Marketing and Management of Innovations, **15(4)**, 2024

The Nexus Between Talent Management Attention and Artificial Intelligence: Evidence from Companies Operating Within the AI Domain

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Type of manuscript: Research paper

Cite as: Alruwaili, N. F., & Mokni, K. (2024). The Nexus Between Talent Management Attention and Artificial Intelligence: Evidence from Companies Operating Within AI Domain. *Marketing and Management of Innovations*, *15*(4), 85–98. https://doi.org/10.21272/mmi.2024.4-07

Received: 30 May 2024
Revised: 20 December 2024
Accepted: 25 December 2024

Publisher & Founder: Sumy State University

Abstract: This study examines the relationship between talent management (TM) attention and the performance of leading artificial intelligence (AI) companies. Using Google Trends data, TM attention is quantified through search queries related to talent acquisition, employee development, and workforce planning, while additional corporate metrics, such as HR performance reports and employee retention rates, are incorporated to increase the robustness of the analysis. AI company performance is measured via the stock returns of Microsoft, Google, Amazon, and NVIDIA, which represent key players in the AI sector. A nonparametric causality-in-quantiles test is applied to capture the asymmetric and heterogeneous effects of TM attention on stock returns across different market conditions, ranging from bearish to bullish scenarios. The results reveal significant causality from TM attention to AI stock performance under bearish and normal market conditions, emphasizing the importance of TM strategies during periods of market stress or stability. In contrast, TM attention exerts limited influence during bullish conditions, where performance is likely driven by other factors, such as market sentiment and technological advancements. A facet-specific analysis highlights that talent acquisition consistently influences stock performance across all market conditions, whereas employee development has a significant effect only during bearish and normal conditions. Workforce planning has limited causal influence, suggesting that its market impact depends on company-specific factors and contextual dynamics. This study makes important contributions to theory and practice by offering a nuanced understanding of TM's role in shaping organisational performance within the dynamic AI landscape. For companies, prioritizing effective TM strategies, particularly talent acquisition and employee development, can enhance resilience and competitiveness. Investors can leverage TM insights to refine portfolio strategies, whereas policymakers are encouraged to implement initiatives such as grants for workforce training or public–private partnerships to foster talent pipelines in the AI sector. These findings underscore the critical interplay between TM practices and market performance, providing actionable insights for navigating the complexities of the rapidly evolving AI industry.

Keywords: talent management; artificial intelligence; nonparametric causality; AI companies; stock markets.
Funding: There is no funding for this research.

1. Introduction. Talent management (TM) has become a keystone in the human resources (HR) strategy due to its pivotal role in an organization's performance (Collings and Mellahi, 2009) and its competitive advantage in the corporate world (Hongal and Kinange, 2020). Notably, when identifying and absorbing talent, HR guarantees efficacity and assurances that the right people are in the right places. Moreover, TM fosters employee appointment, increases productivity, and cultivates a culture of innovation and excellence within the organization (Goldsmith and Carter, 2009). Furthermore, effective talent management not only addresses current workforce needs but also anticipates future skill requirements, helping companies stay nimble in a rapidly evolving business landscape. Ultimately, interest in TM enhances competitiveness and fosters the long-term success of organisations by empowering employees to reach their full potential.

In particular, TM holds special importance for artificial intelligence (AI) companies, as suggested by the nature of the domain of these companies. In fact, skilled AI professionals are interested in innovation and advanced technologies. Thus, effective TM ensures that these companies acquire, nurture, and retain top-tier talent capable of pushing the boundaries of AI research and application. Moreover, in a highly competitive market, where demand for AI expertise is increasing, TM strategies become vital for attracting the best minds. Therefore, AI companies can maintain their competitive edge and drive forward evolution by investing in talent development.

With respect to the above developments, several studies have focused on the interest of TM in organisational development (Gonzalez et al., 2019; Odugbesan et al., 2023; Faqihi and Miah, 2023; Urme, 2023). In this way, the intersection of TM practices and the performance of artificial intelligence (AI) companies has received less attention from scholars, and this issue is still incomplete. Motivated by the fact that this domain encompasses strategies for attracting, developing, and retaining skilled personnel, which are widely recognized as critical determinants of organisational success and innovation within the dynamic landscape of the AI industry, this limitation should be addressed. On the other hand, the performance of AI companies, as reflected in stock market dynamics, serves as a key indicator of development and competitiveness. However, the relationship between TM and AI company performance remains underexplored, particularly in the context of varying market conditions and nuanced facets of talent management practices.

attention to AI company performance, employing a sophisticated approach that accounts for market heterogeneity and facet-specific analyses of TM. More precisely, the main objective of this study is to investigate whether TM attention can foster AI companies' development. In this context, leveraging Google Trends data, a widely utilized tool for gauging public interest through search query analysis, a composite TM variable representing overall TM attention, and specific facets such as talent acquisition (TA), employee development (ED), and workforce planning (WP) are constructed. This analysis employs a quantile framework, allowing for an examination of the relationship between TM attention and AI company performance across different quantile orders, reflecting varying market conditions ranging from bearish to bullish.

In response to this gap in the literature, this paper aims to investigate the causal relationship between talent management (TM) attention and AI company performance, employing a sophisticated approach that accounts for market heterogeneity and facet-specific analyses of TM. Specifically, this study seeks to answer the following research questions:

How does talent management attention influence the stock performance of AI companies under varying market conditions (bearish, normal, and bullish)?

Do different facets of talent management, such as talent acquisition, employee development, and workforce planning, exert differential impacts on AI companies' performance?

The quantile approach allows us to uncover potential asymmetries in the impact of TM attention on AI company performance across different distributional levels to shed light on the contexts in which TM attention exerts the most significant influence on stock market dynamics within the AI sector. Furthermore, by conducting facet-specific analyses, the differential effects of various talent management practices on AI company performance can be disentangled, offering insights into the nuanced mechanisms underlying the TM-performance relationship.

This paper contributes to the growing literature on TM and AI company performance by providing a more complete analysis accounting for market heterogeneity and facet-specific influences. Accordingly, the outputs of such studies have implications for AI companies seeking to optimize their TM strategies, investors evaluating AI company investments, and policymakers shaping policy design in the AI industry. Through a nuanced understanding of the causal relationship between TM attention and AI company performance, this paper aims to inform strategic decision-making and foster sustainable growth and innovation within the dynamic AI landscape.

The remainder of this paper is structured as follows: Section two provides a literature review and discusses key previous studies. Section three presents the data and preliminary analysis. In section four, the methodology used in this study is outlined. Section five focuses on the empirical analysis. Finally, section six concludes the paper.

2. Literature Review. Several studies have been conducted on how modern technologies and HR technologies are adopted in businesses. These modern technologies that have been used extensively in businesses in recent years include digital innovation adoption, big data solutions, business analytics and intelligence, business intelligence systems, human resources information systems (HRISs), e-HRM, social recruiting, SaaS, business intelligence systems, AI-based robotic devices, Robo-advisors, intelligent personal assistants, self-driving vehicles, augmented reality and interactive technology, and implications of AI in recruitment (El-Haddadeh, 2020; Salleh & Janczewski, 2018; Cruz-Jesus et al., 2018; Puklavec et al., 2018; Phahlane, 2017; Alam et al., 2011; Virdyananto, et al., 2017; McDonald et al., 2017; Rahman et al., 2018; Kashi et al., 2016; Yang et al., 2015; Strohmeier, 2007; Puklavec et al., 2018; Lin et al., 2020; Belanche et al., 2019; Han & Yang, 2017; Shaltoni, 2016; Huang & Liao, 2015; Upadhyay & Khandelwal, 2018).

The role of AI in HRM functions specifically in employee recruitment has been addressed in different studies (Del Giudice et al., 2023; Upadhyay & Khandelwal, 2018; Fraij et al., 2022). On the other hand, human resources are currently managed with a changing working environment because of new features introduced by IA technology (Dhamija & Bag, 2020). Artificial intelligence (AI) technology is utilized primarily in hiring, training, employee engagement, and retention, which reduces expenses, saves time, and improves the accuracy of HR tasks (McDonald et al., 2017; Tavana & Hajipour, 2019; Kumar, 2019). In this context, Khan et al. (2024) indicate that organizations adopt AI to automate HRM tasks to address talent management complications and increase talent management complications. Dawson & Agbozo (2024) identified a link between talent management practices, such as planning, recruitment, and performance management, and artificial intelligence and highlighted that AI integration is gradually developing and offers more benefits than drawbacks in enhancing talent management strategies. On the other hand, Jha (2024) reported that incorporating generative AI into HR practices revolutionizes talent management by streamlining recruitment, optimizing employee development, and enhancing engagement. He also indicates that AI-powered systems streamline talent acquisition, personalize learning pathways, facilitate performance management, and foster employee engagement. However, ethical considerations must be carefully navigated to ensure transparency and fairness. Sundarapandiyan Natarajan et al. (2024) reported that AI-powered strategies optimize talent management processes, enhance decision-making and efficiency, mitigate bias, and foster inclusivity in the workforce. Laelawati (2024) reported that AI integration positively impacts HR practices and superior talent management. However, human insight does not significantly affect HR practices or talent management.

In the academic literature, there are many views on the issue of what talent is. There is no simple categorization technique for confirming talent (Waheed et al., 2014). The most expressed view links talent with abilities (Chambers et al., 1998; Michaels et al.,2001; Gallardo-Gallardo et al., 2015). In addition, talent management has been criticized from an academic viewpoint for lacking accuracy, definition, and intellectual foundation (Collings & Mellahi, 2009; Scullion et al., 2010). Nonetheless, several recent contributions have strengthened this emerging field by offering some theoretical frameworks for this field of study, thus providing some hope for the field's potential to advance the study of organizational management (Cappelli, 2008; Collings & Mellahi, 2009; Tarique & Schuler, 2010). The definition of talent management (TM), which focuses on recruiting, hiring, and retaining talent in alignment with the strategic goals of the organization (CIPD, 2023), is being reformed through the intervention of artificial intelligence (AI). Artificial intelligence (AI) is changing the way organizations recruit and retain talent (Parvez et al., 2022). This is in line with the broader idea of technological singularity, which states that AI complements human capabilities (Callaghan et al., 2017) and changes human-centered operational frameworks in the workplace (Gruetzemacher and Whittlestone, 2022; Haefner et al., 2021). In this context, artificial intelligence operationally involves making a machine act in ways that a human would consider intelligent. Moreover, human resources managers are adopting AI for the purpose of conducting various functions of human resources management, starting with manpower planning, recruiting, selecting, and training newly hired talent. AI technology is apparently used for talent acquisition in organisations (Zhang, 2024; Selamat et al., 2024; Paramita et al., 2024). However, several studies have revealed the relationship between TM and AI (Pillai & Sivathanu, 2020). In this era of communication and information technology, workforces of organisations are highly reliant on different types of new technologies to accomplish organisational goals and conduct everyday tasks.

Moreover, AI enables employers to recruit talent through step-by-step methods such as sourcing, screening, matching, and assessing (Alam et al., 2020). Currently, artificial intelligence impacts the ways in which institutions manage their staff, develop human resource plans to increase productivity and increase the level at which staff work efficiently and effectively. On the other hand, AI has become an important mechanism through which organizations can maintain employees' and talent interests, develop skills, guarantee valid vacancies for talent and embrace young workers in organizations (Abdeldayem & Aldulaimi, 2020).

According to the report of the World Economic Forum (2018), the most important challenge facing the future workforce will be the availability of specific skills required to match the enormous technological advancements. In addition, new technological development tends to ensure that the workforce, which is predominantly composed of talent, has the ability to support new technologies. According to Makridaskis et al. (2018), one of the most common mutual human resource (HRM) management strategies for conducting analyses on large amounts of data is machine learning (ML). As the major aim of AI is to clarify how individuals think, understand, learn, and behave logically and intelligently, it also interprets how to construct intelligent tools that are able to think, write, perceive, understand, anticipate, and influence the environment around them (Faqihi & Miah. 2023). Similarly, Sithambaram & Tajudeen (2023) stated that AI usage in HRM generates operational, managerial, strategic, organisational, informational and compliance benefits for organisations. The findings of this study revealed the usage and impact of AI-based software on HRM and thus the better implementation of AI in HRM so that firms can make better AI investment decisions. Liu et al. (2021) showed that human resource management is changing to intelligent talent management with the help of artificial intelligence, big data and internet technology. In addition, it provides recommendations on talent management and operation for the organization from five aspects—intelligent and accurate selection, intelligent training and development, intelligent retention, intelligent utilization and an intelligent talent pool—to help the organization improve its level of talent management and drive its development. Furthermore, Khan 2024) indicated that the utilization of AI for talent management (TM) includes consolidating AI devices to promote various phases of the employee lifecycle, from recruitment and selection to employee development and engagement.

A study conducted by Maya & Thamilselvan (2013) revealed that organisations engaged in talent management can perform better financially than other organisations operating in the same field of service and productivity. The study of Wiradendi (2020) illustrated that talent management influences organisational performance. Consequently, the best practice of talent management is needed to improve organisational performance and address the Industrial Revolution 4.0, especially in the Indonesian workplace environment. The body of literature mentioned above substantially contributes to the enrichment of data and information collected for this study, hence providing a description and analytical perspective for the nexus between talent management and artificial intelligence organisational performance. Although AI-based technology is expanding rapidly, academic research and scholarly works concerning the adoption of AI in organizational contexts are scarce (Alam et al., 2022; Giulia et al., 2023; Maestro & Rana, 2024).

Despite its interest, the literature on the talent management-AI nexus presents a significant gape regarding some issues. Specifically, it insufficiently addresses the predictive power of TM attention to the financial performance of AI companies, particularly in varying market conditions. Moreover, there is a limitation on how specific facets of TM (e.g., talent acquisition, employee development, workforce planning) differentially impact financial performance for major companies operating in the AI domain. Consequently, the present study bridges this gap by using Google Trends data to quantify TM attention and applying a nonparametric causality-in-quantiles approach to explore the relationships under diverse market scenarios. It extends prior work by integrating facet-specific analysis and providing actionable insights for companies, investors, and policymakers navigating the rapidly evolving AI sector.

3. Methodology and research methods.

3.1. The data

In this paper, two sets of data are used. The first is related to TM attention, which is obtained via the Google Trends platform, a widely used tool for gauging public interest through search query analysis. Notably, relevant search terms associated with TM, including 'talent acquisition' (TA), 'employee development’ (ED), and 'workforce planning’ (WP) in the United States, are selected. These terms were chosen on the basis of their significance in the field of TM and their ability to capture different facets of TM. Using Google Trends, monthly search interest data for each selected term are retrieved. After that, an aggregated variable representing TM attention terms based on the same platform is obtained. These variables describe the TM attention, and their facets serve as a quantitative measure of the level of public interest and attention toward talent management practices during the study period, providing valuable insights for the research.

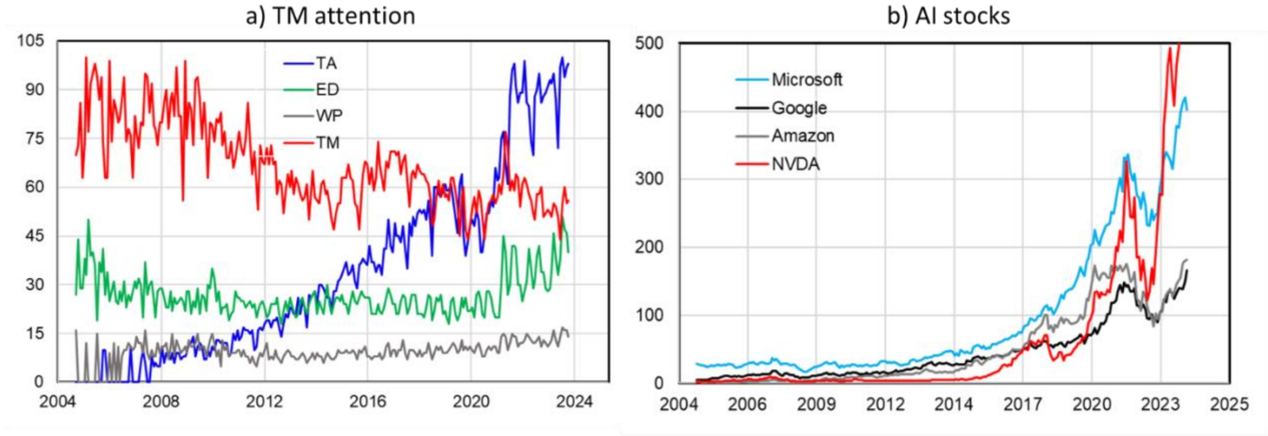

Figure 1. TM attention based on Google trends and AI companies' stock prices
Sources: developed by the authors.

The second set of data pertains to artificial intelligence performance. Following Yousaf et al. (2024) and Yadav et al. (2024), monthly data on stock markets are collected by considering four leading companies operating within the AI domain, such as Microsoft, Google, Amazon, and NVIDIA. These companies were selected on the basis of their significant investments and their strategic place in the AI sector. All the data are collected over a period between January 2004 and April 2024, yielding 244 observations. This period is selected on the basis of the availability of data on the TM attention trends and AI stocks simultaneously.

Considering data at a monthly frequency strikes a balance between capturing meaningful trends and reducing noise inherent in daily or weekly data. Monthly intervals provide a comprehensive view of stock market performance, allowing for robust analysis while avoiding excessive granularity that may obscure long-term patterns.

Table 1. Descriptive statistics and preliminary test of the data

Parameters	Talent Management Attention				AI stocks performance			
	TM	**TA**	**ED**	**WP**	**MSFT**	**GGL**	**AMZ**	**NVIDIA**
Mean	-0.043	1.079	0.167	0.264	1.139	1.675	1.909	2.803
Variance	151.785	302.640	323.427	451.553	41.758	69.559	104.370	186.173
Skewness	0.467	0.157	0.213	0.064	-0.119	0.280	-0.094	-0.407
Ex.Kurtosis	2.201	3.276	1.254	1.768	0.531	1.573	1.798	0.936
JB	55.964	106.085	17.184	30.764	33.202	27.315	31.986	15.075
p value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
ADF	-10.024	-4.474	-10.110	-11.910	-15.882	-16.038	-15.691	-13.663
PP	-42.263	-42.901	-42.924	-72.142	-15.872	-16.084	-15.720	-13.771

Notes: This table contains the descriptive statistics and preliminary tests. JB indicates the Jarque and Bera normality test statistics with the associated p value between parentheses. ADF and PP are the unit root tests of the Augmented Dickey Fuller and Phillips–Perron test statistics, respectively.
Sources: developed by the authors.

On the other hand, the chosen timeframe encompasses significant milestones in the development and proliferation of artificial intelligence technologies. Beginning in 2004, coverage of the early stages of the mainstream adoption of AI, including pivotal advancements such as the introduction of deep learning frameworks and the rise of cloud computing infrastructure, was ensured. Extending the analysis until 2024 enables the examination of recent trends and potential shifts in the AI landscape, safeguarding significance and timeliness in the investigation of stock market dynamics within the AI domain. To measure the performance of AI companies and the monthly changes in TM attention, all series are transformed to the percentage of log differences.

Fig. 1 displays the evolution of the different variables in levels, and Table 1 provides descriptive statistics on the data transformed to the percentage in log-difference. This figure clearly shows that the price series of all stocks exhibited an upwards trend over the period of study, indicating the interesting development of the AI sector. On the other hand, the TM attention series shows high variability during the period of study. The descriptive statistics show positive mean returns of different stocks, with values ranging between 1.139% and 2.803% for Microsoft and NVDA, respectively. For the TM attention variables, the mean value variations are positive except for the aggregated TM variable.

The normality analysis is performed on the basis of the values of skewness and kurtosis. The calculated values of skewness, as an asymmetry measure, are different from zero (the value of the normal distribution) and show positive values for TM attention and negative values for stock returns (except for the Google company), indicating that the TM (stock returns) are skewed to the right (left). Moreover, the kurtosis excess is significant, with values different from 3 (a normal distribution). In addition, the Jarque–Bera statistics (JB) strongly reject the null hypothesis of normality. These results support the use of quantile-based analysis, which is suitable for nonnormal variables. The presence of a unit root test is checked on the basis of standard unit root tests such as the augmented Dicky–Fuller (ADF) and Phillips–Perron (PP) tests. The statistics of these two tests are below the critical values for all considered series, indicating no unit roots and confirming the use of causality analysis between the variables under study.

3.2. Methodology

To investigate the causal relationship between TM attention and AI companies' stocks, the empirical strategy applies the nonparametric causality-in-quantiles test developed by Balcilar et al. (2016). This methodology is particularly suitable for investigating the predictive power of TM attention for AI performance on the basis of AI companies' stocks. This approach can capture nonlinear and heterogeneous causal effects across different quantiles of the stock return distribution. This allows us to discern whether the influence of TM attention on stock returns varies under different market conditions, such as during extreme downturns or upturns, providing a more comprehensive understanding of the dynamic and potentially asymmetric nature of this relationship. Following Jeong et al. (2012), the Granger causality-in-quantile from the TM attention (x_t) to the AI stock returns (y_t) in the τ^{th} quantile's order with respect to the p-order lag-vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ is verified if:

$$Q_\tau\{y_t,\ y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\} \neq Q_\tau\{y_t,\ y_{t-1}, \dots, y_{t-p},\} \quad (1)$$

where $Q_\theta\{y_t\ \ \cdot\}$ is the τ^{th}conditional quantile of y_t depending on t (with $0 < \tau < 1$).

Let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$ and $Z_t = (x_t, y_t)$ be three vectors, and let $F_{y_t|Z_{t-1}}(y_t, z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ be the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. Let $Q_\tau(Z_{t-1}) \equiv Q_\tau(y_t|Z_{t-1})$ and $Q_\tau(Y_{t-1}) \equiv Q_\tau(y_t|Y_{t-1})$; then, $F_{y_t|Z_{t-1}}(Q_\tau(Z_{t-1}), Z_{t-1}) = \tau$ is obtained with probability one. In this context, the hypothesis of causality-in-quantiles can be expressed as:

$$H_0: P\{F_{y_t|Z_{t-1}}(Q_\tau(Z_{t-1}), Z_{t-1}) = \tau\} = 1 \quad (2)$$

$$H_1: P\{F_{y_t|Z_{t-1}}(Q_\tau(Z_{t-1}), Z_{t-1}) = \tau\} < 1 \quad (3)$$

To obtain a metric measure for the practical implementation of the causality-in-quantile test, Jeong et al. (2012) used the following distance measure:

$$J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\} \quad (4)$$

where ε_t and $f_Z(Z_{t-1})$ denote the regression residuals and the marginal density function of Z_{t-1}, respectively. The regression error ε_t arises from the null hypothesis in Equation (3), which is true if and only if $E[\mathbf{1}\{y_t \leq Q_\tau(Z_{t-1}), Z_{t-1}\}] = \tau$, where $\mathbf{1}\{.\}$ is an indicator function.

According to Jeong et al. (2012), the feasible kernel-based test statistic has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \quad (5)$$

where $K(.)$ is the kernel function with bandwidth h. Additionally, p is the lag order, and T is the sample size. $\hat{\varepsilon}_t$ is the estimate of the regression error given by:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\tau(Z_{t-1})\} - \tau \quad (6)$$

where $\hat{Q}_\tau(Z_{t-1})$ is an estimate of the τ^{th} conditional quantile of y_t given Y_{t-1}. The Nadarya–Watson kernel estimator of $\hat{Q}_\tau(Z_{t-1})$ is given by:

$$\hat{Q}_\tau(Z_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L(\frac{Y_{t-1}-Y_{s-1}}{h})\mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1,s\neq t}^{T} L(\frac{Y_{t-1}-Y_{s-1}}{h})} \quad (7)$$

where $L(.)$ is the kernel function and where h is the bandwidth.

4. Results and Discussion

4.1. Causality results

The empirical analysis is conducted in two steps. First, the analysis is based on the aggregated measure of TM to address a global analysis of the causality from TM attention to AI companies' performance. Second, further analysis is needed to provide a more detailed analysis by considering the different facets of TM, such as talent acquisition, employee development, and workforce planning. This analysis allows for a deeper understanding of how different facets of TM impact AI performance and offers valuable insights into the nuanced interplay between TM practices and AI performance.

Table 2 presents the statistics of the nonparametric causality from aggregated TM attention to AI stock returns under different conditions. The test is implemented for a grid of 20 quantile orders (from 0.05 to 0.95). The causality is significant at the 5% level when the test statistic (t statistic) exceeds the critical value of 1.96. An examination of the results in Table 2 reveals that the test statistics reject the null hypothesis of noncausality only for low and medium quantiles' orders. These results indicate that TM attention causes AI performance in terms of stock markets when the latter is bearish or under normal conditions. In contrast, when AI companies are in a bullish condition, TM attention has no predictive power for this sector.

Table 2. Nonparametric causality in quantiles from TM attention to AI stock returns

q	Microsoft	Google	Amazon	NVIDIA
0.05	2.3528*	1.3276	2.5295*	1.0615
0.10	2.5683*	2.8992*	2.9386*	1.9921
0.15	2.4037*	2.6933*	4.0031*	2.9237*
0.20	3.7303*	3.7679*	4.0549*	2.5562*
0.25	3.7793*	3.6948*	5.1627*	2.3540*
0.30	3.0119*	3.7611*	6.1748*	2.7204*
0.35	3.1038*	4.0871*	6.1995*	2.9546*
0.40	3.1786*	3.8160*	6.1896*	2.8325*
0.45	4.2589*	3.7797*	6.1829*	2.0044*
0.50	4.1810*	4.0278*	50064*	2.3489*
0.55	2.2183*	5.1700*	4.1097*	2.4469*
0.60	2.0956*	4.1465*	41864*	2.2728*
0.65	1.9649*	2.8525*	3.0825*	2.3235*
0.70	1.7840	2.8618*	2.1738*	2.4845*
0.75	1.4991	1.9863*	2.8740*	2.0165*
0.80	1.4062	1.7064	1.5406	1.4523
0.85	1.4403	1.5440	1.8047	1.4208
0.90	1.1488	1.2156	1.4546	1.0518
0.95	0.9337	1.1391	1.3035	1.0791

Notes: This table presents the t statistics of the nonparametric causality in quantiles test from TM to the AI stock returns of the top leading companies operating in AI. The causality is significant if the T statistic is greater than the critical value (1.96) at the 5% significance level. (*) * indicates significance at the 5% critical level.

Sources: developed by the authors.

These results suggest that the causality from TM to AI companies' performance depends on their stock values and highlight the importance of considering market conditions when assessing the predictive power of TM attention for AI company performance. During periods of market downturns or normal market conditions, changes in TM attention may serve as valuable indicators of potential changes in AI stock returns. Investors may utilize this information to adjust their investment strategies and portfolio allocations accordingly by accounting for the influence of TM on AI performance during challenging times. However, under bullish market conditions, AI performance is influenced by other factors, such as investor sentiment, market dynamics, and technological advancements. Thus, investors should adopt a nuanced approach, combining TM attention data with broader market indicators to make informed investment decisions in the dynamic AI sector.

Table 3. Quantile causality results from different facets of TM-to-AI stock returns

q	Talent acquisition				Employee development				Workforce planning			
	Microsoft	**Google**	**Amazon**	**NVIDIA**	**Microsoft**	**Google**	**Amazon**	**NVIDIA**	**Microsoft**	**Google**	**Amazon**	**NVIDIA**
0.05	0.7656	0.4012	0.2745	0.2445	2.7832*	0.2939	0.3906	0.3945	0.8438	0.2452	0.4162	0.3781
0.1	2.2236*	2.0022*	1.8988	1.9710*	3.1222*	2.4782*	2.4752*	2.3968*	0.9154	0.6086	0.5048	0.5617
0.15	2.4908*	2.2180*	1.8146	2.0981*	3.4651*	2.6853*	2.6976*	2.4530*	1.4282	0.6140	0.5899	0.8375
0.2	2.4364*	2.2104*	2.3044*	2.1486*	3.5336*	2.6634*	3.3575*	2.4029*	1.6291	0.7794	0.9342	1.4445
0.25	2.5687*	1.8551	1.9558	2.3609*	3.8649*	2.5313*	3.9571*	2.4588*	1.7808	0.4515	0.8793	1.3630
0.3	3.6619*	2.0408*	1.9358	2.3367*	3.8768*	2.4838*	3.8637*	2.4736*	2.1400*	0.5417	0.7066	1.3371
0.35	3.8312*	2.0115*	2.0978*	2.4171*	4.0796 *	2.3986*	3.3224*	2.6012*	2.3230*	0.6041	0.7345	1.3677
0.4	4.7580*	2.0939*	2.0728*	2.3359*	4.0844*	2.4713*	3.2884*	2.7718*	1.8539	0.7155	0.7288	0.8817
0.45	4.9199*	2.0283*	2.0942*	2.1441*	3.7127*	2.2708*	2.9406*	2.6631*	1.7713	0.7536	0.7399	0.8716
0.5	4.6962*	1.8955	2.0514*	2.3849*	3.4552*	2.2473*	2.7271*	2.8285*	1.4267	0.6787	0.7120	1.0314
0.55	4.4069*	1.8627	2.1581*	2.3068*	2.5515*	2.3509*	0.8034	2.6268*	1.3990	0.5171	0.7471	0.8719
0.6	3.3628*	2.1129*	1.9450	2.5080*	2.4000*	2.3920*	0.6176	2.5555*	1.4478	0.6774	0.6974	0.7706
0.65	3.4065*	2.1149*	1.9868*	2.6034*	2.2156*	2.3763*	0.5996	2.5098*	1.4505	0.8104	0.6317	0.9370
0.7	3.2323*	1.9757*	2.0667*	2.6508*	2.2507*	2.4464*	0.6360	2.6550*	1.4653	0.6534	0.4383	0.7531
0.75	3.0111*	1.8901	2.0455*	2.4605*	1.5184	2.3175*	0.5182	2.4560*	1.2475	0.4197	0.4269	0.8592
0.8	1.7598	1.8441	2.2372*	2.4745*	1.6235	2.6480*	0.4673	0.4016	1.4329	0.3531	0.4752	0.4942
0.85	2.1905*	1.9283	2.2607*	2.0591*	1.6524	0.4814	0.5415	0.5952	1.5968	0.2694	0.5414	0.5012
0.9	2.1503*	2.0188*	1.8891	1.8012	1.0267	0.2438	0.5777	0.5874	0.6482	0.4923	0.3760	0.3326
0.95	1.4057	1.8161	1.6004	1.8124	0.5480	0.1467	0.4104	0.2987	0.3881	0.1168	0.1315	0.1595

Notes: This table presents the t statistics of the nonparametric causality in quantiles test from different facets of TM to the AI stock returns of the top leading companies operating in AI. The causality is significant if the T statistic is greater than the critical value (1.96) at the 5% significance level. (*) * indicates significance at the 5% critical level.

Sources: developed by the authors.

For policymakers, these results underscore the need to reorganize the interplay between TM practices and market dynamics within the AI industry. Accordingly, during periods of stress or high market volatility, policymakers may consider the impact of TM attention on AI company performance when formulating strategies and making decisions to support innovation within the AI sector. This could involve initiatives aimed at fostering a favourable environment for talent development and retention, which could positively influence the performance and competitiveness of AI companies during challenging market conditions. Furthermore, policymakers should remain vigilant of shifts in market sentiment and the evolving role of TM attention in shaping investor perceptions within the AI industry, ensuring that regulatory frameworks and policy interventions remain adaptive and responsive to changing market dynamics and investor behaviors.

To provide more insight into the causal relationship running from TM attention to AI performance, the same test is run by considering the different facets of TM attention, such as talent acquisition, employee development, and workforce planning. The results of causality from TA, ED, and WP are provided in Table 3. The results suggest that causality runs depending on the TM facet and AI stock market conditions. Starting with talent acquisition, this facet of TM generally results in AI stock performance under all market conditions and for all selected companies. The second facet of TM (Employee development) causes AI stock performance under bearish and normal market conditions, indicating that TM with respect to employee development improves the prediction of AI stock returns only when the latter are bearish or normal. However, the third facet of TM attention (workforce planning) shows no causality to AI stock markets, except for some very limited cases related to Microsoft AI companies at medium quantiles (0.3 and 0.35).

The results indicate that TM attention focused on talent acquisition consistently influences AI stock performance across all market conditions and for all selected companies. This suggests that strategies related to attracting and acquiring talent have a significant effect on the market perceptions and performance of AI companies. AI companies should prioritize effective talent acquisition practices to enhance their competitive advantage and improve investor confidence. Investors, on the other hand, should consider the strength of talent acquisition strategies as a key factor when evaluating AI companies for investment opportunities.

Policymakers may focus on initiatives that support talent acquisition efforts within the AI sector, such as workforce development programmes and incentives for attracting top talent.

The findings suggest that TM attention regarding employee development influences AI stock performance, specifically during bearish or normal market conditions. This underscores the importance of investing in employee training and development programs to enhance the skills and capabilities of the workforce, particularly in challenging market environments. AI companies should prioritize initiatives aimed at nurturing talent internally to adapt to changing market conditions and maintain resilience. Investors may consider the quality and effectiveness of employee development initiatives as indicators of long-term growth potential for AI companies. Policymakers could support initiatives focused on workforce training and upskilling to ensure that a skilled workforce is capable of driving innovation within the AI industry.

In contrast, TM attention related to workforce planning does not exhibit a significant causal relationship with AI stock markets in most cases, except for limited instances related to specific companies at certain quantiles. This suggests that the market impact of workforce planning strategies may vary depending on company-specific factors or market conditions. AI companies should assess their workforce planning strategies carefully to ensure alignment with market dynamics and strategic objectives. Investors should consider the nuances of workforce planning practices when evaluating AI companies for investment. Policymakers may explore policies aimed at promoting effective workforce planning practices within the AI sector to increase organisational agility and resilience.

In summary, the findings emphasize the importance of different facets of talent management in influencing AI company performance, with implications for strategic decision-making by AI companies, investors, and policymakers. Prioritizing talent acquisition and employee development initiatives can enhance competitiveness and market resilience, whereas effective workforce planning strategies contribute to long-term organisational sustainability within the dynamic AI industry landscape. Research shows that talent management (TM) attention, particularly in talent acquisition and employee development, matters for AI companies in bear and normal market conditions and has large social and economic implications. At the societal level, prioritizing TM strategies involves workforce development, inclusivity and innovation. Companies that invest in talent acquisition and development create opportunities for skills building, diverse workforces and broader innovation ecosystems, which ultimately benefit society through technology.

Economically, good TM practices act as buffers during market downturns and support organisational resilience and investors. The fact that TM attention impacts AI stock performance means that it is key to competitiveness in the global AI industry, driving investments and economic growth. Policymakers can use these insights to design workforce development programs and TM-focused initiatives to drive sustainable growth and national productivity in the fast-evolving AI sector. This integration of TM with organizational and economic priorities is crucial for long-term success in AI-driven economies.

4.2. Robustness analysis

To strengthen the analysis and validate the findings of this study, the talent management variable is revised by adding new metrics such as "corporate HR performance reports" and "employee retention rates". These additional metrics offer a broader perspective on TM focus, capturing not only interest based on searches but also the effectiveness of HR operations and the sustainability of employees within organisations. The nonparametric causality-in-quantiles test is then used again to determine whether the revised TM variable still predicts AI stock performance under different market conditions. The results can be found in Table 4.

Table 4. Causality in quantiles results with additional metrics (corporate HR performance reports and employee retention rates)

q	Microsoft	Google	Amazon	NVIDIA
0.05	2,6236*	3,5485*	1,5901	2,6287*
0.10	3,9551*	3,8775*	1,6769	2,6315*
0.15	3,8313*	3,7878*	1,8983	2,7663*
0.20	2,3370*	3,9358*	1,7868	2,0864*
0.25	2,5284*	2,0692*	1,9666	2,0929*
0.30	2,8846*	2,3219*	2,0377*	2,2179*
0.35	2,9008*	2,5123*	1,9258	2,3741*
0.40	2,5311*	2,3003*	1,9984*	2,0500*
0.45	2,4878*	2,1712*	1,8569	2,5502*
0.50	2,5351*	2,2331*	1,8098	2,6742*

q	Microsoft	Google	Amazon	NVIDIA
0.55	2,7604*	2,2552*	1,8458	2,5738*
0.60	2,4504*	2,0142*	2,0436*	2,5916*
0.65	2,3757*	2,0119*	2,3167*	2,3835*
0.70	2,0989*	1,9620*	2,4734*	2,0967*
0.75	1,8902	2,2412*	2,3146*	1,9678*
0.80	1,8833	1,9234	2,1923*	1,9290
0.85	1,9391	1,7207	1,8718	1,9338
0.90	1,7549	1,6176	1,5923	1,5951
0.95	1,5518	1,4741	1,3543	1,4362

Notes: Notes: This table presents the t statistics of the nonparametric causality in quantiles test from TM with additional metrics (corporate HR performance reports and employee retention rates) to the AI stock returns of the top leading companies operating in AI. The causality is significant if the T statistic is greater than the critical value (1.96) at the 5% significance level. (*) * indicates significance at the 5% critical level.
Sources: developed by the authors.

The results of the causality test with the augmented TM variable strongly align with the initial analysis. In particular, the causality remains significant during both bearish and normal market conditions (0.05–0.50 quantiles) for all four AI companies. This finding reinforces the original conclusion that TM attention has a considerable effect on AI stock performance during times of market stress or stability. For instance, at the 0.10 quantile, the t statistic is significant for Google (3.88) and Microsoft (3.96), reflecting the trends observed in the first analysis.

However, similar to the main findings, the causal relationship diminishes in bullish market conditions (0.70–0.95 quantiles), where the T statistics drop below the critical threshold of 1.96 for all companies. This further indicates that TM attention plays a lesser role when market performance is influenced by other factors, such as investor sentiment or broader economic trends. The addition of these two metrics strengthens the evidence supporting the findings of this study. By including operational and internal performance metrics, the connection between talent management (TM) and AI stock performance can be shown to be influenced not only by external factors (such as Google Trends) but also by real corporate practices. This enhances the argument that effective TM strategies, such as better retention and improved HR performance, are essential for the resilience and success of AI companies in both bearish and stable market conditions. Overall, the robustness analysis highlights the dependability of the main results while providing deeper insights into the complex dynamics of the effect of the TM on firm performance. Future research could build on this framework by incorporating additional metrics, such as employee engagement scores or workforce diversity indices, to investigate other aspects of TM practices.

5. Conclusions. This paper investigates the causal relationship between talent management attention (TM) and the performance of AI companies, as measured by stock returns. Using Google Trends data, a composite TM variable representing overall public interest in talent management practices is constructed, along with an examination of specific facets such as talent acquisition, employee development, and workforce planning. The analysis reveals nuanced findings regarding the influence of TM attention on AI stock performance across different market conditions.

The results based on the overall TM show significant causality from this variable to AI stock performance under bearish and normal conditions of the AI stock market. When interesting to the different facets of TM, the results show that talent acquisition consistently influences AI stock performance across all market conditions and for all selected companies, underscoring its significance in shaping market perceptions and investor confidence within the AI sector. Moreover, TM attention focused on employee development has a causal relationship with AI stock performance, particularly during bearish or normal market conditions, highlighting the importance of investing in human capital development for long-term resilience and growth.

In contrast, TM attention related to workforce planning has a limited causal impact on AI stock markets, suggesting that the market dynamics of workforce planning strategies may vary depending on company-specific factors or market conditions. These findings provide valuable insights for AI companies, investors, and policymakers, guiding strategic decision-making and investment evaluation within the dynamic landscape of the AI industry. Moving forward, it is imperative for AI companies to prioritize effective talent management practices, including talent acquisition and employee development initiatives, to enhance competitiveness and adaptability in volatile market environments. Investors should consider the strength of talent management strategies as a key determinant of AI company performance, whereas policymakers may explore supportive measures to foster talent development and workforce planning within the AI sector. Overall, understanding the intricate relationship between talent management attention and AI company performance is essential for navigating the complexities of the evolving AI landscape and driving sustainable growth and innovation in the industry.

This study offers significant theoretical and practical insights. On the theoretical side, it enhances the understanding of how talent management (TM) practices impact firm performance in innovation-focused industries, especially in different market environments. By using a nonparametric causality-in-quantiles approach and analysing specific facets, this research adds to the literature on TM by revealing the varied and unequal effects of TM elements, such as talent acquisition, employee development, and workforce planning, on the performance of AI stocks.

From a practical standpoint, the findings provide useful recommendations for AI companies, investors, and policymakers. For businesses, the results emphasize the need to focus on talent acquisition and employee development to increase competitiveness and navigate tough market conditions. Investors should consider the effectiveness of TM strategies as a crucial factor influencing firm performance, particularly in bearish and stable market scenarios. Policymakers can use these insights to create targeted programs, such as workforce training initiatives and incentives for talent development, that foster the growth of AI-driven sectors.

The study aims to explore the relationship between TM and AI company performance while focusing on how TM practices affect innovation-driven industries. It also stresses the need for efficient TM strategies for organisational sustainability and competitiveness. State intelligence companies should focus on talent onboarding and development, expand training capabilities and collaborate with academic institutions. The government can support the development of the workforce by providing funds or tax incentives to companies that engage in TM. This study offers specific recommendations for AI companies, investors, and policy makers to increase the innovation, resilience, and sustainable growth of the AI industry.

Like any research, this study has several limitations. It relies on Google Trends data, which may not cover all talent management practices. The observational nature of the study does not definitively establish causality, suggesting the need for experimental or quasiexperimental designs. It also highlights the need to consider external factors such as economic trends and regulatory changes. Future research could explore other aspects of talent management, extend the analysis beyond AI, and conduct longitudinal analyses.

Author Contributions: conceptualization, N. F. A. and K. M.; methodology, K. M.; software, K. M.; validation, N. F. A.; formal analysis, N. F. A. and K. M.; investigation, N. F. A.; data curation, K. M.; writing-original draft preparation, N. F. A, and K. M.; writing-review and editing, N. F. A., and K. M.; visualization, N. F. A; supervision, K. M.; project administration, N. F. A.

Conflicts of interest: The authors declare that they have no conflicts of interest.

Data availability statement: Not applicable.

Informed Consent Statement: Not applicable.

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Взаємозв'язок між управлінням талантами та штучним інтелектом: досвід компаній у сфері ШІ

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Дослідження присвячене аналізу зв'язку між управлінням талантами (УТ) та ефективністю провідних компаній, що працюють у сфері штучного інтелекту (ШІ). Для оцінки уваги до управління талантами використовувалися дані Google Trends, що відображають частоту пошукових запитів, пов'язаних із залученням талантів, розвитком співробітників та плануванням робочої сили. Додатково було враховано корпоративні показники, зокрема звіти про ефективність управління персоналом та рівень утримання співробітників, що забезпечило ширший контекст аналізу. Результативність компаній ШІ оцінювалася на основі динаміки акцій Microsoft, Google, Amazon і NVIDIA, які є ключовими гравцями галузі. Для аналізу було застосовано непараметричний тест причинності у квантилях, який дозволяє виявити асиметричні та неоднорідні ефекти уваги до управління талантами на динаміку акцій за різних ринкових умов: від ведмежих до бичачих сценаріїв. Результати дослідження засвідчили значний вплив уваги до управління талантами на результативність акцій компаній ШІ за умов ведмежого та стабільного ринку. Це підкреслює важливість стратегій УТ у періоди ринкової нестабільності або стабільності. Водночас за бичачих умов вплив УТ є менш вираженим, оскільки результативність здебільшого визначається іншими факторами, такими як ринкові настрої або технологічні інновації. Деталізований аналіз окремих аспектів показав, що залучення талантів стабільно впливає на динаміку акцій за будь-яких ринкових умов. Розвиток співробітників виявляє свій вплив переважно за умов ведмежого та стабільного ринку, тоді як планування робочої сили має обмежений вплив, залежний від специфіки компанії та зовнішнього контексту. Дослідження робить вагомий внесок у теорію та практику, пропонуючи поглиблене розуміння ролі управління талантами у формуванні результативності організацій в умовах динамічного розвитку індустрії ШІ. Для компаній впровадження ефективних стратегій УТ, зокрема у сфері залучення талантів та розвитку співробітників, може стати запорукою стійкості та конкурентоспроможності. Інвестори можуть використовувати дані про УТ для оптимізації портфельних стратегій, а урядам рекомендовано підтримувати ініціативи, такі як гранти на навчання співробітників або державно-приватні партнерства, спрямовані на розвиток талантів у секторі ШІ. Ці результати наголошують на важливості взаємозв'язку між практиками управління талантами та ринковою ефективністю, пропонуючи практичні рекомендації для орієнтування у швидкозмінному середовищі ШІ.

Ключові слова: управління талантами; штучний інтелект; компанії ШІ; фондові ринки.