010)	
Δ Market share	.825	.769	6.053	.031
	(2.812)		(2.807)	
Δ Product market scope	-.001	.758	-.004	.165
	(.004)		(0.003)	
Δ Employee size	-.002	.103	-.000	.000
	(.001)		(.000)	
Δ Asset size	.000	.848	.000	.000
	(.000)		(.000)	
Firm age	.002	.526	-.014	.000
	(.003)		(.002)	
Δ Financial leverage	2.362	.106	.289	.004
	(1.458)		(.100)	
Δ Liquidity	.000	.090	-.000	.000
	(.000)		(.000)	
Δ Gross margin	.000	.102	-.000	.000
	(.000)		(.000)	
Δ Advvertising intensity	13.940	.099	1.063	.495
	(8.434)		(1.557)	
Δ Inventory intensity	10.337	.093	-3.424	.000
	(6.144)		(.597)	
Δ Capital investment intensity	1.064	.234	.109	.641
	(0.895)		(.234)	
Δ Capital intensity	.000	.027	-.000	.000
	(.000)		(.000)	
Merger and acquisition	-1.757	.070	-1.334	.000
	(.971)		(.241)	
Δ Industry growth	16.704	.067	10.266	.000
	(9.097)		(1.761)	
Service industry	-1.048	.098	.271	.000
	(.633)		(.053)	
Regulated industry	1.653	.117	-.725	.000
	(1.054)		(.121)	
Utilities industry	omitted due to collinearity		.869	.000
			(.181)	
Inverse Mills ratio involving internal marketi	-.070	.136		
	(.047)			
Inverse Mills ratio involving external marketi			-.101	.025
			(.045)	
Control function residual for internal marketi	-3.745	.089		
	(2.198)			
Control function residual for external market			-.461	.000
			(.086)	
Control function residual for marketing AI ou	.818	.067	.575	.000
	(.446)		(.099)	
Constant	.378	.007	.652	.000
	(.139)		(.111)	
Year fixed effects	Yes		Yes	
Prob > F	.000		.000	
R-squared	.079		.067	

Notes: n = 2,929. Robust standard errors in parentheses.

References

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson (2024), "Artificial intelligence, firm growth, and product innovation," *Journal of Financial Economics*, 151, 103745.

Blei, David M, Andrew Y Ng, and Michael I Jordan (2003), "Latent dirichlet allocation," *Journal of Machine Learning Research*, 3 (Jan), 993-1022.

Chen, Yiwei and Stephanie Lee (2023), "User-Generated Physician Ratings and Their Effects on Patients' Physician Choices: Evidence from Yelp," *Journal of Marketing*, 88 (1), 77-96.

Cockburn, Iain M, Rebecca Henderson, and Scott Stern (2018), The impact of artificial intelligence on innovation: National bureau of economic research Cambridge, MA, USA.

Feng, Hui, Neil A Morgan, and Lopo L Rego (2015), "Marketing department power and firm performance," *Journal of Marketing*, 79 (5), 1-20.

Lou, Bowen and Lynn Wu (2021), "AI on Drugs: Can Artificial Intelligence Accelerate Drug Development? Evidence from a Large-Scale Examination of Bio-Pharma Firms," *MIS Quarterly*, 45 (3), 1451-82.

McCallum, Andrew Kachites (2002), "Mallet: A machine learning for languagetoolkit," *http://mallet.cs.umass.edu*.

Röder, Michael, Andreas Both, and Alexander Hinneburg (2015), "Exploring the space of topic coherence measures," in Proceedings of the eighth ACM international conference on Web search and data mining.

Sievert, Carson and Kenneth Shirley (2014), "LDAvis: A method for visualizing and interpreting topics," in Proceedings of the workshop on interactive language learning, visualization, and interfaces.