HASTE MAKES WASTE: A MODERATED MEDIATION MODEL OF THE MECHANISMS LINKING ARTIFICIAL INTELLIGENCE ADVANCEMENT TO FILM FIRM PERFORMANCE

Zexia Wang and Wucheng Han

School of Economics and Management
University of Electronic Science and Technology of China, Chengdu, China

ABSTRACT

Artificial intelligence (AI) has emerged as a transformative force in the modern film industry, revolutionizing production processes and redefining audience experiences. This study delves into the mechanisms through which AI advancement impacts film firm performance, with a focus on the mediating roles of innovation speed and quality, and the moderating effect of human-machine collaboration. Employing a resource-based view, we construct a moderated mediation model and analyze data from 355 global film firms. Our findings reveal that AI advancement positively influences film firm performance, with innovation quality serving as a significant mediator. However, the mediating role of innovation speed is not pronounced. Moreover, the degree of human-machine collaboration positively moderates the relationships between AI advancement and both innovation speed and quality. However, its moderating role between AI advancement and firm performance is not significant. The study underscores the theoretical and practical implications of utilizing advanced AI to foster innovation and competitive advantage in film firms.

KEYWORDS

AI advancement, innovation speed, innovation quality, human-machine collaboration, film firm performance.

1. INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force in the modern film industry, particularly through its applications in subfields such as deep learning, natural language processing, and computer vision (Zheng and Wang, 2024). These technologies are revolutionizing film production processes and redefining audience engagement. AI's advanced capabilities are extensively applied in screenplay analysis, film editing, special effects, and audience behavior analytics. By analyzing vast arrays of script and film data, AI identifies common features of successful films and generates innovative scripts, significantly enhancing production efficiency (Huang et al., 2023). Furthermore, AI analyzes audience feedback and preferences, rapidly processes large datasets, and shortens production cycles, enabling creative teams to produce high-quality films that meet market demands more effectively.

Bibhu Dash et al: CCSITA, VISCOM, ELE, BCYIoT, EDIT, AIDD - 2024
pp. 163-177, 2024. IJCI – 2024 DOI:10.5121/ijci.2024.130510

Artificial Intelligence (AI) advancement refers to the progression of AI technologies or applied sciences in becoming more accurate, reliable, precise, powerful, efficient, and capable (Chen et al., 2023; Bahoo et al., 2023). This advancement enables AI technologies to handle complex tasks, learn, and self-optimize. It is evident not only in the increasing complexity of algorithms and models but also in their superior performance in data processing, pattern recognition, natural language processing, machine learning, and deep learning (Loureiro et al., 2021). In the film industry, AI's advanced features are uniquely manifested in several key areas: firstly, AI plays a critical role in screenplay writing, plot design, and character development, analyzing extensive script data and audience feedback to generate and refine initial script drafts tailored to viewer preferences, thereby enhancing creative efficiency and content quality (Zheng and Wang, 2024). Secondly, AI utilizes big data analytics to predict audience preferences and market trends, providing personalized movie recommendations and helping film companies to craft more precise marketing strategies (Wu and Monfort, 2023). Lastly, AI's application in special effects production and video editing significantly boosts operational efficiency and outcomes, automating complex tasks and reducing manual labor, which enhances the quality of visual effects (Huang et al., 2023).

Applying AI correctly while preserving the commercial and artistic integrity of films is crucial. However, as the film industry evolves and audience demands diversify, film enterprises face the challenge of effectively leveraging AI to enhance both work quality and corporate performance. First, many companies lack the technological infrastructure and skilled personnel needed to integrate AI into existing processes (Huang et al., 2023). Additionally, AI's effectiveness depends on high-quality, complete data (Kemp, 2024), but film companies often struggle with poor data quality and missing information. Moreover, the industry's reliance on creative and cultural elements poses challenges for AI replication. These issues underscore the complexity of AI implementation and its impact on corporate performance, making it essential to assess AI's potential and explore related mechanisms and moderating factors.

Furthermore, while advanced AI significantly boosts the speed and quality of innovation within film companies, its impact on firm performance still requires empirical validation. AI applications in screenplay writing, video editing, special effects, and market analysis not only accelerate production but also enhance final product quality (Liu et al., 2023). However, despite AI's ability to analyze extensive data and identify successful film patterns, aiding creators in aligning with market expectations (Han et al., 2024), it also results in convergence in plot, characters, and visual effects. This convergence diminishes the viewing experience and erodes brand differentiation. Although such strategies may yield short-term gains, the lack of genuine innovation could undermine sustained audience interest and market position (Wu and Monfort, 2023). Therefore, a critical question arises: can AI's advancment truly enhance firm performance through improved innovation speed and quality? This study seeks to address this key inquiry.

Finally, the role of human-machine collaboration in leveraging artificial intelligence to enhance innovation speed and quality, thereby impacting film enterprise performance, remains underexplored. On one hand, film companies must redesign workflows and adjust team structures to maximize human-machine synergy after adopting AI technologies (Simón et al., 2024; Bouschery et al., 2023). On the other hand, potential deficiencies in financial and technical personnel resources may hinder continuous adaptation to rapidly evolving AI technologies, affecting the efficacy of AI application and the efficiency of human-machine collaboration (Li et al., 2021). Consequently, whether human-machine collaboration can effectively harness the capabilities of advanced AI to boost performance in the film industry remains an unresolved scholarly question.

Building on the previous analysis, this study seeks to investigate the following questions: (1) Can AI advancement enhance film enterprise performance? (2) Does AI advancement impact film enterprise performance by improving innovation speed and quality? (3) What role does the degree of human-machine collaboration play in these processes? To address these questions, we developed a moderated mediation model to explore the mechanisms through which AI advancement affects film enterprise performance, analyzing the mediating effects of innovation speed and quality, along with the moderating effect of human-machine collaboration. Data were collected from 355 respondents across global film enterprises via the Prolific academic platform and analyzed using the PLS-SEM method.

This research contributes in several ways: First, it delves into the specific context of film enterprises, exploring how advanced AI influences firm performance and underscores the strategic role of AI as a resource in this sector, thereby addressing a significant gap in the literature (Krakowski et al., 2023). Second, it dissects the differentiated mediating mechanisms between AI advancement and film enterprise performance, emphasizing the critical role of innovation quality over speed in securing competitive advantages for film enterprises (Wang et al., 2021). Third, it examines the role of human-machine collaboration as a boundary condition, elucidating its pivotal function in the application of AI within film enterprises, thus providing both theoretical insights and practical guidance for leveraging AI to enhance innovation capabilities in the film industry.

2. THEORETICAL FOUNDATION AND HYPOTHESES DEVELOPMENT

2.1. Resource-Based View

The Resource-Based View (RBV) argues that a firm's competitive advantage derives from its unique resources and capabilities, which should be valuable, rare, inimitable, and non-substitutable (VRIN) to sustain competitive advantage. According to RBV, firms must strategically identify, acquire, and exploit these resources to achieve long-term competitive advantage and performance enhancements. These resources include both tangible assets, such as equipment and capital, and intangible assets, such as brands, patents, technology, and corporate culture (Lavie, 2006). RBV emphasizes that a firm's unique resources are foundational to its strategy formulation and execution, enabling it to maintain a lead in competitive markets (Helfat et al., 2023).

With the rapid advancement of technology, Artificial Intelligence (AI) has increasingly become a pivotal strategic resource for businesses. As a highly advanced technology, AI significantly enhances operational efficiency and decision quality through data analysis, machine learning, and intelligent decision support (Fountaine et al., 2019). Within the RBV framework, AI is characterized by its scarcity, difficulty to imitate, and substantial value, making it a crucial resource for gaining competitive advantages (Kemp, 2024). AI's ability to process and analyze vast quantities of data to extract valuable insights enables more precise strategic decision-making. This data-driven decision model not only increases market responsiveness but also optimizes resource allocation and enhances overall operational efficiency (Sullivan and Wamba, 2024). Additionally, AI's high degree of intelligence and self-learning capabilities allows it to continually adapt and optimize business operations, further solidifying its role as a strategic resource (Haefner et al., 2023).

In the film industry, AI as a strategic resource plays a critical role in driving innovation. For instance, through natural language processing and machine learning algorithms, AI can autonomously generate initial script drafts and optimize plots based on audience feedback, thereby enhancing creative efficiency and content quality (Zheng and Wang, 2024). Furthermore, AI's application in market analysis and forecasting helps film companies better understand audience demands and market trends, enabling them to devise more accurate marketing strategies and drive cinematic innovation (Wu and Monfort, 2023). Additionally, AI's role in special effects production and video editing not only raises the technical standards and visual effects of films but also propels technological innovation within the industry (Huang et al., 2023). By optimizing resource allocation and improving decision quality, AI not only enhances the innovative capabilities of film companies but also provides them with a significant competitive edge in a fiercely competitive market. Overall, as a strategic resource, AI significantly promotes innovation and development in film companies through enhancing content creation, market analysis, and technical application capabilities.

2.2. AI Advancement and Film Firm Performance

AI advancement reflects a high level of innovation and exceptional performance in the development and application of artificial intelligence technologies. This encompasses the most recent and effective uses of AI in processing complex tasks, optimizing decision-making processes, and enhancing productivity (Chen and Tajdini, 2024; Chen et al., 2023). AI's superior capabilities are evident in several key areas. First, AI systems continuously self-improve by analyzing extensive datasets, enabling them to adapt to diverse and dynamically changing environments. This adaptability enhances decision accuracy and efficiency (Mikalef and Gupta, 2021). Second, through machine learning and data mining, AI provides precise and rapid decision support for market analysis, risk assessment, and customer behavior forecasting, which are critical for strategic business planning, marketing, and operational optimization (Bag et al., 2021). Third, AI autonomously performs complex and repetitive tasks, significantly boosting production efficiency and reducing human error, with applications ranging from robotic operations in manufacturing to intelligent customer service in the service sector (Babina et al., 2024; Zhai and Liu, 2023).

In the film industry, the advancement of AI technologies is crucial for enhancing the efficiency and effectiveness of production, marketing, and distribution processes. AI-driven tools for scriptwriting, editing, and visual effects optimize workflows, significantly reducing both production time and costs, thereby boosting overall efficiency and promoting firm growth (Babina et al., 2024). Additionally, AI enables data-driven decision-making by leveraging big data to better understand audience preferences and market trends. This approach allows firms to make more informed decisions about content creation, marketing strategies, and distribution channels, and to optimize marketing efforts with personalized content targeting specific audiences, ultimately enhancing performance (Xiong et al., 2023; Bag et al., 2021). Furthermore, AI technologies such as chatbots and recommendation systems enhance customer engagement, increasing viewer retention and subscription levels for streaming services, which in turn improves customer satisfaction and loyalty, leading to better firm performance (Chen and Tajdini, 2024; Kemp, 2024). Based on this, we propose the following hypothesis:

Hypothesis 1: AI advancement has a positive effect on film firm performance.

2.3. AI Advancement, Innovation Speed, and Film Firm Performance

Innovation speed, defined as the time span from the conception of new ideas to their introduction in the market, reflects a company's ability to respond swiftly to market demands and technological advancements (Hsiaog and Wu, 2024). A higher innovation speed enables companies to quickly launch new products, securing a market lead and competitive advantage (H. L. Zhang et al., 2020). Film companies, leveraging AI and other advanced technologies, can significantly shorten the timeline from concept development to film release. For instance, AI-driven scriptwriting and editing tools expedite content generation and modifications, thus accelerating the production process (Zheng and Wang, 2024). Furthermore, by analyzing audience data and market trends, film companies can swiftly adjust production and marketing strategies to release films that meet market demands , maintaining a competitive edge in a fiercely competitive market (Kemp, 2024; Krakowski et al., 2023).

AI advancement profoundly influences the innovation speed of film companies. First, the application of AI technology can greatly automate the film production process. AI-driven tools for scriptwriting and video editing can drastically reduce the time from concept to final product , enhancing the efficiency and speed of film production by minimizing human intervention and accelerating the editing process (Han et al., 2024). Second, AI enables film companies to use big data to analyze and respond to market changes in real-time, quickly identifying market trends and audience preferences, which optimizes decision-making processes. This capability allows for rapid adjustments in film production and distribution strategies, thus shortening the product development cycle and enhancing innovation speed (Liu et al., 2023; Aslam et al., 2024). Third, AI provides a suite of innovative tools and platforms, such as virtual reality (VR), augmented reality (AR), and deep learning algorithms, which accelerate various aspects of film production and facilitate rapid experimentation and iteration, further increasing the speed of innovation (Huang et al., 2023). Based on the analysis above, the following hypothesis is proposed:

Hypothesis 2a: AI advancement has a positive effect on innovation speed.

Innovation speed enhances competitive advantages for film companies. Specifically, a higher rate of innovation enables film companies to rapidly introduce new works to the market, thereby seizing market opportunities and capturing a larger market share. Research indicates that companies able to swiftly respond to market demands generally hold a competitive edge (Zhang et al., 2020). By accelerating innovation speed, film companies can release a greater number of movies in shorter periods, allowing for flexible adjustments in content and marketing strategies, which in turn increases market exposure and box office revenues (Chen et al., 2010). Additionally, the continuous and rapid release of high-quality, innovative works enhances a film company's brand value and reputation. Audience loyalty and identification often stem from regular exposure to new and engaging content. The increased pace of innovation not only improves the quality and appeal of films but also strengthens audience trust and reliance on the brand (Guo et al., 2020). Furthermore, a high rate of innovation aids in improving resource allocation and management effectiveness. By expediting the innovation process, companies can better utilize their resources, reduce waste, and increase productivity , which in turn enhances operational efficiency and overall firm performance (Zhai and Liu, 2023; Czarnitzki et al., 2023). Based on this analysis, the following hypothesis is proposed:

Hypothesis 2b: Innovation speed has a positive effect on film firm performance.

The relationship between AI advancement, innovation speed, and film firm performance is evident in several key aspects. First, AI accelerates film production through enhanced automation and optimized resource allocation, directly boosting innovation speed. This enables film enterprises to bring new works to market more quickly, thereby enhancing firm performance (Yang, 2022; Liu et al., 2023). Second, AI allows film companies to leverage big data for real-time analysis and response to market changes, quickly identifying trends and audience preferences. This data-driven approach facilitates the rapid launch of innovative products that meet market demands, improving decision-making accuracy and efficiency, accelerating product development and marketing strategies, and shortening the innovation cycle, thus enhancing market competitiveness and firm performance (Li et al., 2024; Volkmar et al., 2022). Third, AI tools such as project management and collaboration platforms enhance the integration of technology and creativity, improving team collaboration efficiency and enabling rapid innovation experiments and product iterations (Xiong et al., 2020). This integration not only elevates the technical level of film production but also increases the speed of innovation, allowing companies to meet audience expectations more swiftly, thereby further boosting firm performance (Mühlroth and Grottke, 2020). Based on these insights, the following hypothesis is proposed:

Hypothesis 2c: Innovation speed mediates the relationship between AI advancement and film firm performance.

2.4. AI Advancement, Innovation Quality, and Film Firm Performance

Innovation quality refers to the superiority and uniqueness of innovation outcomes, including their market competitiveness, user acceptance, and long-term benefits, demonstrating an enterprise's excellence in technology, design, and market alignment (Wang et al., 2021; Griffin and Page, 1996). High-quality innovation not only meets user needs but also sets market trends, driving sustainable corporate growth and enhancing brand value (Guo et al., 2020). In the film industry, innovation quality manifests in several ways: firstly, high-quality innovation is evident in the originality of storylines and their appeal to audiences, with film companies utilizing big data and AI technologies to deeply explore audience preferences and create content that is both innovative and competitive (Li et al., 2024). Secondly, high-quality innovation results from the perfect integration of technology and art. For instance, by employing advanced special effects and high dynamic range imaging (HDR) technologies, film companies can produce works with superior visual effects, thus enhancing the viewer's experience (Huang et al., 2023). Thirdly, high-quality films can establish and solidify a brand's image in the market, forming a stable audience base and increasing brand loyalty (Wu and Monfort, 2023).

For film companies, AI advancement plays a crucial role in enhancing innovation quality. Firstly, advanced AI technology, by analyzing extensive audience data and market trends, enables film companies to recommend customized content based on audience preferences, providing precise insights and suggestions for high-quality film production. This data-driven approach significantly enhances the quality and market competitiveness of film content (Rust and Huang, 2021). Secondly, AI's application in film special effects and visual production, such as deep learning and image processing technologies, can create more realistic and striking visual experiences, directly enhancing the visual quality and appeal of films (Bahoo et al., 2023). AI can automate complex special effects tasks, thereby improving production efficiency and output quality (Li et al., 2023). Thirdly, AI technology can perform data-driven quality control at all stages of film production, significantly enhancing the overall quality of films. By analyzing data in real-time during the filming process, AI can promptly identify and correct potential issues, ensuring high-quality completion of each production phase (Aslam et al., 2024). Based on this analysis, the following hypothesis is proposed:

Hypothesis 3a: AI advancement has a positive effect on innovation quality.

High innovation quality confers significant advantages for film companies. First, high-quality innovation through superior content creation and high-level visual effects significantly enhances audience viewing experiences, not only increasing audience satisfaction but also boosting the likelihood of word-of-mouth promotion, further enhancing firm performance (Hennig-Thurau et al., 2006). Second, high-quality innovative works help shape the brand image of film companies, attracting more viewers and more investment and collaboration opportunities, thereby strengthening their market competitiveness. Research shows that businesses that consistently release high-quality innovative works generally establish strong brand identification and trust among audiences, thus securing a competitive edge in the market (Wang et al., 2023). Third, high-quality innovation reflects the internal innovation capability and management level of film companies. By continually enhancing innovation quality, companies can accumulate more experience and knowledge, improve the creativity and execution ability of internal teams, and generate more high-quality innovative outcomes, further enhancing firm performance (Jia et al., 2024). Based on this analysis, the following hypothesis is proposed:

Hypothesis 3b: Innovation quality has a positive effect on film firm performance.

For film companies, the artificial intelligence advancement significantly enhances the quality of film content by analyzing extensive audience data and market trends to tailor content to audience preferences, thus increasing viewer satisfaction and market competitiveness (Rust and Huang, 2021). Additionally, the sophistication of AI plays a crucial role in the production of film effects and visual enhancements, directly improving the visual quality and appeal of films, thereby strengthening their market attractiveness and firm performance (Sullivan and Wamba, 2024). Moreover, AI's advanced capabilities are evident in data-driven quality control throughout the film production process. This method of quality management significantly enhances the overall quality of films, thus increasing viewer satisfaction and firm performance (Wang et al., 2023). For example, by analyzing data in real-time during filming, AI can promptly identify and rectify potential issues, ensuring high-quality completion of each production phase, thereby reducing production costs and enhancing efficiency (Davenport and Ronanki, 2018). Based on this analysis, the following hypothesis is proposed:

Hypothesis 3c: Innovation quality mediates the relationship between AI advancement and film firm performance.

2.5. The Moderating Role of Human-Machine Collaboration in Film Production

The degree of human-AI collaboration refers to the depth and breadth of cooperation between humans and artificial intelligence systems within workflows. This concept highlights a spectrum from simple tool use to highly complex collaborative relationships, where AI acts not just as an assistive tool but as a strategic partner, jointly participating in decision-making and innovation processes (Wilson and Daugherty, 2018). In the film industry, this collaboration manifests in various aspects of film creation such as scriptwriting, editing, and special effects production, where AI can draft scripts based on extensive data analysis, and human screenwriters then refine these drafts to enhance both efficiency and quality of the content (Hutchinson, 2021). Furthermore, film companies use AI for market analysis and audience preference forecasting, optimizing marketing strategies through human-AI collaboration. AI analyzes viewing data and feedback to provide precise market insights and recommendations, while human marketing teams develop specific marketing plans and activities based on this data, ensuring that marketing content delivery aligns with best user experience practices (Davenport and Ronanki, 2018). Additionally, in film production management, AI assists with project management and resource allocation, using real-time data analysis to optimize production processes and resource utilization, while human managers use AI-generated insights to make informed decisions, ensuring projects proceed on schedule and within budget (Haenlein and Kaplan, 2019).

In film enterprises, a high level of human-AI collaboration effectively merges human creative thinking with AI's efficient data processing capabilities, accelerating the innovation process. For instance, in film production, AI can rapidly produce initial scripts and video edits, allowing human screenwriters and editors to make creative adjustments and refinements, significantly shortening the time from concept to final product (Wilson and Daugherty, 2018), ensuring that film companies can quickly respond to market demands (Glikson and Woolley, 2020).

Additionally, under high levels of human-AI collaboration, film companies can enhance innovation quality through advanced AI's precise analysis and human artistic judgment. For example, AI can provide creative and design suggestions by analyzing audience feedback and market trends, while humans can use this data for creative expression and artistic adjustments, not only improving the quality of content creation but also optimizing special effects and visual appeal, ensuring high-quality film output and increasing the originality and market appeal of the film products (Loureiro et al., 2021). Lastly, the advantages of AI in data analysis, market forecasting, and resource management, combined with human capabilities in strategic decision-making, creative planning, and market execution, can lead to more efficient resource allocation and more precise marketing strategies (Davenport and Ronanki, 2018), significantly enhancing the firm's market competitiveness and financial performance (Rust and Huang, 2021).Based on the above discussion, this paper proposes the following hypotheses:

Hypothesis 4: Human-machine collaboration degree positively moderates the relationships between AI advancement and *(a)* innovation speed, *(b)* innovation quality, *(c)* film firm performance, such that the relationships are stronger with a higher level of human-machine collaboration.

Hypothesis 5: Human-machine collaboration degree positively moderates the indirect effect of *(a)* innovation speed and *(b)* innovation quality between AI advancement and film firm performance, such that the indirect relationships are stronger with a higher level of human-machine collaboration.

The conceptual framework underpinning our inquiry is illustrated in Figure 1.

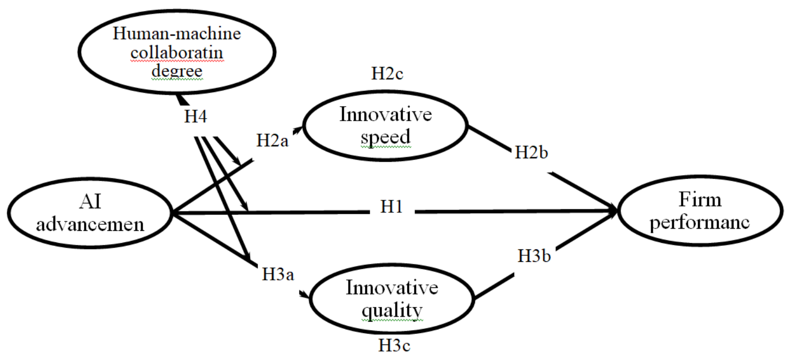


Figure 1 Research model.

3. METHOD

3.1. Data Collection and Sample

This study aims to explore the mechanisms by which artificial intelligence (AI) advancement impacts the performance of film companies, focusing on the mediating effects of innovation quality and speed, as well as the moderating effect of the degree of human-AI collaboration. To this end, we designed a questionnaire comprising three sections: the first section measures AI advancement, innovation speed, innovation quality, firm performance, and the degree of human-AI collaboration; the second section collects demographic and organizational information about respondents, including gender, age, education level, position, area of responsibility, the age of the company, number of employees, and scope of operations; the third section involves open-ended questions regarding the company's application of AI, strategic actions, future development, and skill requirements.

An online survey was conducted via the Prolific platform, known for its effectiveness in management research surveys (Jeesha and Purani, 2021; Kossyva et al., 2023). This platform offers access to a diverse global workforce, and its validity and reliability for data collection have been confirmed by several studies (Peer et al., 2017), showing no significant differences from traditional paper-based surveys. Prior to the main survey, we conducted a pilot study with 100 questionnaires distributed to senior managers of global film companies to verify the authenticity and validity of the responses. Measures included: (1) asking respondents to provide the name or URL of their company while ensuring confidentiality; (2) verifying the existence of these companies and any related news online based on the country information from our backend; (3) examining the open-ended responses to assess respondents' understanding of AI applications in their companies; and (4) analyzing the relevance of responses to assess the validity of the survey. This preliminary phase confirmed the high authenticity and credibility of the data collected through the Prolific academic platform. Subsequently, we distributed 400 questionnaires, achieving an 88.75% response rate with 355 valid responses. Descriptive statistics of these respondents and their organizations are detailed in Table 1, providing an insightful overview of the sample characteristics.

Table 1 Descriptive statistics of respondent information.

Characteristics	Types	Number	Percentage
Gender	Male	212	59.72%
	Female	143	40.28%
Age	≤25 years old	60	16.90%
	26-35 years old	152	42.82%
	36-45 years old	95	26.76%
	＞46 years old	48	13.52%
Education	Junior college and below	74	20.85%
	Undergraduate	202	56.90%
	Master degree	72	20.28%
	Doctoral and Postdoctoral	7	1.97%
Position	Chairman or general manager	57	16.06%
	Senior management	73	20.56%
	Middle management	165	46.48%
	Other	60	16.90%
Responsible field	Research and Development (R&D)	29	8.17%
	Technology	73	20.56%
	Product	112	31.55%
	Marketing	69	19.44%
	Human Resources (HR); Finance; Public Relation	14	3.94%
	Others	58	16.34%
Established years	＜3 years	60	16.90%
	3-5 years	70	19.72%
	5-10 years	78	21.97%
	＞10 years	142	40.00%
Number of employees	≤100	239	67.32%
	101-300	49	13.80%
	301-500	26	7.32%
	501-1000	15	4.23%
	≥1001	26	7.32%

3.2. Measurement

In this study, we adopted measurement items for all variables from prior research, with detailed items provided in the appendix. We assessed all variables using a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). To gauge AI advancement, we utilized a five-item scale developed by Chen et al. (2023). For innovation speed, we adapted a four-item scale from Zhang et al. (2020). The measurement of innovation quality employed a five-item scale from Wang et al. (2023). Firm performance was assessed using four items based on the empirical framework of Han et al. (2024). To evaluate the degree of human-machine collaboration, we adapted a four-item scale from Timothy et al. (2010). The study also included control variables, divided into two main categories: the first addressed respondent demographics such as gender, age, education level, and job position, while the second focused on organizational characteristics including the length of establishment, employee count, and scope of operations.

3.3. Data Analysis

For data analysis and hypothesis testing, our research employed Partial Least Squares Structural Equation Modeling (PLS-SEM), recognized for its robustness and adaptability in handling complex structural models in management studies (Han et al., 2024). This approach is advantageous for its capacity to manage models incorporating multiple variables—as in this study, which involves five distinct variables (Hair et al., 2012). PLS-SEM excels in evaluating both mediating and moderating effects, offering deep insights into the model's underlying dynamics (Hashi and Stojcic, 2013). Its applicability across a wide range of sample sizes makes it suitable for diverse study scales (Hair et al., 2019). To assure the reliability and validity of our findings, we utilized a bootstrap methodology with 5000 sub-samples to validate the mediating effects within the model. Using Smart PLS 4 software, the analysis was structured in two phases: initially assessing the measurement model to ensure accurate reflection of the theoretical constructs, followed by evaluating the structural model to test the research hypotheses according to (Henseler et al., 2016).

4. RESULTS

4.1. Common Method Bias

To enhance data reliability and minimize common method bias, the survey was designed for anonymous completion, with questions randomized to mitigate order effects (Palacios-Manzano et al., 2021). We assessed potential multicollinearity through the variance inflation factor (VIF), considering values over 5 as indicative of concerns; however, all VIF scores remained below this threshold, indicating no issues with multicollinearity (Hair et al., 2019). Additionally, Harman's single-factor test showed the first factor accounted for 35.63% of the variance, with a KMO value of 0.942. We also implemented the unmeasured latent common method factor (ULCMF) technique, which suggested minimal common method variance (Podsakoff et al., 2003). Confirmatory factor analysis validated a five-factor model (χ^2/df = 1.925, CFI = 0.964, TLI = 0.959, RMSEA = 0.031), which performed better than a one-factor model ($\Delta\chi^2$ = 1505.202, Δdf = 10, $p < 0.001$), and exhibited only minor differences when compared to the ULCMF model, thus confirming the robustness of our measurements against common method bias ($\Delta\chi^2/df$ = 0.689, ΔCFI = 0.008, ΔTLI = 0.010, and ΔRMSEA = 0.005). These findings are comprehensively detailed in Table 2.

Table 2 Common method bias analysis.

Model	χ^2	*df*	CFI	TLI	RMSEA
Single-factor model	1928.721	230	0.700	0.670	0.144
Five-factor model	423.519	220	0.964	0.959	0.031
ULCMF	243.449	197	0.972	0.969	0.026

4.2. Measurement Model

The model structure of this study was tested for reliability and validity, as shown in Table 3. First, all items in the five variables had factor loadings greater than 0.7, which supports the reliability of the indicators (Hair et al., 2012). Second, the Cronbach's alpha (α) of all variables was higher than 0.8, which is consistent with the interval that should be higher than 0.7. Moreover, the composite reliability (CR) values were higher than 0.8, which is greater than the minimum standard criterion of 0.5, indicating that the construct reliability of the scale is excellent (Hair et al., 2019). Third, the average variance extracted (AVE) of all variables is greater than 0.5, indicating that the indicator variable can effectively reflect its latent variable, which has good reliability and validity, which supports the convergent validity of the scale construct measure (Henseler et al., 2016).

Table 3 The Measurement model results.

Variables	Item	Factor loading	T-Value	α	CR	AVE
AI Advancement (AIA)	AIA1	0.829	37.605	0.900	0.924	0.669
	AIA2	0.788	28.646			
	AIA3	0.872	62.019			
	AIA4	0.841	45.112			
	AIA5	0.851	48.222			
	AIA6	0.718	24.535			
innovation speed (IS)	IS1	0.687	16.146	0.751	0.842	0.575
	IS2	0.646	12.831			
	IS3	0.843	46.782			
	IS4	0.837	42.357			
innovation quality (IQ)	IQ1	0.626	12.712	0.826	0.878	0.591
	IQ2	0.84	50.215			
	IQ3	0.806	32.828			
	IQ4	0.783	26.461			
	IQ5	0.773	26.673			
Firm performance (FP)	FP1	0.89	59.166	0.894	0.926	0.759
	FP2	0.889	63.832			
	FP3	0.819	30.717			
	FP4	0.885	65.389			
Human-machine collaboration degree (HMC)	HMC1	0.86	41.868	0.901	0.931	0.771
	HMC2	0.882	55.949			
	HMC3	0.89	59.814			
	HMC4	0.879	59.906			

Finally, the paper examines the discriminant validity between the variables, as shown in Table 4. The AVE of each construct should be compared with the squared inter-structural correlation (as a measure of shared variance) for that same construct and with all other reflectivity measures in the structural model. In addition, the shared variance of all model configurations should not be greater than their AVE (Hair et al., 2019). The heterotrait-monotrait (HTMT) ratios of correlations are all below the threshold of 0.9 (Voorhees et al., 2016), indicating the discriminant validity of the scale.

Table 4 Discriminant validity.

	AIA	IS	IQ	FP	HMC
AIA	**0.818**	0.799	0.788	0.736	0.732
IS	0.673	**0.758**	0.887	0.699	0.537
IQ	0.691	0.710	**0.769**	0.823	0.450
FP	0.666	0.582	0.725	**0.871**	0.409
HMC	0.659	0.454	0.389	0.371	**0.878**

Note: HTMT ratio over the diagonal (italics). Fornell–Larcker criterion: square root of AVE in diagonal (bold) and construct correlations below the diagonal.

4.3. Structural Model Evaluation

In this paper, we measure the R^2 and f^2 values of endogenous building blocks as in-sample predictive power, with R^2 values of 0.75, 0.50 and 0.25 being considered substantial, moderate and weak. $R^2_{IS} = 0.484$, $R^2_{IQ} = 0.518$, $R^2_{FP} = 0.584$, indicating the high explanatory power of the model (Henseler et al., 2016). Meanwhile, Q^2 is an indicator that combines out-of-sample predictive power and in-sample explanatory power (Hair & Sarstedt et al., 2019), and the blinded results have Q^2 values well above zero at an omission distance of 7 ($Q^2_{FP} = 0.451$; $Q^2_{IQ} = 0.491$; $Q^2_{IS} = 0.455$), indicating the high predictive accuracy of the constructed structural model (Cepeda-Carrion et al., 2019).

4.4. Hypothesis Testing

The hypothesis testing results are illustrated in Table 5 and Figure 2. The findings demonstrate that AI advancement positively impacts film firm performance ($\beta = 0.308$, $t = 5.38$), thereby supporting Hypothesis 1. The path coefficient for the impact of AI advancement on innovation speed is 0.601 ($t = 10.723$), suggesting that AI advancement positively influences innovation speed, supporting Hypothesis 2a. Conversely, the path coefficient for innovation speed affecting firm performance is 0.024, with a t-value of 0.387, indicating that Hypothesis 2b is not supported. Additionally, the path coefficient for the impact of AI advancement on innovation quality is 0.711, with a t-value of 15.462, supporting Hypothesis 3a. The influence of innovation quality on firm performance is significant with a path coefficient of 0.495 ($t = 7.681$), confirming Hypothesis 3b.

The mediation effects of innovation speed and innovation quality between AI advancement and firm performance were assessed using a bootstrap method with 5,000 subsamples. The analysis revealed that the path coefficient of innovation speed between AI advancement and firm performance is 0.010 ($t = 0.256$), with a Variance Accounted For (VAF) value of 0.027 (less than 0.2), indicating that innovation speed does not mediate the relationship between AI advancement and firm performance, confirming Hypothesis 4a. Conversely, the path coefficient for innovation quality is 0.332, with a t-value of 6.044 and a VAF of 0.485 (greater than 0.2 and less than 0.8), indicating partial mediation and supporting Hypothesis 4b (Han et al., 2024).

Table 5 Structural model and hypothesis testing results.

	path	T-value	f²	95%CI		H	Supported
Direct effects					VIF		
AIA→FP	0.308	5.38***	0.096	[0.207, 0.495]	3.120	H1	YES
AIA→IS	0.601	10.723***	0.373	[0.488, 0.707]	1.878	H2a	YES
AIA→IQ	0.711	15.462***	0.558	[0.617, 0.799]	1.878	H2b	YES
IS→FP	0.024	0.387	0.001	[-0.102, 0.143]	2.377	H3a	NO
IQ→FP	0.495	7.681***	0.207	[0.339, 0.596]	2.543	H3b	YES
Moderating effects							
Moderating effects→IS	0.175	4.116***	0.061	[0.089, 0.255]	1.067	H5a	YES
Moderating effects→IQ	0.176	4.484***	0.066	[0.097, 0.250]	1.067	H5b	YES
Moderating effects→FP	0.064	1.471	0.009	[-0.022, 0.149]	1.161	H5c	NO
Indirect effects					VAF		
AIA→IS→FP	0.010	0.256		[-0.064,0.087]	0.027	H4a	NO
AIA→IQ→FP	0.332	6.044***		[0.228,0.444]	0.485	H4b	YES

Note: N=355; *p<0.05, p<0.01, *p<0.001.

The results of the moderating effect analysis demonstrate that the degree of human-AI collaboration positively moderates the relationship between AI advancement and both innovation speed (β = 0.175, t = 4.116) and innovation quality (β = 0.176, t = 4.484), supporting H4a and H4b, as depicted in Figure 3. However, the moderating effect of human-AI collaboration on the relationship between AI advancement and firm performance is not significant (β = 0.064, t = 1.471), indicating that H4c is not supported.

Furthermore, using bootstrapping for confidence interval estimation, we analyzed the conditional influence of human-AI collaboration on the indirect effects of innovation speed between AI advancement and firm performance. The index for the first moderated mediating path is 0.003 (95% CI = [-0.019, 0.027]), indicating a non-significant moderated mediation effect, thereby not supporting H5a. This suggests that human-AI collaboration does not strengthen the indirect effect of AI advancement on firm performance through innovation speed. Conversely, the index for the second moderated mediating path is 0.082 (95% CI = [0.045, 0.120]), indicating a significant moderated mediation effect where human-AI collaboration enhances the indirect relationship between AI advancement and firm performance through innovation quality, supporting H5b.

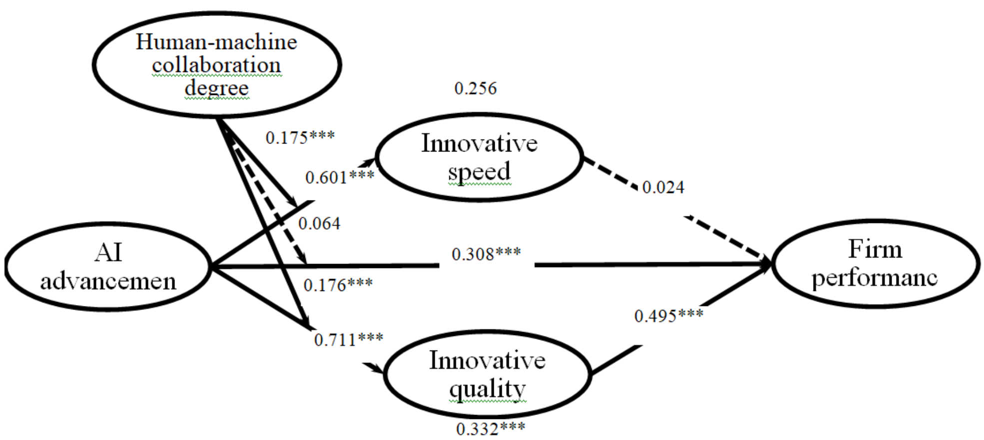
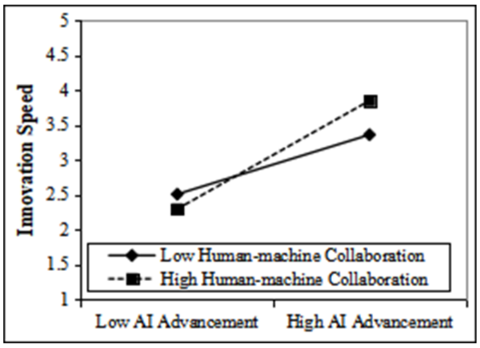


Figure 2 Path testing result.



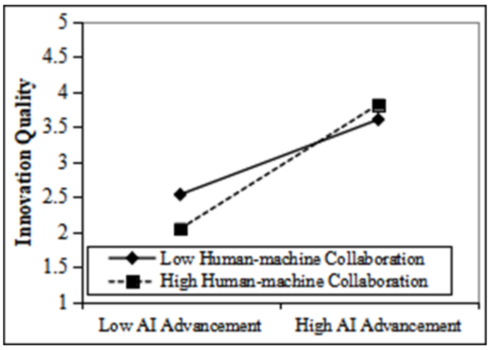


Figure 3 The moderating effect of the degree of human-machine collaboration.

Table 6 The results of the moderated mediation effect of the degree of human-machine collaboration

Path	Moderator	Mediation effect	Standard deviation	BootLLCI	BootULCI
HMC*AIA→IS→FP	Low	0.319	0.063	0.196	0.442
	Median	0.484	0.042	0.401	0.567
	High	0.576	0.045	0.487	0.664
HMC*AIA→IQ→FP	Low	0.350	0.061	0.023	0.471
	Median	0.540	0.041	0.460	0.621
	High	0.646	0.044	0.560	0.732

Notes: N=355; 5000 bootstrap samples.

REFERENCES

[1] Aslam, M. S., Qammar, A., Ali, I., Yaqub, M. Z., Ahmed, F., & Mohapatra, A. K. (2024) "Fostering innovation speed and quality in ICT firms: The role of knowledge governance mechanisms, absorptive capacity and environmental dynamism", Technological Forecasting and Social Change, Vol. 205, DOI: http://doi.org/10.1016/j.techfore.2024.123460.

[2] Babina, T., Fedyk, A., He, A. L., & Hodson, J. (2024) "Artificial intelligence, firm growth, and product innovation", Journal of Financial Economics, Vol. 151, DOI: http://doi.org/10.1016/j.jfineco.2023.103745.

[3] Bag, S., Gupta, S., Kumar, A., & Sivarajah, U. (2021) "An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance", Industrial Marketing Management, Vol. 92, pp. 178-189, DOI: http://doi.org/10.1016/j.indmarman.2020.12.001.

[4] Bahoo, S., Cucculelli, M., & Qamar, D. (2023) "Artificial intelligence and corporate innovation: A review and research agenda", Technological Forecasting and Social Change, Vol. 188, DOI: 10.1016/j.techfore.2023.122264.

[5] Barney, J. (1991) "Firm resources and sustained competitive advantage", Journal of Management, Vol. 17, No. 1, pp. 99-120.

[6] Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023) "Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models", Journal of Product Innovation Management, Vol. 40, No. 2, pp. 139-153.

[7] Cepeda-Carrion, G., Cegarra-Navarro, J. G., & Cillo, V. (2019) "Tips to use partial least squares structural equation modelling (PLS-SEM) in knowledge management", Journal of Knowledge Management, Vol. 23, No. 1, pp. 67-89, DOI: http://doi.org/10.1108/JKM-05-2018-0322.

[8] Chan-Olmsted, S. M. (2019) "A review of artificial intelligence adoptions in the media industry", International Journal On Media Management, Vol. 21, No. 3-4, pp. 193-215.

[9] Chen, J., Damanpour, F., & Reilly, R. R. (2010) "Understanding antecedents of new product development speed: A meta-analysis", Journal of Operations Management, Vol. 28, No. 1, pp. 17-33.

[10] Chen, J., & Tajdini, S. (2024) "A moderated model of artificial intelligence adoption in firms and its effects on their performance", Information Technology & Management, DOI: http://doi.org/10.1007/s10799-024-00422-5.

[11] Chen, S., Su, Y., Tufail, B., Lam, V. T., Phan, T. T. H., & Ngo, T. Q. (2023) "The moderating role of leadership on the relationship between green supply chain management, technological advancement, and knowledge management in sustainable performance", Environmental Science and Pollution Research, Vol. 30, No. 19, pp. 56654-56669.

[12] Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023) "Artificial intelligence and firm-level productivity", Journal of Economic Behavior & Organization, Vol. 211, pp. 188-205, DOI: http://doi.org/10.1016/j.jebo.2023.05.008.

[13] Davenport, T. H., & Ronanki, R. (2018) "Artificial intelligence for the real world", Harvard Business Review, Vol. 96, No. 1, pp. 108-116.

[14] Fountaine, T., McCarthy, B., & Saleh, T. (2019) "Building the AI-powered organization", Harvard Business Review, Vol. 97, No. 4, pp. 62-73.

[15] Glikson, E., & Woolley, A. W. (2020) "Human trust in artificial intelligence: Review of empirical research", Academy of Management Annals, Vol. 14, No. 2, pp. 627-660.

[16] Griffin, A., & Page, A. L. (1996) "PDMA success measurement project: Recommended measures for product development success and failure", Journal of Product Innovation Management, Vol. 13, No. 6, pp. 478-496.

[17] Guo, F., Bo, Q. W., Tong, X., & Zhang, X. F. (2020) "A paradoxical view of speed and quality on operational outcome: An empirical investigation of innovation in high-tech small and medium-sized enterprises", International Journal of Production Economics, Vol. 229, DOI: http://doi.org/10.1016/j.ijpe.2020.107780.

[18] Haefner, N., Parida, V., Gassmann, O., & Wincent, J. (2023) "Implementing and scaling artificial intelligence: A review, framework, and research agenda", Technological Forecasting and Social Change, Vol. 197, DOI: http://doi.org/10.1016/j.techfore.2023.122878.

[19] Haenlein, M., & Kaplan, A. (2019) "A brief history of artificial intelligence: On the past, present, and future of artificial intelligence", California Management Review, Vol. 61, No. 4, pp. 5-14.

[20] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019) "When to use and how to report the results of PLS-SEM", European Business Review, Vol. 31, No. 1, pp. 2-24, DOI: http://doi.org/10.1108/ebr-11-2018-0203.

[21] Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012) "The use of partial least squares structural equation modeling in strategic management research: A review of past practices and recommendations for future applications", Long Range Planning, Vol. 45, No. 5-6, pp. 320-340, DOI: http://doi.org/10.1016/j.lrp.2012.09.008.

[22] Han, W., Li, X., Zhu, W., Lu, R., & Zu, X. (2024) "Knowledge digitization and high-tech firm performance: A moderated mediation model incorporating business model innovation and entrepreneurial orientation", Technology in Society, Vol. 77, DOI: http://doi.org/10.1016/j.techsoc.2024.102536.

AUTHOR

Zexia Wang is a fourth-year Ph.D. candidate at the University of Electronic Science and Technology of China, specializing in Business Administration with a focus on Innovation and Entrepreneurship Management. Under the guidance of Professor Ruoyu Lu, Zexia Wang's research explores the intersections of innovation dynamics, entrepreneurship ecosystems, and business strategy.

In addition to their academic pursuits, Zexia Wang has substantial professional experience in the film industry, having worked at the New York Film Academy in the United States. During this time, Zexia Wang played a significant role in the promotion and management of several high-profile film projects with Paramount Pictures. This blend of practical industry experience and academic expertise provides a unique perspective on the evolving landscape of business innovation and creative industries.