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SUMAR – SOMMAIRE – CONTENTS – INHALT

STUDIA UNIVERSITATIS BABEȘ-BOLYAI OECONOMICA
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EXPLORING THE DYNAMICS OF INNOVATION IN THE ERA OF ARTIFICIAL INTELLIGENCE

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Abstract: Artificial Intelligence (AI) is revolutionizing the landscape of innovation, presenting both unprecedented opportunities and many challenges for individuals, organizations, and societies. The purpose of this paper is to investigate what will happen with innovation in an AI era, through a comprehensive analysis of the dynamics of innovation in the era of AI. Based on a bibliometric analysis we explore the paper annual publication number, the trend topic, the word count and the international interest for this subject. Through an in-dept analysis we observed some transformative changes that will arise: Data-Driven Decision Making, Personalized Customer Experiences, Supply Chain Optimization, Innovation in Financial Services, AI-Powered Entrepreneurship, Job Displacement and Reskilling, Ethical and Regulatory Considerations. By integrating insights from both bibliometric analyses and scenario planning exercises, we offer a nuanced understanding of the opportunities and challenges arising from AI-driven innovation and provide strategic recommendations for navigating the complex terrain of the AI era. The findings contribute to the academic discourse on AI and innovation, inform evidence-based decision-making, and inspire proactive responses to the transformative forces shaping our collective future.

JEL Classification: O30, O33, M21

Keywords: artificial Intelligence, AI, innovation, innovation management

1. Introduction

The evolution of modern society has reached a point where a new tool, Artificial Intelligence (AI), seems to transform its development capabilities. With its rapid evolution and expanding capabilities, AI has emerged not only as a powerful tool

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for automating tasks and processing data but also as a catalyst for transformative innovation across various sectors. As AI permeates deeper into the fabric of society, its impact on the innovation process becomes increasingly significant and complex.

The innovation process, long regarded as the lifeblood of economic growth and societal progress, is undergoing a profound redefinition in the era of AI. Traditional models of innovation, characterized by linear progressions from research to development to commercialization, are being reshaped by the capabilities of AI to augment human ingenuity, automate routine tasks, and unlock new realms of possibility (Gama & Magistretti, 2023). However, alongside the promises of enhanced efficiency and unprecedented breakthroughs, AI also poses formidable challenges and raises critical questions about the nature, dynamics, and implications of innovation in the 21st century (Sjodin et al., 2023).

The main *research question* address in this paper can be formulates as: *What will happen with innovation an AI-dominated era?* We seek to clarify the complexity involved in this symbiotic relationship and provide insights that might guide strategic decision-making, policy development, and future research directions by analysing the fundamental mechanisms, causes, and results of innovation in the AI era.

The purpose of the paper is to investigate the intricate interplay between AI and innovation, focusing on both the opportunities and challenges that arise as AI becomes increasingly integrated into the innovation ecosystem. Through a comprehensive review of existing literature, theoretical frameworks, and empirical evidence, we try to elucidate the dynamics of innovation in the AI era and identify key drivers, barriers, and implications for various stakeholders.

To reach our objectives, the paper is organized as follows: first, we provide a conceptual framework elucidating the fundamental concepts of AI and innovation and their interrelationships. Next, we review the existing literature on the impact of AI on different stages of the innovation process. Second, we examine the socio-economic, ethical, and regulatory dimensions of AI-driven innovation, considering implications for industry, academia, government, and society at large. Finally, we conclude with reflections on the future of innovation in the AI era and propose further research directions.

2. Materials and Methods

To investigate the dynamics of innovation in the era of Artificial Intelligence (AI), a systematic review of relevant literature was conducted. The Clarivate Web of Science database was selected as the primary source for this review due to its comprehensive coverage of academic journals, conference proceedings, and other scholarly publications across various disciplines. The search was conducted using the following keywords and Boolean operators: "artificial intelligence" AND "innovation".

The search was limited to peer-reviewed articles published in English-language up to the date March 2024. The criteria for including the papers in the study refers to studies that explicitly examined the relationship between AI and innovation, comprising diverse perspectives from the field of business, economics, and management. Articles focusing on specific applications of AI in innovation processes, theoretical frameworks, empirical studies, case analyses, and critical reflections were considered for inclusion. The graphical representation of the interrogation process was created using LucidChart software (Lucid, 2022) and is presented in Figure 1.

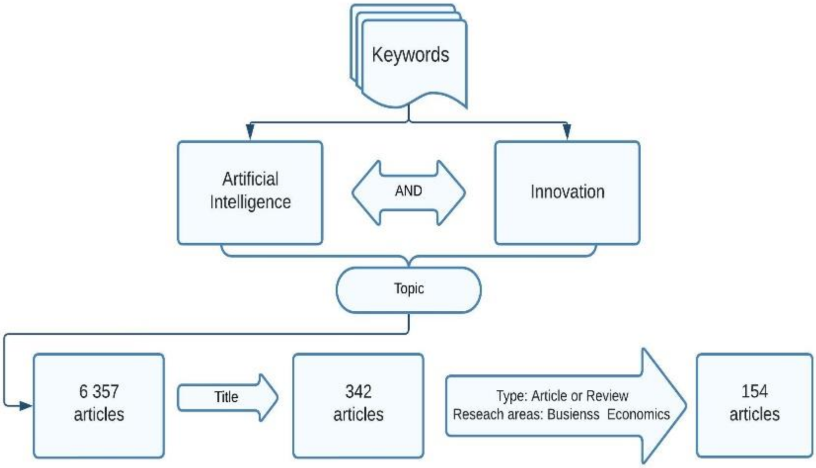

Figure 1. The flow diagram of data collection

Using the two keywords and the condition so that both of them to be present in the topic of the papers, a number of 6 357 articles were revealed. To refine the dataset, some key filters were applied. The first filter was to select only papers where the keywords appeared in the title. Additionally, the results were filtered to papers in the category type "article" or "review" and from the research areas "business economics". Following the initial search, duplicate records were removed, and the titles and abstracts of the remaining articles were screened to assess their relevance to the research question. The full-text screening was performed to identify articles meeting the inclusion criteria. The final set of articles included in the literature review constituted the basis for synthesizing existing knowledge, identifying trends, gaps, and emerging themes in literature. By applying the filters, a dataset of 154 articles resulted.

Journal articles from the scientific dataset were exported as plain text files, having essential data such as article titles, author keywords, author names, and citation information. The exported data underwent manual standardization to ensure compatibility with the requirements of the software tools used for analysis. To analyze the bibliometric characteristics and visualize the intellectual structure of the literature on AI and innovation, two software tools were employed: Bibliometrix (Aria & Cuccurullo, 2017) and VOSviewer (Jan van Eck & Waltman, 2010).

3. Results and Interpretation

3.1. The evolution of the annual number of published articles

The annual publication trends provide valuable insights into the evolving interest in the field of AI and innovation. Figure 3 illustrates the number of papers published annually, focusing on the research topic of "wood and cement." On the horizontal line is presented the year of publication and on the vertical is presented the number of papers published each year.

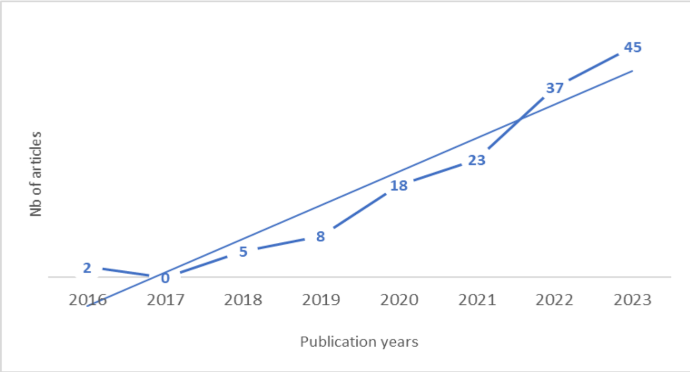

Figure 2. The evolution of annual number of published papers

Even if the article analyzed covered the years from 2016 to 2023 the upward trajectory in research publications is obvious. It can be observed that although in 2016 were published only 2 papers and in 2017 no paper was published in the last five years from 2019 the number of articles increased substantially reaching 45 papers published in 2023.

3.2. The trend topic analysis

To gain a deeper understanding of the evolving themes within the AI and innovation research landscape, we conducted a trend topic analysis, as illustrated in Figure 3. This analysis draws from data extracted from the Web of Science database and offers insights into the keywords and concepts that have gained prominence over time.

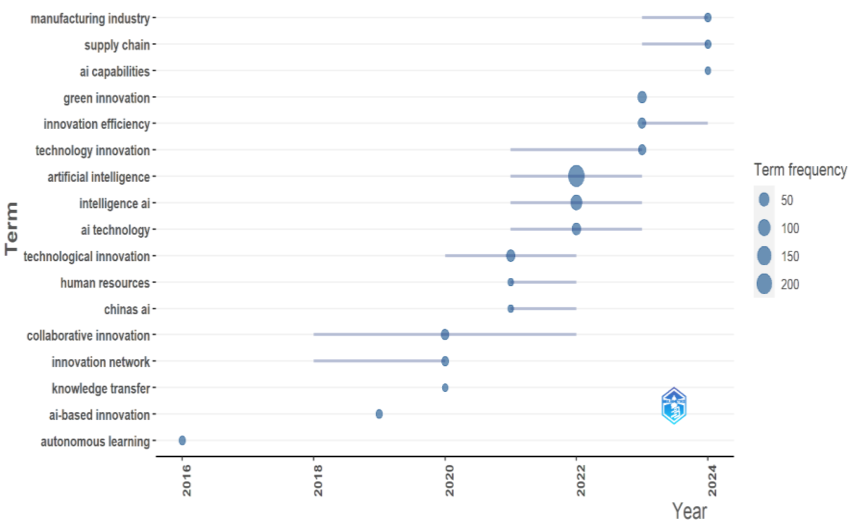

Figure 3. The trend topic analysis

Figure 3 provides a visual representation of this analysis, employing lines and bubbles to convey term frequency and temporal usage. The size of each bubble corresponds to the frequency of the associated term, with larger bubbles indicating more frequent usage.

Over the years, research on AI and innovation has evolved significantly. Early studies primarily concentrated on examining autonomous learning, knowledge transfer, innovation network or collaborative innovation. This foundational research laid the groundwork for subsequent investigations.

As the field matured, researchers explored novel possibilities of using AI as a technology and what impact it has on the human resources involved. In the same time technological innovation is one of the direction that the researchers focused. The pick point of the article intelligence studies was reached in 2022 where the term appears as the most frequently used.

Lately the trend topic reveals an interest to subject like the influence of AI on green innovation, supply chains or manufacturing industry. This trend topic analysis provides a glimpse into the dynamic nature of AI and innovation research as emerging keywords and concepts continue to gain prominence, they shape the trajectory of future investigations and innovations in the field.

3.2. The word analysis

To further analyze how are influenced the main characteristics of innovation by artificial intelligence we performed a word count analysis. With the help of the Bibliometrix software the image from figure 4 was generated. For this image we considered the abstract of the papers included in the sample database. The size of the word and positioning close to the center of the image reveal a big frequence of using that word.

In the center of the image from figure 4 we can distinguish words like impact, performance, management, knowledge, AI, future, or technology. This arrangement of the words indicates that most of the researchers when dealing with this subject wondered about the impact of AI on the innovation process. Their main concern is related to ways of improving the performance of organizations, increasing knowledge, or improving the management process.

Figure 4. The word count analysis of papers dealing with innovation and AI

AI has a grater application in the technology industry, so it is somehow obvious that words like technology, information technology or industry to be presented in the image. Other words that are visible are growth, firm performance, framework, perspective, capabilities, or digital transformation. All these words reveal the same interest in how AI will improve innovation. In general, from the words used we can identify a positive reaction to AI and even some new direction of research and development, creating a framework for AI or analyzing the big data needed to train AI. Environmental issues are also analyzed and words like sustainability, evolution or environmental innovation are also used.

For a deeper understanding of the interconnected themes and topics within the research of innovation and AI a keyword co-occurrence analysis was performed. Figure 5 presents a visual representation of the keywords co-occurrence network map, generated using the VOSviewer software. In this map, keywords are represented by bubbles, with larger bubbles indicating higher keyword frequency. Lines connecting keywords signify their co-occurrence in the same papers, while clusters of keywords sharing similar themes are delineated by distinct colors.

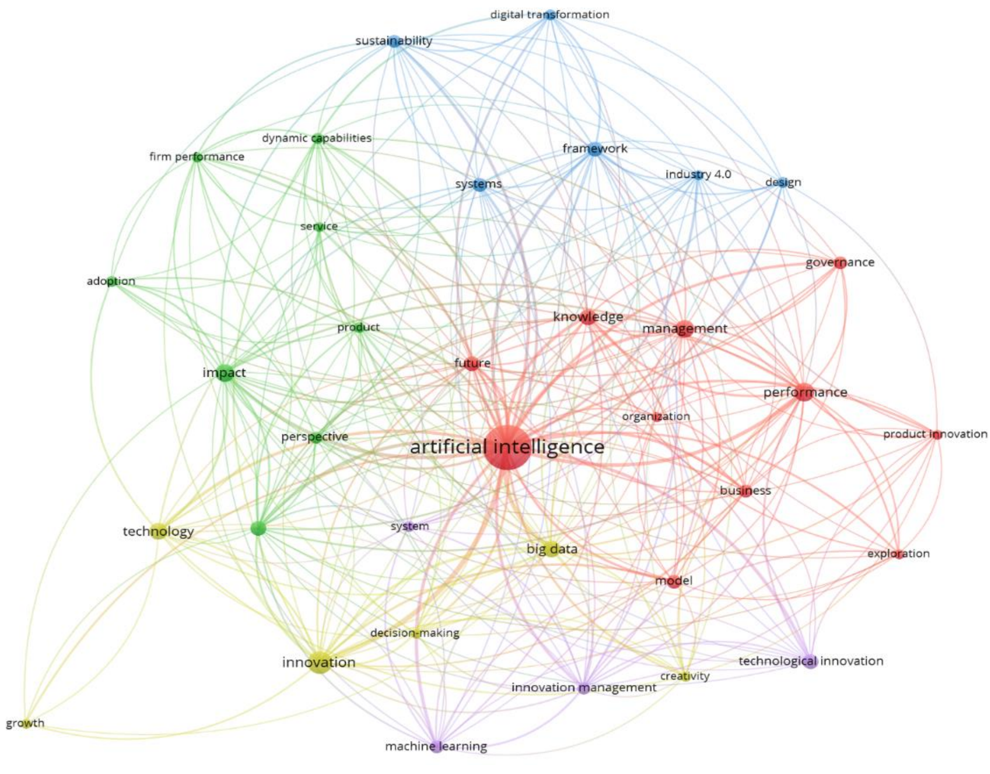

Figure 5. The keywords co-occurrence network map

The dataset analyzed in this map comprises 794 keywords, each with a minimum co-occurrence of 5 times, resulting in the inclusion of 39 papers. The map is organized into five clusters, each with its unique characteristics. The red cluster is the most extensive, featuring 11 keywords, followed by the green cluster with 8, the blue cluster with 6, the yellow cluster with 6, and the smallest cluster, the purple cluster, with 4 keywords.

The spatial arrangement of keywords on the map is determined by their frequency of usage in the analyzed papers, with the most frequently used keywords positioned at the center. For instance, the keyword "artificial intelligence," situated in the heart of the map, is the most used term, given the context of all research papers. It boasts a total link strength of 226 and an occurrence of 96. Although the keyword "artificial intelligence" dominates the entire map, other keywords can be observed in the same cluster, like performance, management, or knowledge. At the edge of the map can be observed keywords like growth, which is mainly related to growth of AI, innovation, and technology in general.

The clustering of keywords suggests the same conclusions as in case of word count and topic analysis. It can be observed a positive approach regarding the development of the AI technology and its effect on the innovation process, while at the same time the research is yet in its early stages remaining some questions regarding the perspectives and the suggests potential future avenues for exploration.

3.3. The international interest for the research topic

The field of AI and its connection to innovation continues to evolve, driven by the contributions of various authors and research teams. In this section, the focus is on an analysis of the authors' affiliations, highlighting the global distribution of research.

Based on the sample database of selected papers a world map was generated (figure 6), with the help of Bibliometrix software highlighting the number of papers published in each country. The map is generated based on the frequency of researchers from each country appearing as authors in the selected papers. The darker the blue color, the higher the frequency of authors from that country is.

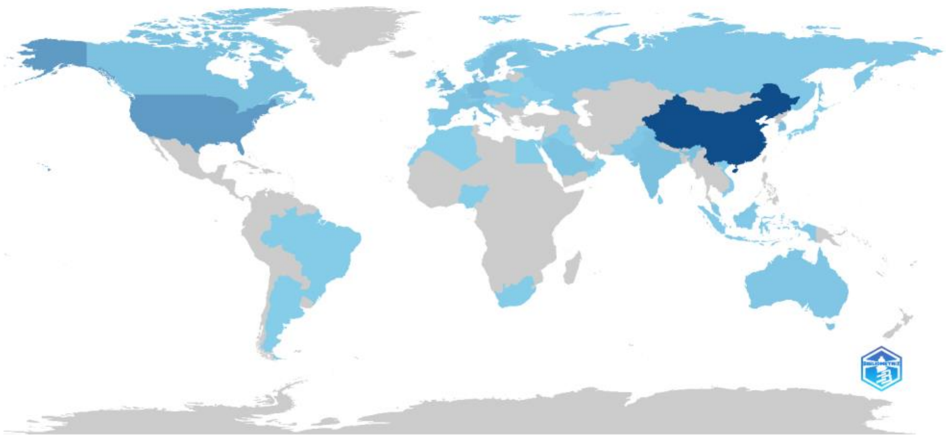

Figure 6. The top countries' scientific production

The country’s scientific production map reveals a global interest for this research topic. From the entire map the most papers in this subject are written by authors form China, a frequency of 115 followed by USA, frequency of 44, and by Germany and UK with a frequency of 17.

4. Discussions – future research agenda

The field of Artificial Intelligence (AI) is in a continuous and rapid evolution, influencing almost all fields of research. As noticed so far, the interest for this subject increased substantially in the last two years when more and more researchers try to establish the impact and changes brought by an AI era. In case of innovation The AI era has undergone significant evolution across various sectors. With more and more papers addressing this subject in the following part we performed an in-dept analysis of the literature, to identify the main topics and future research agendas.

The rapid advancement and application of AI technologies have led to a paradigm shift comparable to the dawn of the internet (Wei et al., 2018). This evolution is evident in the architectural advancements of AI systems, transitioning from a "foundation-model-as-a-connector" to a "foundation-model-as-a-monolithic architecture" (Lu, 2024). As AI continues to enter in different fields, the creation of innovative intelligent products is on the rise, contributing to the realization of the AI era.

Moreover, the era of AI has not only impacted technology and industry but has also brought about fundamental reforms in economic, social, and political domains (Wang, 2022). This transformation has created new opportunities in cultural industries, emphasizing the importance of understanding the global value chain position within the AI landscape (Brem et al., 2023). The educational sector has also been significantly influenced by AI, with a focus on cultivating innovative talents equipped with the necessary skills for the new technological and economic landscape (Dopazo, 2023).

In the context of innovation and entrepreneurship education, the integration of AI technologies has led to new teaching frameworks and methodologies, reflecting the changing dynamics of the AI era (Abdelkafi et al., 2015). The evolution of AI in telecommunications and wearable electronics led a shift towards a future intertwined with AI and the Internet of Things (Arenal et al., 2020).

As AI continues to shape various industries and domains, the need for responsible AI design and management becomes crucial to ensure ethical and sustainable AI applications (Gonzalez-Esteban & Calvo, 2022). The evolving landscape of AI innovation necessitates a multidimensional approach, considering technical, managerial, and societal perspectives to harness the full potential of AI technologies (Pan et al., 2019). The impact of AI varies across different sectors, as it is focused more on exploration rather than exploitation (Johnson & Watt, 2022).

The studies published so far indicate that the development of AI technology will lead to a lot of changes in the structure of organizations. It is suggested that each organization should consider opening a division specialized in AI management (Bahoo et al., 2023). The shift to new ways of thinking and accumulating knowledge should be done through pilot tests (Goto, 2023).

There is evidence of a positive impact of AI if its potential is fully used, especially in case of continuous market changes (Sullivan & Wamba, 2024). Positive impact was observed also in case of green innovation (Liang et al., 2023) so AI can contribute to increase the environmental performance of organizations (Yin et al., 2023). Positive impact was observed in the case of open innovation practices also (Kuzior et al., 2023; Sahoo et al., 2024). AI can improve frugal innovation that can lead to positive social transformation and overall progress (Govindan, 2022).

Studies have shown that the implementation of AI led to higher innovation results (Rammer et al., 2022). Given the unpredictable character of innovation the problem of identifying the promising innovation project with the help of AI is still a challenge (Sjodin et al., 2023). We are still discovering the potential of AI, and we can expect that AI can revolutionize innovation management. In theory it has the potential to replace the work done by humans, delivering higher quality and efficiency, providing instrumental assistance beyond human capabilities (Haefner et al., 2021). However, it is hard to believe that will eliminate humans from the innovation process (Rampersad, 2020; Truong & Papagiannidis, 2022).

The interest in this topic of research is increasing and we can expect that the potential of AI will be better understood and used. For the moment, in the business and economic sector, some transformative changes can be observed:

Automation of routine tasks. Routine and repetitive jobs will continue to be automated by AI technologies, freeing up human resources for more strategic and creative work (Babina et al., 2024). Businesses may experience a boost in production and efficiency because of this automation, freeing up resources for higher-value endeavors.

Data-Driven Decision Making. Businesses can use AI to leverage massive data for better informed decision-making (Alghamdi & Agag, 2023). Large volumes of data may be mined for insightful information by sophisticated analytics and machine learning algorithms, which enables companies to see patterns, forecast consumer behavior, and streamline processes (Yablonsky, 2019).

Personalized Customer Experiences. AI-powered personalization will show up more and more in customer service and marketing (Li, 2022). Companies will use AI to evaluate consumer behavior and preferences in order to provide recommendations, services, and products that are customized to each customer's requirements and interests.

Supply Chain Optimization. Supply chain management can be improved by artificial intelligence (AI) through demand prediction, inventory optimization, and the detection of possible bottlenecks or disruptions (Hendriksen, 2023). Businesses may benefit from lower expenses, more productivity, and better risk management because of this optimization (Belhadi et al., 2024).

Innovation in Financial Services. By facilitating developments in fields like algorithmic trading, fraud detection, risk assessment, and personalized wealth management, artificial intelligence (AI) is transforming the financial services sector (Yubo, 2021). AI is being used by both major financial institutions and fintech startups to spur innovation and improve client experiences (Santos & Qin, 2019).

AI-Powered Entrepreneurship. AI makes entrepreneurship more accessible by removing entry barriers and facilitating large-scale innovation (Siemon et al., 2022). Startups and small firms can compete with larger rivals by utilizing AI tools and platforms for tasks like chatbots for customer service, marketing automation, and predictive analytics (Chen, 2021).

Job Displacement and Reskilling. While there are many advantages to AI advancement, there are also worries about job displacement and the need for labor reskilling (Polyportis & Pahos, 2024). Companies will have to spend money on programs for employee upskilling and training if they want to guarantee that people can prosper in an AI-driven economy and adjust to the changing environment.

Ethical and Regulatory Considerations*.* Ethical and regulatory issues will gain importance when artificial intelligence is incorporated more deeply into commercial operations. To win over customers and stakeholders, businesses need to handle concerns like data privacy, algorithmic bias, and transparency.

In general, we can state that there is a great deal of room for innovation in the business and economic fields during the AI era to increase productivity, competitiveness, and value creation. But achieving these advantages will cost money, time, and a dedication to the moral and appropriate application of AI.

Conclusions

The era of AI has arrived and is here to revolutionize the way we carry out our human activities. By exploring the complicated interaction between AI technologies and innovation, we tried to add some clarity on how to effectively utilize AI's potential while limiting risks and maximizing social benefits.

The research results suggest that AI is significantly transforming the innovation process by automating tasks, enhancing learning and adaptability, creating new opportunities, rethinking management strategies, and acting as both an originator and facilitator of innovation, which may affect global competitiveness and the nature of human jobs. The main transformative changes identified refer to a personalized customer experiences, the supply chain optimization, more innovative financial services, AI-powered entrepreneurship, job displacement and reskilling. In this rush for change we must also develop good ethical and regulatory considerations.

The evolution of innovation in the era of AI is characterized by transformative changes that can lead to future marked by prosperity, inclusion, and sustainability.

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THE IMPACT OF SOCIAL NORMS ON FOREIGN DIRECT INVESTMENTS

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Abstract: This study examines the impact of social norms, measured through the Cultural Tightness-Looseness (CTL) index, on foreign direct investments (FDI) across 67 countries. I aimed to highlight a new approach from the sphere of cultural influences on bilateral FDI flows and to demonstrate the direct connection between the strictness imposed by a country's social norms and the investment decisions based on them. The results obtained were in line with the initial expectations, validating the level of constraint/permissiveness as a truly influential factor in relation to foreign direct investments.

JEL Classification: F21, G11, G15, Z10

Keywords: foreign direct investment, cultural tightness-looseness, economic growth.

1. Introduction

The global economy has always been full of mysteries waiting to be uncovered and challenges for which solutions had to be found. From the Great Economic Depression of 1929 to 1933 and up to contemporary crises, this essential element of social life has always been in a continuous dynamic. The speed at which events impacting the economy occur seems to be faster than ever, so all decisions must be made thoughtfully, analyzing all available information.

It is important to note that the prosperity of an economy largely depends on the investments made within it. Whether domestic or foreign, their impact is crucial when it comes to improving the quality of life for a country's citizens, a desire pursued since ancient times.

Considering all these aspects, I found it useful to study the influencing factors that determine the level of foreign direct investment (FDI) in a country. In this way, I first reviewed the existing literature and how various factors previously studied affect FDI flows, and then I venture towards a new possible direction of study, focusing on the relationship between social norms and the level of foreign direct

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investments between two countries. Whether we are talking about explicit norms, represented by laws and written regulations, or, on the contrary, implicit norms that include unwritten rules and customs, their essence is captured through the concept of Cultural Tightness – Looseness (CTL). This concept was first introduced by Michele Gelfand, the theory referring to the degree of constraint or permissiveness of social norms and rules in a culture or society and how they influence the behavior and mindset of people in that environment.

Specifically, in this study I aim to highlight how a country's CTL index manifests in relation to the foreign direct investments undertaken by it, as a result of the effect that the strictness or permissiveness of social norms in that country has on investment decisions.

Thus, the paper is structured as follows. In the first part, I presented some theoretical concepts, accompanied by a review of the specialized literature. Next, I described the data used as well as the methodology on which the study is based. Afterwards, I presented the results, and finally, I reviewed the conclusions reached and possible future directions of study.

2. Literature review

Foreign direct investment refers to the capital placements made by companies or even individuals outside their country of residence, aiming to exploit the business opportunities offered by the destination country. Over time, it has been demonstrated that one of the major advantages of these types of investments is their impact on a country's economic growth, which in turn leads to its economic development. Therefore, the importance of economic growth at the national level is undeniable, and foreign direct investments contribute significantly to it. The specialized literature in the field indicates a positive relationship between these two variables, with numerous empirical studies investigating the impact of foreign direct investment on economic growth, focusing on the various channels through which this influence manifests.

In 2006, Johnson hypothesized that foreign investments, in the form of technological improvements and physical capital contributions, significantly impact the evolution of an economy. To test this hypothesis, he used a panel of 90 countries and found that the impact is particularly observed in developing countries and less so in developed ones—a somewhat expected outcome given the growth potential in emerging economies. Thus, most recent empirical studies on these two variables highlight foreign direct investments as the most important channel for technology diffusion, which subsequently contributes to the development of an economy. Technology diffusion is considered the primary source of convergence between countries and the achievement of sustainable development (Elmawazini et al., 2008).

Recent literature seems to offer a careful evaluation of the host country's degree of acceptance of the dynamic relationship between foreign capital inflows and economic growth. Generally, FDI is viewed positively, given its contribution to job creation, increased labor productivity, the efficiency of resource allocation, the increase in the competitiveness of economies, and the reduction of regional disparities (Barrell and Pain, 1997; Kaminski and Smarzynska, 2001; Alfaro, 2003; Gorg and Greenaway, 2004; Moura and Forte, 2010). For instance, according to a study conducted by the European Commission in 2009, the accession of new states to the European Union was accompanied by an average economic growth of these economies of approximately 1.75% during the 2000-2008 period. A decisive factor in this outcome, besides the improvement of the macroeconomic and institutional framework, was the increase in productivity driven by foreign direct investments and the technology transfer facilitated by these investments.

Starting from the fact that foreign direct investments represent a major component of the globalization process, having at the same time a stimulating role in a country's economy, it is of major interest to study the variables that determine the different levels of these investments from one state to another.

First, a major category of FDI determinants consists of rational factors, predominantly quantifiable factors related to the macroeconomic aspect, with the most mentioned in the specialized literature being Gross Domestic Product. GDP measures the added value generated by the production of goods and services within an economy over a specific period. A bidirectional relationship has been demonstrated between these two variables, where the evolution of one directly affects the other – on one hand, the larger a country's GDP, the more it will attract a significant number of foreign investors. On the other hand, a high level of FDI leads to accelerated economic growth (Kok & Ersoy, 2009). Similarly, Resmini (2000) found that in countries with greater development potential, higher FDI flows can also be noticed, as investors can fully exploit the available resources.

Furthermore, to better understand the reasons why the level of foreign direct investment differs from one nation to another, it is important to consider a number of behavioral factors that either favor or inhibit an investor's decision to make a cross-border capital placement.

One initial approach, based on the level of religiosity exhibited by a nation's citizens, was studied by Miller (2003), who highlighted the connection between religion and an individual's anxiety level, suggesting that risk-averse individuals are often characterized by a strong belief system to alleviate their anxieties and avoid uncertainty in their lives. Recently, several studies have empirically documented the correlation between religiosity and risk aversion (Hilary & Hui, 2009; Liu, 2010; Dohmen et al., 2011), explaining the hesitant attitude of individuals from highly religious countries when it comes to making investment decisions in foreign countries. Subsequently, Hong et al., in an article published in 2023, strengthened the existing research on religious diversity and its influence on foreign direct investment. They showed that religious differences inhibit FDI flows between two countries, using religious distances calculated directly as the difference between two demographic religious distributions. Moreover, the previously mentioned study highlighted that the negative effect of religious differences on FDI flows is mitigated in host countries with greater religious diversity, as in such contexts, the ideas and personal values of each individual are accepted by others.

In another context, it is also of interest to focus on other factors related to human behavior, whose influence cannot be neglected when it comes to foreign direct investments.

Literature has established individual values, in the form of principles and beliefs that guide a person's behavior and decision-making process, as being closely linked to FDI flows. One approach derived from individual values and correlated with the investment domain is investor trust, which springs from their sentiment towards a particular action and is cultivated over time through experiences and interactions with other market actors. In this regard, existing empirical research brings to the forefront the direct connection between individual trust and the abundance of foreign direct investments. More precisely, a study conducted by Guiso, Sapienza, and Zingales in 2009 showed that a significant level of trust that dominates bilateral relations between two states favors foreign investments.

Additionally, we must also consider the impact of cultural values - specifically the six cultural dimensions defined by Dutch researcher Geert Hofstede - have on the level of foreign direct investments. This model has become a paradigm for comparing national cultures, as it delimits cultural characteristics into the following categories: Power Distance, Uncertainty Avoidance, Individualism/Collectivism, Masculinity/Femininity, Long-Term/Short-Term Orientation, and Indulgence/Strictness. All these have been the subject of numerous studies, which have ultimately demonstrated the existing connections between cultural dimensions and foreign direct investments (Tang, 2012; Husted & Allen, 2006).

3. Predictions

Building on the ideas developed in the studies I previously analyzed, I aim to improve the state of knowledge in the field of foreign direct investments and the factors that influence it. The novelty I intend to introduce into the specialized literature focuses on investigating how social norms affect the flow of foreign direct investments. Based on Gelfand's findings (2011), which measure the level of cultural tightness or looseness within a society, we know that stricter nations, which impose clear rules expected to be followed by citizens, tend to develop a high degree of aversion to risk-taking and deviation from traditional societal norms. Additionally, countries that fall into this category tend to be more conservative, rarely accepting to engage in any form of relationship with other states that are guided by different principles compared to those accepted in the domestic space. Considering the collective behavioral traits that accompany this high degree of strictness imposed by social norms in a country – a behavior that is also reflected in the economic decision-making process – I strictly focus on how such a society relates to the opportunities for establishing investment relationships with another state through foreign direct investments directed towards the targeted destination. More precisely, I intend to test whether the bilateral FDI flow is indeed affected by the strict social norms of the country of origin, based on the following research hypothesis: *Societies that are more restrictive in terms of social norms will make fewer investments outside their borders.*

4. Data

The analysis is based on data collected from a sample of 67 countries, representing both developed and emerging economies. The representativeness of the sample is guaranteed by the fact that there are significant flows of foreign direct investments between these states, as evidenced by the databases provided by the International Monetary Fund (IMF). The volume of FDI flows is reported annually for pairs of countries, starting from 2009, an aspect I considered when selecting the analysis period, this study being based on the available data from 2009 to 2021.

Furthermore, for the countries included in the sample, I collected the Cultural Tightness-Looseness index values for each of them and then I added to the database values of other variables that also play an important role in determining the size of investment flows between two countries.

I mention from the beginning that in order to facilitate the effective comparison of each investment flow recorded between two countries over the course of a year, I worked with the logarithmic values of foreign direct investments, the dependent variable becoming as follows:

$$Invest_{ij,t} = ln\ (1 + the\ abs.value\ of\ the\ invest._{ij,t})$$

there $the\ abs.value\ of\ the\ invest._{ij,t}$ represents the absolute value of foreign direct investments between two countries in year t.

When it comes to the CTL index, I used one of the measures developed by Uz in 2015, *The Combination Index*, which consists of a sequence of approaches. It begins with a targeted analysis of individual domains, followed by a broader analysis encompassing a wider range of domains, all with the aim of extracting the degree of constraint/permissiveness within a nation.

In my analysis, in addition to the exogenous variable represented by the CTL index, I also used a series of control variables to quantify the effect of various factors on the level of foreign direct investments recorded between the countries in the sample. Therefore, considering the empirical evidence from the studies mentioned in the theoretical section, I included the most relevant control variables in the built models: GDP, GDP per capita, trade openness, geographical distance, contiguity between states, religious distance, legal system, and the World Governance Index.

To build the regressions that would help validate the initially formulated hypothesis, I compiled a database by collecting, for each country included in our sample, the corresponding values of the variables that were determined to have or potentially have an influence on our endogenous variable – foreign direct investments logarithms. Table 1 thus illustrates the descriptive statistics of the variables used in the attempt to estimate optimal econometric models that reflect the relationship between the CTL index and FDI flows.

Between 2009 and 2022, the largest bilateral FDI flow recorded within the sample was between France and the United Kingdom, occurring in the first year of the reference period, with an absolute value exceeding $55 billion. Regarding the CTL index, it has an average value of 60.009 among the countries included in the sample, with Morocco being the most restrictive country, having an index value of 0, while the most permissive country is Belgium, with a maximum value of 119.8.

Table 1. Descriptive statistics

Variable	Obs.	μ	σ	Min	Max
Dependent variable					
ln(1+FDI)	53494	2.225	5.851	0.000	24.743
Independent variables					
CTL_C (home country)	29642	60.009	26.830	0.000	119.8
CTL_C (host country)	29642	60.009	26.830	0.000	119.8
ln(GDP home country)	53494	26.454	1.691	19.559	30.780
ln(GDP host country)	53494	26.454	1.691	19.559	30.780
ln(GDP/cap home country)	53494	9.462	1.230	6.624	11.547
ln(GDP/cap host country)	53494	9.462	1.230	6.624	11.547
Home trade openess	53494	0.009	0.037	0.000	1.946
ln(geographic distance)	53494	8.597	0.910	4.493	9.892
Common border	53494	0.051	0.220	0.000	1.000
Linguistic distance	52662	0.865	0.306	0.000	1.000
Religious distance	52662	0.720	0.293	0.000	0.998
Same legal system	53494	0.631	0.483	0.000	1.000
WGI	53494	62.435	23.385	3.332	96.748
Financial literacy	51492	42.848	14.783	21	71
Power Distance	53494	57.457	23.544	0.000	100.000
Individualism/Collectivism	53494	46.363	25.909	0.000	100.000
Masculinity/Femininity	53494	46.528	21.287	0.000	95.000
Uncertainty Avoidance	53494	63.285	25.597	0.000	100.000
Long-Term Orientation	53494	43.311	23.447	0.000	100.000
Indulgence/Strictness	53494	42.451	26.542	0.000	100.000

Source: Author's own research, using Stata.

5. Methodology

To empirically test the proposed study hypothesis, I estimated linear regressions using the Ordinary Least Squares (OLS) method, based on panel data collected for each country included in the sample. Ultimately, I was able to capture the relationships between the variables through the following regressions:

The benchmark regression, which exclusively captures the influence of the control variables on the level of foreign direct investments between two countries, providing a reference point against which to observe the changes that occur when additional variables are added to the model:

$$Invest_{ij,t} = a_0 + Control\ var. + \varepsilon_{i,t}$$

I then investigated the relationship between the CTL index of the home country and FDI flows, starting from the regression below:

$$Invest_{ij,t} = a_0 + a_1 x\ CTL\_C_i + Control\ var. + \varepsilon_{i,t}$$

where CTL_C_i is the CTL index of the country of origin; lower values indicate stricter social norms, while higher values illustrate a greater degree of permissiveness of social norms.

Similarly, I analyzed the relationship between the CTL index of the destination country and FDI flows, according to the model:

$$Invest_{ij,t} = a_0 + a_2 x\ CTL\_C_j + Control\ var. + \varepsilon_{i,t}$$

where CTL_C_j is the CTL index of the destination country.

Next, I built an econometric model that captures the impact of social norms in both countries involved in investment relationships:

$$Invest_{ij,t} = a_0 + a_1 x\ CTL\_C_i + a_2 x\ CTL\_C_j + Control\ var. + \varepsilon_{i,t}$$

Last but not least, I built a regression using the CTL index of the country of origin, exclusive of the effects of Hofstede's six cultural dimensions:

$$Invest_{ij,t} = a_0 + a_3 x\ CTL\_C\_rez_i + Control\ var. + \varepsilon_{i,t}$$

where $CTL\_C\_rez_i$ is the CTL index of the country of origin adjusted for the effects of the cultural dimensions.

6. Results

Throughout numerous attempts to construct the most representative regressions, I juggled the variables in such a way as to find the optimal combination that best reflects the impact of social norms on foreign direct investments and thus I developed the models summarized in Table 2.

First, I state that all regressions were built using time effects to capture the common variance across all units within a given year, thereby aiming to eliminate potential bias caused by time-varying factors that are not directly measured.

The benchmark regression in the first column of the table captures the impact of all variables besides the social norms on foreign direct investments, providing a reference point for observing changes once additional variables are added to the model. Among the essential variables included in the benchmark regression are the natural logarithm of GDP for both the country of origin and the destination country. We observe that the GDP of the destination country is the primary factor influencing the absolute volume of investments, with a direct relationship reflected by a coefficient of 0.518, which is significant with a 99% probability. The standard error is only 0.045, leading us to believe that indeed, the larger the GDP of the destination country, the more attractive it is to investors, and as a result it will attract more FDI flows. Additionally, in the benchmark regression, we note that factors with an indirect influence on FDI include geographical distance and religious distance. Both of them are significant at a 1% confidence level, but the latter has a stronger impact with a coefficient of -1.632.

The following three estimated regressions include, in turn, the CTL index of the country of origin, the CTL index of the host country, and the simultaneous action of both. From the results obtained, it appears that only the CTL index of the country of origin influences the decision to make a foreign direct investment, as evidenced by the coefficient value of 0.044 in regression (2) and 0.048 in regression (4); in both cases, these coefficients are significant at a 1% confidence level. The same cannot be said for the CTL index of the destination country, which does not appear to have a significant impact on the explained variable, with its coefficients being almost null in both cases. In this context, the influence of control variables remains similar to that observed in the case of the benchmark regression, the GDP still being a major factor of influence. Additionally, the similarity between the legal systems of the two countries establishing investment relationships is also notable, especially in regression (4), where it has a coefficient of 1.206, indicating that legal system identity positively influences the foreign direct investments.

Table 2. The impact of CTL on FDI

Variable	ln(1+FDI)						
	(1)	(2)	(3)	(4)	(5) (%)	(6)	(7) (%)
CTL_C (home country)		0.044*** (0.004)		0.048*** (0.006)	19.00		
CTL_C (host country)			0.003 (0.004)	0.008 (0.006)	3.50		
CTL_C_rez (home country)						0.048*** (0.005)	13.03
ln(GDP home country)	0.233*** (0.042)	0.522*** (0.077)	0.217*** (0.057)	0.555*** (0.106)	11.88	0.484*** (0.074)	10.69
ln(GDP host country)	0.518*** (0.045)	0.807*** (0.071)	0.556*** (0.065)	0.883*** (0.101)	19.35	0.845*** (0.071)	21.85
ln(GDP/cap home country)	0.289*** (0.061)	0.197** (0.097)	0.287*** (0.085)	0.211 (0.134)	3.81	0.802*** (0.087)	15.04
ln(GDP/cap host country)	0.043 (0.058)	-0.009 (0.090)	-0.103 (0.095)	-0.262* (0.151)	-4.72	-0.062 (0.091)	-1.16
Home trade openess	6.569*** (1.868)	-1.585 (5.423)	8.194 (5.071)	5.608 (5.331)	2.25	-3.871 (5.507)	-1.61
ln(geographic distance)	- 1.465*** (0.098)	- 1.946*** (0.140)	- 1.627*** (0.132)	- 2.209*** (0.193)	-30.61	- 2.059*** (0.140)	-29.10

Common border	0.108 (0.497)	-0.239 (0.647)	-0.065 (0.648)	-0.794 (0.827)	-2.88	-0.345 (0.646)	-1.20
Religious distance	-1.632*** (0.260)	-2.608*** (0.409)	1.473*** (0.345)	-2.056*** (0.559)	-8.45	-3.010*** (0.413)	-12.88
Same legal system	0.562*** (0.128)	0.921*** (0.206)	0.650*** (0.179)	1.206*** (0.297)	8.23	1.053*** (0.210)	7.61
WGI	0.041*** (0.003)	0.011** (0.004)	0.045*** (0.004)	0.011* (0.006)	4.22	0.010** (0.004)	3.92
Control variables	YES	YES	YES	YES	YES	YES	YES
Time effects	YES	YES	YES	YES	YES	YES	YES
F_stat	45.73	46.47	28.54	33.08	254.06	45.17	426.13
R^2	0.193	0.256	0.211	0.281	0.281	0.254	0.254
Observations	52662	28810	29187	15607	15607	28810	28810

Symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Starting from the model with the CTL indices of both countries as exogenous variables, I estimated a beta regression, revealing that social norms in the country of origin influence FDI flows by 19%, while the norms of the host country affect the exogenous variable by only 3.5%. These weights further confirm that, when making an investment decision, the cultural characteristics of the country of origin tend to be more significant, which means that the frequency and size of investments directed towards foreign economies will be dictated by the rigor of the cultural norms in the origin country.

To ensure that the significant exogenous variable is exclusively the CTL index measuring the strictness of social norms in the country of origin, I estimated an additional regression, shown in column (6) of the table, illustrating the influence of a new variable, suggestively named CTL_C_rez, while keeping the control variables unchanged. This new measure was obtained by removing the effects of other cultural factors derived from Hofstede's cultural distances from the CTL index values. Analyzing the results, it can be observed that the coefficient of the newly introduced variable remains 0.048, being significant at a 1% confidence level. The identity between it and the coefficient of the CTL index of the country of origin from regression (4) is not accidental, as it reinforces the idea that the country of origin is the main pillar determining foreign investments, especially since, in regression (6), the standard error is even smaller, at only 0.005.

The last regression in Table 2 is also a beta regression built based on the previous model, and it helps identify the two main factors directly influencing FDI flows: the CTL index of the origin country, with the effects of cultural dimensions excluded and the GDP of the destination country. Additionally, geographic distance also has a considerable impact, however, in the opposite direction this time. This variable must be carefully considered when estimating regressions aimed to determine the factors influencing foreign direct investments.

Robustness tests

To ensure that the previous estimations are accurate, I applied a series of robustness tests to the initially built regressions, thereby observing any significant changes in the coefficients corresponding to the variables, as well as their significance and estimation errors.

By comparing the results from the new regressions in Table 3 with those obtained from the classical estimation, it can be observed that they are similar, which is very favorable. One notable difference to address, however, concerns the values of the CTL index coefficients for the host country, which have decreased to zero. This further emphasizes that social norms in the country in which the investment is made do not have a direct influence on the investment decision, especially when other variables of greater importance are also included in the equation. On the other hand, generally speaking, some parameters either decrease in value or lose their significance, but this does not necessarily affect the overall interpretation of the regressions.

Table 3. Estimation of Tobit models

Variable	ln(1+FDI)			
	(1)	(2)	(3)	(4)
CTL_C (home country)	0.009*** (0.001)		0.009*** (0.001)	
CTL_C (host country)		-0.000 (0.001)	0.000 (0.001)	
CTL_C_rez (home country)				0.007*** (0.001)
Control variables	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
Observations	28810	29187	15607	28810

Symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Furthermore, Table 3 shows that the standard errors have significantly decreased for all obtained coefficients. This is a positive development that further reinforces the validity of the models. Overall, testing the regressions with the new Tobit models confirms that there is an important and non-negligible relationship between the social norms of the origin country and the investment flows that emerge over time.

Moving forward, I will also consider a new model available for estimating regressions and which aids in testing the initially obtained results: the Probit model. Table 4 briefly illustrates the parameters estimated using this model, which largely follow the same pattern as those mentioned in the case of the Tobit models.

However, it should be noted that in the regressions illustrating the impact of social norms on foreign direct investments, I transformed the initial endogenous variable, which quantified the volume of FDI flows between pairs of countries over the reference years, into a dummy variable that expresses only the presence or absence of these investments. Specifically, if foreign investments were recorded, the variable was assigned a value of 1; otherwise, it was assigned a value of 0.

In the Probit models as well, the coefficients generally decreased, however they remained significant, which is particularly important for the main exogenous variable—the CTL index specific to the origin country. Additionally, the absence of a relationship between social norms in the host country and the recorded foreign investment flows at that level can also be observed, suggesting that not all factors included in the model do necessarily have an influence on the endogenous variable.

Table 4. Estimation of Probit models

Variable	Investment decision (yes/no)			
	(1)	(2)	(3)	(4)
CTL_C (home country)	0.010*** (0.001)		0.010*** (0.001)	
CTL_C (host country)		-0.000 (0.001)	0.000 (0.001)	
CTL_C_rez (home country)				0.008*** (0.001)
Control variables	YES	YES	YES	YES
Time effects	YES	YES	YES	YES
Observations	28810	29187	15607	28810

Symbols ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

7. Conclusions

The empirical study led to optimal results on the basis of which a series of arguments can be formulated that ultimately support the initial hypothesis.

Specifically, I was able to demonstrate that in terms of social norms, only those at the level of the foreign direct investment origin country have a significant impact on an individual's decision to make capital placements beyond the borders of their home country. This is a direct influence, meaning that as the CTL index of the origin country decreases – indicating stricter norms imposed on citizens – investments are likely to be nearly nonexistent or at an extremely low level. To better understand this causal relationship, it is important to note that in such countries, any deviation from the norms imposed by the central authority is harshly punished. As a result, an investor will be hesitant to invest in a foreign country due to the fear of deviating from the strict rules of his home country. On the other hand, permissive societies, as reflected by a high CTL index, will see a significant volume of FDI flows. This is because such societies encourage and support individuals to explore the unknown and be open to the novelties and changes characteristic of the dynamic modern world. These individuals are less likely to hesitate to venture beyond their borders and seek profits from investing in economies where development potential is high or production factors (capital and labor) are cheap, even if this involves taking considerable risks.

In conclusion, the final thoughts can be summarized in a few lines that emphasize potential future research directions equally. Thus, I consider this paper to be useful when it comes to understanding the impact of social norms on foreign direct investments. The dynamics of the contemporary economy make the volume of FDI increase significantly day by day, however, for an investment to truly generate benefits for both parties involved, it must always be preceded by a review of the relevant literature.This study is both revealing and paves the way for new, unexplored research directions that await exploration in the coming years.

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THE NEXUS BETWEEN INVESTORS' SENTIMENT AND HEDGE FUNDS RISK PREMIUMS

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Abstract: In this study, we analyzed how the systematic risk of hedge funds affects different portfolio strategies. Using monthly returns data from a sample of developed market hedge funds grouped by five strategies, we identified the systematic factors influencing returns variation from January 2003 to December 2023. Market, size effect, momentum, investment effect, and bond spread were found to be the main risk factors explaining hedge fund returns dynamics. We proposed an enhanced version of the Fung and Hsieh (2004a) model, which demonstrated improved representativity with Baker and Wurgler sentiment index included as a risk premium. The quantile regression revealed that for most strategies, the estimated models performed better for the bottom quantiles.

JEL Classification: G11, G12, C58

Keywords Hedge funds, Risk premiums, Sentiment index, Asset pricing

1. Introduction

Modern capital markets represent a complex and interconnected financial ecosystem, where economic cycles, geopolitical events, and technological developments profoundly influence the return-risk characteristics of securities. In this dynamic context, investors and professionals strive to identify investment strategies - ranging from simple to sophisticated - to outperform the market, often combining fundamental, technical, or quantitative analysis. The diversity of financial instruments available in the market adds an additional layer of complexity, necessitating a deep understanding of market mechanisms and their respective risk factors.

To navigate this complexity, researchers and practitioners have developed various asset pricing models aimed at identifying and quantifying the risk factors that influence asset returns. Given the complexity and high risk associated with these financial instruments, such studies are crucial in enhancing our understanding of managing risky assets. The ongoing debate between passive market positioning, which replicates index performance, and actively developing sophisticated portfolio management

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strategies to achieve higher returns, highlights the need for a reasonable justification for the additional costs and risks associated with active strategies.

This study helps in identifying the relevant sources of systematic risk based on the broad strategy approached, further complementing our capacity to understand and manage the dynamics of such risky assets.

2. Literature review

The initial asset pricing model, known as the Capital Asset Pricing Model (CAPM), was introduced by William Sharpe in 1964. CAPM is a unifactorial model that asserts a security's return is strongly related with the overall market movement, rewarding investors for selecting riskier assets characterized by a beta coefficient greater than one. Despite its extensive practical use, CAPM is criticized for its overly simplistic assumptions: all market participants are rational, manifesting risk adversity; they have equal access to information and the same time to evaluate it, all at no cost; they construct portfolios using only the mean and variance of return distributions; they can borrow unlimited capital at a risk-free rate; markets are perfect with no taxes, inflation, or transaction costs and assets are fully negotiable and infinitely divisible. In response to these criticisms, alternative models have been developed to more realistically address the return-risk characteristics of securities. One notable approach is the Arbitrage Pricing Theory (APT), proposed by Stephen Ross in 1976. APT extends CAPM by suggesting that a security's return can be explained through a linear relationship involving multiple systematic factors. Unlike CAPM, which assumes that markets are efficient with all information reflected in asset prices, APT allows for short-term imbalances between an asset's fundamental value and its market value, offering arbitrage opportunities for above-market returns. However, APT's limitation lies in its lack of specificity regarding which factors to consider, giving investors the flexibility to determine the tailored factors for the asset in question. Later on, Fama and French (1993) proposed a three-factor model as an extension of the CAPM, providing a better explanation for the systematic component of securities returns. In addition to the market risk premium, they introduce two additional risk factors: a size factor and a value factor. The size factor, SMB (small minus big), represents the excess return of a portfolio of small-cap companies over large-cap companies. The value factor, HML (high minus low), captures the excess return of a portfolio of high book-to-market stocks over a portfolio of low book-to-market stocks. This model opens new avenues in financial research and contributes to a deeper understanding of the sources of risk in securities. By incorporating these two additional factors, the Fama and French model enhances the prediction accuracy of asset returns and encourages further exploration of market behavior dynamics.

Carhart (1997) builds on the Fama-French three-factor model by adding a momentum factor, originally developed by Jegadeesh and Titman (1993). This momentum factor, WML (winners minus losers), reflects the tendency for an asset's return to follow its previous return trend, whether upward or downward, thereby enhancing the Fama and French model's explanatory power. Using a mutual funds database devoid of survivorship bias, Carhart formulates the WML factor by adopting a strategy of buying top-decile (winner) funds and selling bottom-decile (loser) funds, based on their performance over the past 12 months, excluding the most recent month.

Evidence from Titman et al. (2004), Novy and Marx (2013) and others indicates that the Fama-French three-factor model is not complete as it fails to account for a significant portion of return variations linked to profitability and investments. Titman et al. find a negative correlation between overinvestment and returns, while Novy and Marx (2013) identifies a positive relationship between returns and profitability, defined as the ratio of gross profitability (sales minus cost of goods sold) to the value of assets. This suggests that profitability is a key component of value investing, involving the financing of productive over unproductive assets. Inspired by this evidence, Fama and French (2015) introduced a five-factor model that incorporates profitability and investment factors. The profitability factor, RMW (robust minus weak), represents the extra returns of high-profitability stocks over low-profitability ones. The investment factor, CMA (conservative minus aggressive), captures the excess returns of conservatively investing companies over those investing aggressively. This model explains 71% to 94% of return variations for the studied portfolios. However, Fama and French noted its limited accuracy in predicting low returns for small-cap stocks with high investment and low profitability. The five-factor model thus advances asset pricing literature by deepening the understanding of return determinants.

The widespread growth of hedge fund industry since 2000 has led to many studies on hedge fund performance, systematic characteristics, and the timing ability of managers. Hedge funds, which are private investment vehicles that pool money from a limited number of investors, often employ complex strategies to achieve above-average returns, making them high-risk assets.

William Fung and David A. Hsieh (2004a) made a significant contribution to the asset pricing literature by developing a seven-factor model specifically for hedge funds. This model identifies different factors affecting various hedge fund strategies: long/short equity funds are impacted by two equity factors, fixed income funds by two bond factors, and trend-following funds by three trend-following factors. The equity factors consist of the return on the S&P 500 and a size premium, which is calculated as the difference in returns between the Wilshire 1750 Small Cap Index and the Wilshire 750 Large Cap Index. The bond factors are defined by the monthly change in the yield of 10-year Treasury bonds and the change in the spread between the yield of Baa ranked bonds and the 10-year Treasury yield. Fung and Hsieh's (2001) trend-following factors are constructed from portfolios of lookback straddles, reflecting the returns of option portfolios with futures contracts on bonds, exchange rates, and commodities as underlying assets. Thus, the development of asset pricing models reflects an evolving intellectual pursuit, advancing from simple risk-return dynamics to more sophisticated approaches. These models have significantly influenced financial theory, enhancing the understanding of complex securities in dynamic markets. They have also equipped industry professionals with advanced tools and quantitative techniques for asset evaluation and portfolio management.

3. Database and variables

We used the Hedge Funds Research database as a proxy for hedge fund evolution, from which we obtained monthly returns of hedge fund portfolios with global exposure, representing the hedge fund industry well. Each strategy has 252 observations of monthly returns, covering a 21-year period from January 2003 to

December 2023. Hedge funds are grouped based on strategy: Equity Hedge, Event Driven, Macro, Funds of Hedge Funds, and Relative Value. Portfolios are then calculated by applying equal weight to each hedge fund included in the portfolio. Each strategy will be presented below, mentioning the main points drawing investment decisions.

Equity Hedge strategies involve both long and short positions in equities and equity derivatives, utilizing a blend of quantitative and fundamental analysis. These strategies can vary from broad diversification to sector-specific focus, and they differ in terms of net exposure, leverage, holding periods, market capitalizations, and valuation ranges. Generally, Equity Hedge managers maintain at least 50% equity exposure and can be fully invested in both long and short positions.

Event Driven strategies target companies engaged in corporate transactions like mergers, restructurings, or financial distress. Managers invest across the capital structure, from senior to subordinated securities, frequently incorporating derivatives. These strategies are sensitive to both equity and credit markets and are highly dependent on fundamental analysis. Success relies on external events affecting the company's capital structure.

Macro strategies trade based on economic variables and their impacts on equity, fixed income, currency, and commodity markets. Managers use both discretionary and systematic approaches, employing top-down and bottom-up analysis, with varying holding periods. Unlike Relative Value strategies, which focus on valuation differences, Macro strategies anticipate movements in underlying instruments driven by macroeconomic factors. Though both Macro and Equity Hedge strategies might hold equities, Macro is driven by broader economic factors, while Equity Hedge centres on company-specific fundamentals.

Relative Value strategies seek to capitalize on valuation discrepancies between multiple securities, using a mix of fundamental and quantitative techniques. These strategies can involve equities, fixed income, and derivatives. Fixed income strategies within this category often depend on quantitative analysis to spot favourable risk-adjusted spreads. In contrast to Event Driven strategies, which hinge on the outcomes of corporate transactions, Relative Value strategies focus on profiting from pricing differences between related securities.

The factors for the Fama and French models were sourced from the Kenneth R. French website, corresponding to developed markets. The SIZE factor included in the Fung and Hsieh models was constructed as the return difference between the Russell 2000 index and the S&P500, with returns obtained from the Bloomberg database. The YLDCHG and BAAMTSY factors were constructed as per their definitions detailed later in this study, using data downloaded from the Federal Reserve Bank of St. Louis website. Trend-following factors - PTFSBD, PTFSFX, and PTFSCOM - were downloaded from David A. Hsieh's website, and the BW_SENT index was taken from Jeffrey Wurgler's website.

Table 1. Summary Statistics Overview

The table provides a summary of descriptive statistics for hedge fund portfolio returns and risk premiums utilized in estimating asset pricing models. According to the Sharpe ratio, the Relative Value portfolio provides the best excess return per unit of total risk. The Augmented Dickey-Fuller (ADF) test applied to the time series indicates the presence of a unit root; *** denotes the rejection of the null hypothesis at a 99% confidence level.

Variable	Observations	Mean	Standard deviation	Sharpe ratio	ADF Test
Equity hedge	252	0.51%	2.48%	16.30%	-13.00***
Event-driven	252	0.56%	1.97%	22.77%	-11.48***
Macro	252	0.37%	1.42%	18.48%	-15.51***
Funds of HF	252	0.31%	1.50%	13.53%	-12.13***
Relative value	252	0.45%	1.33%	25.65%	-10.68***
RF	252	0.11%	0.14%	-	-2.21
Mkt-RF	252	0.75%	4.49%	-	-14.50***
SMB	252	-0.01%	1.56%	-	-14.50***
HML	252	0.05%	2.31%	-	-12.70***
WML	252	0.30%	3.29%	-	-12.93***
RMW	252	0.28%	1.28%	-	-11.95***
CMA	252	0.09%	1.61%	-	-7.28***
SIZE	252	-0.03%	4.24%	-	-21.35***
YLDCHG	252	0.00%	0.26%	-	-14.60***
BAAMTSY	252	-0.01%	0.24%	-	-12.85***
PTFSBD	252	0.07%	20.04%	-	-13.76***
PTFSFX	252	-0.67%	19.50%	-	-15.08***
PTFSCOM	252	0.02%	14.68%	-	-14.58***
BW_SENT	234	-0.02%	0.49%	-	-1.77

Source: Author's Computation

4. Methodology

In evaluating risk premiums in hedge funds, we adopted the methodologies of Fama and French (1993, 2015), Carhart (1997), and Fung and Hsieh (2004a) to identify the most important components of systematic risk.

Therefore, the first model estimated was Fama and French (1993) 3-factor model as presented below:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \varepsilon_{it} \quad (1)$$

Where R_{it} represents the return of hedge fund portfolio i over period t, R_{Mt} is the market portfolio return composed of stocks listed on NYSE, NASDAQ, and AMEX, weighted based on market capitalization, R_{Ft} represents the risk-free rate, specifically the rate of 1-month T-bills issued by the Fed, SMB_t represents the excess return of a portfolio of low capitalization stocks over a portfolio of high capitalization stocks, and HML_t is the excess return of a portfolio of high book-to-market stocks over a portfolio of low book-to-market stocks.

The second model is the improved version suggested by Carhart (1997) with the addition of momentum factor:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}WML_t + \varepsilon_{it} \quad (2)$$

Where WML_t is the return difference between a portfolio of stocks that were top-performing during the previous year and a portfolio of stocks that were bottom-performing during the previous year.

The last version of the model presented is the Fama and French (2015) 5-factor model, which includes two additional factors to account for other market anomalies:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \varepsilon_{it} \quad (3)$$

Where RMW_t is the excess return of a diversified portfolio of high-profitability companies over a portfolio of low-profitability companies, and CMA_t is the excess return of a diversified portfolio of companies investing conservatively over a portfolio of companies investing aggressively.

Additionally, we continued our analysis with a model designed specifically for evaluating hedge fund performance, which is the Fung and Hsieh (2004) 7-factor model:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SIZE_t + \ + \beta_{3i}YLDCHG_t + \beta_{4i}BAAMTSY_t + \beta_{5i}PTFSBD_t + \beta_{6i}PTFSFX_t + \beta_{7i}PTFSCOM_t + \varepsilon_{it} \quad (4)$$

Where $SIZE_t$ represents the excess return of the Russell 2000 index over the S&P500 index, YLDCHGt is the monthly change in the ten-year Treasury constant maturity yield issued by Fed, $BAAMTSY_t$ is the monthly change in the yield spread of Baa ranked bonds and the previous mentioned factor, $PTFSBD_t$ is the trend following factor quantifying return of a portfolio of lookback straddles on bonds, $PTFSFX_t$ is the return of a portfolio of lookback straddles on foreign exchange, and $PTFSCOM_t$ is the return of a portfolio of lookback straddles on commodities.

Lastly, we suggest an improved version of Fung and Hsieh (2004a) model adding Baker and Wurgler sentiment index as a risk premium as presented below:

$$R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SIZE_t + \beta_{3i}YLDCHG_t + \beta_{4i}BAAMTSY_t + \beta_{5i}PTFSBD_t + \beta_{6i}PTFSFX_t + \beta_{7i}PTFSCOM_t + \beta_{8i}BWSENT_T^{\perp} + \varepsilon_{it} \quad (5)$$

$$BWSENT_t^{\perp} = -0.198CEFD_t^{\perp} + 0.225TURN_{t-1}^{\perp} + 0.234NIPO_t^{\perp} + 0.263RIPO_{t-1}^{\perp} + 0.211S_t^{\perp} - 0.243P_{t-1}^{D\text{-}ND,\perp}$$

Where $\text{BWSENT}_t^{\perp}$ is the orthogonlized value of Baker and Wurgler (2006) sentiment index, $\text{CEFD}_t^{\perp}$ is the close-end funds discount, $\text{TURN}_{t-1}^{\perp}$ represents a proxy for the volatility of NYSE, $\text{NIPO}_t^{\perp}$ represents the number of IPOs in period t, $\text{RIPO}_{t-1}^{\perp}$ is the average first day returns of IPOs listed during period t, $S_t^{\perp}$ represents the equity share in new issuance, $\text{P}_{t-1}^{D-ND,\perp}$ is the dividend premium, calculated as the log difference of dividend payers and dividend nonpayers.

5. Empirical results and discussions

Table 2 presents estimations for Fama and French (1993) three-factor model. The market is the primary variable explaining return variation for all strategies, while the size effect is significant for all strategies except the Macro portfolio. The regression demonstrates good explanatory power, especially for Equity Hedge, Event-Driven, and Funds of Hedge Funds portfolios, but it fails to explain the variation of Macro funds, illustrating the complex dynamics of this strategy. Event-Driven, Macro, and Relative Value portfolios have generated significant alpha, suggesting the value added by the skill of hedge fund managers.

Table 2. Fama and French 3-factor model

The table presents the estimated parameters of model 1, applying OLS method for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels.

Variable	Equity hedge	Event-driven	Macro	Funds of HF	Relative value
α	0.036	0.182***	0.194**	0.013	0.181***
β_1	0.492***	0.350***	0.089***	0.257***	0.209***
β_2	0.352***	0.356***	0.089	0.243***	0.192***
β_3	0.017	0.136***	0.041	-0.024	0.072***
R^2 adj	0.907	0.819	0.093	0.720	0.615

Source: Author's Computation

Carhart (1997) model, represented in table 3 adds momentum factor, which captures the inertia effect in returns. This factor proves to be statistically significant for Equity Hedge, Macro, and Fund of Hedge Funds portfolios, improving the regression's representativity for 4 out of 5 strategies. In the Macro portfolio, the adjusted R-squared coefficient improves from 9.3% to 16.5% with the addition of the momentum factor.

Table 3. Carhart 4-factor model

The table presents the estimated parameters of model 2, applying OLS method for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}WML_t + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels.

Variable	Equity hedge	Event-driven	Macro	Funds of HF	Relative value
α	0.017	0.17***	0.124	-0.034	0.181***
β_1	0.502***	0.356***	0.124***	0.279***	0.209***
β_2	0.35***	0.355***	0.082	0.239***	0.192***
β_3	0.033	0.146***	0.099***	0.015	0.073***
β_4	0.038**	0.023	0.134***	0.089***	0.001
R^2 adj	0.909	0.820	0.165	0.748	0.613

Source: Author's Computation

Table 4. Fama and French 5-factor model

The table presents the estimated parameters of model 3, applying OLS method for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels

Variable	Equity hedge	Event-driven	Macro	Funds of HF	Relative value
α	0.092*	0.216***	0.182**	0.042	0.195***
β_1	0.464***	0.328***	0.1***	0.231***	0.181***
β_2	0.312***	0.331***	0.099*	0.221***	0.18***
β_3	0.088***	0.207***	-0.027	0.074**	0.207***
β_4	-0.074*	-0.023	-0.026	0.011	0.078
β_5	-0.198***	-0.167**	0.131	-0.203***	-0.244***
R^2 adj	0.915	0.826	0.095	0.738	0.654

Source: Author's Computation

The five-factor Fama and French model presented in table 4 reveals the significance of the profitability effect only in the Equity Hedge portfolio, suggesting that funds in these portfolios generally do not have significant exposure to profitable companies and investment decisions are driven by other criteria. However, the investment effect is much more visible and significant for 4 out of 5 strategies. In the presence of RMW and CMA, the value factor becomes significant for Equity Hedge and Funds of Hedge Funds, indicating that the information contained in this variable is better reflected when these two additional factors are included. Overall, this model has better representativity, explaining more effectively the systematic component in the evolution of hedge funds. According to this model, 4 out of 5 portfolios have generated alpha. The regression estimation results for the seven-factor model of

Fung and Hsieh are presented in table 5. The explanatory power is considerably improved for Macro and Relative Value portfolios, indicating their exposure to risk factors more specific to hedge funds. The representativity, measured by adjusted R-squared, increases by 14.5 percentage points for Macro and 11.8 percentage points for Relative Value portfolios. Compared to other estimated models, this one best suits the Macro strategy, indicating statistically significant coefficients for all trend-following factors, reflecting dynamic exposure across multiple asset classes based on the economic situation.

Table 5. Fung and Hsieh basic model

The table presents the estimated parameters of model 4, applying OLS method for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + + \beta_{2i}SIZE_t + + \beta_{3i}YLDCHG_t + \beta_{4i}BAAMTSY_t + \beta_{5i}PTFSBD_t + \beta_{6i}PTFSFX_t + \beta_{7i}PTFSCOM_t + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels.

Variable	Equity hedge	Event-driven	Macro	Funds of HF	Relative value
α	0.05	0.224***	0.166**	0.029	0.237***
β_1	0.46***	0.278***	0.141***	0.215***	0.106***
β_2	0.029**	0.039***	-0.007	-0.005	0.02**
β_3	-1.526***	-2.426***	-0.349	-1.916***	-3.138***
β_4	0.445	0.28	0.086	0.024	-0.427**
β_5	0.002	-0.003	0.011**	0.001	-0.004
β_6	0.003	0.001	0.02***	0.004	-0.003
β_7	-0.005	-0.01**	0.015**	-0.003	-0.008***
R^2 adj	0.882	0.804	0.24	0.705	0.772

Source: Author's Computation

Table 6. Fung and Hsieh model with Baker and Wurgler sentiment index

The table presents the estimated parameters of model 5 for Equity hedge portfolio, applying both OLS and quantile regression methods for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SIZE_t + \beta_{3i}YLDCHG_t + \beta_{4i}BAAMTSY_t + \beta_{5i}PTFSBD_t + \beta_{6i}PTFSFX_t + \beta_{7i}PTFSCOM_t + \beta_{8i}BWSENT_T^{\perp} + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels.

Equity hedge	OLS	τ = 0.1	τ = 0.25	τ = 0.5	τ = 0.75	τ = 0.9
α	0.067	-1.08***	-0.397***	0.036	0.58***	1.068***
β_1	0.466***	0.477***	0.482***	0.488**	0.467***	0.422***
β_2	0.026*	0.015	0.035	0.042	0.043*	0.03*
β_3	-1.318***	0.532	0.043	0.539	0.42	0.879*
β_4	0.59**	-0.932	-1.259*	-0.995	-1.001**	-2.029***

β_5	0.003	-0.008	-0.003	0.004	0.007	0.013
β_6	0.002	0.005	0.007	0.004	0.005	0.003
β_7	-0.006	-0.014	-0.004	-0.004	-0.005	0.005
β_8	-0.066	0.076	-0.212	-0.218	-0.008	0.051
R^2 adj	0.882	0.7	0.664	0.644	0.62	0.622

Source: Author's Computation

Including the Baker and Wurgler sentiment index as a risk premium in the Fung and Hsieh model further enhances explanatory power compared to the basic model and others. The sentiment index balances the model and better explains the information carried by other variables, even though the sentiment index itself is not statistically significant for any strategy.

Ultimately, we conducted a quantile regression analysis for the Fung and Hsieh model, including the Baker and Wurgler sentiment index, to evaluate how the regression fits across different performance ranks. We divided our analysis into five quantiles: 10%, 25%, 50%, 75%, and 90%. The estimation outputs are presented for each portfolio, starting with Table 6 and continuing through Table 10.

For the Equity Hedge portfolio, the representativity is highest at the bottom 10% quantile and continuously decreases as we move to higher quantiles. A possible explanation could be that bottom performers are more exposed to systematic risks due to the lack of timing and selectivity skills of hedge fund managers.

Table 7. Fung and Hsieh model with Baker and Wurgler sentiment index

The table presents the estimated parameters of model 5 for Event-driven portfolio, applying both OLS and quantile regression methods for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SIZE_t + \beta_{3i}YLDCHG_t + \beta_{4i}BAAMTSY_t + \beta_{5i}PTFSBD_t + \beta_{6i}PTFSFX_t + \beta_{7i}PTFSCOM_t + \beta_{8i}BWSENT_T^{\perp} + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels.

Event-driven	OLS	τ = 0.1	τ = 0.25	τ = 0.5	τ = 0.75	τ = 0.9
α	0.243***	-0.791***	-0.225***	0.246***	0.649***	1.236***
β_1	0.278***	0.26***	0.265***	0.275***	0.285***	0.313***
β_2	0.039***	0.03	0.034	0.044**	0.022	0.018
β_3	-2.308***	0.657	0.177	0.137	0.176	0.705
β_4	0.36	-2.614***	-2.134***	-2.183***	-1.625**	-2.282***
β_5	-0.003	-0.01	-0.004	-0.007	-0.003	0.009
β_6	0	0.005	0.001	0.002	0.004	-0.001
β_7	-0.009**	-0.009	-0.006	-0.008	-0.007	-0.005
β_8	-0.076	0.163	-0.228	-0.133*	-0.262**	-0.165
R^2 adj	0.811	0.607	0.569	0.548	0.505	0.48

Source: Author's Computation

For the Event-Driven strategy, we observe a similar pattern of decreasing representativity as we move to higher quantiles. Additionally, we notice the statistical significance of certain coefficients at specific performance rankings compared to OLS. The bond spread, measured by the excess return of BAA-rated bonds over the 10-year constant maturity yield, shows a negative exposure dynamic. Furthermore, for the 0.5 and 0.75 quantiles, the Baker and Wurgler sentiment index is significant, indicating that investor sentiment negatively influences the return variation of hedge funds.

In the Macro portfolio, the significance of trend-following factors in the top quantiles suggests dynamic asset allocation in various situations. Compared to other portfolios, the representativity of the regression increases at higher quantiles, likely due to the more dynamic allocation strategies employed by top performers.

Table 8. Fung and Hsieh model with Baker and Wurgler sentiment index

The table presents the estimated parameters of model 5 for Macro portfolio, applying both OLS and quantile regression methods for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SIZE_t + \beta_{3i}YLDCHG_t + \beta_{4i}BAAMTSY_t + \beta_{5i}PTFSBD_t + \beta_{6i}PTFSFX_t + \beta_{7i}PTFSCOM_t + \beta_{8i}BWSENT_T^{\perp} + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels.

Macro	OLS	τ = 0.1	τ = 0.25	τ = 0.5	τ = 0.75	τ = 0.9
α	0.191**	-1.212***	-0.624***	0.177	1.001***	1.812***
β_1	0.176***	0.179***	0.159***	0.217***	0.151***	0.141***
β_2	-0.022	-0.026	-0.041	-0.026	-0.039	-0.046
β_3	-0.282	-1.514**	-1.267**	-0.888*	0.347	0.333
β_4	-0.512	-0.851**	-1.159	0.312	0.649	-0.501
β_5	0.012**	0.008	0.011	0.018***	0.012**	0.014
β_6	0.021***	0.014	0.011	0.025***	0.025***	0.035*
β_7	0.014**	0.011	0.007	0.021**	0.027***	0.031*
β_8	-0.013	0.12	0.232	-0.124	-0.124	0.052
R^2 adj	0.317	0.157	0.155	0.173	0.211	0.241

Source: Author`s Computation

Table 9. Fung and Hsieh model with Baker and Wurgler sentiment index

The table presents the estimated parameters of model 5 for Funds of Hedge Funds portfolio, applying both OLS and quantile regression methods for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SIZE_t + \beta_{3i}YLDCHG_t + \beta_{4i}BAAMTSY_t + \beta_{5i}PTFSBD_t + \beta_{6i}PTFSFX_t + \beta_{7i}PTFSCOM_t + \beta_{8i}BWSENT_T^{\perp} + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels.

Funds of HF	OLS	τ = 0.1	τ = 0.25	τ = 0.5	τ = 0.75	τ = 0.9
α	0.045	-0.988***	-0.391***	0.161***	0.535***	0.897***
β_1	0.229***	0.211***	0.276***	0.256***	0.236***	0.221***
β_2	-0.013	0.006	0.005	-0.007	-0.007	-0.019

β3	-1.839***	-0.106	-0.343	-0.261	-0.179	0.336
β4	-0.111	-2.149***	-1.239***	-1.163***	-1.636***	-2.012***
β5	0	0.004	-0.001	0.006	0.002	0.007***
β6	0.005	-0.003	0.004	0.006*	0.007**	0.006*
β7	-0.003	-0.006	0.001	-0.001	-0.003	-0.005
β8	0.106	-0.062	-0.134	0.165	0.156	-0.056
R^2 adj	0.712	0.477	0.459	0.433	0.443	0.457

Source: Author's Computation

For the Funds of Hedge Funds portfolio, the representativity remains almost constant across all quantiles. However, we observe the significance of the bond spread compared to OLS and the FX premium in the top quantiles.

Table 10. Fung and Hsieh model with Baker and Wurgler sentiment index

The table presents the estimated parameters of model 5 for Relative value portfolio, applying both OLS and quantile regression methods for the following regression: $R_{it} - R_{Ft} = \alpha_i + \beta_{1i}(R_{Mt} - R_{Ft}) + \beta_{2i}SIZE_t + \beta_{3i}YLDCHG_t + \beta_{4i}BAAMTSY_t + \beta_{5i}PTFSBD_t + \beta_{6i}PTFSFX_t + \beta_{7i}PTFSCOM_t + \beta_{8i}BWSENT_T^{\perp} + \varepsilon_{it}$ over the period 01.01.2003 – 31.12.2023, *, **, *** indicates statistically significant coefficients for 90%, 95%, 99% confidence levels.

Relative value	OLS	τ = 0.1	τ = 0.25	τ = 0.5	τ = 0.75	τ = 0.9
α	0.259***	-0.478***	-0.114*	0.269***	0.637***	1.018***
β1	0.114***	0.115***	0.128***	0.129***	0.136***	0.099***
β2	0.017*	0.022	0.022	0.014	0.008	0.029**
β3	-3.136***	-0.761**	-0.719***	-0.861***	0.025	0.175
β4	-0.519***	-3.272***	-2.822***	-2.502***	-2.163***	-2.372***
β5	-0.004	-0.009	-0.008**	-0.002	0.004	0.005**
β6	-0.003	-0.003	0.003	-0.001	-0.002	-0.005*
β7	-0.008***	-0.003	0.001	-0.004	-0.008**	-0.003
β8	0.055	0.107	0.019	-0.062	0.069	-0.187
R^2 adj	0.779	0.581	0.48	0.41	0.39	0.409

Source: Author's Computation

Lastly, in the Relative Value portfolio, there is a decrease in representativity as we move to higher quantiles, with 5 out of 8 factors being statistically significant at the 0.9 quantile.

6. Conclusion

Among all risk factors, the market, size effect, investment effect, momentum, and bond spread are the most important in explaining return variation across hedge fund portfolios. In quantile regression, we find that, except for the Macro strategy, the representativity of the Fung and Hsieh model, when including the Baker and Wurgler sentiment index, is better for the bottom quantiles. This may result from a lack of timing and selectivity skills of managers at these ranks. Overall, the sentiment index improves the explanatory power of the Fung and Hsieh model. Although the index itself does not statistically influence most portfolio returns, it helps balance the model and reflect the information present in the other variables. The R-squared of all portfolios increased by an average of 2 percentage points compared to the basic model, with the most significant increase coming from the Macro portfolio, where representativity improved by 7.7 percentage points. The Macro strategy proved to be the most dynamic, with the Fung and Hsieh asset pricing model for hedge funds performing better compared to the Fama and French models and the Carhart model, which is primarily designed for equities.

This study provides more insight into the complex relationship between risk and returns for hedge funds, identifying the most important sources of risk influencing return variation across different hedge fund strategies.

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DIGITAL INFLUENCERS: CATALYSTS FOR CUSTOMER ENGAGEMENT AND PURCHASE INTENTION

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Abstract: Social Media Influencer (SMI) marketing represents a contemporary addition to the arsenal of digital advertising tools. Digital Content Creators are individuals who regularly share a variety of content, including visuals, audio recordings, and updates, across multiple social media platforms to shape consumers' perceptions of a brand and its products. The focus of this study is to examine how the credibility aspects of social media influencers (expertise, attractiveness, and trustworthiness) influence purchase intention and brand intimacy while also considering the mediating role of consumer engagement. This study used a quantitative, cross-sectional design with convenience sampling targeting social media-active individuals. Data were collected via a questionnaire distributed through email and social media, selecting participants who followed influencers. To gather data, 250 participants were engaged in an online questionnaire distributed via Google Forms. The findings indicate that the credibility dimensions of SMIs, particularly their attractiveness and trustworthiness, positively influence brand intimacy and purchase intention. Furthermore, consumer engagement serves as a critical mediator, connecting the authenticity of social media influencers with purchase intention and brand intimacy. In line with these results, it becomes evident that consumer engagement indirectly influences influencer credibility (trustworthiness and attractiveness), purchase intention, and brand intimacy. Notably, expertise does not exert any discernible impact on either brand intimacy or purchase intention. This study's

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outcomes provide valuable insights for marketing managers, underscoring the significance of partnering with influencers who possess a high level of trust within their respective marketing niches.

JEL classification: M3, O30.

Keywords: social media influencers, credibility, customer engagement, purchase intention, brand intimacy.

1. Introduction

In today's fast-paced digital landscape, digital platforms have become an integral part of our daily lives, transforming the way we interact, share information, and connect with others. In 2022, a staggering 4.95 billion individuals harnessed social media networks to access the internet, with over 50% of them using these platforms to explore products and services offered by several brands (Sokolova and Kefi, 2019). Social media has, therefore, emerged as a potent tool for businesses to engage with potential customers, enabling them to reach millions of individuals simultaneously (Sajid, 2016). This extensive reach wields a substantial influence on shaping consumer purchasing decisions (Pütter, 2017). In contrast to traditional brand messaging, consumers increasingly place their trust in peer reviews when evaluating products and services (Lamberton and Stephen, 2016). Social media platforms offer an ideal environment for this practice, given the interconnectedness of online consumers.

With the advent of social media platforms, users who regularly share personal stories, reviews, and content on social networks have morphed into influential figures, commonly referred to as "social media influencers" (Khamis et al., 2017). These influencers also generate revenue through sponsored content and incentives from brands (Lou and Yuan, 2019). In contrast to traditional celebrities, social media personalities have gained prominence through their active engagement on social media platforms, including images, stories, and videos (Ismagilova, 2020; Zafar et al., 2020). Corporate expenditures in influencer marketing are projected to exceed $24 billion annually by 2024, signalling the growing recognition of the potential of this approach among businesses [62].

Influencer marketing has emerged as a popular method for brands to increase their exposure and connect with customers in recent years (Hair et al., 2017). When influencers endorse a brand, they lend it credibility and foster trust among their followers, leading to favourable perceptions of the brand and a stronger emotional connection (Wang et al., 2021). The concept of "brand intimacy" describes this emotional bond between customers and a specific brand (v et al., 2019).

This research aims to enhance our understanding of these areas that warrants further investigation (Wang, T., and Lee, 2021; Jin and Ryu, 2020). Specifically, it seeks to explore the factors contributing to the credibility of social media influencers and identify the elements influencing their followers' purchase intentions. By delving into these dimensions, the study intends to unravel the sources of influencer credibility and their impact on consumer behaviour. Additionally, the study investigates how consumer engagement effectively influences brand intimacy, an area that has yet to be extensively explored as part of customer interactions.

2.Literature Review

Influencers Credibility Dimensions

The perceived credibility of a public figure is the extent to which an individual views the blogger's opinions as unaltered, genuinely realistic, and true (Cosenza et al., 2015). It is worth noting that the trustworthiness of the person conveying the message, or the message source, is a critical component for message effectiveness (Husnain and Toor, 2017). Credibility, in this context, refers to the level of trust placed in both the information and the individuals delivering it (Ohanian, 1990). In the realm of influencer marketing, the central concept revolves around leveraging respected online figures, often referred to as content creators, to convey a brand's message or products, whether customized or not, to their audience, thereby influencing their attitudes, outcomes, and behaviours (De Veirman et al., 2017). Credibility encompasses various dimensions related to "one's expertise and willingness to maintain performance-enhancing credentials" (Dwivedi et al., 2018). Therefore, we are going to analyse the dimensions of trustworthiness, expertise, and attractiveness.

Trustworthiness

Trustworthiness can be defined as the extent to which the representative is perceived as honest, reliable, and authentic in the eyes of the audience (Ismagilova et al., 2020). The concept of trust in discourse pertains to the listener's level of reliance on and acceptance of the individual influencing them, and the message being conveyed (Abdulmajid and Wahid, 2012). Trustworthiness encompasses the trustor's confidence in the trustee's qualities and attributes (Kosiba et al., 2018). In essence, for social media influencers (trustees) to establish trustworthiness, end-users (trustors) must be convinced that the blogger's statements are credible.

To create a positive impression and foster trust, influencers should provide accurate and truthful information about both informational and functional products. When consumers place their trust in a seller or influencer, they are more likely to trust that product or influencer in the future (Pham et al., 2021; Shamhuyenhanzva et al., 2016). Hu et al. (2019) assert that when making online purchases, consumers are often susceptible to persuasion from highly reliable information sources. Consequently, if an influencer can establish an authentic and trustworthy image, they will find it easier to capture the attention of a more engaged audience. (Wang and Scheinbaum, 2018) conducted an examination of the significance of trustworthiness in the beauty market, focusing particularly on the role of popular figures. They identified a strong correlation between social media influencers and the beauty industry, which was pivotal in reshaping consumer perceptions. In turn, (Silva et al., 2020) delved into the impact of product endorsements by digital influencers on the Instagram platform and how this engagement influenced product recommendations. Trustworthiness has been identified as the primary credibility factor with a significant impact on the behaviour of followers (Wiedmann and Von Mettenheim, 2020). Building on these findings, the current study posits that the trustworthiness of social media influencers is a key factor in establishing their credibility and influencing the purchase intentions of their social media followers. Consequently, the following hypotheses are formulated:

H1a: There is a significant impact of Trustworthiness on Purchase intention.
H1b: There is a significant impact of Trustworthiness on Brand Intimacy.

Expertise

Expertise has been characterized by Elaziz and Mayouf (2017) as the apparent competence of the source to offer valid affirmations. Therefore, the source is seen as someone qualified to deliver accurate evidence or knowledgeable about a certain topic (Elaziz and Mayouf, 2017). In the social media domain, the perceived amount of insight, competence, or understanding of an influencer is characterized as expertise. The skill of an influencer is comparable to qualities that directly impact the amount of belief necessary in convincing customers to purchase something suggested (v et al., 2022; Wang and Scheinbaum, 2017).

According to Zhu et al. (2016), when customers embark on shopping and encounter products that are unfamiliar to them, they typically lean on the insights of individuals with dedicated knowledge to gauge the practicality and value of these offerings. It is the expertise of influencers that will shape their credibility, as well as shape customers' buying behaviours and intentions (Schouten et al., 2021). Schouten et al. (2021) also suggested that the impact of the alignment between a product and its endorser on credibility is more conspicuous for influencers than for traditional celebrity endorsers. This is because digital creators have excellently positioned themselves as experts within specific domains of the interweb, such as 'technology enthusiasts,' 'fitness experts,' 'beauty enthusiasts,' or 'fashion aficionados,' and regularly communicate product material to their online supporters (Balog et al., 2008).

Influencer expertise affects followers' attitudes as well as their purchase intentions (AlFarraj et al., 2021). When deciding whether to adopt a product, consumers take into account their interactions with social media influencers (Martínez-López et al., 2020). Expert social media influencers can readily inspire consumers to follow their advice and knowledge on a particular subject (Chetioui et al., 2020). Hence, the expertise possessed by social media influencers plays a significant role in shaping the extent of customer engagement and, consequently, their purchase intentions.

H2a: There is a significant impact of Expertise on Purchase intention.
H2b: There is a significant impact of Expertise on Brand Intimacy.

Attractiveness

In the realm of effective advertising, the concept of source attractiveness is heavily shaped by the source's resemblance, closeness, and popularity to the audience (McGuire, 1985). Resemblance pertains to the perceived similarity between the audience (social media followers) and the source, closeness involves the familiarity-based understanding of the source, and likability is based on an affinity for the source due to their facial attractiveness and performance (McGuire, 1985). An influential factor in capturing public attention within messages is the attractiveness of influencers. Their attractiveness has a profound impact on community behaviour, as they tend to be more popular when they possess qualities deemed attractive (Djafarova and Rushworth, 2017).

As per Tingchi Liu et al. (2007), attractive endorsers are more likely to positively impact customer purchase intentions. The attitudes of customers towards specific companies and their purchase intentions can be swayed by the actions of social media influencers. To gain customer trust and foster long-term relationships, these digital celebrities must consistently demonstrate their mastery of their content. Previous research has shown that when brand information or recommendations come from attractive and knowledgeable individuals perceived as experts, it has a favourable effect on customer behaviour toward those brands (AlFarraj et al., 2021). Therefore, the physical attractiveness of the source can be leveraged to enhance the impact of advertisements (Singh and Banerjee, 2018; Weismueller et al., 2020]. Endorsers with attractive characteristics have the potential to impact buyers' attitudes, leading to a purchase intention (Sokolova and Kefi, 2019). Furthermore, Lou and Yuan (2019) have demonstrated that the attractiveness of influencers can potentially enhance brand visibility and inspire the level of trust consumers place in the content they produce. Consequently, the following hypotheses are formulated:

H3a: There is a significant impact of Attractiveness on Purchase intention.
H3b: There is a significant impact of Attractiveness on Brand Intimacy.

Consumer Engagement

In the realm of marketing, consumer engagement, as defined by Pansari and Kumar (2018), signifies the depth of the interactive relationship established by a customer with a company. This concept finds its roots in relationship marketing (Vivek et al., 2012). Within the context of social media and online platforms, much of the research has predominantly focused on the action-based facet of consumer engagement. This includes activities such as liking, sharing thoughts, and other interactive behaviours (Barger et al., 2016). Additionally, these investigations have shed light on the consequences of engagement on consumer behaviours, encompassing aspects like electronic Word-of-Mouth (eWOM) and purchase intentions (Mainardes and Cardoso, 2019).

As Social Media Influencers play an increasingly significant role in consumers' decision-making processes, brands are now distributing brand-related content through influencers' profiles [30]. Moreover, influential individuals on social media platforms can enhance digital engagement through factors like the content they produce and the type of ads they share. Their ability to interact and adapt contributes to heightened customer engagement, as influencers leverage their insights to understand and address the societal needs of their audience (Khalid et al., 2018). Social Media Influencers' channels provide consumers with opportunities to explore brand-related content, and engagement occurs when they view and interact with influencers' videos and stories related to the brand on various social platforms (Cheung et al., 2021).

Consumer engagement and purchase intention

Research by Mirabi et al. (2015) suggests that highly engaged consumers generate 23% more revenue due to their increased spending per transaction and more frequent purchases. This, in turn, enhances the customer's lifetime value while reducing the costs associated with acquiring new customers. In theory, highly engaged consumers are likely to encourage friends and family to become customers as well (Mirabi et al., 2015). A similar finding (Algharabat et al., 2018), supported the role of customer engagement in the retailing industry in influencing consumer purchase intention and value co-creation. Tiruwa et al. (2016) discovered links between customer engagement in Facebook online brand groups and purchase intent. Husnain and Toor (2017) emphasized that customer interaction has a significant impact on purchase intention in the context of social media advertising in Pakistan. They pointed out that the improvement of consumer connection, communication, and the sharing of information about products and services have contributed to heightened customer engagement, subsequently influencing purchase intent. Therefore, this study will investigate the following hypothesis:

H4: There is a significant impact of Consumer Engagement on Purchase Intention.

Consumer engagement and brand intimacy

Consumer engagement plays a pivotal role in cultivating a sense of closeness between consumers and brands (Junior et al., 2022). This, in turn, piques consumers' curiosity to learn more about the brand and actively engage with it. For the success of businesses, establishing robust connections between consumers and brands is paramount (Ki et al., 2020). When consumers follow bloggers on social media platforms and become part of virtual communities, their commitment increases as they interact with brands. This heightened engagement results in positive feelings towards the brand (Machado et al., 2019). Consumer engagement nurtures brand intimacy and the business-to-consumer connection, ensuring fruitful partnerships (Ladhari et al., 2020).

When social media influencer (SMI) activities enhance customer connections, such as sharing their expertise and experiences through personalization, consumers' favourable perceptions of the brand soar (Mathur, 2018). As outlined in the following hypothesis, the study proposes a direct connection between customer engagement and brand intimacy:

H5: There is a significant impact of Consumer Engagement on Brand Intimacy.

Mediating Role of Consumer Engagement

While customer engagement serves as a significant predictor of thoughts, intentions, and actions (Harrigan et al., 2017; Prentice et al., 2019), it's essential to recognize that the direct impact of source characteristics, such as attractiveness and expertise, on purchase intentions is channelled through brand attitude (Vrontis et al., 2021). This implies that source attributes alone may not wield a substantial influence on purchase intentions. Instead, source qualities exert a positive effect on consumer attitudes, which, in turn, drive purchase intentions. As noted by AlFarraj et al. (2021), even when social media influencers possess a high degree of credibility, consumers must actively engage with the influencers' content and actions to foster a favourable intention towards the targeted companies or products. Hence, the following hypotheses are put forward:

H6a: Consumer Engagement significantly mediates the relationship between Trustworthiness and Purchase Intention.

H6b: Consumer Engagement significantly mediates the relationship between Expertise and Purchase Intention.
H6c: Consumer Engagement significantly mediates the relationship between Attractiveness and Purchase Intention.

Numerous studies have acknowledged the role of consumer engagement as an intermediary in various marketing contexts. For instance, Rao and Aslam (2019) noted that consumer engagement acts as a mediator in the connection between brand affection and customer loyalty. Similarly, Toor et al. (2017) found that consumer engagement becomes a mediator between social network interactions and customer purchase intent. Moreover, Prentice et al. (2019) underscored the importance of consumer engagement as a mediator between internal and external factors and sustainable consumption behaviour.

Despite the existing research on the relationships between consumer engagement, the credibility dimensions of social media influencers, and brand intimacy, there is a dearth of studies exploring the role of consumer engagement as an intermediary among these constructs. Therefore, we present the following hypothesis:

H7a: Consumer Engagement significantly mediates the relationship between Trustworthiness and Brand Intimacy.
H7b: Consumer Engagement significantly mediates the relationship between Expertise and Brand Intimacy.
H7c: Consumer Engagement significantly mediates the relationship between Attractiveness and Brand Intimacy.

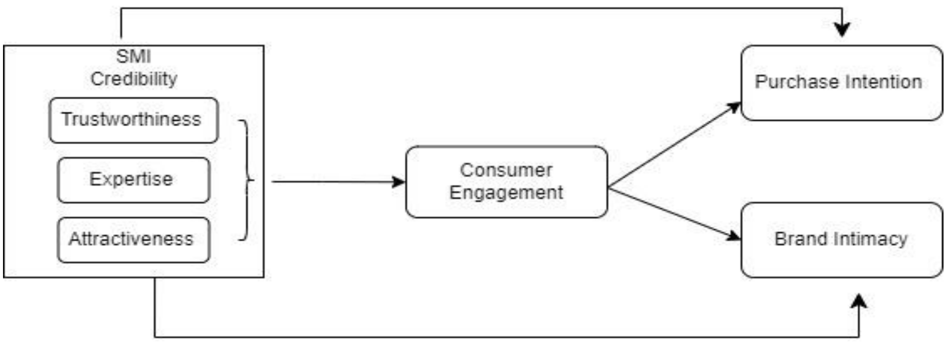

Figure 1. Theoretical framework

3.Methodology

This study used a quantitative approach employing a cross-sectional study design. Data collection was facilitated through the distribution of a questionnaire, disseminated through various channels, such as email and social media platforms like Facebook and Instagram. To gather data from our specific target demographic, a convenience sampling method was employed. This choice was driven by the characteristics of our study population, mainly comprising individuals actively engaged in social media and following influencers.

Following the questionnaire distribution, participants were initially asked about their interaction with influencers on the platform. They were specifically questioned about whether they followed any influencers and, if so, were requested to provide the social media handle of their favourite influencer. Subsequently, only participants who confirmed following influencers and could provide their favourite influencer's name were selected to proceed with the questionnaire.

The questionnaire items were derived from previous research and employed a five-point Likert scale for measurement (table 1). To study Trustworthiness we included four distinct items from Lou and Kim (2019), Attractiveness is assessed through three items from Duran and Kelly (1988), and Expertise is evaluated using four items from Lou and Yuan (2019). To assess the mediating variable, Consumer Engagement, we thoughtfully integrated six items from Cheung et al. (2022). For measuring Purchase Intention, we adopted two items from the established work of Chetioui et al. (2020). The second dependent variable, Brand Intimacy, was assessed using a questionnaire adapted from Read et al. (2019).

Table 1. Dimensions and items

Dimension	Items	References
Trustworthiness	• I trust the influencer's opinion. • I think the influencer shares his or her honest opinion. • I trust the influencer's messages more than one coming directly from a brand. • I trust the influencer's knowledge about the product/service she or he endorses.	Lou & Kim, 2019
Expertise	• I feel this influencer knowns a lot. • I consider this influencer an expert on his/her area. • I feel this influencer is competent to make assertions about things that this youtuber is good at. • I consider this influencer sufficiently experienced to make assertions about his/her area.	Lou & Yuan, 2019
Attractiveness	• I think this influencer is handsome/ pretty. • This Influencer is somewhat attractive. • I have a better relationship with this influencer than other influencers.	Duran & Kelly, 1988
Consumer Engagement	• Participating in activities on [SMI]'s channels get me thinking about the brand endorsed by the [SMI]. • Participating in activities on [SMI]'s channels stimulate my interest in learning more about the brand endorsed by the [SMI]. • I feel very positive when I use the brand endorsed by the [SMI]. • I feel good when I use the brand endorsed by the [SMI].	Cheung et al., 2022

Dimension	Items	References
	• I spend a lot of time using the brand endorsed by the [SMI] compared with other brands. • I use the brand endorsed by the [SMI] the most.	
Brand Intimacy	• I feel more confident that the brand understands its customers. • I feel that I would be more comfortable describing the brand to someone who was unfamiliar with it. • I feel that I am more familiar with the range of goods and services that the brand offers. • I feel that I have become more knowledgeable about the brand. • I feel that I am likely to be following the brand's social media feed one year from now.	Read et al., 2019
Purchase Intention	• I most frequently have intentions to purchase products advertised by the fashion influencers. • I follow generally recommended products and/or services advertised by the fashion influencers I follow.	Chetioui et al., 2020

4.Data Analysis and Results

The sample of this study is characterized by a predominantly female composition, accounting for 71.7% of the total, while males make up the remaining 28.3% (Table 2). This distribution clearly indicates a higher representation of females compared to males in the study. When examining the age groups, the data reveals a substantial level of interest among younger individuals. The largest proportion of respondents falls within the 18-25 years age group, constituting 76.1% of the participants. The 26-33 years age group makes up 18.3%, while those aged 34 years or older represent 5.6% of the sample. These findings underscore a clear preference for participation among the younger age groups.

Table 2. Respondent Profile

	Respondent Profile	Frequency	Percentage
Gender	Male	71	28.3
	Female	180	71.7
Age	18-25 years	191	76.1
	26-33 years	46	18.3
	34 or above	14	5.6
Time you spend on social media	2-3 hours	88	35.1
	4-5 hours	100	39.8
	6-7 hours	63	25.1

Furthermore, the analysis provides insights into the distribution of the percentage of time dedicated to social media usage. Most respondents reported spending 2-3 hours (35.1%), closely followed by 4-5 hours (39.8%), and 6-7 hours (25.1%). These results emphasize the significant level of engagement among respondents with social media platforms, with a substantial portion allocating several hours of their daily routine to these online activities.

The data analytics process unfolded in two distinct stages. Initially, alongside Cronbach's alpha, we employed Confirmatory Factor Analysis (CFA) to assess the measurement model's validity and reliability of the measures. Subsequently, we harnessed Structural Equation Modeling (SEM) to scrutinize the structural pathways within the conceptual model and conducted a moderation analysis.

Before subjecting the formulated hypotheses to testing, the research team conducted a reliability analysis employing Cronbach's alpha, a metric with a strong track record in prior studies. As per Pallant (2020), reliability values surpassing 0.7 are generally considered satisfactory, while values exceeding 0.8 are regarded as even more favourable. Upon scrutinizing the details presented in Table 3, it becomes apparent that the Cronbach's alpha value obtained falls within the acceptable range of 0.7, thereby validating the dataset's reliability.

Table 3. Reliability

Variables	**Cronbach’s Alpha**
Trustworthiness	0.826
Expertise	0.809
Attractiveness	0.787
Consumer Engagement	0.886
Brand Intimacy	0.822
Purchase Intention	0.751

Confirmatory Factor Analysis (CFA) was employed to estimate the model, and an assessment of the research study's validity was conducted following the approach outlined by Hair et al. (2017). In accordance with this method, items with factor loadings below 0.5 were eliminated from the analysis. As indicated in Table 4, three items were excluded due to factor loadings falling below the 0.5 threshold. These items were TRU1 from the Trustworthiness construct, EXP2 from the Expertise construct, and BI4 from the Brand Intimacy construct.

The composite reliability values in the research surpassed the 0.70 criterion recommended by Hair et al. (2017). Additionally, all constructs exhibited an average variance extracted (AVE) exceeding 0.50, consistent with the standards established by Hair et al. (2017). The model's appropriateness was further assessed by examining the goodness-of-fit criteria ($\chi 2/DF = 2.859$, GFI = 0.911, IFI = 0.936, CFI = 0.935). These values also fell within the acceptable range of threshold values.

The CFA test was conducted to confirm construct validity, assessing both discriminant and convergent validity. Applying Fornell and Larcker (1981) criteria for discriminant validity (Table 5), we observed that the square roots of AVE values exceeded the expected correlation values between the variables. As a result, the findings from the measurement model provide robust evidence for reliability, convergent validity, and discriminant validity. These results provide a high level of confidence in affirming all the expected relationships within the structural model.

Table 4. Validity

Variables	Items	Loadings	CR	AVE
Trustworthiness	TRU2	.805		
	TRU3	.667	0.823	0.610
	TRU4	.858		
Expertise	EXP1	.565		
	EXP3	.814	0.796	0.573
	EXP4	.859		
Attractiveness	ATT1	.827		
	ATT2	.886	0.823	0.613
	ATT3	.608		
Consumer Engagement	CE1	.577		
	CE2	.714		
	CE3	.811	0.891	0.582
	CE4	.912		
	CE5	.716		
	CE6	.806		
Brand Intimacy	BI1	.561	0.804	0.511
	BI2	.816		
	BI3	.794		
	BI5	.659		
Purchase Intention	PI1	.817	0.759	0.612
	PI2	.746		

In our analysis, we identified a discriminant validity issue between the constructs Trustworthiness (TRU) and Expertise (EXP), as indicated by a high correlation (0.781) compared to the AVE values. This suggests that there may be an overlap between these constructs. However, we have decided to keep TRU and EXP distinct in our analysis for several reasons.

First, the theoretical literature consistently defines trustworthiness and expertise as distinct entities, each capturing distinct features of user behavior. Theoretical frameworks in consumer behavior differentiate between these constructs due to their unique impacts on user behavior (Filieri et al 2023). Additionally, Previous studies has consistently treated trust and experience as independent constructs due to their distinct effects on user behavior and decision-making. Trustworthiness relates to a source's perceived honesty and reliability, which determines the emotional connection and credibility that an influencer builds with their audience. Expertise, on the other hand, refers to the influencer's perceived skill and knowledge, which influences the cognitive appraisal of the information presented.

Secondly, other validity and reliability studies undertaken in this study confirm the distinction between TRU and EXP. measuring example, our factor analysis shows that items designed to measure trust load strongly on the trust factor, whereas items measuring experience load on the experience factor, showing that respondents see these as distinct terms. Additionally, internal consistency (Cronbach's alpha) for each construct supports their reliability as separate measures.

Table 5. Discriminant Validity

	BI	TRU	EXP	ATT	CE	PI
BI	**0.866**					
TRU	0.398	**0.941**				
EXP	0.371	0.781	**0.757**			
ATT	0.464	0.306	0.170	**0.783**		
CE	0.715	0.409	0.319	0.535	**0.763**	
PI	0.722	0.354	0.291	0.497	0.718	**0.782**

Path Analysis

After assessing the validity and reliability, the structural path test was conducted to investigate both causal effects and potential mediating roles (Figure 2). In a broader context, the structural model was examined to confirm the validity of the conceptual framework and scrutinize the research hypotheses, following the recommendations of Anderson and Gerbing (1988), Byrne (2013), and Hair et al. (2010). Moreover, we appropriately evaluated the model by considering goodness-of-fit criteria ($\chi^2/DF = 3.270$, GFI = 0.940, IFI = 0.928, CFI = 0.927, RMR = 0.021).

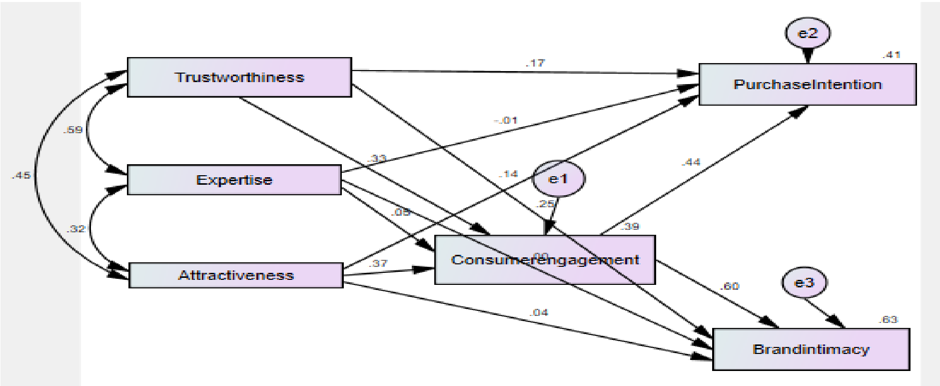

Figure 2. Path analysis

The analysis of direct effects yields several findings. Hypotheses H1b, H3b, H4, and H5 receive strong support with high levels of significance ($p < 0.001$). On the other hand, Trustworthiness exhibits a positive and statistically significant influence on Purchase Intention ($p < 0.01$), thus validating Hypothesis H1a, while Hypothesis H3a garners support at a significance level of ($p < 0.05$). However, Expertise fails to show a significant impact on both Purchase Intention and Brand Intimacy ($p > 0.05$), leading to the rejection of Hypotheses H2a and H2b. Additionally, it's noteworthy that Attractiveness does not significantly impact Brand Intimacy ($p > 0.05$).

Table 6. Result of Path Analysis

Hypothesis	Path	Estimates	t-value	p-value	Decision
H1a	TRU→PI	0.174	2.589	0.010	Accepted
H1b	TRU→BI	0.253	4.734	***	Accepted
H2a	EXP→PI	-0.006	-0.093	0.926	Rejected
H2b	EXP→BI	-0.003	-0.062	0.950	Rejected
H3a	ATT→PI	0.145	2.437	0.015	Accepted
H3b	ATT→BI	0.041	0.877	0.381	Rejected
H4	CE→PI	0.438	7.030	***	Accepted
H5	CE→BI	0.605	12.200	***	Accepted

In the context of mediating effects, the results underscore the crucial and positive indirect role of consumer engagement in shaping both trustworthiness and purchase intention, in line with hypothesis H6a ($p < 0.001$). Additionally, consumer engagement exerts a beneficial and indirect influence on attractiveness and purchase intention, thus confirming the validity of H6c ($p < 0.001$). However, the mediating role of consumer engagement in the link between expertise and purchase intention does not materialize ($p > 0.001$), leading to the rejection of hypothesis H6b. Furthermore, consumer engagement's impact on trustworthiness and brand intimacy is robust, supporting H7a ($p < 0.001$), as well as its impact on attractiveness and brand intimacy, endorsing H7c ($p < 0.001$). Conversely, the mediating role of consumer engagement in the connection between expertise and brand intimacy is not supported, resulting in the dismissal of hypothesis H7b. For the mediation analysis, AMOS software was employed, which included bootstrapping resampling rounds and a bias-corrected method at a 95% confidence level. This approach ensures the reliability and robustness of the generated findings (Table 7).

Table 7. Results of Mediation

Hypothesis	Path	Estimates	p-value	Decision	Type of mediation	Implication
H6a	TRU→CE→PI	0.197	0.001	Accepted	Partial	Both direct and indirect effects are significant, indicating that Consumer Engagement partially mediates the relationship. This suggests that trustworthiness influences purchase intention both directly and through its impact on consumer engagement.
H6b	EXP→CE→PI	0.026	0.524	Rejected	None	Neither the direct nor indirect effects are significant, indicating no mediation. This suggests that expertise does not influence purchase intention directly or

Hypothesis	Path	Estimates	p-value	Decision	Type of mediation	Implication
						through consumer engagement.
H6c	ATT→CE→PI	0.165	0.000	Accepted	Partial	Both direct and indirect effects are significant, indicating that Consumer Engagement partially mediates the relationship. This suggests that attractiveness influences purchase intention both directly and through its impact on consumer engagement.
H7a	TRU→CE→BI	0.296	0.001	Accepted	Partial	Both direct and indirect effects are significant, indicating that Consumer Engagement partially mediates the relationship. This suggests that trustworthiness influences brand intimacy both directly and through its impact on consumer engagement.
H7b	EXP→CE→BI	0.039	0.552	Rejected	None	Neither the direct nor indirect effects are significant, indicating no mediation. This suggests that expertise does not influence brand intimacy directly or through consumer engagement.
H7c	ATT→CE→BI	0.249	0.000	Accepted	Full	The direct effect is not significant, but the indirect effect is significant, indicating full mediation. This suggests that attractiveness influences brand intimacy entirely through consumer engagement.

5. Discussion

Three key dimensions of social media influencer credibility were explored: attractiveness, expertise, and trustworthiness. The primary research question focused on whether these influencer dimensions influenced purchase intention and brand intimacy. The findings unequivocally confirm a substantial and significant relationship between perceived trustworthiness and purchase intention. This aligns with prior research highlighting the positive influence of credible and influential sources on customers' purchase intentions and brand preferences (AlFarraj et al., 2021; Weismueller et al., 2020). The consistency between this study's findings and previous empirical evidence underscores the significance of this research.

Regarding the link between expertise and purchase intention, the results indicate that expertise does not have a significant impact on purchase intention. These findings are not in line with studies by Weismueller et al. (2020) and Chekima et al. (2020). However, it's essential to acknowledge that previous research has also reported insignificant results in this context. For example, Gomes et al. (2022) found no substantial correlation between expertise and purchase intention. This emphasizes the idea that while digital influencers are occasionally regarded as authorities in their respective fields, expertise alone may not significantly influence consumers' purchase intentions. The influence of an influencer's expertise may vary depending on factors such as cultural context and the nature of the products being endorsed (Gomes et al., 2022). Cultural variations can alter the dynamics of influence, highlighting that expertise can yield different outcomes in distinct cultural contexts.

The study's third dimension focuses on the attractiveness of digital content creators, revealing a positive and statistically significant correlation with purchase intention. This finding is consistent with earlier research, such as Lou and Kim (2019), which identified a strong connection between influencer attractiveness and purchase behaviour. Shirazi et al. (2022) research also emphasized the robust link between social media influencers' credibility (attractiveness) and customers' buying inclinations. These findings reinforce the ongoing importance of influencer attractiveness in shaping purchase intentions.

In relation to the impact of the credibility aspects of social media influencers, it becomes apparent that trustworthiness exerts a significant and undeniable influence on brand intimacy. Surprisingly, no prior research, to the best of our knowledge, has explored the relationship between brand intimacy and social media influencer credibility. This study underscores that the trustworthiness of influencers has a substantial and favorable impact on brand intimacy. In contrast, both attractiveness and expertise do not appear to significantly affect brand intimacy. Clearly, the trustworthiness of influencers enhances brand intimacy by establishing a sense of credibility and authenticity. Consumers rely on the recommendations of trustworthy influencers to forge genuine emotional connections with brands, whereas attractiveness and expertise may not yield the same level of influence in this context.

The findings further confirmed the mediating role of consumer engagement between the credibility dimensions of social media influencers and purchase intention. The data revealed that consumer engagement mediates the relationships between trustworthiness, attractiveness, and purchase intention, consistent with previous research (Jiménez-Castillo and Sánchez-Fernández, 2019; Ki and Kim, 2019). However, there has been no previous research on consumer engagement's potential mediating role between brand intimacy and social media influencers. According to this study's results, consumer engagement does mediate the relationships between trustworthiness, attractiveness, and brand intimacy. Trustworthy and attractive influencers tend to foster stronger consumer engagement, which, in turn, enhances emotional connections and brand intimacy, providing a pathway through which these attributes positively impact brand intimacy. However, consumer engagement does not serve as a bridge between expertise, purchase intention, and brand intimacy. This result is reasonable, as expertise may not be as influential in the context of this study, given its specific nature.

6.Conclusion

This research presents substantial contributions in both theoretical and practical aspects. This study offers empirical evidence on the impact of social media influencer credibility factors on consumer engagement, purchase intention, and brand intimacy. It's noteworthy that this research establishes the vital role of digital influencers, demonstrating their considerable positive influence on brand intimacy and purchase intention. Moreover, this research extends our current understanding of brand intimacy by exploring the intricate relationship between consumer engagement and brand intimacy. These findings contribute to a richer comprehension of how contemporary consumers engage with businesses and establish strong connections in the digital era. Furthermore, this study solidifies the mediating role of consumer engagement in the relationship between influencer credibility factors and brand intimacy, deepening our understanding of these intricate dynamics.

On a practical note, the research offers valuable guidance for brand managers and decision-makers actively involved in or contemplating the use of influencer marketing strategies. It underscores the significance of selecting well-matched social media influencers in specific product or service niches. Strategic partnerships with these influencers can help organizations effectively target their desired consumer segments, stimulating purchase motivation, enhancing visibility, promoting special offers, fostering stronger customer relationships, and ultimately elevating brand intimacy.

There are several limitations of the research study that warrant consideration for future research. First, the study's relatively small sample size may restrict the generalizability of findings. Future investigations could address this limitation by using larger sample sizes to enhance the study's representativeness. Second, the use of convenience sampling may introduce bias in the results, as the sample was not randomly selected but rather consisted of individuals who were actively engaged in social media and following influencers. This limits the generalizability of the findings to a broader population. Third, the study specifically mentions the distribution of the questionnaire on platforms like Facebook and Instagram. The findings may not be representative of other social media platforms or the broader online influencer landscape. Fourth, the study examines only three independent variables related to influencer credibility and two dependent variables related to purchase intention and brand intimacy. It may not account for the full complexity of consumer behaviour and influencer marketing. Fifth, qualitative methodologies may also be employed in future research to uncover additional influencer characteristics that impact consumers' purchase intentions. Finally, the potential overlap between the constructs Trustworthiness (TRU) and Expertise

(EXP), indicated by a high correlation coefficient compared to the Average Variance Extracted (AVE) values. Despite theoretical distinctions in the literature, which define trustworthiness and expertise as separate entities with distinct impacts on user behavior, we maintained TRU and EXP as distinct constructs in our analysis. Further validity and reliability analyses, including factor analysis and internal consistency tests, supported the distinction between TRU and EXP. However, future research could explore alternative measurement strategies to address this issue more comprehensively.

Since this study found no impact of influencers' expertise on purchase intention and brand intimacy, future research could also consider factors such as the influencers' area of specialization and the types of products they endorse to explore whether results vary. Consequently, it is advisable to expand the study into longitudinal research that spans different participants or adopt an experimental approach to capture evolving consumer reactions.

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A COMPARISON OF THE INTANGIBLE ASSET RELATED STANDARDS, IAS38, IVS210 AND ISA620 USING SIMILARITY ANALYSIS

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Abstract: This article attempts to describe the standards dealing with intangible asset treatment by multiple regulatory bodies and subsequently compare them using content and similarity analysis. The specific standards debated are IAS 38 from an accounting perspective, IVS 210 from a valuation perspective, and ISA 620 from an auditing perspective. The similarity analysis is conducted using two tools. First, Voyant tools are used to perform a text similarity analysis of the standards' text bodies in portable document format. The technique employed is principal component analysis. The second tool is SPSS version 25, which employs various similarity and dissimilarity measures such as simple matching, Jaccard, and Euclidean coefficient, indicating that the similarity of the standards is rather mediocre in relative terms.

JEL classification: *O30, M40, M48*

Keywords: intangibles, assets, standards, regulation, similarity

1. Introduction

Based on current literature, some researchers (Lev., 2008) support development cost capitalisation, while others like Penman, (2009) consider the uncertainty of realizing future economic benefits from R&D a reason to rely more on the combination of income statements and disclosures. It is essential to present the currently implemented professional standards, used to report and evaluate internally generated assets in order to identify the advantages and disadvantages of the existing regulatory framework and the degree of their convergence.

Gong and Wang, (2016) conducted a research to measure the changes in value relevance of research and development expenses after IFRS adoption. They discovered that institutional factors play a significant role in the value relevance changes during the transition from national GAAP to IFRS. Aboody and Lev, (1998) support that development cost capitalisation of software is more informative to investors and that US GAAP should extend capitalisation to other intangibles. They

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identify though that capitalisation is pushed back by financial analysts mainly because it causes them to create erroneous forecasts, thus making their work more complicated. This view that capitalisation complicates the forecasting process is also supported by Dinh et al., (2015b).

The core research question is: Are the provisions of the standards in the matter sufficient to ensure R&D accountability and SH protection? Based on the associated literature there is no definitive answer, mainly due to the uncertainty related to R&D projects (Barker and Penman, 2020). There are valid arguments in favour and against the current standards, although the mission of any standard is the net positive result and not an absolutely efficient framework, which would seem rather unrealistic. Ciftci and Zhou, (2016) present the contradicting views regarding capitalisation and subsequently the importance of intellectual property protection legislation in relevance to disclosures of R&D projects.

The standards regulating intangible assets are IAS 38 for accounting, IVS 210 for evaluation and there is no specific audit focused intangible asset standard with the exception of the ISA 620 which mentions the option of assistance by an auditor's expert in the case of "the valuation of complex financial instruments, land and buildings, plant and machinery, jewellery, works of art, antiques, intangible assets, assets acquired and liabilities assumed in business combinations and assets that may have been impaired" (IAASB, 2021). Invoking an expert has two major drawbacks, the first one is the extra audit cost generated by the additional friction. Cheng et al. (2016) found that development cost capitalisation results in increased audit costs in China due to the high risk and additional work required, especially from industry experts who are nonetheless expensive by definition. Kuo and Lee (2017), conducted a similar research across 21 countries and once again found evidence that development cost capitalisation increases audit costs due to the elevated possibility of earnings management. Additionally, they found that the robustness of the legal framework pertaining to investor protection has an adverse effect on audit costs. However, they do not identify if this legal framework includes intellectual property rights protection. The protection of intellectual property rights is in fact as important for intangibles, as the right of ownership for tangible assets. The obvious disadvantage of intangible assets is the relative easiness with which they can be duplicated or in some cases reverse engineered, causing significant loss of value for the inventors involved with development. This leads to the second drawback which is intensely insinuated by Kuo and Lee (2017); the confidentiality required in an audit of internally generated intangible assets can only be safeguarded by non-disclosure agreements that any auditor or his expert would be reluctant to sign and the audited entity would be wary of its enforcement if it was based in a jurisdiction with loose intellectual property rights legal framework.

Tuttici et al. (2007) investigated the effect of the auditors' size and reputation along with the securities commission's enhanced monitoring on the reliability of development cost capitalisation conducted by public entities in Australia. Their results seem to indicate that the auditors' quality and the securities commission's vigilance motivate management to use development capitalisation more prudently than in cases where the auditor is not among the big five or the securities commission is lightly involved. They also find that, younger R&D intensive firms with high leverage levels, which used to promote high growth, capitalised more often. The industry sector also plays a significant role in the capitalisation decision.

The paper's main pillars will consist of a professional standards' presentation describing their content and a subsequent similarity analysis combined with content analysis. Content analysis will be the first step in identifying the necessary variables to be used in the similarity analysis. Descriptive content analysis seems to be the most appropriate for the professional standards' analysis (Neuendorf, 2017). The process of defining the variables necessary begins with the thorough presentation of each professional standard related to internally generated intangible assets.

The main hypothesis for the current paper is that the professional standards share a similar approach to internally generated assets' valuation and recognition. The aim of the similarity analysis will be to show the convergence and the divergence of the standards on specific framework segments pertaining to internally generated intangible assets.

Description of the content of the professional standards

An overview of IAS 38

Area of implementation and exceptions

IAS 38 regarding intangible assets outlines the accounting requirements for intangible assets, which are non-monetary assets without physical substance and uniquely identifiable (either by being separable or arising from contractual or other legal rights). Intangible assets meeting the relevant recognition criteria are initially measured at cost, subsequently measured at cost or using the revaluation model, and amortized on a systematic basis over their useful lives (unless the asset has an indefinite useful life, in which case it is not amortised) (IASB, 2022).

The objective of IAS 38 is to prescribe the accounting treatment for intangible assets; which are not treated, specifically, according to another IFRS. The Standard requires an entity to recognize an intangible asset if, and only if, certain criteria are met. The standard also specifies how to measure the carrying amount of intangible assets and requires certain disclosures regarding intangible assets (IASB, 2022: IAS 38.1).

At this point it is important to mention certain basic definitions related to the topic that will facilitate a more cohesive understanding of the framework.

The definition of the intangible asset itself: an identifiable non-monetary asset without physical substance. An asset is a resource that is controlled by the entity as a result of past events (for example, purchase or self-creation) and from which future economic benefits (inflows of cash or other assets) are expected. (IASB, 2022: IAS 38.8) Thus, the three critical attributes of an intangible asset are:

1. identifiability
2. control (power to obtain benefits from the asset)
3. future economic benefits (such as revenues or reduced future costs)

Identifiability is the most complicated attribute as a concept and thus some elaboration is in order: an intangible asset is identifiable when it: (IASB, 2022:IAS 38.12) is separable (capable of being separated and sold, transferred, licensed, rented, or exchanged, either individually or together with a related contract) or arises from contractual or other legal rights, regardless of whether those rights are transferable or separable from the entity or from other rights and obligations (Negkakis, 2015; Mirza et al., 2008).

Recognition and valuation requirements

The recognition and valuation of intangible assets must meet the following requirements:

- The definition of the intangible asset as mentioned above
- the recognition criteria

These requirements are valid for the costs regarding the initial generation as well as any additions, replacements or maintenance. However, replacements and additions are uncommon for intangible assets with the exception of whichever is defined in the interpretation of IFRS 20 stripping costs in the production phase of a surface mine (Negkakis, 2015).

Negkakis and Tachinakis (2013) provide some clarifications regarding the definition, specifically they describe the unclear term identifiable as to be distinguished so that any financial benefits could be sold, traded or borrowed.

In terms of recognition IAS 38 requires an entity to recognize an intangible asset, whether purchased or self-created (at cost) if, and only if (IASB, 2022:IAS 38.21)

- it is probable that the future economic benefits that are attributable to the asset will flow to the entity; and
- the cost of the asset can be measured reliably.

This requirement applies whether an intangible asset is acquired externally or generated internally. As long as the definition and the recognition criteria are met then the asset can be initially valued at cost (Negkakis, 2015; Mirza et al., 2008).

Intangible asset categories based on possession method

It is often difficult and complicated to assess whether an internally generated intangible asset qualifies for recognition because of problems in:

1. Identifying whether and when an identifiable asset comes into existence that will generate expected future economic benefits; and
2. Determining the cost of the asset reliably. In some cases, the cost of generating an intangible asset internally cannot be distinguished from the cost of maintaining or enhancing the entity's internally generated goodwill or of running day-to-day operations.

Hunter et al. (2012), seem to agree that managers are challenged by the task of measuring intangible related inputs and output in a clear and concise manner that would attribute values per intangible with precision.

In addition to complying with the general requirements for the recognition and initial measurement of an intangible asset, an entity applies additional requirements and guidance to all internally generated intangible assets.

To assess whether an internally generated intangible asset meets the criteria for recognition, an entity classifies the generation of the asset into:

1. a research phase; and
2. a development phase.

Although the terms 'research' and 'development' are defined, the terms 'research phase' and 'development phase' have a broader meaning for the purpose of this standard.

If an entity cannot distinguish the research phase from the development phase of an internal project to create an intangible asset, the entity treats the expenditure on that project as if it were incurred in the research phase only. However, obviously entities could possibly abuse the distinction since it would accumulate massive losses in their financial statements, at least until their intangible asset would begin to generate some profits, assuming of course that it is a startup company relying strictly on that single project coming to fruition. In other cases, with projects in various stages, such a method would decrease the entity's profits by the cost of resources dedicated to research as well as development (Negkakis, 2015;IASB, 2022).

The following diagram illustrates how the two phases evolve over time:

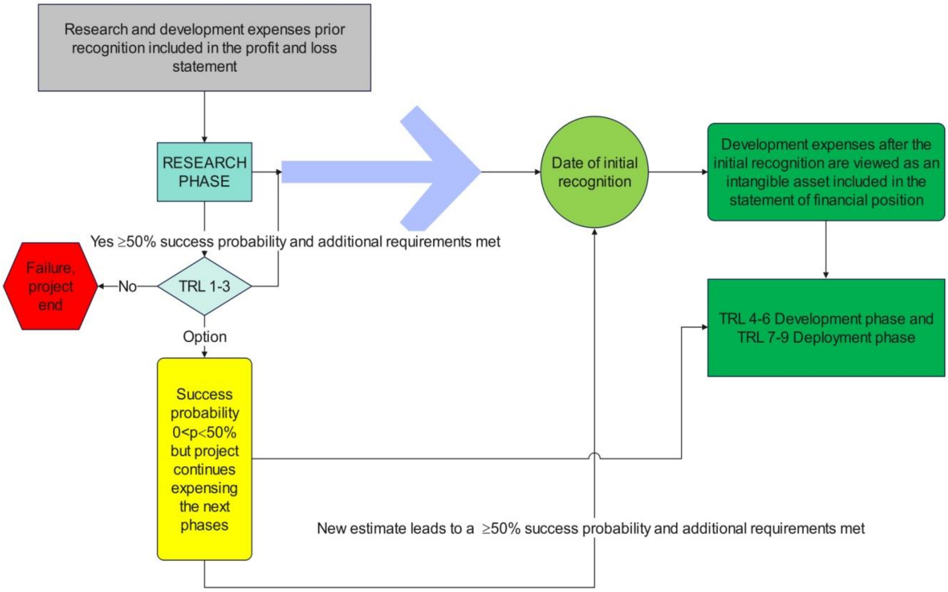

Diagram 1 R&D Phases and Relevant Decisions
Source: author's own projection

Intangible assets with finite useful life

Amortisation commences at the point in time when the intangible asset becomes ready for use or it is in the appropriate operating condition and position according to the management. On the other hand, the amortisation ceases at the former between the date of sale availability and retirement of the intangible asset (IASB, 2022).

In regards to the residual value of an intangible with finite useful life, it should be zero unless there is a third party commitment to buy the asset at the end of its useful life or there is an active market for it with the capability to determine the residual value through that market which would also present the possibility of a purchase at the end of its useful life. The revision of the residual value should be at least annual, at the end of the fiscal year and any alterations should be treated according to IAS 8. It is noted that any increase of the residual value can be larger than or equal to the book value, while the amortisation should be zero until the subsequent decrease of the residual value below the book value (Negkakis, 2015).

Intangible assets with indefinite useful life

The intangible assets with indefinite useful life cannot be amortized. However, according to IAS 36, an inspection of the intangibles is required to determine any impairment to the recoverable amounts in comparison with the book value. The inspection should take place annually and whenever there is an indication of impairment.

The following diagram illustrates how the intangible asset's useful life is treated:

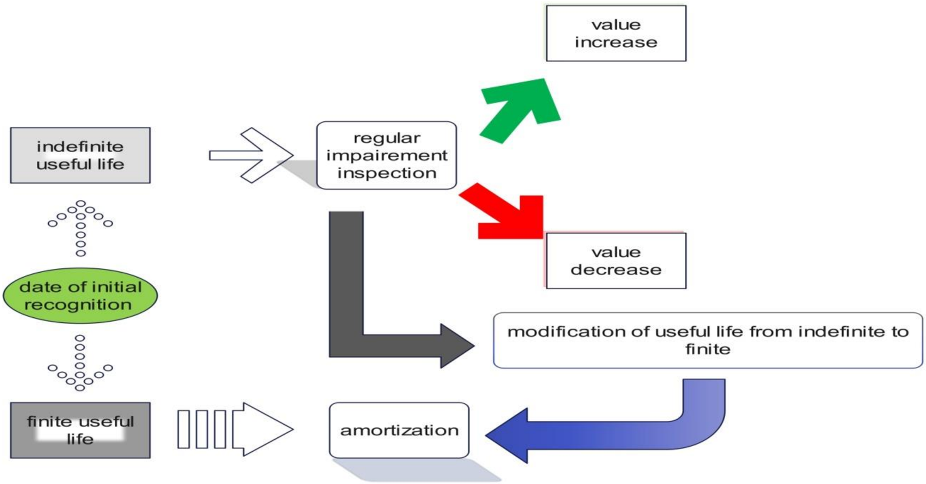

Diagram 2 Treatment Depending on the Useful Life of the Intangible
Source: author's own projection

An overview of IVS 210

The definition of intangible assets provided by the IVSC (2021) is "An intangible asset is a non-monetary asset that manifests itself by its economic properties. It does not have physical substance but grants rights and/or economic benefits to its owner." The definition is similar to the one observed in IAS 38, although there is a clear emphasis here to the economic properties of the asset as an indication of creation (Parker, 2016).

The intangibles are classified, by valuation regulators, in five distinct categories, the intangibles that interest this article belonging in the fifth category described as: "Technology-based: Technology-related intangible assets that arise from contractual or non-contractual rights to use patented technology, unpatented technology, databases, formulae, designs, software, processes or recipes." The hard science patents and software clearly belong in this category. As a result, the valuation method indicated as most suitable for this category or its elements will be the one of most interest.

The standard also provides a list of purposes concerning intangible asset valuations; among these purposes are financial reporting purposes, tax reporting purposes and litigation disputes. All of which have been mentioned as important to stakeholders (Parker, 2016).

The subject intangible items of this paper would fall broadly under the category of technology. The practical difficulty of this approach is to distinguish the revenue portion attributed to the specific subject intangible asset. For example, a mobile phone usually incorporates thousands of patents so it is difficult to separate which part of the phone's cost is resulting from each patent or other intangible asset (Leroux and Quenedey, 2011).

The treatment of intangible assets from an auditing standard perspective and other issues

The auditing landscape, while meticulously structured through various standards, occasionally presents areas of nuanced complexity. Among these, the International Auditing and Assurance Standards Board's (IAASB) ISA 620 stands out, primarily focusing on the "use of the work of an auditor's expert" rather than explicitly addressing intangible assets or a specific asset category. Despite this, the evolving nature of intangible assets, often rooted in groundbreaking research and innovation, necessitates a deeper exploration of their audit implications. This discourse aims to shed light on the unique challenges and considerations inherent in the audit of intangible assets. Additionally, the discourse highlights the standard's relevance to intangible assets but also navigates the broader implications for audit practice, particularly in ensuring the accuracy and integrity of financial reporting in this complex domain. There is no dedicated international standard on audit regarding intangible assets (IAASB, 2021). Perhaps the only, indirectly relevant, international standard on audit is the ISA 620, where the "use of the work of an auditor's expert" is mentioned (IAASB, 2021). It is the case of "the valuation of complex financial instruments, land and buildings, plant and machinery, jewellery, works of art, antiques, intangible assets, assets acquired and liabilities assumed in business combinations and assets that may have been impaired" (IAASB, 2021).

The involvement of experts, while indispensable for their insight and proficiency in these unique domains, introduces a layer of complexity to the audit process (Cheng et al., 2016; Kuo and Lee, 2017). This complexity stems not only from the specialized nature of the assets but also from the potential risks associated with the expert's deep engagement with the entity's confidential and sensitive information. Looking closer, into the implications of such expert involvement, it becomes apparent that ensuring objectivity and mitigating information leak risks are paramount, thereby setting the stage for a discussion on the standard's provisions for managing these challenges and the broader implications for audit cost and security.

Tuttici et al. (2007) investigated the effect of the auditors' size and reputation in combination with the securities commission's enhanced monitoring. The securities commission monitored if the publicly traded entities in Australia capitalised development costs in a prudent manner. Their results seem to indicate that the auditors' quality and the securities commission's vigilance motivate management to use development capitalisation more prudently than in cases where the auditor is not among the big four or the securities commission is lightly involved.

Methodology

This article introduces a dual-methodological approach designed to dissect the nuances of financial reporting, valuation and auditing standards.

Initially, the paper delves into Automated Textual Analysis, leveraging the computational prowess of Principal Component Analysis (PCA) via Voyant tools (version 2.6.2; Sinclair & Rockwell, 2023). This sophisticated analysis scaffolds an objective similarity assessment within a corpus encompassing pivotal standards: IAS 38 (IASB, 2022), IVS 210 (IVSC, 2021), and ISA 620 (IAASB, 2021). By processing these texts, PCA elucidates patterns and associations that may not be immediately apparent, presenting a quantitative metric of textual congruence that serves as a foundation for further qualitative scrutiny. An Automated Textual Analysis employs a statistical approach to compare texts, focusing on their quantifiable aspects rather than interpreting their intrinsic meanings, as outlined by Abdi and Williams (2010).

Following the delineation of professional standards in the previous Section, the initial phase embarks on an exhaustive content analysis, complemented by the precedent automated similarity analysis via Voyant tools (version 2.6.2; Sinclair & Rockwell, 2023). Anchored in the methodological frameworks proposed by Neuendorf (2017) and Miles et al. (2014), this multifaceted approach undertakes a meticulous scrutiny of each standard. The aim is to navigate through the textual corpus, pinpointing critical variables that resonate with the focal points of the research, followed by statistical analysis using similarity and dissimilarity measures.

According to Abdi and Williams (2010), Principal Component Analysis, commonly known as PCA, is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The process of creating these dimensions in PCA is a multi-step procedure that begins with the standardization of the feature set (Aggarwal, 2018; Bishop, 2006; Greenacre, 2007; Jollife, 2002). In practical terms, this means adjusting the original variables, which could be word frequencies in various documents, to have a standardized mean of zero and a standard deviation of one. This normalization is critical as it places all variables on the same scale, allowing for a fair comparison.

The PCA output is visually represented in a two-dimensional scatter plot, providing an intuitive grasp of the textual congruence among IAS 38, IVS 210 and ISA 620. This quantification lays the groundwork for deeper qualitative examination, directly tying back to the article's focus on R&D accountability and stakeholder protection.

The similarity analysis, crucial to this research, will unfold in two distinct yet interconnected methods. This bifurcated approach is essential for a meticulous dissection of the professional standards, ensuring a thorough and nuanced understanding of their provisions and implications.

It's crucial to note that unlike the PCA conducted using Voyant Tools (version 2.6.2; Sinclair & Rockwell, 2023), the second similarity analysis method transcends mere textual structure to consider the context and interpretative nuances of the standards' documentation. Content analysis, by its nature, involves a subjective interpretation of the text, aiming to capture the underlying meaning and implications, whereas PCA, in its automated form, primarily quantifies text, based on the frequency and distribution of terms, offering a more structural than semantic comparison (Abdi and Williams, 2010; Aggarwal, 2018; Bishop, 2006; Greenacre, 2007; Jolliffe, 2002).

Following the content analysis the analysis themes have been formed and are presented:

a) Recognition and measurement.

b) Disclosure and reporting.

c) Valuation of intangible assets

d) Audit considerations

The initial analysis theme centres on the concept of recognition and measurement, pivotal to accounting and valuation standards. It establishes the conditions for the recognition of intangible assets and dictates their initial and subsequent measurement. IAS 38 emerges as the prevailing standard within this theme, offering explicit criteria for the recognition and measurement of intangible assets. Thorough analysis is required to understand the practical implications for accounting. The comparison of these criteria with those suggested in IVS 210 and ISA 620 aligns accounting recognition with valuation standards and auditing guidelines, ensuring consistency in financial reporting.

The second theme pertains to disclosure and reporting. Transparency in reporting is critical for stakeholders to comprehend the valuation basis of intangible assets and the assumptions influencing their value over time. Originating from IAS 38, this theme calls for detailed disclosure about valuation methods, useful life, and R&D expenditures, crucial for users of financial statements to evaluate the economic benefits of intangible assets. Examining how IVS 210 and ISA 620 address these disclosures reveals the extent of rigour and detail expected in valuation and auditing practices.

Addressing the valuation of intangible assets, the selection of appropriate valuation techniques and the application of fair value are significant in reflecting the true worth of intangible assets within financial statements. The major query financial statements aim to resolve is the accuracy and fairness of the presented values. Exploring IAS 38 is crucial, especially when used together with IVS 210. IVS 210 is important because it offers detailed instructions on how to apply acceptable methods for valuing intangible assets. This analysis is also focused on understanding the risks associated with the unpredictable and changing future advantages of intangible assets, which play a significant role in determining their value.

The final theme focuses on audit considerations. While no dedicated audit standard for intangibles exists, ISA 620 is the closest standard indirectly associated with intangible assets. It provides guidance on the use of valuation experts and the assessment of risks related to the valuation of intangible assets, essential elements of the audit process. Reflecting on how these considerations are manifested in IAS 38 and IVS 210 assists in evaluating whether financial statements present a true and fair view of the intangible assets' value. Furthermore, this theme encompasses the evaluation of management's estimates, a critical aspect of auditing intangible assets due to their subjective and complex nature.

Each theme has been meticulously chosen to reflect a crucial aspect of intangible asset accounting and valuation, ensuring a comprehensive analysis across the domains of recognition, measurement, disclosure, valuation, and auditing perspectives.

For every analysis theme, specific elements that represent variables have been formed after content analysis similar to the methodology presented by Deaconu and Buiga (2010). These analysis elements, which are used as binary variables within each theme, serve as pivotal points of scrutiny.

Under the theme of Recognition and Measurement, the variables include 'Recognition Criteria', 'Initial Measurement', 'Subsequent Measurement', and 'R&D Costs'. These elements are critical in establishing the conditions that intangible assets must meet to be recognized in the financial statements and the methodology applied in their valuation at inception and in subsequent periods. 'R&D Costs' specifically addresses the accounting treatment of research and development expenditures, which are often significant for intangible assets.

For Disclosure and Reporting, the variables are 'Valuation Method Disclosure', 'Useful Life Disclosure', and 'R&D Expenditure Disclosure'. These elements ensure that the financial statements provide a clear and complete picture of how intangible assets are valued and amortized over time, along with the expenses incurred in their development. The disclosures are instrumental for users of financial statements to assess the sustainability and the long-term profitability of the assets.

In the Valuation of Intangible Assets theme, the analysis is focused on 'Permitted Valuation Techniques', 'Use of Fair Value', and 'Guidance on Uncertainty'. These variables are central to understanding the methods and approaches permissible for valuing intangible assets, the role that fair value plays in this process, and how uncertainty is accounted for, which can significantly impact the valuation of such assets.

The final theme, Audit Considerations, includes variables such as 'Risk Assessment', 'Use of Valuation Experts', and 'Evaluation of Management's Estimates'. These elements are key to the audit process, where the reliability and accuracy of the intangible asset valuations are verified. 'Risk Assessment' involves identifying and evaluating the risks associated with valuing intangible assets. 'Use of Valuation Experts' considers the necessity and impact of specialist input in the audit process, and 'Evaluation of Management's Estimates' scrutinizes the assumptions and judgments made by management in the valuation of intangible assets.

Each analysis element within the respective themes is intricately linked to the overarching standards—IAS 38, IVS 210 or ISA 620 and plays a vital role in the rigorous framework for accounting, reporting, valuation, and auditing of intangible assets. These elements collectively form the basis for addressing the second research question: Are the provisions of the standards sufficient to ensure R&D accountability and shareholder protection? By dissecting the components of recognition criteria, disclosure norms, valuation techniques, and audit processes, the analysis aims to determine the adequacy of these standards in promoting transparency and reliability in the reporting of R&D activities. The scrutiny of each variable contributes to a comprehensive understanding of whether the standards effectively safeguard shareholder interests by mandating accountability in the treatment and presentation of R&D investments. Thus, the examination of these elements is not just a study of compliance, but a critical appraisal of the standards' capacity to uphold financial integrity and protect shareholders in the dynamic and often opaque realm of intangible asset valuation.

In the progression of the manual content analysis, the second critical phase begins, the similarity analysis, which draws inspiration from the methodology proposed by Deaconu and Buiga (2010). At this juncture, the binary variables delineated in the content analysis undergo a meticulous statistical examination. The variables are presented in Table 1 below. Echoing Deaconu and Buiga's (2010) systematic approach, the process juxtaposes the attributes of the standards using a suite of statistical measures tailored to the binary nature of the data.

Table 1 presents the analysis themes and their relevant elements, variables. The table organizes information across columns and rows: the columns represent the standards IAS 38, IVS 210, and ISA 620, indicating their applicability to various analysis elements. The rows are divided by the analysis themes, each listing specific binary variables evaluated across the standards.

Table 1. Variable Presentation per Analysis Theme and Standard

Analysis Theme	Analysis Element of the Theme	IAS 38	IVS 210	ISA 620
Recognition and Measurement	Recognition criteria	Present	Present	Absent
	Initial measurement	Present	Absent	Absent
	Subsequent measurement	Present	Absent	Absent
	R&D costs	Present	Absent	Absent
Disclosure and Reporting	Valuation method disclosure	Present	Present	Absent
	Useful life disclosure	Present	Present	Absent
	R&D expenditure disclosure	Present	Absent	Absent
Valuation of Intangible Assets	Permitted valuation techniques	Present	Present	Present
	Use of fair value	Present	Present	Absent
	Guidance on uncertainty	Present	Present	Present
Audit Considerations	Risk assessment	Present	Present	Present
	Use of valuation experts	*Present	*Present	Present
	Evaluation of management's estimates	Present	Present	*Present

*Present means the specific information is typically expected to be covered by the standard, but a direct quote was not provided from the content analysis.

Source: Author's own projection

Table 1 presents values derived from an in-depth content analysis for each thematic element, which will be encoded as binary nominal variables in SPSS (IBM

Corp., 2017) to perform similarity and dissimilarity assessments. For each variable ‘present’ is coded as value 1 and ‘absent’ as value 0.

Key to this phase is the judicious selection of similarity measures. This choice is predicated on the characteristics of the data gleaned from the content analysis and incorporates an array of statistical instruments. These include non-parametric correlations apt for binary variables such as the Simple Matching Coefficient, Dice, Rogers and Tanimoto coefficient, Sokal and Sneath I coefficient, Jaccard coefficient and the Euclidean Distance Coefficient, which is a dissimilarity measure (Han et al., 2012; Tan et al., 2014). This eclectic mix of tools reflects the thorough approach embodied in Deaconu and Buiga’s (2010) work, ensuring a comprehensive and multi-faceted examination of the standards.

The similarity measures are calculated as follows: The simple matching coefficient is calculated by taking the number of matching attributes (both present and absent) and dividing by the total number of attributes (Tan et al., 2014).

The range of values are from 0 to 1, where a value of 1 indicates perfect similarity (all attributes match), while a value of 0 indicates no similarity (no attributes match).

The Dice Coefficient is calculated as two times the count of common elements between both sets over the sum of elements in set A and B. In this case the sets are the standards’ documents, ISA38, IVS 210 and ISA 620, interchangeably in sets of two. The Dice coefficient gives more weight to the number of shared attributes between the two sets. This can be particularly useful when assessing the similarity of two samples where the presence of common characteristics is more significant than their differences (Tan et al., 2014). Again the values range from 0 to 1, where a value of 1 indicates perfect similarity (all attributes match), while a value of 0 indicates no similarity (no attributes match).

The Rogers and Tanimoto coefficient is calculated by taking the sum of matching present and absent attributes and dividing by the sum of this number plus twice the sum of non-matching attributes, it is similar to the simple matching coefficient but puts more emphasis on the disagreements (Han et al., 2012;Tan et al., 2014). Again the values range from 0 to 1, where a value of 1 indicates perfect similarity (all attributes match), while a value of 0 indicates no similarity (no attributes match).

The Sokal and Sneath 1 coefficient is another variant of similarity measure that adjusts for agreements and disagreements, calculated similarly to Rogers and Tanimoto but with different weights (Tan et al., 2014).

Again the values range from 0 to 1, where a value of 1 indicates perfect similarity (all attributes match), while a value of 0 indicates no similarity (no attributes match).

The last similarity measure is the Jaccard coefficient, it is calculated as the size of the intersection of two sets divided by the size of the union of the sets, once again its values range from 0 to 1. A value of 1 means the sets are identical; a value of 0 means they share no elements and most notably, it does not consider the joint absence of attributes (Han et al., 2012;Tan et al., 2014).

The Euclidean distance coefficient is a dissimilarity measure which is based on the 'straight line' distance between two points in multidimensional space, calculated using the Pythagorean theorem as indicated by various publications (Bishop, 2006; Han et al., 2012; Hastie et al., 2008; Tan et al., 2014). The range of values starts from 0 and can go to infinity, where a value of 0 indicates no distance between points (perfect similarity), while higher values indicate greater dissimilarity. Unlike the other coefficients, which were similarity measures, for Euclidean distance, lower values signify similarity.

Leveraging the analytical prowess of SPSS (IBM Corp., 2017), the similarity scores that form the backbone of the analysis are calculated. SPSS serves not just as a calculation resource but as a critical interpretive ally, aiding in the elucidation of the complex relationships and distinctions between the standards.

The culmination of this phase is the analysis and synthesis of the quantitative findings into an intelligible narrative. This narrative is instrumental in unravelling the nuances of R&D accountability and the safeguarding of stakeholder interests within the ambit of professional standards. By harmonizing quantitative rigour with qualitative insight, this phase endeavours to unravel the layered complexity of the standards, offering an exhaustive and insightful exposition.

Results

Similarity analysis using automated text processing

The following scatter plot, referred to as Image 1, offers an insightful depiction of the similarity relationships among the IAS 38, IVS 210 and ISA 620 standards. Each point on the scatter plot represents a document from the corpus, namely IAS 38, IVS 210 and ISA 620, which have been uploaded to Voyant tools (version 2.6.2; Sinclair & Rockwell, 2023) as pdf document files. The spatial arrangement of these points reveals how similar these documents are in terms of their word usage. This visual representation, derived from the frequency matrices of the 53 most prevalent terms in the documents, serves as a preliminary similarity analysis. While the intricate calculations underpinning the principal component analysis (PCA) are automated and thus not detailed here, the significance of the axes is worth noting. The horizontal axis, or Dimension 1, accounts for 73.43% of the total variance, indicating its substantial role in differentiating the documents. The vertical axis, or Dimension 2, explains a lesser but still notable 26.57% of the variance.

The PCA scatter plot, generated by Voyant tools (version 2.6.2; Sinclair & Rockwell, 2023), shows that ISA 620 is positioned distinctly apart from IAS 38 and IVS 210, suggesting a relative dissimilarity with these standards. Conversely, IAS 38 and IVS 210 appear in closer proximity along the more influential Dimension 1, suggesting greater similarity between them based on the analysed terms. Despite this, the distance between IAS 38 and IVS 210 along Dimension 2 should not be overlooked, as it indicates there are still significant differences to consider.

The analysis presented in Image 1 underpins the distance of ISA 620 from the other two standards, namely IAS 38 and IVS 210. The rationale is that the initial PCA has highlighted fundamental dissimilarities with the other two standards, which may overshadow finer comparative nuances. Meanwhile, the relative closeness of IAS 38 and IVS 210 along the principal axis of variation warrants a deeper investigation to uncover the subtleties and specifics of their convergence and divergence.

This refinement of the analysis sets the stage for a focused evaluation of the IAS 38 and IVS 210 standards, examining their thematic overlaps and divergences to provide a robust understanding of their implications for R&D accountability and shareholder protection.

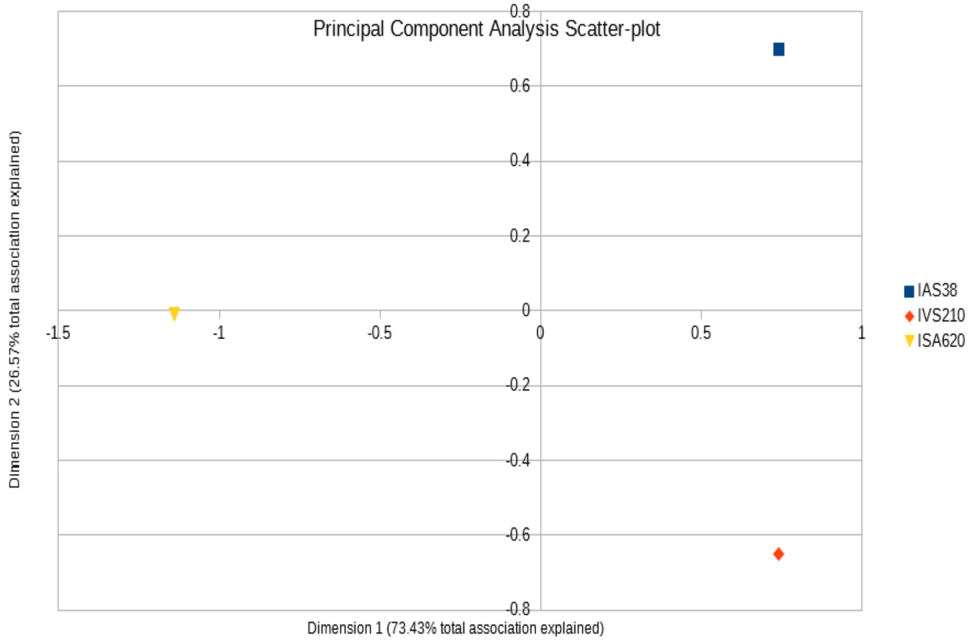

Image 1 PCA Scatter Plot Similarity Analysis
Source: Author's own projection

Dimension 2, orthogonal to Dimension 1, captures the secondary pattern of variance at 26.57%. The y-coordinates suggest a divergence between IAS 38 and IVS 210 along this dimension, as indicated by their opposite signs. IAS 38's positive y-value contrasts with IVS 210's negative y-value, implying that they differ in the secondary patterns of word usage captured by this component.

ISA 620, positioned at a y-value of zero, does not exhibit a significant positive or negative correlation with Dimension 2, suggesting its neutrality or lack of significant contribution to the patterns captured by this secondary dimension.

The scaling of the scatter plot is relative, and the actual values of the coordinates are influenced by the scaling and transformation process inherent in PCA. There are no fixed minimum or maximum values for these coordinates; rather, their range is determined by the spread of the original data, the standards' documents, across the calculated dimensions.

Elucidating Standards' Similarity: A Manual Content Analysis Approach processed with/in SPSS

The next tables contain the results of the SPSS (IBM Corp., 2017) similarity and dissimilarity measures for the binary variables per analysis theme in standard pairs.

Table 2. Comparison Analysis Results on Recognition and Measurement Theme

Binary Variables	Analysis theme: Recognition and Measurement		
Measures	IAS 38/IVS 210	IAS 38/ISA 620	IVS 210/ISA 620
Simple matching coefficient*	0.25	0	0.75
Dice*	0.4	0	0
Rogers and Tanimoto coefficient*	0.143	0	0.6
Sokal and Sneath I coefficient*	0.4	0	0.857
Jaccard coefficient*	0.25	0	0
Euclidean distance coefficient**	1.732	2	1

Notes: *Similarity measure; **Dissimilarity measure

Source: Author's own projection

In the detailed similarity analysis of the 'Recognition and Measurement' theme presented in Table 2, the binary variable measures were calculated to discern the extent of alignment between IAS 38/IVS 210, IAS 38/ISA 620, and IVS 210/ISA 620. This theme, which includes pivotal elements such as recognition criteria, initial and subsequent measurement, and R&D costs, forms the foundation of accounting for intangible assets.

When considering measures that primarily focus on the presence of attributes, such as the Jaccard coefficient, the analysis revealed a moderate similarity of 0.25 between IAS 38 and IVS 210, and no similarity between IAS 38, and ISA 620. This indicates a substantial disparity between IAS 38, IVS 210 and ISA 620 in the acknowledgment and quantification of R&D costs, suggesting divergent methodological approaches in the standards.

On the other hand, measures that account for both the presence and absence of attributes, such as the Simple matching coefficient and the Rogers and Tanimoto coefficient, demonstrated a higher degree of similarity between IVS 210 and ISA 620, with values of 0.75 and 0.6 respectively. This reveals a nuanced compatibility in the absence of certain criteria as well as their presence, suggesting a broader congruence in their overall frameworks for recognition and measurement.

The Dice and Sokal and Sneath I coefficients, which balance the importance of present and absent values, showed a more pronounced similarity between IAS 38 and IVS 210 with values of 0.4, indicating a shared perspective in the treatment of R&D. However, these coefficients registered no similarity between IAS 38 and ISA 620, underscoring the stark contrasts in their respective standards.

The Euclidean distance coefficient, a dissimilarity measure sensitive to the absence of shared attributes, corroborated these insights by revealing greater distances between IAS 38 and ISA 620 at 2, and a lesser distance between IVS 210 and ISA 620 at 1. This aligns with the earlier observations of IVS 210 and ISA 620 sharing more in common, potentially due to similar omissions in the standards, than either does with IAS 38.

These measures collectively highlight the intricate dynamics of standard provisions. They underscore the importance of considering both the presence and absence of criteria in the complex landscape of intangible asset accounting, thereby offering a comprehensive view of the standards' alignment and divergence in ensuring R&D accountability and stakeholder protection.

Table 3. Comparison Analysis Results on Disclosure and Reporting Theme

Binary Variables	Analysis theme: Disclosure and Reporting		
Measures	IAS 38/IVS 210	IAS 38/ISA 620	IVS 210/ISA 620
Simple matching coefficient*	0.667	0	0.333
Dice*	0.8	0	0
Rogers and Tanimoto coefficient*	0.5	0	0.2
Sokal and Sneath I coefficient*	0.8	0	0.5
Jaccard coefficient*	0.667	0	0
Euclidean distance coefficient**	1	1.732	1.414
Notes: *Similarity measure; **Dissimilarity measure			

Source: Author's own projection

As indicated in Table 3, in the thematic exploration of 'Disclosure and Reporting' within financial standards, the binary variables highlight how IAS 38 and IVS 210 often align in their disclosure requirements, as evidenced by a Simple matching coefficient of 0.667. This suggests a substantial overlap in the presence of disclosure elements between these two standards, indicating a shared commitment to transparency in valuation methods, useful life estimations, and R&D expenditure reporting.

The Dice coefficient amplifies this observation, with a high score of 0.8, underscoring that not only do these standards have similar disclosure requirements, but also that these requirements constitute a significant portion of their reporting frameworks. This is indicative of a concerted effort by the standards to ensure that valuation methodologies and the expected longevity of assets are clearly communicated.

However, when comparing IAS 38 with ISA 620, the absence of a similarity score across all measures, and the high value of the Euclidean distance coefficient of 1.732, points to a stark contrast between IAS 38 and ISA 620. This divergence suggests that ISA 620's disclosure requirements are either not as extensive or are approached in a fundamentally different manner compared to IAS 38, which may lead to variations in stakeholder interpretation and understanding.

Similarly, IVS 210 and ISA 620 show a modest Simple matching coefficient of 0.333 and a Rogers and Tanimoto coefficient of 0.2, indicating some commonalities in their absence of disclosures, yet these figures also reflect notable differences in the standards. The modest score in the Sokal and Sneath I coefficient at 0.5 reaffirms this notion, suggesting that while there are some convergences, there is also a discernible disparity in the reporting obligations under these standards.

Interestingly, the Jaccard coefficient for the comparisons involving ISA 620 consistently registers zero, reinforcing the notion that when it comes to the presence of specific disclosure items, ISA 620 diverges significantly from the other two standards.

The Euclidean distance coefficient, which serves as a dissimilarity measure, provides a numerical representation of the gaps between the standards, with higher distances indicating greater divergence. A distance of 1 between IAS 38 and IVS 210 is the smallest among the comparisons, denoting closer proximity and a smaller gap in disclosure practices, whereas the distance of 1.732 between IAS 38 and ISA 620 is indicative of a more pronounced disparity, which is mirrored by the distance of 1.414 between IVS 210 and ISA 620.

These findings, encapsulated within the 'Disclosure and Reporting' theme, reveal a complex web of disclosure requirements, where IAS 38 and IVS 210 share a closer affinity, and ISA 620 stands apart. It is important to contextualize the role of ISA 620. While IAS 38 and IVS 210 are standards dedicated explicitly to the treatment of intangible assets, ISA 620 is associated with intangibles indirectly through its guidance on using experts in audits. As such, the mentions of intangible assets within ISA 620 are incidental and not the primary focus, which explains the limited disclosure requirements related to intangible assets when compared to IAS 38 and IVS 210. This nuanced context underscores why ISA 620 exhibits a significantly different profile in the similarity analysis, reflecting its distinct purpose and scope within the financial reporting and auditing landscape. This delineation is vital for understanding the nuances of stakeholder protection and the sufficiency of R&D accountability as prescribed by these standards.

Table 4. Comparison Analysis Results on Valuation of Intangible Assets Theme

Binary Variables	Analysis theme: Valuation of Intangible Assets		
Measures	IAS 38/IVS 210	IAS 38/ISA 620	IVS 210/ISA 620
Simple matching coefficient*	1	0.667	0.667
Dice*	1	0.8	0.8
Rogers and Tanimoto coefficient*	1	0.5	0.5
Sokal and Sneath I coefficient*	1	0.8	0.8
Jaccard coefficient*	1	0.667	0.667
Euclidean distance coefficient**	0	1	1
Notes: *Similarity measure; **Dissimilarity measure			

Source: Author’s own projection

For the 'Valuation of Intangible Assets' theme, as indicated in Table 4, measures like the simple matching and Jaccard coefficients, which focus primarily on the presence of attributes, suggest a strong similarity between IAS 38 and IVS 210, with a perfect match indicated by a coefficient of 1. These measures show that where valuation techniques, the use of fair value, and guidance on uncertainty are explicitly mentioned (present), IAS 38 and IVS 210 are in complete agreement.

The Dice and Sokal and Sneath I coefficients, which also consider the absence of attributes, reinforce this alignment, indicating a robust congruence in both what is included and excluded within the standards. This suggests that not only do IAS 38 and IVS 210 share common valuation elements, but they also concur on what is not considered or excluded from their provisions.

The Rogers and Tanimoto coefficient, which gives equal weight to matches on both present and absent attributes, still presents a perfect score of 1 for IAS 38 and IVS 210. This implies that both the presence and absence of valuation elements are harmoniously mirrored across these two standards.

The Euclidean distance coefficient, being a dissimilarity measure, corroborates the similarity findings by indicating no distance between IAS 38 and IVS 210. This indicates a perfect alignment and no divergence in valuation practices as prescribed by these standards.

When considering ISA 620, the moderate values across similarity measures indicate that, while ISA 620 does pertain to valuation through its guidance on the use of experts, it does not match the specificity and focus of IAS 38 and IVS 210 on the valuation of intangible assets. The Euclidean distance coefficients of 1 for comparisons involving ISA 620 align with this interpretation, suggesting a clear but not extreme departure from the other two standards.

In summary, the analysis underscores a nuanced difference: IAS 38 and IVS 210 are tightly coupled in their approach to the valuation of intangible assets, sharing a common framework for both the inclusion and exclusion of valuation elements. ISA 620, while still relevant to the valuation process, operates from a different vantage point, focusing on the auditing aspect and the use of expert valuations, which is reflected in its moderate similarity scores and corresponding dissimilarity distance.

Table 5. Comparison Analysis Results on Audit Considerations Theme

Binary Variables	Analysis theme: Audit Considerations		
Measures	IAS 38/IVS 210	IAS 38/ISA 620	IVS 210/ISA 620
Simple matching coefficient*	1	1	1
Dice*	1	1	1
Rogers and Tanimoto coefficient*	1	1	1
Sokal and Sneath I coefficient*	1	1	1
Jaccard coefficient*	1	1	1
Euclidean distance coefficient**	0	0	0
Notes: *Similarity measure; **Dissimilarity measure			

Source: Author's own projection

The 'Audit Considerations' theme, shown in Table 5, presents a strikingly uniform set of results across all measures and pairings of the standards. With each similarity coefficient measuring at 1 and the dissimilarity (Euclidean distance) coefficient at 0, this suggests an absolute congruence between IAS 38, IVS 210, and ISA 620 in terms of the elements under this theme: risk assessment, the use of valuation experts, and the evaluation of management's estimates.

Given that these measures, whether emphasizing the presence of attributes or a combination of both presence and absence, yield a perfect score, we can infer that these three standards share a completely aligned approach in their audit considerations. This alignment is quite comprehensive, as it does not vary across different types of measures those sensitive only to the presence of attributes and those sensitive to both presence and absence alike.

In interpreting these results, it's essential to note that while IAS 38 and IVS 210 directly address intangible assets, ISA 620 is associated with these assets indirectly through the audit process. Despite ISA 620's broader focus on auditing beyond just intangible assets, the findings indicate that when it comes to audit considerations relevant to intangible assets, ISA 620 fully aligns with the specific provisions of IAS 38 and IVS 210. This might be due to the nature of audit standards, which tend to be more universal and applicable across different areas of financial reporting, including intangible assets.

Thus, these results do not imply that ISA 620 is as detailed or prescriptive about intangible assets as IAS 38 and IVS 210 are; rather, it suggests that where ISA 620 does touch upon intangibles, it does so in a manner consistent with the frameworks established by the other two standards. This consistency is crucial for ensuring the reliability and thoroughness of audits in the context of intangible assets and underscores the interconnectedness of standards when it comes to audit practices.

Table 6. Comparison Analysis Results on Overall Similarity

Binary Variables	Analysis theme: Overall similarity		
Measures	IAS 38/IVS 210	IAS 38/ISA 620	IVS 210/ISA 620
Simple matching coefficient*	0.692	0.385	0.692
Dice*	0.818	0.556	0.714
Rogers and Tanimoto coefficient*	0.529	0.238	0.529
Sokal and Sneath I coefficient*	0.818	0.556	0.818
Jaccard coefficient*	0.692	0.385	0.556
Euclidean distance coefficient**	2	2.828	2
Notes: *Similarity measure; **Dissimilarity measure			

Source: Author's own projection

The overall similarity analysis, encapsulating all the themes pertinent to intangible assets, yields a nuanced picture of the relationships between the standards IAS 38, IVS 210 and ISA 620. The Simple Matching Coefficient, which equally considers matches of both presence and absence of attributes, indicates a moderate similarity between IAS 38/IVS 210 and IVS 210/ISA 620, with scores of 0.692, and a less pronounced similarity between IAS 38/ISA 620, at 0.385.

The Dice coefficient and the Sokal and Sneath I coefficient, which give more weight to the presence of attributes, suggest a higher degree of similarity between IAS 38/IVS 210 and IVS 210/ISA 620, with values over 0.7, indicative of a strong overlap in the characteristics considered in these standards. The Jaccard coefficient, known for emphasizing the presence of attributes without giving weight to joint absences, presents a similar trend but with slightly lower similarity scores.

The Rogers and Tanimoto coefficient, with its balanced emphasis on both present and absent values, shows a relatively lower similarity across all pairings, most notably between IAS 38/ISA 620, where it drops to 0.238, underscoring the differences in their treatment of intangible assets.

The Euclidean distance coefficient, as a measure of dissimilarity, reinforces these findings with higher scores indicating greater divergence, particularly between IAS 38/ISA 620, which scores the highest at 2.828, suggesting the most pronounced differences between these standards.

It is important to consider that IAS 38 and IVS 210 are directly focused on intangible assets, while ISA 620's connection to intangibles is more tangential, reflected in the limited mentions of intangible assets within it. Therefore, the results for ISA 620, particularly in its comparison with IAS 38, must be interpreted with an understanding of its broader auditing scope, which may not delve into the specifics of intangible assets as deeply as the other two standards.

Overall, these similarity measures, with their varying focus on the presence and absence of attributes, provide a composite view of the congruity and divergence among the standards. They underscore the robust alignment between IAS 38 and IVS 210, while also highlighting the relative distance of ISA 620 due to its different purview and indirect association with intangible assets.

Conclusion

The conclusions drawn from these analyses are multifaceted. Firstly, they affirm the robustness of IAS 38 and IVS 210 in their convergent treatment of intangible assets, suggesting that stakeholders can rely on a coherent framework for R&D accountability.

Secondly, the consistency of ISA 620 with the other standards in audit-related aspects reinforces the reliability of audits concerning intangible assets, despite its broader scope.

The analysis conducted in this paper exposes inherent vulnerabilities within IAS 38, IVS 210, and ISA 620, particularly concerning the uncertainty embedded in managerial judgement and expert evaluations. The provision in IAS 38 that allows for the capitalisation of development costs based on a probability threshold opens the door to earnings manipulation, given that managerial incentives can skew the estimations of economic benefits (Dinh et al., 2015a). This subjectivity does not adequately safeguard against over or underestimation, which can be driven by motivations ranging from bonus optimization to tax advantages.

Similarly, IVS 210's (IVSC, 2021) reliance on discount rates for valuing intangible assets introduces an arbitrary element that may not reflect true risk, again inserting a layer of judgement into the valuation process. The standards, while offering a framework, do not provide a fail-safe mechanism to counter the potential arbitrariness of these estimations.

The challenges extend into the auditing domain, as illustrated by ISA 620. The requirement to seek expert opinions introduces additional costs and raises concerns over the confidentiality of proprietary information (Basu and Waymire, 2008; Ciftci and Zhou, 2016; Hunter et al., 2012). This is particularly relevant when considering the valuation and audit of advanced technologies, such as AI systems. The unique characteristics of such technologies, including their development costs, the expertise needed for their evaluation, and the difficulty in forecasting their generated cash flows, pose significant challenges (Warren and Casey, 2023, 'The Dichotomy of AI: MIT Professor Sandy Pentland Examines Whether It Poses a Threat or Opportunity to Humanity').

These observations are not merely theoretical; they have practical implications. For instance, considering an AI technology's development costs, raises questions about capitalisation and the practicality of finding an expert capable of auditing its complex capabilities without infringing on proprietary rights. Moreover, determining an appropriate discount rate for the projected cash flows generated by AI, and accounting for regulatory risks, presents complex dilemmas that the current standards do not explicitly address.

Therefore, the current standards, despite their intent to enhance accountability and protect stakeholders, fall short when confronted with the complexity and rapid advancement of intangible assets, particularly in the technology sector. Stakeholders are left to navigate a landscape where the standards provide insufficient guidance on practical applications, leaving a gap that could be exploited to the detriment of financial transparency and integrity.

The conclusion of this article, therefore, points to a need for the evolution of these standards. It calls for a framework that can more accurately reflect the risk, value, and uncertainty of intangible assets, especially cutting-edge technologies. Future iterations of these standards should consider incorporating more objective, quantifiable metrics and enhanced guidance to mitigate the subjectivity of managerial judgement and expert evaluations. The goal should be to construct a robust, adaptable framework that can keep pace with innovation and more effectively shield stakeholders from the risks inherent in the valuation and reporting of intangible assets.

Moving forward, these findings imply the necessity for continued harmonization of standards, particularly as the business environment evolves and the importance of intangibles escalates. Future revisions of standards should consider these alignment insights to further strengthen the framework for intangible assets and enhance stakeholder trust.

In conclusion, this paper establishes a clear picture of the current landscape of financial standards as they pertain to intangible assets. It paves the way for ongoing discourse on the efficacy of these standards in safeguarding shareholder interests and the transparent reporting of R&D activities, thus contributing to the broader goal of financial integrity in the global economy.

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