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Human Capital Assessment via Large Language Models alignment

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Abstract

This study presents a new methodological framework that combines clustering techniques with large language models (LLMs) to analyze intangible assets in various fields of research. By applying this approach to human capital, we reveal that its definition and perception vary considerably from one region to another and evolve over time, reflecting differences in socioeconomic development, institutional frameworks, and geopolitical contexts. Our financial analysis confirms that these regional variations in the perception of human capital have important implications for investment performance. Specifically, strategies that incorporate human capital development scores generate significantly different returns in emerging markets compared to developed markets, highlighting the importance of tailored portfolio approaches. Furthermore, our asset valuation results highlight the central role of human capital development in explaining emerging market dynamics, particularly during periods of geopolitical turmoil, when companies with stronger human capital demonstrate greater resilience and stability.

Keywords: Human capital, asset pricing, clustering, BERT, LLM.

JEL classification: G12, C38, C63, J10, J24.

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Olivier Coz graduated in Financial Economics and Sustainable Finance from EDHEC Business School and MINES Paris PSL, and is currently pursuing a Master's degree in Random Modelling, Finance, and Data Science at Université Paris Cité. He joined the Amundi Research Institute in Paris in 2024 as a Quantitative Researcher Intern, contributing to the research on the impact of human capital on investment performance. Prior to this, he was a Quantitative Analyst at La Banque Postale AM, where he worked on the development of scoring models and extra-financial data quality analysis. His work focuses on quantitative signal generation and the analysis of non-financial factors on asset performance.

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Raphaël completed his PhD in Economics at Université Paris-Saclay, with a dissertation entitled "Evaluation of Carbon Pricing Policies: Social Fairness, Economic Costs, and Global Mechanisms." His research examined the social and economic implications of the environmental transition, contributing to a better understanding of the public perception and acceptance of carbon tax policies. His findings have been published in academic journals, and he received the Young Researcher Award at the Global Conference on Environmental Taxation (GCET) in 2024.

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1 Introduction

In the aftermath of the COVID-19 pandemic, the concept of human capital has gained renewed interest, both in academic literature and in corporate strategy, particularly through Sustainability reporting and Human Resources (HR) practices. As the world of work undergoes rapid transformation driven by the consequences of the pandemic, heightened geopolitical tensions and the accelerated expansion of artificial intelligence, organizations are faced with a new set of challenges.

Human capital, broadly defined as the collective knowledge, skills, abilities, and experiences possessed by individuals within an organization (Schultz, 1961; Becker, 1964), is recognized as a driving force behind innovation, productivity, and overall business performance. As economies worldwide transition towards knowledge-intensive sectors, the strategic management of human capital has become an imperative for sustaining competitive advantage. Subsequent research has expanded this definition to include a wide array of intangible assets, such as employee engagement, corporate culture, and organizational effectiveness (Edvinsson and Malone, 1997). In economic models, human capital emerges as an important factor in driving performance, underpinning the essential role of the labor force's quality and quantity in determining economic growth and productivity. In economic growth theory, particularly the Solow Growth Model (Solow, 1957), the Gross Domestic Product (GDP) growth is explained by substantial factors such as increases in labor, increases in capital and a residual i.e., everything else that can contribute to growth in GDP. The residual is also known as the Total Factor Productivity (TFP) and can include technological progress, increases in production and other unnoticed factors. The augmentation of the Solow model by Mankiw et al. (1992) represents a significant theoretical advance, positioning human capital alongside physical capital at the heart of the economic growth process. This framework explains how disparities in income per capita across countries can be largely attributed to differences in savings, education, and population growth rates. Incorporating human capital into the aggregate production function, the model aligns income shares for production factors with empirical evidence, underscoring the transformative potential of education and training investments. Building on this foundational perspective, empirical studies by Pelinescu (2015) and Cammeraat et al. (2021) offer compelling support for the critical role of human capital in enhancing labor productivity and fostering economic development. The first analysis, employing a panel methodology, reveals a positive correlation between GDP per capita and indicators of human capital quality, such as number of patents and education levels among employees, in the EU. Similarly, the second analysis illuminates how investments in informal training significantly boost industry productivity, highlighting the importance of innovation and the multifaceted nature of human capital in improving performance. In their study, Hanushek and Woessmann (2012) examine the relationship between educational achievement and GDP growth, finding a strong and stable correlation. They also explore various estimation approaches to address causality, and consistently find that cognitive skills have a significant impact on economic growth.

Moreover, numerous studies have shown a strong, positive link between human capital and organizational performance. A meta-analysis by Crook et al. (2011) found that human capital is strongly related to performance. If we focus on the link between working conditions and performance, research has shown that factors such as training, work environment, and career development significantly impact work motivation, which in turn affects employee performance (Sugiarti, 2022). Additionally, poor workplace conditions, including physical exertion, environmental conditions, and hazards, have been found to negatively impact employee performance in terms of following organization rules, quality, cooperation, task concentration, creativity, and absenteeism (Kahya, 2007). It is also relevant to consider the relationship between human capital losses, Human Resource Management (HRM) investments, and organizational performance. Shaw et al. (2013)'s study explores the impact of human capital losses on the inimitability of human capital stores and organizational performance. The findings suggest that while human capital losses initially diminish the inimitability of human capital stores, the negative effects are attenuated as human capital losses increase. Furthermore, the study highlights the role of HRM investments in moderating these effects, showing that high HRM investments can mitigate the negative relationship between human capital losses and workforce performance. Considering these findings, it follows that working conditions play a crucial role in shaping employee performance. By creating a supportive work environment, offering relevant training programs, and addressing workplace hazards, organizations can promote employee motivation and engagement, ultimately leading to improved performance. Other studies focus on the relationship between job satisfaction and performance. The discussion about how human capital influence a company's success highlights the importance of job satisfaction. When employees are happy at work, they use their skills more effectively, which benefits the entire organization. Bontis and Serenko (2007) further show that good practices in managing human capital not only make employees happier but also improve their skills. Edmans (2011) offers another perspective by looking at how companies known for treating their employees well perform in the stock market by tracking the stock returns of companies listed in the "100 Best Companies to Work For in America". The author found that these companies tend to outperform others in the market. This approach not only shows the financial benefits of employee satisfaction but also suggests that the market might undervalue intangible assets such as a positive workplace. Melián-González et al. (2015) and Luo et al. (2016), who analyze feedback from hundreds of companies, show that overall happiness at work and satisfaction with certain aspects such as leadership, pay, and work-life balance can influence how well a company performs. These studies use the vast amount of data on Glassdoor.com to get a wide-ranging view of the impact of employee satisfaction across different sectors. Luo et al. (2016), in particular, use Natural Language Processing (NLP) techniques to sift through Glassdoor.com reviews and identify which component of satisfaction matter most to company performance. They point out that innovation, quality, and teamwork are key positive factors, but also note some areas of satisfaction such as safety that could have a negative impact on firm performance. On another front, Song (2024) finds a positive correlation between ESG performance and efficiency of the company's human capital investment.

The growing importance of human capital is reflected in the increasing attention it receives from investors and other stakeholders. For example, interest in well-being has spread (Wright and Cropanzano (2004), Nielsen et al. (2017), Kersemaekers et al. (2018)), and since a few years ago, new trends in measurement of well-being are leading to the development of more rigorous and scientifically sound methods to compare well-being between countries (Stiglitz et al. (2018), OECD (2020), Ruggeri et al. (2020), OECD (2024)). At the regulatory level, the adoption of rules by the U.S. Securities and Exchange Commission (SEC) aims at addressing the current lack of standardized Human Capital Management (HCM) disclosures (SEC, 2020). The SEC reports rules on human capital that apply to issuers subject to Regulation S-K. The approach has evolved from requiring disclosure of headcount only, to requiring principles-based reporting of material human capital issues in 2020. Due to inconsistencies in the implementation, the SEC Investor Advisory Committee recommended in 2023 that all public issuers be required to disclose standardized metrics, such as workforce composition, turnover, compensation and diversity, to improve transparency and comparability for investors[1]. We can also cite organizations such as the International Financial Reporting Standards (IFRS) Foundation: the International Sustainability Standards Board (ISSB[2]) incorporating now the Integrated Reporting Framework (IR) (Integrated Reporting, 2017) and the Sustainability Accounting Standards Board (SASB[3]) (SASB, 2020), and in addition to the Global Reporting Initiative (GRI[4]), which currently supplies or works on some frameworks in the guidance of human capital disclosures. Beyond that, recent initiatives of the World Bank in 2018 in their "Human Capital Project" (HCP)[5] underscores the significance of investing in human capital. It emphasizes that by improving skills, health, knowledge, and resilience, individuals can become more productive, flexible, and innovative. Moreover, the World Bank stresses the need for policymakers to recognize human capital as a central driver of sustainable growth and poverty reduction. In the HCP, the World Bank includes a measure of the human capital assessing what a child born today can expect to achieve by the age of 18, given the health and education risks involved in the country (Kraay (2019), Demirgüç-Kunt and Torre (2020)).

Data providers are also increasingly reporting data on human capital, with the MSCI ESG Ratings Methodology (MSCI ESG Research LLC, 2023a,b,c,d) considering four sections in their human capital score: health and safety, human capital development, labor management and supply chain labor standards. On another side, Sustainalytics' ESG Risk Rating framework assesses companies based on various subindustry-specific indicators, such as freedom of association policy, collective bargaining agreements, discrimination policy, diversity programs, employee turnover rate, and human capital development programs, among others (Sustainalytics, 2023). We can also mention London Stock Exchange Group (LSEG) that tracks working conditions, health and safety, career development and training or diversity and inclusion initiatives, under the "Workforce" category of the Social pillar (LSEG, 2024). Fortune's "100 Best Companies to Work For" (via Great Place to Work) assesses employee satisfaction and likewise anticipates key organizational outcomes such as workers retention, agility and overall business performance[6]. Furthermore, Equileap focuses data on gender equality, race and ethnicity diversity, and human and labor rights[7]. Along the same lines, Bloomberg tracks gender performance accross different angle (leadership & talent pipeline, equal pay & gender pay parity, inclusive culture, anti-sexual harassment policies and external brand) with its Bloomberg Gender-Equality Index (Bloomberg, 2023). This development underscores the recognition that human capital is a multifaceted concept that encompasses not only the knowledge and skills of employees but also the broader organizational factors that influence their well-being, growth, and effectiveness. As such, the measurement and management of human capital have become critical concerns for companies seeking to optimize their performance and attract investment in an increasingly competitive and rapidly evolving business landscape.

Although many data providers offer harmonized indicators for assessing human capital but an important methodological question arises: to what extent have employees' concerns shown temporal consistency? To investigate this matter, we draw upon the studies of JUST Capital, a non-profit research organiza-

[1] See `https://www.sec.gov/files/20230914-draft-recommendation-regarding-hcm.pdf`

[2] Fore more information see: `https://www.ifrs.org/projects/work-plan/human-capital/#current-stage`

[3] See: `https://sasb.ifrs.org/standards/process/projects/human-capital/`

[4] See: `https://www.globalreporting.org/standards/standards-development/topic-standards-project-for-labor/`

[5] See: `https://www.worldbank.org/en/publication/human-capital`

[6] See: `https://fortune.com/ranking/best-companies/#methodology`

[7] See: `https://equileap.com/data/`

tion, ranks the companies of the Russell 1000 according to how they perform on social issues of relevance to the American population. In 2024, fair compensation, workforce investment, ethical treatment of customers, affordable prices, environmental responsibility, community engagement and climate compliance were the core priorities of Americans (across political, ideological, and demographic lines) according to their business survey[8]. Yet Americans' opinions have evolved over time. Indeed, JUST Capital found that while Americans still expect companies to balance their profits with their impact on society, a growing proportion (56% compared with far fewer four years ago) now consider shareholders to be a company's top priority, marking a shift from the greater support previously given to workers. Evidence supports the argument that opinions have evolved in response to a changing socioeconomic and organizational context. Therefore, it is essential to examine whether these changes are being implemented on a global scale or to what extent these indicators might be equally valid to assess the different regions of the globe. To address this question, a first insight is to focus on the results of the AON's 2025 Employee Sentiment Study (AON, 2025). This report integrates geographical snapshots of employee sentiment in 23 different countries, including a number of Asian and European countries, two regions with different sociopolitical frameworks and economic priorities, resulting in varied expressions of human capital challenges and strategies. This report shows intra-regional patterns manifested by a degree of alignment in terms of employee expectations that is probably influenced by common cultural, economic, and institutional conditions. In countries such as France, Germany, the Netherlands and Portugal, employees place the emphasis on paid time-off and retirement benefits, transparent and ethical leadership, and job security and stability. Although satisfaction with benefits varies, there is a regional alignment on traditional job protection and long-term security. Across countries such as China, India and Singapore, employees generally set priorities on medical and financial security, career development (particularly with the advent of AI), work-life balance. The focus on preparing for the future and employers' investment in skills is apparent across the region. It can certainly be argued that questions of human capital respond to local norms and are subjective to the history, ideologies, demographic evolution and economic & social environment of each country.

The significance of human capital is particularly pronounced in emerging markets, where the dynamics of economic growth, labor market dynamics, and innovation trends present distinct opportunities and challenges. Characterized by rapid industrialization, a burgeoning workforce, and an increasing emphasis on technological advancement, emerging markets offer a fertile ground for exploring the impact of human capital on business performance (Tran and Vo, 2020). The study of Tran and Vo (2020) on Vietnamese listed firms provides empirical evidence underscoring the pivotal role of human capital efficiency in driving firm performance across multiple sectors in an emerging market context. Their findings confirm that higher levels of human capital efficiency positively contribute to profitability measures such as return on assets (ROA) and return on equity (ROE), substantiating the magnified impact of human capital investments in rapidly developing economies. Also, Wang and Chang (2005) highlighted the complex cause-effect relationships among various elements of intellectual capital, including human capital, innovation, and process capital, within Taiwan's IT industry. Their research underscores the importance of human capital in fostering innovation and driving business performance in emerging markets. Gogan et al. (2016a) investigated the impact of intellectual capital, which encompasses human capital and other elements such as corporate culture and structure, on the performance of companies in Romania. Their findings

[8] See https://justcapital.com/reports/2024-americans-views-on-business-survey/

highlight the importance of investing in intellectual capital, including human capital, to enhance business performance in emerging markets. The study of Al Frijat and Elamer (2025) aims to examine the role of human capital effectiveness as a key factor in corporate sustainability and organizational performance in emerging economies. Adding to this conversation, Capozza and Divella (2019) explore how human capital affects firm innovation in emerging economies. They argue that looking beyond formal R&D to include the skills and knowledge of the entire workforce is crucial. Their work suggests that both well-educated employees and seasoned managers matter, but the focus should be on strategic HR practices that boost specific technical skills and competencies.

This paper focuses on the impact of human capital in emerging and developed markets, utilizing Natural Language Processing (NLP) on unstructured data and structured data to assess and compare companies' scores on human capital, enabling a systematic evaluation of talent developing, retaining, and attraction in these regions. The paper is organized as follows: For Section 2, based on the literature and reports, we develop tools such as clustering or aligning Large Language Models (LLM) to qualitatively understand the definitions of human capital. Building upon these results, in Section 3, we focus on a financial application by constructing human capital strategies on emerging and developed markets and analyze their impact in the market. Thus, we find that human capital development emerges as one of the most influential factors explaining emerging markets movements from 2019. Finally, Section 4 offers concluding remarks.

2 Natural Language Processing to understand the concept of Human Capital

The rise of NLP has opened new frontiers for assessing and quantifying human capital's impact on business performance. Pioneering studies of Li et al. (2021) and Preuss (2021) have employed NLP techniques to focus on corporate culture, a key component of human capital. Recently, Otani et al. (2025) offer an overview of how NLP techniques can be applied to various human resources tasks, from recruitment to employee management.

2.1 Human Capital Assessment via Embedding-Based N-Gram Clustering

In this part, we develop a thematic dictionary centered on the concept of human capital. Understanding the full scope of human capital can be challenging due to different perspectives and categorizations in the literature. To ensure that we consider the widen possible range of components of human capital, an in-depth review of the literature is needed. Vidotto et al. (2017) conducted a literature review to identify the most frequent components of human capital. Based on their review, the authors identified several key components of human capital, including talent, education, experience, knowledge, skills, attitudes, creativity, and leadership. Similarly, Demers et al. (2024) introduce a lexicon using the *"word2vec"* model (Mikolov et al., 2013) to categorize human capital disclosures into five key areas: DEI, health and safety, labor relations and culture, compensation and benefits, and demographics. We adopt a similar approach for creating our dictionary, but instead using an embedding-based n-gram clustering method (similarly to Bennani et al. (2024)) to analyze a wide range of papers related to human capital. Building on the methodology of Tilly et al. (2025), we apply advanced clustering and embedding techniques to map the dimensions of human capital in our data set. With this approach, we expect to capture every components and its associated vocabulary.

2.1.1 Methodology

As a pre-processing step, we select eighty documents (academic papers, presentations, reports) mostly related to human capital[9]. The documents in the corpus were selected based on their relevance and trends, identified through downloads on SSRN, Google Scholar searches, and exploration in the tool Research Rabbit[10], all centered around the key term "human capital". The documents were then imported, and the cleaning process began. Accordingly, we split each document of the selected texts into smaller chunks in a way that is optimized for the use of embedding tasks. Each chunk text is then cleaned by removing undesired text such as urls, numbers or numerical tables, stopwords, mention (at signs, hashtags), dates, punctuation, and extra space. We expand all contractions in the text and then lemmatize it to reduce words to their dictionary form. These steps are necessary to improve the quality of the data.

Next, unigrams and bigrams are extracted from each text segment. These n-grams are embedded using the SentenceTransformers library's `all-mpnet-base-v2` model[11], which is a fine tuned version of the `microsoft/mpnet-base model` (Song et al., 2020), adapted using the S-BERT-based architecture (Reimers and Gurevych, 2019) optimized to produce sentence embeddings. This model was selected for its performance in textual semantic similarity tasks and for its balance between accuracy and computational efficiency. The embedded vectors are then clustered using the K-means algorithm (Lloyd (1957), MacQueen (1967)), with 40 clusters applied by default or 2 clusters if the segment contains less than 100 words. We use 40 clusters to ensure sufficient semantic granularity, making it easier to filter out groups that are not related to the concept of human capital. Each cluster is assessed for its relevance to the following predefined, definitions of human capital, such as:

> *"Human capital is the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being."*
>
> OECD (2001)
>
> *"Human capital is the stock of skills that the labor possesses."*
>
> Goldin (2016)
>
> *"Human capital is a key factor for growth, development and competitiveness. This link works through multiple pathways at the individual, firm and national level. Learning and working provide people with livelihoods, an opportunity to contribute to their societies and, often, meaning and identity. Workers' skills lead to productivity and innovation in companies. At the national level, equality of opportunity in education and employment contribute to economic development and positive social and political outcomes."*

[9] Available in Table 9 Appendix A.1

[10] Fore more information, the tool is available in the following link https://www.researchrabbit.ai

[11] For more information, see https://huggingface.co/sentence-transformers/all-mpnet-base-v2

World Economic Forum (2017)

"Human capital – People's competencies, capabilities and experience, and their motivations to innovate, including their: alignment with and support for an organization's governance framework, risk management approach, and ethical values ability to understand, develop and implement an organization's strategy loyalties and motivations for improving processes, goods and services, including their ability to lead, manage and collaborate"

IFRS Foundation (2021)

In addition to incorporating the various definitions of human capital identified in the literature, we have also selected terms that are semantically related to the concept, based on the comprehensive literature review carried out as part of this study:

"human capital, knowledge, competencies, skills, know-how, good health, education, well being"

Definitions are then embedded using the same approach, ensuring consistency with previous processing steps. To assess semantic alignment, we calculate the cosine similarity (Salton et al., 1975) (1) between the vector representations of the embedded definitions of the relevant terms (A) and the centroids of the clusters (B). Then a threshold of 0.15 is used to only retain clusters somewhat aligned with human capital concepts. This filtering, with a low threshold, eliminates a significant proportion of irrelevant data (more than the half of clusters) and keeps all potentially interesting clusters.

$$\text{cosine\_similarity}(\mathbf{A}, \mathbf{B}) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} \tag{1}$$

Given the initial segmentation of the bibliography, similar or identical clusters may arise independently within different text segments. To address this, a second round of clustering is conducted on all n-grams in the retained clusters. This re-clustering process merges related clusters, thereby refining the thematic dictionaries and reducing redundancy. To ensure robust results, we perform K-means clustering on a range of cluster numbers (from 10 to 150 in increments of 10) and determine the optimal number of clusters using the Davies-Bouldin score (2) (Davies and Bouldin, 1979), the Calinski-Harabasz score (3) (Calinski and Harabasz, 1974) and the Silhouette score (4) (Rousseeuw, 1987).

$$S_{DB_{(j)}} = \frac{1}{K} \sum_{i=1}^{K} \max_{i \neq i'} \frac{d(j,i) - d(j,i')}{M_{i,i'}} \tag{2}$$

where $d(j,i)$ is measured as the average dispersion between a data point j to its cluster C_i and $M_{i,i'}$ represents the distance between vectors of clusters C_i and $C_{i'}$ where $i \neq i'$.

$$S_{CH_{(j)}} = \frac{(N-K)\, d(\mu_i, \mu)}{(K-1) \sum\limits_{i=1}^{K} (d(j, \mu_i))} \tag{3}$$

that is defined as the ratio between the inter cluster variance $d(\mu_i, \mu)$ and the intra cluster variance $d(j, \mu_i)$, where N is the number of observations and K, the number of clusters.

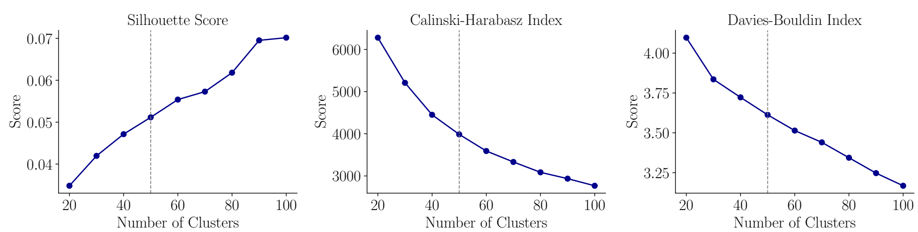
$$S_{SIL_{(j)}} = \frac{\min(d(j,i')) - d(j,i)}{\max(d(j,i), \min(d(j,i')))} \tag{4}$$

where $d(j,i)$ represents the average distance between j and all other observations of cluster C_i and $\min(d(j,i'))$ the "smallest" average distance between the observation j and all other observations of cluster $C_{i'}$ where $i \neq i'$.

2.1.2 Human Capital Term Identification Results

Although clustering quality measures such as the Silhouette score, Calinski-Harabasz Index (CHI) and Davies-Bouldin Index (DBI) generally guide the selection of the optimal number of clusters, in our case these measures did not clearly indicate a single best solution. Figure 1 shows the clustering scores performed for different cluster numbers (from 20 to 100 clusters). Based on the evolution of the clustering metrics, 50 clusters represent a balanced choice. Thus, Silhouette scores remained low overall (with a maximum of around 0.087 at 150 clusters), which is to be expected given the narrow semantic focus of our corpus on human capital, a domain where topics naturally overlap. We find that 50 is at the turning point where the curve starts flattening (marginal gains after 60 or 70 clusters). The CHI rewards high distance between clusters and low variance within clusters. The line in the figure shows a downward trend, with increasing cluster granularity, but the rate of decline slowed significantly after 50, suggesting a potential loss of cluster cohesion beyond this point. In contrast, the DBI is maximum under lowest values and steadily decreases with the number of clusters. The scores are already significantly better than at lower values (e.g., 3.61 at 50 vs. 4.52 at 10).

Figure 1: Clustering Scores to find the optimal number of clusters



Source: Authors' calculations, Amundi Investment Institute.

Based on this combination of quantitative stability, local maxima and semantic interpretability, we selected 50 clusters as a balanced choice. Beyond 50 clusters, our scores indicate that gains in cohesion and separation become marginal, while risking overfragmentation of the data. It is important to note that these clusters should be interpreted as sub-themes rather than broad, distinct topics, given the narrow thematic focus of our data. The purpose is to uncover granular variations within the overall theme of human capital, rather than segmenting the corpus into totally disjoint domains.

The clusters are illustrated in Figure 2 through word clouds that visually represent the prominence of terms within each cluster. This visualization helps to quickly assess the thematic focus of each cluster. We then employ the Python library KeyBERT[12] that uses BERT embeddings (we apply the lightweight sentence embedding model `paraphrase-MiniLM-L12-v2`) to extract the most relevant keyword from each cluster based on semantic similarity. Although this model helps identify the topic associated with each cluster, the results require refinement from a human perspective.

Thus, post-refining, some categories and subthemes emerge from the detected clusters (for more details, see Table 10 in Appendix A.2). For instance,

[12]See https://github.com/MaartenGr/KeyBERT for more information

Figure 2: Wordcloud representation of the clusters

Source: Authors' calculations, Amundi Investment Institute.

themes referring to the institutional frameworks are identified within the clusters such as education, economy and finance, the labor market, management and organization aspects, as well as the policy dimension. Transverse components embedded in "human capital & skills" and "performance & quality" are also part of the thematic highlighted by keywords such as core human capital (human cultural for example or human value in the cluster "value"), competencies and skills, emotional and psychological factors or productivity and efficiency. The latter are increasingly recognized as essential for fully exploiting the potential and activation of human capital in a complex and constantly changing world. In another area, the "social conditions & development" theme integrates concepts such as health and well being, individual risks (words such as security, protection, safety, vulnerability stem from this cluster), life course (problematic around retirement for example), poverty and inequality or social conditions and furthermore, show how human capital can be fragile, constrained, unequal or poorly distributed across the globe. Moreover, human capital issues appear not only prominently but also with a broader global scope. Indeed, the "politics & governance" framework addresses geopolitical issues, which is relevant because geopolitical repercussions can significantly affect the labor market. Indeed, in the event of conflict, countries can be affected by brain drain, disruption of education systems and fragmentation of skilled labor markets. In addition, strategic competition between countries, for example, refocuses the attraction of talent. In the case of the supply chain (which is also emerging in the "production & supply chain" cluster), in light of geopolitical and human capital considerations, offshoring manufacturing may necessitate new skills or, alternatively, contribute to a weakening of the labor market. Furthermore, assessing supply chain issues from a human capital perspective is a challenge, as human capital is intangible, hard to measure and its impact is difficult to isolate from other factors influencing supply chain performance. Finally, the themes "sustainability & environment" or governance embedded within the broader category of "policy & governance" also clearly emerge from the clusters, highlighting the interconnections among the various ESG components.

Nevertheless, these findings should be interpreted in light of certain limitations. Notably, clustering based on academic articles has certain limitations, as it often highlights a wide range of concepts related to research methods or analytical tools. In our case, this can be misleading, as some clusters appear to relate to the concept of human capital, while they primarily reflect research themes or analytical approaches rather than the concept itself. Another limitation lies in the potential omission of relevant concepts, as the clustering process relies on algorithmic decisions, which may not fully capture the semantic nuances or theoretical relevance of certain themes. In our case, for example, keywords related to *innovation* were not captured as a distinct cluster[13] . This is particularly significant given that innovation, as modern Schumpeterian endogenous growth theory emphasizes, is at the heart of economic growth, with human capital being a key element (He and Wang, 2024). According to Mariz-Pérez et al. (2012), although intellectual capital has been studied since the mid-20th century, the relationship between human capital and innovation is not consistently defined in the literature. Some theoretical models regard human capital as a fundamental input that fuels innovation through strategic investment, while others classify innovation as a distinct form of capital. Nevertheless, it is widely accepted that human capital plays an essential role in stimulating innovation within organizations. In light of recent research, Cui and Diwu (2024) show that improving employees' skills and knowledge significantly improves companies' innovation efficiency, with digital transformation and risk-taking behavior acting as key mediators in this relationship. The absence of this concept in the results illustrates how algorithmic groupings can under-represent essential dimensions of a subject when they are not guided by theoretical frameworks. One possible solution is to align large language models (LLMs) with a clearly defined

[13]Some concepts related to innovation are integrated in the "value" cluster (value creation, intellectual value)

conceptual framework of human capital, in order to improve the relevance and accuracy of the thematic clustering. A further semantic complication is that the value cluster encompasses all value-related elements and may therefore span multiple themes, as it concerns how value is perceived, created, measured, and applied across contexts. For example, it can relate to human capital & skills (human value, knowledge value, employee value, talent value, skills value, learning value, education value) or to performance & quality (value creation, value added, valuation techniques, performance value, quality value, economic value, financial value, value measurement, valuing performance).

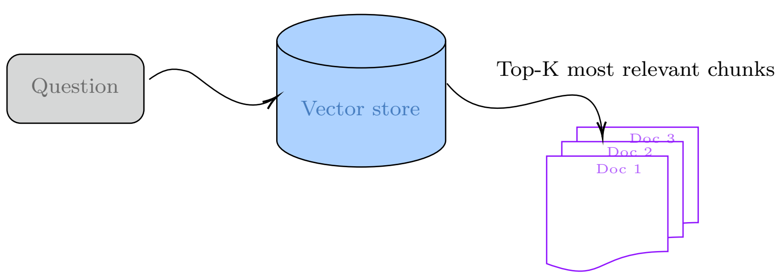
2.2 Aligning LLM with geographical and temporal definitions of human capital

As already mentioned in Section 2.1, the current clustering approach does not differentiate the various dimensions of human capital across temporal or spatial contexts. This limitation underscores the need for a more nuanced modeling strategy or one that performs analytical segmentation not only according to thematic content, but also according to geography and historical trends. The purpose of this section is to align LLMs with the evolution of human capital interests in different regions, as well as over time, specifically annually since 2020. To do this, we propose training our model on a corpus of political and corporate reports that reflect these dynamics.

2.2.1 Mitigating Hallucination in Large Language Models with Retrieval Augmented Generation (RAG) approach

Rather than training an LLM from scratch, which would be computationally and data-intensive, we adopt a Retrieval Augmented Generation (RAG) approach (Lewis et al., 2021). This framework allows for the integration of external domain-specific knowledge into the generation processes without the need for a complete reformulation of the model. As clustering does not allow for precise differentiation between the different dimensions of human capital, either in time or geographical space, it proved to be insufficient to achieve our objective. This limitation led us to adopt the RAG framework not only as a cost-effective alternative, but also as a strategy better suited to dynamic, context-sensitive research and reasoning.

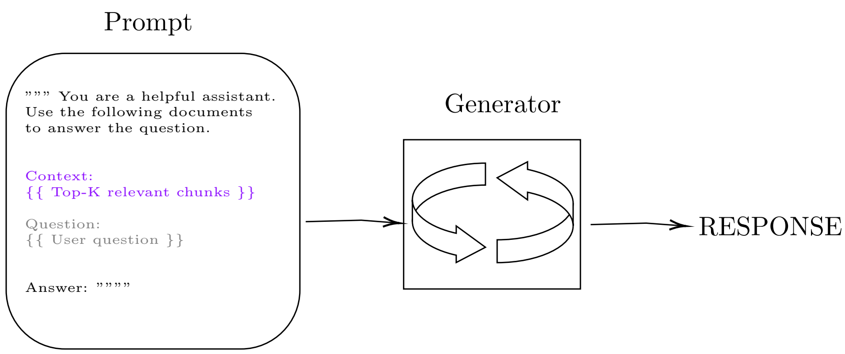
Figure 3: Naive Retriever Chain



Source: Amundi Investment Institute.

A RAG framework combines a Retriever and a Generator and the retrieval module plays a key role in enriching the model generation process with relevant knowledge documents. As illustrated in Figure 3, the retrieval module accepts a query or user question and uses it to search a vector store, which contains dense vector representations of preindexed document chunks. These document representations are usually obtained using an embedding model (for example, based on BERT or similar transforming coders). The vector store acts as a semantic memory, retrieving the content that is most similar to the query in vector space. Then, the retriever calculates the similarity (often cosine or inner product) between the query vector and the stored vectors, and returns the most relevant documents (Top-K chunks). Thereafter, the Top-K most relevant

Figure 4: Naive Generator Chain



Source: Amundi Investment Institute.

documents are passed on to the Generator as described in Figure 4 on to the context, which integrates them with the original query to produce a contextual response. This retriever-based mechanism enables the RAG system to handle dynamically updated or domain-specific knowledge without having to retrain the entire language model, offering both efficiency and adaptability.

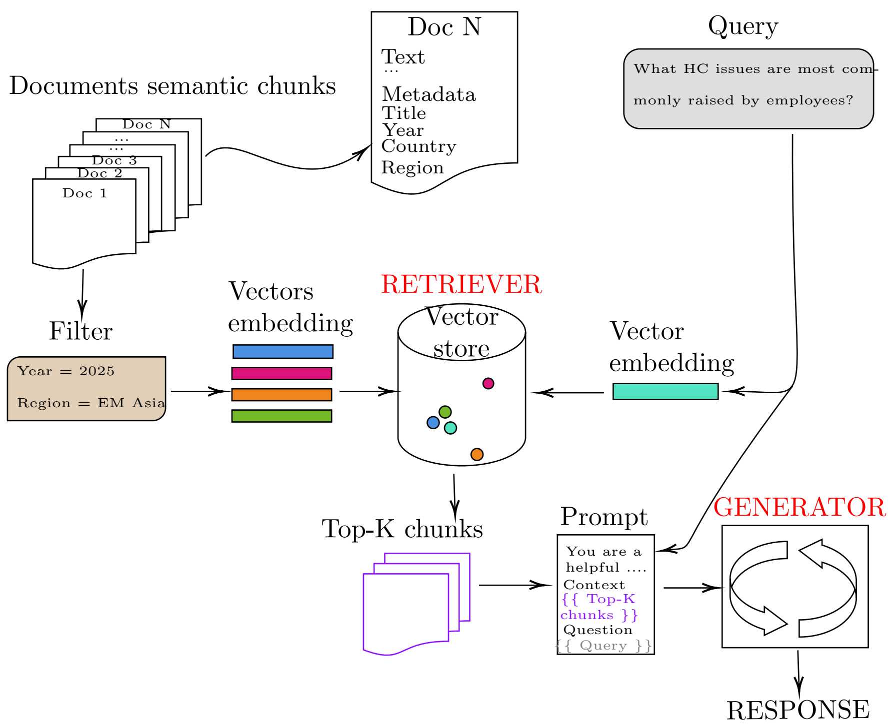
Moreover, the retriever sensitivity to key hyperparameters significantly affects the relevance of the documents retrieved and the factual consistency of the results generated. The hyperparameters used during document pre-processing is a critical hyperparameter in RAG systems. The size of the chunks, for example, directly affects the quality of the retriever and by extension, the factual base of the model's outputs. In fact, the generator hallucination is mainly due to the quality of the documents retrieved by the retriever, hence a trade-off between small and large documents chunks. As a matter of fact, smaller document chunks tend to improve retriever precision by allowing for a finer match between queries and relevant content. This can help reduce the risk of hallucinations, as the retrieved segments are more likely to be directly aligned with the user's query. However, smaller chunks also provide the generator with less contextual information per query, which can limit the consistency or completeness of the answers generated. In contrast, larger chunks preserve greater contextual continuity, which can be beneficial for generation, but they can reduce search accuracy by introducing unrelated or diluted content. Thus, selecting an appropriate chunk size requires striking a balance between search granularity and contextual appropriateness in order to optimize overall system performance.

The choice of the number of retrieved passages forwarded to the language model (or Top-K chunks) is also very sensitive, and has a direct impact on both the token budget and the relevance of the information in the final prompt. In fact, a higher "k" increases the likelihood of including useful or contextual information in the retrieved set, thus improving the relevance of the model's result. However, this comes at the cost of consuming a greater number of input tokens, which may approach or exceed the maximum context window of the language model. This trade-off necessitates careful tuning: if "k" is too small, relevant information may be missed; if k is too large, important content may be diluted or truncated, reducing the quality of generation.

2.2.2 Integrated Retrieval Filtering and Prompt Steering for Factual Alignment

Our study implements a Retrieval-Augmented Generation (RAG) framework to analyze the concept of human capital across both temporal and geographic dimensions. Accordingly, this study relies primarily on policy reports derived from large-scale employee surveys (for instance on well-being, engagement, or workplace expectations), published between 2020 and 2025[14]. The report typically concludes with a section that presents the survey results disaggregated by country, accompanied by interpretive commentary. Each report is segmented by its data-centric pages, which typically contain discrete findings or visual summaries.

Figure 5: Retrieval Filtering for Factual Alignment



Source: Amundi Investment Institute.

For each page, we extract country mentions using a Named Entity Recognition (NER) model (Grishman and Sundheim, 1996) and assign a region label based on a predefined country-to-region mapping. If multiple countries from different regions appear on the same page, the page is duplicated and tagged accordingly to preserve regional specificity. To facilitate document filtering and reduce the potential for hallucination by the language model, we annotate each page with metadata, including country and year. This annotation enables us to constrain the scope of retrieved content during inference, ensuring that the model is not required to resolve conflicting or ambiguous geographic or temporal references. In other words, we reduce the cognitive burden on the model by eliminating the need for additional filtering within the response generation

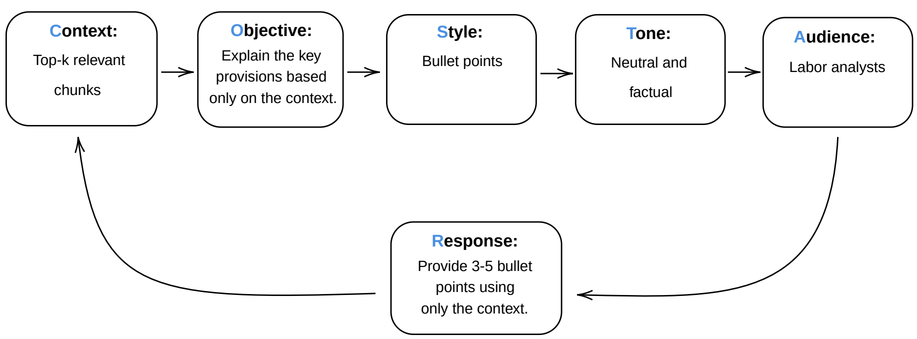
[14]The detail of the reports is available in Table 12 of Appendix A.3

phase. Following annotation, we merge the content with its associated metadata and perform semantic chunking to ensure that each chunk remains contextually coherent. The resulting chunks are then embedded and stored in a Facebook AI Similarity Search (FAISS) based vector store (Matsui et al., 2018). A RAG chain is constructed using the GPT-4o (OpenAI ChatGPT, May 2024), with a custom prompt designed to guide generation based on retrieved evidence. During inference, we ask the following question:

"What human capital issues are most commonly raised by employees or HR in the region {region selected}?"

The variable {region selected} refers to a predefined group of countries, detailed in the Appendix[15]. These countries are also explicitly listed within the prompt to guide the model's understanding. We include the countries in the prompt because, even with metadata filtering, a text chunk may contain information from countries outside the target region. Furthermore, the retriever component returns the top 5 most relevant chunks, which are used as context for the final response generated by the model. Figure 5 outlines the key stages of the methodological pipeline developed for this purpose.

Figure 6: CO-STAR: Prompt Engineering to improve Factual Alignment



Source: GovTech Singapore's Data Science & AI team, illustration by Amundi Investment Institute.

Another method of improving the factual alignment of LLM is to deal with prompt engineering. Accordingly, we use a structured prompt based on the CO-STAR framework (Context, Objective, Style, Tone, Audience, Response) with additional constraints to reduce hallucination. Developed by GovTech Singapore's Data Science & AI team[16], the CO-STAR framework serves as a practical model for structuring effective prompts. The prompt explicitly asks the model to rely only on the given context, and to acknowledge uncertainty where appropriate (see Figure 6). Thus, information flows sequentially, starting with the injection of relevant context (recovered Top-K document chunks), followed by a clearly defined objective and output format (bullet points). The model is tasked with responding with points in a neutral, factual tone, suited to a target audience of labor analysts. The arrows closing the loop emphasize that the final response must be based exclusively on the context provided, thus minimizing hallucination and ensuring alignment with the input constraints.

[15]See Table 13 Appendix A.4 for regional definitions.
[16]For more information, see https://towardsdatascience.com/how-i-won-singapores-gpt-4-prompt-engineering-competition-34c195a93d41/

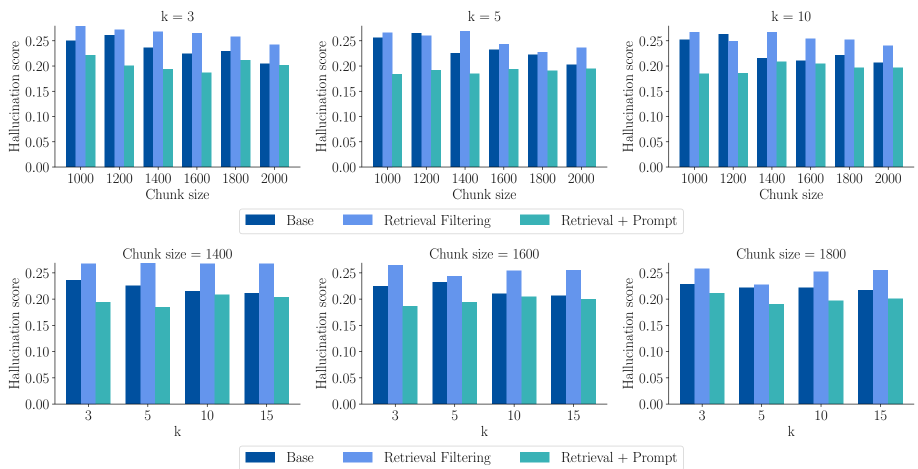
Figure 7 shows the hallucination scores for the methods described above. This score reflects the degree of semantic misalignment between the model response and the retrieved context. A score close to 0 indicates high alignment (low hallucination), while a score close to 1 indicates low alignment (high hallucination). Accordingly, we first compute the maximum cosine similarity score between the LLM response and all Top-K retrieved chunks, as follows:

$$\text{Maximum cosine-similarity} = \max_{1 \le i \le k} \text{cosine\_similarity}(\mathbf{r}, \mathbf{c}_i) \tag{5}$$

where $\mathbf{r} \in \mathbb{R}^d$ be the embedding of the LLM-generated response, and $\mathbf{c}_i \in \mathbb{R}^d$ be the embedding of the i^{th} retrieved chunk among the top-k documents. We define the hallucination score as following:

$$\text{Hallucination score} = 1 - \text{Maximum cosine-similarity} \tag{6}$$

Figure 7: Hallucination score by filtering on retriever hyperparameters using ChatGPT 4-o



Source: Amundi Investment Institute.

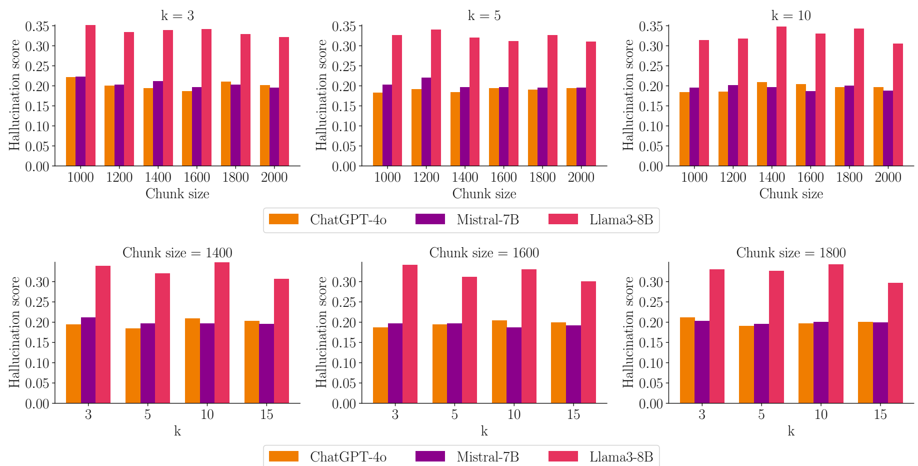
The purpose of this analysis is to assess the LLM's ability to respond accurately to the prompt without introducing content from irrelevant training documents retrieved due to inadequate filtering. The baseline model operates without any filtering or prompt steering mechanisms. The corresponding input prompt is structured as follows:

"What human capital issues are most commonly raised by employees or HR in the year {year selected} and in the region {region selected}?".

Compared to the models with filtering, our prompt specifically instructs users to consider the region and the year of the report. While Figure 7 shows that the hallucination scores are relatively low for the baseline model without additional filtering, this score is calculated based on the Top-K documents retrieved and the model's corresponding response. However, the retrieved documents may not always align with the specified filters. For instance, when querying for the Emerging Market Asia (EM Asia) region in the year 2025, some retrieved documents reference countries such as Japan or Hong Kong, which are not part of the defined region, and include reports from prior years (2022-2023). Hence the need to add a filter before the retriever. Moreover, the scores for both the

"Retrieval Filtering" and "Retrieval + Prompt" Steering methods represent averages computed across all regions and years. The Figure 7 demonstrates that, regardless of the selected hyperparameters (i.e., the value of k or the chunk size), the "Retrieval + Prompt" model consistently outperforms the others. For the latter model, the trend indicates that as the value of "k" increases (from 3 to 15), the hallucination score also increases. This suggests that selecting a smaller "k", around 3 to 5, is optimal for minimizing hallucination. A similar pattern is observed when $k = 5$ is fixed and chunk size is varied: shorter chunks consistently lead to lower hallucination scores, indicating that the model is more precise when provided with more fine-grained context.

Figure 8: Hallucination score by filtering on retriever hyperparameters using different LLMs



Source: Amundi Investment Institute.

Figure 8 presents hallucination scores across different LLMs, aiming to compare the performance of ChatGPT-4o with that of Mistral-7B (Jiang et al., 2023) and LLaMA3-8B (Llama Team, AI at Meta, 2024). For all three models, the evaluation is conducted using a consistent methodology that incorporates both retrieval filtering and prompt steering. The results show that ChatGPT-4o consistently outperforms LLaMA3 across all hyperparameter configurations and in most cases Mistral. Notably, the scores for ChatGPT-4o and Mistral-7B are often very close (frequently below 0.2) indicating stable and robust performance. In contrast, LLaMA3-8B yields higher scores, typically ranging between 0.3 and 0.35, suggesting greater susceptibility to hallucination, even when both retrieval and prompt steering filters are applied. One possible explanation for LLaMA3-8B's higher hallucination scores is its more limited contextual window compared with ChatGPT-4o or Mistral-7B. The amount of retrieved content provided in the prompt may have exceeded or diluted its effective input capacity, leading to less grounded responses. For instance, the maximum number of tokens is set to 8192 for LLaMA3-8B versus 32768 for Mistral-7B in the quantized versions we are using. These results highlight the importance of model selection and response anchoring techniques for minimizing hallucination in LLM output.

2.2.3 Key issues by regions

With the input data prepared, we retrieve responses generated by ChatGPT-4o (OpenAI ChatGPT, May 2024) and, for each combination of k and chunk size, select those exhibiting the lowest hallucination scores. From these selected responses, we extract key concepts and apply clustering techniques to identify patterns and normalize concept groupings. Each resulting cluster is then assigned a thematic label based on the underlying conceptual coherence. Thus, Figure 9 present a comparative overview of employees' top concerns between 2020 and 2024 in various regions of the world, segmented into emerging markets (EM) and developed markets (DM). Each chart highlights only the top-ranked concerns per region, providing a snapshot of human capital priorities in each region.

Accordingly, we note key regional specificities. In EM Asia, for instance, employee engagement emerges as the most significant concern. Employee engagement in EM Asia remained low and uneven between 2021 and 2025, with persistent disengagement, notable declines in key markets such as India and China, and growing retention challenges as a large part of the workforce actively seeks new employment opportunities. Challenges relating to well-being, training and development are also notable, reflecting wider concerns about employee support and capacity building. In the APAC (Asia Pacific) region, well-being issues are the most highlighted issue, suggesting that mental health and work-life balance are at the heart of employee sentiment. Discrimination in the workplace and employee engagement also feature prominently among the top concerns, reflecting a growing sensitivity to inclusion and organizational culture, even if levels of engagement remain uneven across the region.

Then, in Europe, and more specifically in the EMEA (Europe Middle East & Africa) region, employee engagement has shown a strong association with turnover. Despite appearing contradictory, the two are connected through shared underlying concerns, pointing to a deeper alignment in organizational priorities. From 2020 to 2024, global employee engagement remained low with regional disparities, and by 2024, increasing turnover among even satisfied employees highlighted deeper issues such as stress and career uncertainty beyond basic job satisfaction. Concepts such as fair compensation, ethical practices, and career opportunities appear to be gaining momentum, reflecting a favorable trend in organizational priorities. For the Developed Market Europe (DM Europe) region, the distribution of concerns is balanced, with the challenges of employee engagement (Western Europe having the lowest employee engagement percentage in 2021 and 2022) and well-being again taking priority. Upskilling and digitization also appear, suggesting that the focus is on adapting to technological change. But, the presence of demographic trends and upskilling as concerns reflects also the region's adaptation to an aging workforce and evolving job requirements. Finally, in EM America (Emerging Market America), similar to DM Europe, wellbeing challenges and employee engagement are among the highest concerns. Upskilling also features strongly, indicating continued investment in human capital amid evolving labor market dynamics. In DM America (Developed Market America), wellbeing challenges stand out as the most pressing issue, with financial security and ethical practices also included. This pattern suggests that employees in developed American markets are highly attuned to both mental health and organizational integrity.

Moreover, cross-regional similarities are emerging. For instance, wellbeing challenges are a consistent top concern across all regions (except in EMEA region), reflecting a global prioritization of mental health, work-life balance, and psychological safety. Employee engagement is also widely cited, and take a large score in emerging markets, often varying by region and over time, employee en-

Figure 9: Most valued human capital concepts by regions

Source: Amundi Investment Institute.

gagement levels remained generally low throughout this period. Despite regional and economic differences, many markets show a growing concern with ethical, and supportive workplace environments. Common patterns also appear within emerging markets and within developed markets, underscoring the distinctions between these two groups. Developed markets such as DM America and DM Europe include concerns related to financial security, labor rights, ethical practices, and resilience, which may reflect mature labor environments and expectations beyond basic organizational support. Emerging markets, particularly EM Asia and EM America, place greater emphasis on training and development, talent retention, and engagement, reflecting a developmental focus on workforce capability and retention strategies. Finally, technological adaptation, represented by digitalization and automation, appears in some regions (e.g., APAC, Europe, EM America) but is notably absent in others, suggesting variable perceptions of its urgency.

Table 1: Employee concerns in the APAC region in 2020 vs 2024

(a) Employee concerns in 2020

Category	**Sub-category**
Pandemic impact	COVID-19 economic impact
Wellbeing challenges	Stress and emotional well-being Comparatively favorable life impact
Demographic trends	Job disruptions by demographics
Environmental and governance concerns	Dissatisfaction with government and environment

(b) Employee concerns in 2024

Category	**Sub-category**
Digitization and automation	Cross-border remote work Technological and economic transitions
Talent attraction	Diverse talent Talent attraction (sub) Global talent acquisition
Workplace discrimination	Skill gaps
Immigration policies	Immigration policies
Childcare initiatives	Childcare initiatives

Source: Amundi Investment Institute.

Table 2: Employee concerns in the EM Asia region in 2020 vs 2024

(a) Employee concerns in 2020

Category	**Sub-category**
Pandemic impact	Pandemic economic disruptions
Wellbeing challenges	Emotional and wellbeing issues
Employee engagement	Employee engagement challenges
Job satisfaction	Life satisfaction variance
Environmental and governance concerns	Governance and environmental concerns

(b) Employee concerns in 2024

Category	**Sub-category**
Digitization and automation	Workforce automation
Talent attraction	Talent attraction
Emotional challenges in the workspace	Resistance to organizational change
Demographic trends	Aging and declining working-age populations
Talent retention	Retention challenges
Employee engagement	Employee engagement
Workforce augmentation	Workforce augmentation

Source: Amundi Investment Institute.

Another point of interest is the evolution of employee concerns since 2020. To explore this, Table 1 and Table 2 illustrate how these concerns have changed over time (in 2020 vs 2024), with a particular focus on Asia. As a matter of fact, we point out that 2020 concerns reflect the immediate impact of the COVID-19 pandemic and a rising awareness of sustainability issues. In 2020, concerns were largely reactive (e.g., pandemic impact, job satisfaction). By 2024, the concerns are more strategic and future-facing (e.g., talent attraction, automation). While wellbeing was a dominant concern in 2020, in 2024 it is addressed through adjacent issues like emotional challenges and childcare initiatives, indicating a shift toward structural supports for wellbeing. As far as sustainability and pandemic concerns are concerned, environmental issues and the impact of the pandemic are no longer among the top priorities. This may indicate that organizations now consider these areas as part of their baseline operations or that they have redirected their attention to emerging challenges. In 2024, issues such as discrimination in the workplace (skills gaps) and immigration policies emerge in 2024, especially in the APAC DM, indicating greater awareness of diversity, equity and inclusion.

Looking at the regional breakdown, emerging markets in Asia are focusing on building talent pools and adapting to technology, in line with rapid economic development. Developing economies in the APAC region are tackling mature labor market issues such as inclusion, immigration and work-life support, themes more prevalent in established economies with aging populations and skills shortages. But companies in the EM Asia region, particularly in East Asia, are also concerned about the impact of aging and shrinking working-age populations, which is expected to significantly influence labor markets by 2030.

A similar conclusion can be drawn in the European region. As shown in Table 14 and Table 15 in Appendix A.5, employee concerns in both Europe EM and DM Europe have shifted markedly between 2020 and 2024. In 2020, the focus was largely on well-being, employee engagement (potentially a consequence of the COVID-19) and sustainability issues such as ethical practices and environmental concerns. In 2024, however, the focus was on longer-term labor market challenges, such as talent retention, digitization, diversity and inclusion, and demographic trends, underlining the shift from reactive crisis management to strategic workforce development and social equity. As with EM Asia, Europe EM focuses on talent development and retention in a growing economic context, while developed markets (Europe or Asia DM) focus on inclusion, demographic change and flexible working, which are typical concerns of mature labor markets.

In conclusion to this section, we can outline one particular limitation associated with the use of the GenAI and more particularly the generator of the RAG process. It lies in the steering model's reliance on chunk-based input. As a matter of fact, when multiple countries are discussed across consecutive chunks, there are instances where a country mentioned in a previous chunk is not explicitly referenced in the current one. In such cases, the model may fail to capture the full context, potentially leading to misinterpretations or incomplete readings of the content. However, it is reassuring to note that employee concerns do not vary significantly from one region to another. When we segment the data according to emerging and developed markets, both groups remain marked by similar priorities. This consistency is also evident over time, as we observe a shift from sustainability related concerns in 2020 to issues more closely linked to structural challenges in 2024.

3 Financial application in Emerging Markets

As indicated in Section 1, human capital plays a key role in shaping organizational performance. In this section, we draw on the results obtained from LLM analysis to explore the link between human capital and financial performance.

3.1 Human Capital Portfolio construction in Emerging Markets

Employee priorities vary significantly across regions, as mentioned in Section 2.2. Tables 3 and 4 summarize the main employee concerns between developed and emerging markets from our documentation sources and LLM summarization. It is worth noting that, in developed markets (Table 3), the most prominent concern is wellbeing challenges (35.19%), followed by employee engagement (22.22%) and digitalization and automation (11.11%). Other notable issues include workplace discrimination (9.26%), upskilling (7.41%), and demographic trends (7.41%), suggesting a mature market context where workforce aging, inclusion, and modernization are central. In contrast, emerging markets (Table 4) reveal a different pattern. While employee engagement remains the top concern (26.23%), talent attraction and retention ranks second (18.03%), significantly ahead of wellbeing challenges (14.75%). Issues such as turnover (11.48%) and career development (including training, emotional support, and opportunities, all at 6.56%) underscore the dynamic and growth-oriented challenges faced by companies operating in these environments.

Table 3: Importance of employee-related concepts in Developed Markets (2020-2024)

Employee concerns	**Importance (in %)**
Wellbeing challenges	35.19
Employee engagement challenges	22.22
Digitalization and automation	11.11
Workplace discrimination	9.26
Upskilling	7.41
Demographic trends	7.41
Turnover	7.41

Source: Amundi Investment Institute.

Emerging markets offer opportunities through their labor force. While their formal sectors can be as regulated as those in developed economies, the size of the informal sectors and the youthfulness of the population often mean that overall labor mobility is higher than in many advanced economies, where strict labor regulations and demographic aging weigh more heavily on employment dynamics (ILO, 2023; Asif M. et al., 2022; La Porta and Shleifer, 2014). The fact that "attracting and retaining talent" is one of the main concerns in these markets seem to indicate both increased awareness and strong potential for transformation. Companies in emerging economies therefore have the opportunity to strengthen their talent strategies. Our work consists of using structured data from MSCI to explore the impact of human capital on firm performance in emerging markets. The MSCI framework for assessing human capital management includes a comprehensive thematic score alongside four detailed subscores. These metrics provide insights into various aspects of workforce management, crucial for sustainable and ethical business practices. To assess companies'

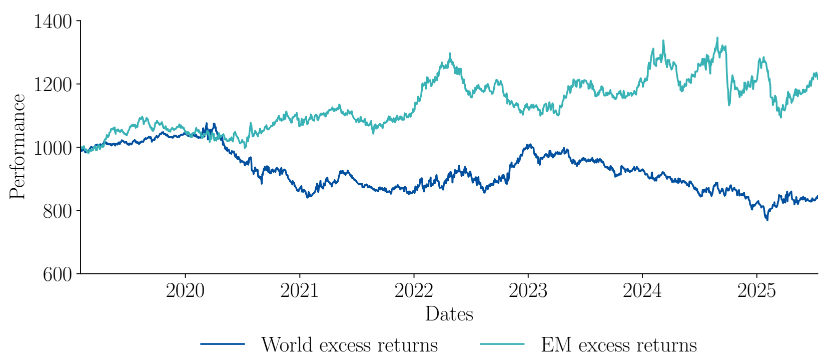
Table 4: Importance of employee-related concepts in Emerging Markets (2020-2024)

Employee concerns	Importance (in %)
Employee engagement challenges	26.23
Talent attraction & retention	18.03
Wellbeing challenges	14.75
Turnover	11.48
Digitalization and automation	9.84
Training and skills development	6.56
Emotional challenges in the workplace	6.56
Career opportunities	6.56

Source: Amundi Investment Institute.

readiness to address the most employee concerns identified in Table 4, our focus is specifically oriented to the "Human Capital Development" scores. These scores offer a structured comparative measure of how firms develop, retain, and attract high-caliber talent (MSCI ESG Research LLC, 2023b) and are particularly relevant in emerging markets where the dynamics of the workforce is rapidly evolving. By tracking these scores, we capture the dynamic evolution of human capital strategies in emerging markets, with the expectation that these advances will increasingly translate into long-term asset performance and value creation. Our strategy focuses on designing emerging market portfolios with a human capital orientation, targeting firms that excel in talent development and retention.

Figure 10: Investment level of World vs Emerging markets excess returns strategies



Source: MSCI, Author's calculations.

Accordingly, we construct a long portfolio including the top 20% of companies with the highest scores and a short portfolio comprising the bottom 20% of companies within the MSCI Emerging Markets universe. We adjust these scores by the 60 days average daily trading volume of each company to account for liquidity due to the homogeneity of scores across companies. Portfolio weights are assigned on a capitalization-weighted basis, and excess returns are computed as the difference between the highest quintile (Q1) and the lowest quintile (Q5). For comparative purposes, we replicate this methodology for the MSCI World index, which primarily represents developed markets, in order to contrast the performance of emerging market and developed market strategies. Thus, Figure 10 shows the performance of both strategies since 2019. Net asset values indicate that the emerging market strategy generates positive alpha, whereas the developed market (MSCI World) strategy produces negative alpha. Overall, the emerging market strategy outperforms its developed market counterpart.

Table 5: Performance metrics for Human Capital Development Scores in World vs Emerging markets

	Emerging Market			World		
Metrics (in %)	Q1	Q5	Q1-Q5	Q1	Q5	Q1-Q5
annualized perf.	12.14	6.04	4.52	18.88	20.68	-3.51
annualized vol.	16.61	17.91	10.78	15.66	20.59	10.34
ratio	73.01	33.74	41.96	120.55	100.44	-33.93

Source: MSCI, Author's calculations.

Table 5 reports the performance metrics for the human capital development score based on both the MSCI Emerging Markets and MSCI World universes in USD. In Emerging markets, the strategy generates a positive long/short return of 4.52%, indicating that companies with higher human capital development scores outperform those with lower scores. This return differential is achieved with volatility comparable to that of its counterpart in developed markets and translates into positive risk adjusted performance with a ratio of 41.96%. In contrast, the same strategy applied to developed markets generates a negative return spread of -3.51% and a negative riskâadjusted performance, suggesting that the factor fails to generate alpha in this context. These results suggest that this aspect of the human capital scores has a stronger predictive power in emerging markets compared to developed markets. To validate this theory, we will use "Health and Safety" scores of MSCI as a proxy for employee well being. Given that well being challenges account for 35.19% of employee related concerns in developed markets (Table 3), analyzing these scores allows us to test whether the predictive power of human capital dimensions differs between the regions.

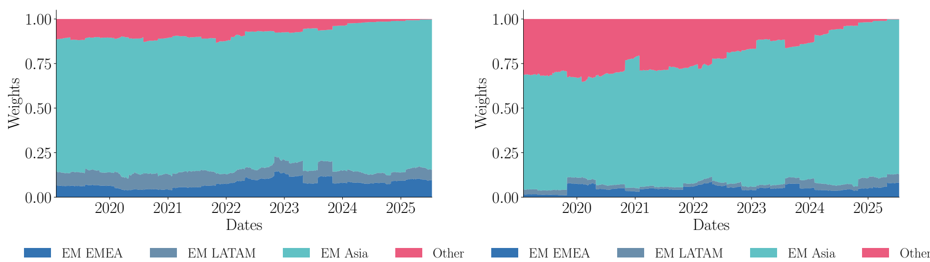
Table 6: Performance metrics for Health and Safety Scores in World vs Emerging markets

	Emerging Market			World		
Metrics (in %)	Q1	Q5	Q1-Q5	Q1	Q5	Q1-Q5
annualized perf.	0.08	-3.50	1.98	15.42	10.29	2.98
annualized vol.	19.97	20.16	15.03	18.10	21.57	9.10
ratio	0.38	-17.35	13.16	85.18	47.71	32.77

Source: MSCI, Author's calculations.

Table 6 presents the performance metrics for health and safety scores in Emerging Markets versus the World. The data show that in Emerging Markets, the annualized performance for the long/short strategy based on Health and Safety Scores is positive at 1.98%, with a risk-adjusted ratio of 13.16%. In contrast, the World universe exhibits higher annualized performance and risk-adjusted ratio (respectively 2.98% and 32.77%). These results support the theory that these scores, have varying predictive power across markets. While the strategy yields positive returns in both universes, the stronger risk-adjusted performance in developed markets and the performance of the Q1 and Q5 strategies suggest that health and safety scores are a more stable and significant factor for employee well-being and company performance in these markets. This aligns with the earlier observation that well-being challenges represent a substantial 35.19% of employee concerns in developed markets, reinforcing the importance of these practices in driving sustainable performance.

Figure 11: Weights decomposition per region of the long/short portfolio in Emerging market universe



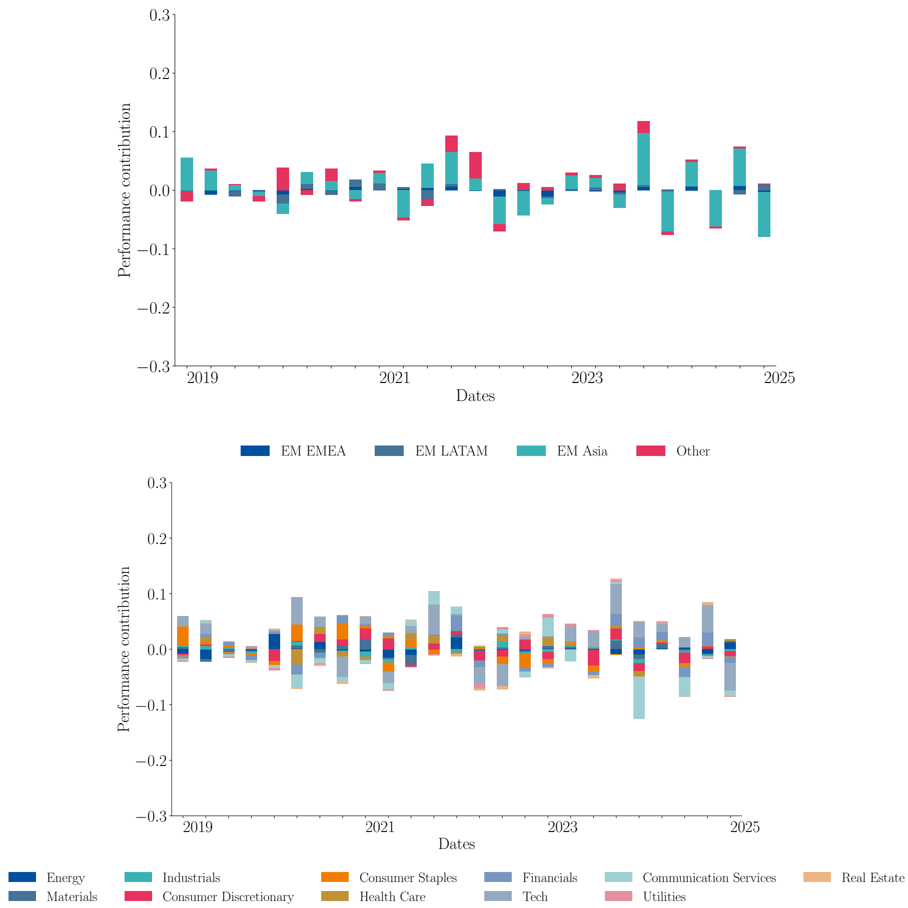
(a) Q1 portfolio weights

(b) Q5 portfolio weights

Source: MSCI, Author's calculations.

Now, let us examine the human capital development scores portfolio in emerging markets. Considering the decomposition of portfolio weights, Figure 11a and Figure 11b show that, on average since the start of the backtest in 2019, approximately 78% of both the Q1 and Q5 portfolios are allocated to EM Asia. The remaining regional weights are relatively balanced in the long portfolio, averaging between 7.2% and 7.8% per region when EM EMEA takes on average 5% of the allocation, and 3% on average in EM Latin America. This concentration in EM Asia is reflected in performance, as illustrated in Figure 12, which presents the performance contribution of the long/short portfolio within the Emerging Markets universe. The results indicate that EM Asia is the primary driver of both positive and negative performance. From a sectoral perspective, the technology sector emerges as the largest contributor to portfolio performance, followed by communication services, consumer discretionary and staples, financial, consumer staples, energy, and health care. A similar observation can be made for long/short portfolios constructed in the developed markets universe, where North America dominates the allocation (see Figure 16a and 16b in Appendix A.6). On average over the period, North America accounts for approximately 56% of the long portfolio and approximately 80% of the short portfolio. Europe accounts for approximately 30% of the long portfolio, compared to only 6% of the short portfolio. This concentration is also reflected in the regional contribution to performance: as the Figure 17 in Appendix A.6 shows, North America is the main contributor to portfolio returns, both positive and negative.

Figure 12: Performance contribution of the region and sectors in the Emerging Market long short portfolio

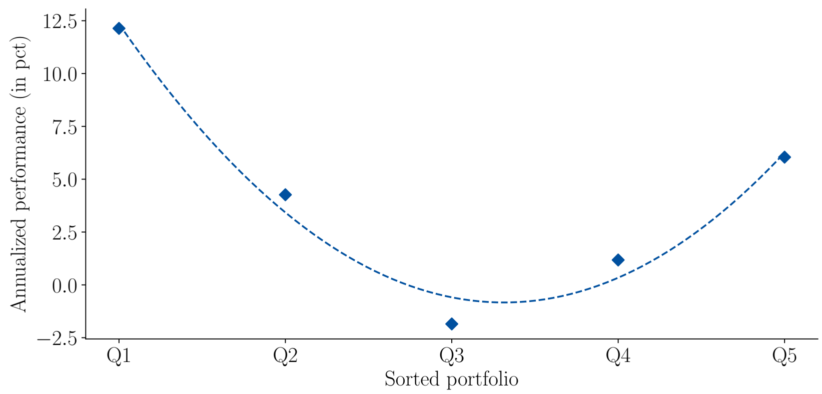


Source: MSCI, Author's calculations.

Moreover, Figure 13 shows the annualized performance of the quintile portfolios within the Emerging Markets strategy. The results show a monotonic trend between the best-performing quintile (Q1) and the worst-performing quintile (Q5), with Q1 posting the best annualized performance of around 12.5%. In contrast, Q3 posted slightly negative returns, while Q4 remained slightly positive. Q5 shows a notable rebound compared to the intermediate quintiles but remains significantly lower than Q1. These returns ultimately indicate that investors significantly favor firms that are leaders in human capital development within emerging markets.

Analyzing the performance of the strategy is essential to assess its role as a systematic factor in explaining market returns. In this context, the human capital development score based strategy can be interpreted as a cross-cutting factor that distinguishes companies based on the quality of their intangible assets. Our performance metrics indicate that this factor offers a significant positive premium for emerging market, suggesting that companies implementing a policy of developing, retaining, and attracting talent also performs well. This pattern is consistent with the idea that better working conditions and investments in human capital can strengthen employee engagement and operational efficiency, thereby contributing to improved stock returns in emerging markets, while in developed markets the premium is negative.

Figure 13: Annualized performance of the quintiles for Emerging Market strategy



Source: MSCI, Author's calculations.

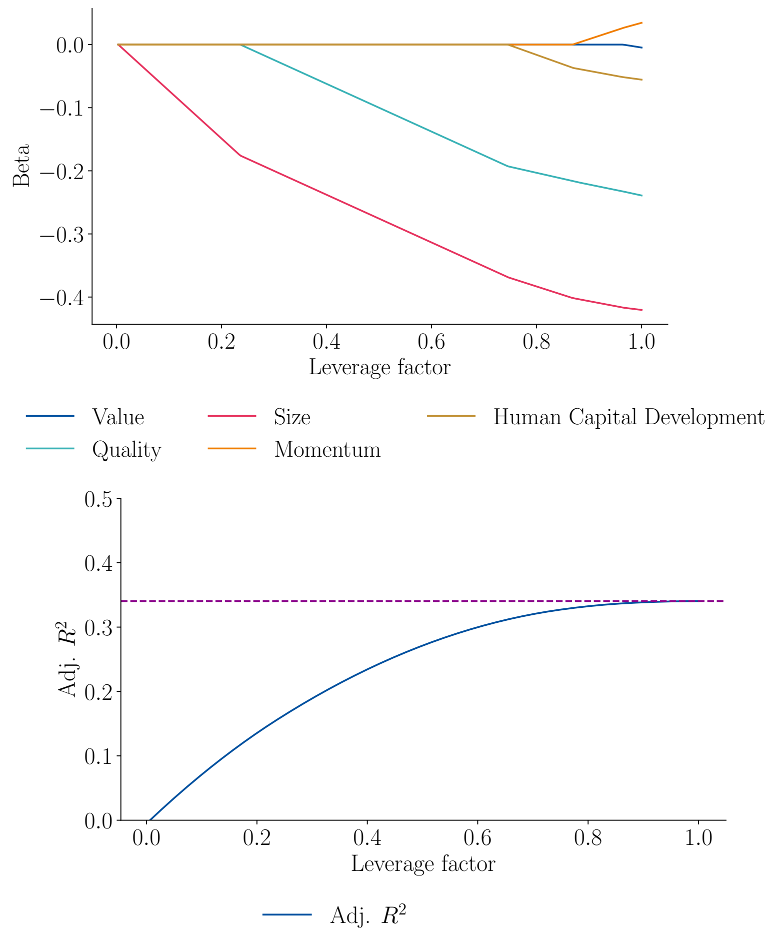
3.2 Human Capital in Asset Pricing Models

Adding human capital in an asset pricing model is not recent. Mayers (1973) extends the Capital Asset Pricing Model (CAPM) by incorporating nonmarketable assets as part of investors' wealth, showing that asset returns should reflect covariation with both market returns and aggregate human capital. Building on this idea, Fama and Schwert (1977) provide empirical support by including a proxy for human capital in asset return regressions and find that this variable does not improve the ability to explain the expected return of assets. Jagannathan and Wang (1996) further develop this line of research by introducing a conditional CAPM where time-varying labor income growth factor plays a significant role in explaining the cross-section of expected returns. Palacios-Huerta (2003) emphasizes the importance of properly measuring human capital returns and demonstrates that the component improves asset pricing performance. Kim et al. (2011) develop a three-factor asset pricing model that replaces traditional Fama-French factors with the consumption growth factor, the market factor and with a future labor income growth factor. They show that the latter captures human capital risk and improves the explanation of stock return patterns. More recently, Palacios (2014) continued this exploration by refining the measurement and pricing of human capital risk. Also, (Roy and Shijin, 2018; Maiti and Balakrishnan, 2018; Roy and Santhakumar, 2019) have explored the integration of human capital into asset pricing models, suggesting that it is a significant factor for explaining asset returns. The findings of Khuram et al. (2021); Ayub et al. (2022); Khuram et al. (2022a,b, 2023) show that the quality of human capital, measured through employee motivation, skills, and innovation culture, acts as a price factor that explains variations in returns beyond the Fama-French dimensions. The inclusion of a candidate human capital factor in this models reduces residual alphas and improves explanatory power, indicating that workforce quality carries a distinct and non-redundant risk premium.

Table 7: Variance inflation factor (VIF) for EM equity factors

Factors	Size	Quality	HC Dev.	Momentum	Value
VIF	1.18	1.43	1.37	1.06	1.17

Figure 14: Beta and adj. R^2 of the Lasso regression

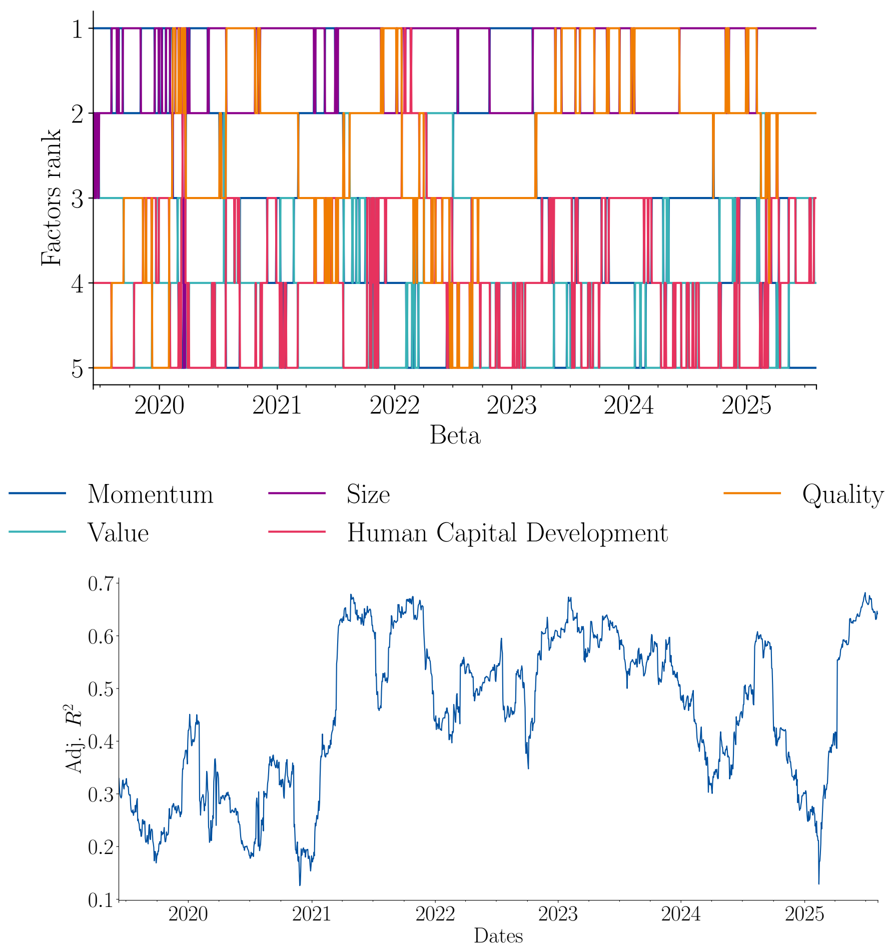


Source: Amundi Investment Institute.

Our objective is to assess whether human capital is priced in emerging markets as a distinct factor, not embedded in one of the equity traditional factors. For that, we process to a regression where our period of analysis is beginning in February 2019 until August 2025. After confirming the absence of multicollinearity through the VIF analysis (O'Brien, 2007) in Table 7, we proceed to run a linear regression on the full dataset to explain market movements. The explanatory variables consist of long/short factors (long vs. market) based on quality, size, value, and momentum, to which we add the human capital development strategy to evaluate its incremental contribution. Our approach employs a Lasso regression framework in order to test its incremental explanatory power for the market.

The results presented in Figure 14, indicate that our strategy ranks as the third most important variable in the model, after size (which dominates due to a strong size bias in the market) and quality. All factors display negative coefficients, suggesting the statistical relationship after removing market influence. Our factor also exhibits a negative coefficient, albeit with a lower magnitude, indicating a modest inverse relationship with the market. A second key finding is that the model achieves an adjusted R^2 of 34.03% when including our factor. When we re-run the regression excluding our factor, the adjusted R^2 falls to 33.80%, confirming that our factor contributes a small but measurable increase in explanatory power. In addition, an important element of the paper is that when we run rolling regressions, thereby shortening the estimation periods, human capital emerges as one of the most influential factors explaining market movements. In the Figure 15, we rank the factors by importance using rolling regressions with a 90-day window across all dates. The results show that during certain periods (notably around March 2020 and from January to April 2022), human capital ranks among the top two factors influencing the market. During these two periods, crises such as the COVID-19 shock and geopolitical turmoil (the war between Russia and Ukraine) reinforced the importance of workforce resilience and adaptability, making human capital a key differentiator between countries. Moreover, in 27% of cases, it ranks third that is still a significant position. These results are robust, as the corresponding periods are associated with relatively high explanatory power: the average Adj.R^2 is approximately 45% when human capital ranks first or second, and about 49% when it ranks third.

Figure 15: 90 Days Rolling rank and Adj. R^2



Source: Amundi Investment Institute.

4 Conclusion

This study presents a methodological framework integrating clustering techniques and large language models that can be applied beyond our case, offering an innovative approach to analyzing intangible assets in multiple research contexts. In this article, using large language models, we demonstrate that the definition and perception of human capital are not fixed, but vary considerably from region to region and evolve over time. These variations reflect differences in socioeconomic development, institutional frameworks, and geopolitical contexts, highlighting the importance of adopting a dynamic and context-sensitive approach when analyzing human capital in global markets.

Financial analysis allows us to confirm that variations in the perception of human capital from one region to another have tangible implications for investment performance. Specifically, our results show that strategies incorporating human capital development scores generate significantly different returns in emerging markets compared to developed markets, highlighting the need for tailored approaches to portfolio construction. This reinforces the value of integrating qualitative information from large language models with quantitative financial measures in order to capture the multifaceted nature of human capital. Altogether, our framework provides a robust tool for investors and researchers seeking to understand and capitalize on the dynamics of human capital in an increasingly complex global economy.

Moreover, our asset pricing analysis also highlights that human capital development plays a central role in explaining emerging market movements, with evidence that during periods of geopolitical turmoil, companies with stronger human capital development tend to demonstrate greater resilience and generate more stable returns. Geopolitics emerges clearly in our textual analysis: in the clustering component, one cluster is directly linked to the definition of human capital, and in the LLM based approach, similar patterns emerge. More broadly, geopolitical challenges that include global uncertainty, regional conflicts and shifting alliances, are increasingly influencing the dynamics of the labor market. In the EMEA region, for example, the combined effects of inflation, commodity price volatility, and the post-pandemic recovery in 2023 have reshaped labor markets. These changes will continue to drive demand for new skills in emerging sectors and accelerating transitions such as green and energy transformation.

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A Appendix

A.1 Source used for clustering process

Table 8: Papers from the reference list used for clustering

BibTeX Ref.	Title
Kotter and Heskett (1992)	Corporate culture and performance
Becker (1993)	Human capital: a theoretical and empirical analysis with special reference to education
Benhabib and Spiegel (1994)	The role of human capital in economic development evidence from aggregate cross-country data
Grossman (1999)	The human capital model of the demand for health
Woessmann (2000)	Specifying human capital: a review, some extensions, and development effects
Barro (2001)	Human capital and growth
OECD (2001)	The well-being of nations
Becker (2002)	The age of human capital
Wright and Cropanzano (2004)	The role of psychological well-being in job performance: a fresh look at an age-old quest
Ciscel and Smith (2005)	The impact of supply chain management on labor standards: the transition to incessant Work
Kor and Leblebici (2005)	How do interdependencies among human capital deployment, development, and diversification strategies affect firms' financial performance?
Wang and Chang (2005)	Intellectual capital and performance in causal models evidence from the information technology industry in Taiwan
Bontis and Serenko (2007)	The moderating role of human capital management practices on employee capabilities
Kwon (2009)	Human Capital and its measurement
Acemoglu and Autor (2011)	Skills, tasks and technologies: implications for employment and earnings
Baron (2011)	Measuring human capital
Edmans (2011)	Does the stock market fully value intangibles? Employee satisfaction and equity prices
Edmans (2012)	The link between job satisfaction and firm value, with implications for corporate social responsibility
Hanushek and Woessmann (2012)	Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation
Mariz-Pérez et al. (2012)	The relevance of human capital as a driver for innovation
Graff Zivin and Neidell (2013)	Environment, health, and human capital

Table continues on next page

BibTeX Ref.	Title
Langenhan et al. (2013)	Psychosocial risks: is risk management strategic enough in business and policy making?
Shaw et al. (2013)	A resource-based perspective on human capital losses, HRM investments, and organizational performance
Zhao et al. (2013)	The impact of supply chain risk on supply chain integration and company performance: A global investigation
Diaz-Fernandez et al. (2014)	A contingent approach to the role of human capital and competencies on firm strategy
McGuirk et al. (2015)	Measuring the impact of innovative human capital on small firms' propensity to innovate
Melián-González et al. (2015)	New evidence of the relationship between employee satisfaction and firm economic performance
Pelinescu (2015)	The impact of human capital on economic growth
Goldin (2016)	Human Capital
Gogan et al. (2016b)	The impact of intellectual capital on organizational performance
Luo et al. (2016)	Employee satisfaction and corporate performance: Mining employee reviews on glassdoor.com
Muda and Rahman (2016)	Human capital in SMEs life cycle perspective
Diaz-Fernandez et al. (2017)	Human capital and human resource management to achieve ambidextrous learning: A structural perspective
Integrated Reporting (2017)	Creating value: the value of human capital reporting
Nielsen et al. (2017)	Workplace resources to improve both employee well-being and performance: A systematic review and meta-analysis
Vidotto et al. (2017)	A human capital measurement scale
World Economic Forum (2017)	The global human capital report 2017
Kersemaekers et al. (2018)	A workplace mindfulness intervention may be associated with improved psychological well-being and productivity. A preliminary field study in a company setting
Maiti and Balakrishnan (2018)	Is human capital the sixth factor?
Stiglitz et al. (2018)	For good measure: advancing research on well-being metrics beyond GDP
Capozza and Divella (2019)	Human capital and firms' innovation: evidence from emerging economies
Chemmanur et al. (2019)	How does online employee ratings affect external firm financing? evidence from glassdoor
Roy and Santhakumar (2019)	Is human capital the sixth factor? Evidence from US data

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BibTeX Ref.	Title
Tamayo-Torres et al. (2019)	Boosting sustainability and financial performance: the role of supply chain controversies
Munir et al. (2020)	Supply chain risk management and operational performance: The enabling role of supply chain integration
OECD (2020)	How's Life? 2020: measuring well-being
Park and Rahmani (2020)	Employee satisfaction and firm innovation performance
Ruggeri et al. (2020)	Well-being is more than happiness and life satisfaction: a multidimensional analysis of 21 countries
SASB (2020)	Preliminary framework on human capital and the SASB standards
Semet (2020)	The social issue of ESG analysis
Tran and Vo (2020)	Human capital efficiency and firm performance across sectors in an emerging market
Cammeraat et al. (2021)	The role of innovation and human capital for the productivity of industries
IFRS Foundation (2021)	International <IR> framework 2021
Khuram et al. (2021)	ESG - Environmental, Social & Governance investing: introducing the human capital factor
Semet et al. (2021)	ESG and sovereign risk: what is priced in by the bond market and credit rating agencies?
Li et al. (2021)	Measuring corporate culture using machine learning
Nirino et al. (2021)	Corporate controversies and company's financial performance: exploring the moderating role of ESG practices
Preuss (2021)	Natural Language Processing: to analyze corporate culture
Abraham and Mallatt (2022)	Measuring human capital
Ayub et al. (2022)	Measuring an intangible asset: the human capital factor
Khuram et al. (2022b)	ESG - Environmental, Social & Governance Investing: creating an innovation culture score, using human capital factor data
Bloomberg (2023)	Gender reporting framework 2023
Khuram et al. (2023)	ESG - Human capital factor: what drives employees, intrinsic or extrinsic factors?
MSCI ESG Research LLC (2023a)	MSCI ESG ratings methodology: health & safety key issue
MSCI ESG Research LLC (2023b)	MSCI ESG ratings methodology: human capital development key issue
MSCI ESG Research LLC (2023c)	MSCI ESG ratings methodology: labor management key issue
MSCI ESG Research LLC (2023d)	MSCI ESG ratings methodology: supply chain labor standards key issue

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BibTeX Ref.	**Title**
Backhaus et al. (2024)	Organizational change: challenges for workplace psychosocial risks and employee mental health
Cui and Diwu (2024)	Human capital upgrading and enterprise innovation efficiency
LSEG (2024)	Environmental, Social and Governance scores from LSEG
OECD (2024)	Measuring subjective well-being across OECD countries
Song (2024)	Corporate ESG performance and human capital investment efficiency
Vandenbroucke et al. (2024)	Do companies walk the talk? Commitments and actions in global supply chain labor standards
Woessmann (2024)	Skills and earnings: a multidimensional perspective on human capital
Al Frijat and Elamer (2025)	Human capital efficiency, corporate sustainability, and performance: evidence from emerging economies
AON (2025)	2025 Human capital employee sentiment study
Hosseinioun et al. (2025)	Skill dependencies uncover nested human capital
Rott and Thulliez (2025)	The financial materiality of human capital: how employee knowledge, skills and engagement can drive long-term growth and efficiencies
Workplace Options and IIRSM (2025)	The impact of psychological safety on employee engagement and risk management

Source: Amundi Investment Institute.

A.2 Clustering results

Table 10: Thematic Classification of Human Capital-Related Themes, Sub-themes and Keywords

Theme	Sub-theme	Keywords
Economy & Financial Development	Economic Growth & Models	Economy, Economic Growth Dynamic, Economic Modeling
	Financial Capital & Investments	Equity - Stock, Investment, Wealth Accumulation
	Income & Earnings	Income - Earnings
	Production & Supply Chains	Production and Supply Chains
Educational Systems & Analytical Tools	Analytical Tools & Methods	Analysis Practice, Cross-country Analysis, Dataset Panel, Measurement and Metrics, Quantitative Modeling, Research, Scoring Metrics, Statistics
	Educational Content & Systems	Education - Benefits, Impact Assessment, Research Resources
Human Capital & Skills	Capital Typologies	Capital Typologies
	Competencies and Skills	Cognitive Processing, Competencies Skills, Training Practice, Workforce Performance
	Core Human Capital	Individual, Human Capital, Human Cultural, Value
	Psychological & Motivational Aspects	Cognitive Perspectives, Satisfaction Strategies
Labor Market & Services		Customer Services, Labor, Unemployment Rates
Management & Organization		Corporate Management & Performance, Management, Organization, Project & Framework Design, Strategic Advantage
Performance & Quality	Performance	Performance Improvement, Performance Modeling
	Productivity & Efficiency	Value
Policy & Governance		Geopolitical and International Frameworks, OECD, Policy - Governance, Population Surveys and Demographics
Social Conditions & Development		Health - Well being, Individual Risks, Life Course and Future Generations, Poverty and Inequality, Social Conditions
Sustainability & Environment		Sustainability - Environment

Source: Amundi Investment Institute.

A.3 Source used for RAG process

Table 11: Reports from the reference list used for RAG process

BibTeX Ref.	Title
Hayes et al. (2020)	Global workplace study 2020: full research report
World Economic Forum (2020)	The future of jobs report 2020
Gallup (2021)	State of the global workplace: 2021 report
Hayes et al. (2022)	Global workplace study 2022: full research report
AON (2023)	Global wellbeing survey report 2022–2023
Gallup (2022)	State of the global workplace: 2022 report
PwC (2022)	Asia pacific workforce hopes and fears survey 2022
PwC (2022)	Global workforce hopes and fears survey 2022
Gallup (2023)	State of the global workplace: 2023 report
PwC (2023a)	Global workforce hopes and fears survey 2023
PwC (2023b)	Skilled for the future? Findings from survey of 15,748 european workers
World Economic Forum (2023)	The future of jobs report 2023
AON (2024)	2024 Global benefits trends study
Gallup (2024)	State of the global workplace: 2024 report
PwC (2024)	Global workforce hopes and fears survey 2024
PwC (2024)	Global workforce hopes and fears survey 2024: chinese mainland report
WorkL (2024)	Global workplace report 2024
AON (2025)	2025 employee sentiment study
Deloitte Insights (2025)	2025 global human capital trends
Gallup (2025)	State of the global workplace: 2025 report
World Economic Forum (2025)	The future of jobs report 2025

Source: Amundi Investment Institute.

A.4 Region mapping for LLM filtering

Table 13: Mapping of Regions to Associated Countries

Region	Countries
EM Asia	China, India, Indonesia, Thailand, Malaysia, Philippines, Taiwan, Korea
APAC DM	Australia, Japan, New Zealand, Singapore, Hong Kong
DM Europe	Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom
EMEA	Czech Republic, Greece, Hungary, Poland, Turkey, Egypt, Kuwait, Qatar, Saudi Arabia, United Arab Emirates, South Africa
Americas DM	United States, Canada
Americas EM	Brazil, Mexico, Chile, Peru, Colombia, Argentina

Source: Amundi Investment Institute.

A.5 Regions concerns

Table 14: Employee concerns in the DM Europe region in 2020 vs 2024

(a) Employee concerns in 2020

Category	Sub-category
Employee engagement	Employee engagement
Wellbeing challenges	Life evacuation Daily stress and negative emotions
Environmental and governance concerns	Environmental satisfaction
Ethical practices	Workplace respect

(b) Employee concerns in 2024

Category	Sub-category
Digitization and automation	Digitization and automation Flexible work arrangements
Upskilling	Upskilling
Workplace discrimination	Skills gap
Demographic trends	Economic and demo trends Demographic trend
Diversity equity and inclusion (DEI)	DEI programs

Source: Amundi Investment Institute.

Table 15: Employee concerns in the EMEA region in 2020 vs 2024

(a) Employee concerns in 2020

Category	Sub-category
Employee engagement	Employee engagement
Well-being challenges	Emotional well-being
Pandemic impact	Pandemic related disruptions
Environmental and governance concerns	Environmental disatisfaction
Ethical practices	Workplace treatment and respect

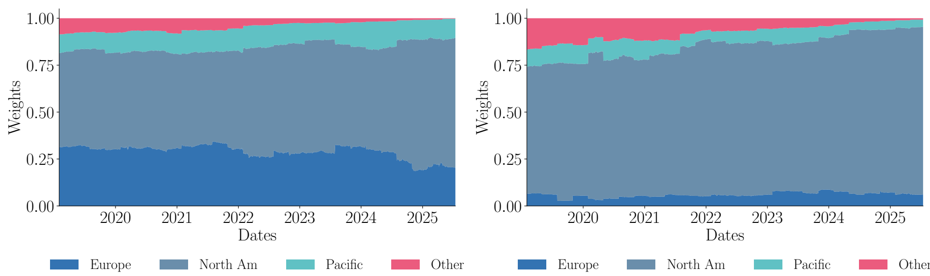
(b) Employee concerns in 2024

Category	Sub-category
Talent retention	Industry and firm level attractiveness barriers Talent retention concerns Talent availability challenges
Talent attraction	Talent development outlook
Hiring disparities	Regional hiring optimism disparities

Source: Amundi Investment Institute.

A.6 Performance of the investment strategies

Figure 16: Weights decomposition per region of the long/short portfolio in the Developed Market

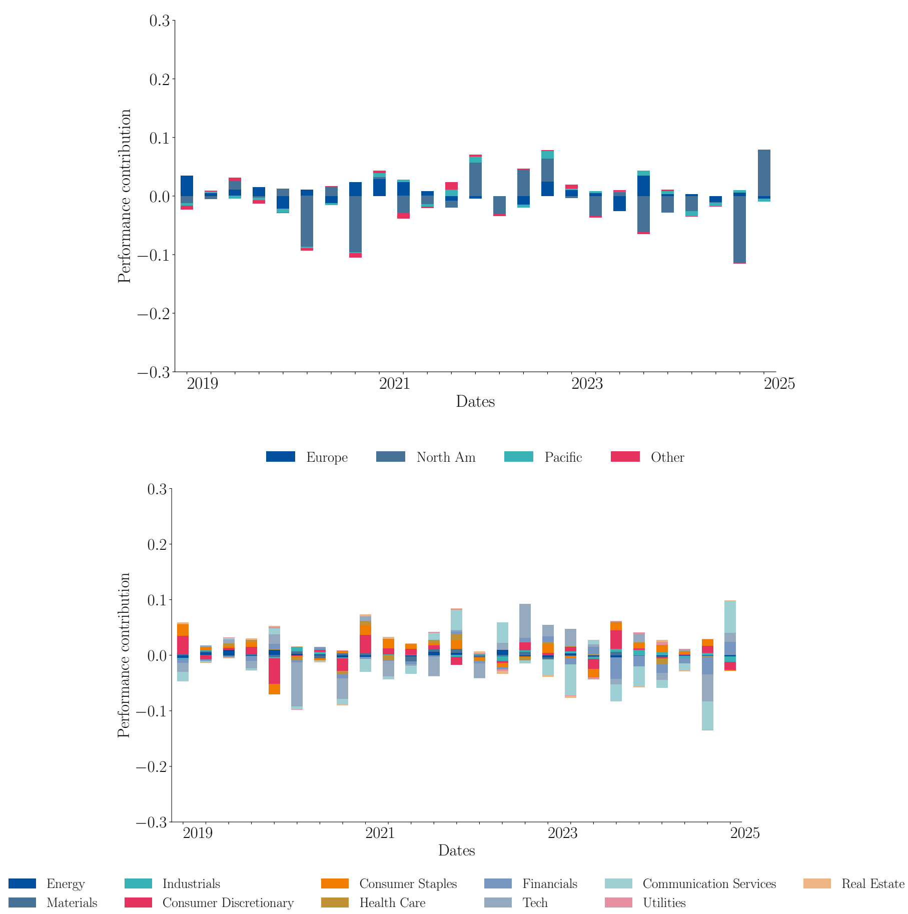


(a) Q1 portfolio weights

(b) Q5 portfolio weights

Source: MSCI, Author's calculations.

Figure 17: Performance contribution of the region and sectors in the Developed Market long short portfolio



Source: MSCI, Author's calculations.

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