Management Solutions
Making things happen

Trust and reputation: proactive management of reputational risk

R&D

www.managementsolutions.com

Design and Layout
Marketing and Communication Department
Management Solutions

Photographs
Photographic archive of Management Solutions
iStock

Contents

Introduction

"It takes many good deeds to build a reputation. One mistake is enough to destroy it"
Benjamin Franklin[1]

For years now, there has been a growing interest[2] in trust and reputation related areas across industry sectors. Some of these areas include corporate social responsibility, regulatory compliance, good financial results, innovation, communication, brand identity, or the incorporation of ESG[3] criteria in management. In short, areas that impact the long-term sustainability of organizations.

Recent scientific studies based on more than 300 publications[4] have confirmed a causal relationship between these areas and reputation: sustainability leads to trust, and trust leads to good corporate reputation, which in turn generates income and profitability. This confirms the intuition that it is essential to pay the utmost attention to preserving stakeholder trust as the pillar of corporate reputation and other intangible assets that ultimately are the drivers of profitability.

But, what are trust and reputation?

On a textbook definition level, trust is the firm belief in the reliability, truth, or ability of someone or something, and reputation is the beliefs or opinions that are generally held about someone or something[5] . Both definitions are inherently subjective to some extent: trust and reputation are based on perception and opinion, not necessarily on verified facts, are built from information that comes from different stakeholders (analysts, specialists, market participants, etc.) in different formats and media (publications, reports, news, social networks, etc.).

This subjectivity is especially relevant in a context characterized by immediacy and ease of access to communications: information spreads to online media and social networks in a matter of seconds, users share data and opinions on the web in real time and with hardly any filters. This means that a reputation crisis can develop at high speed, with the truthfulness of the facts often relegated to the background and left unchecked due to lack of time to confirm them, which poses a challenge to managing the impact of such a crisis.

All this has led to a greater interest in reputational risk across industries. This risk is often incorporated into the ESG risk framework (as prescribed by the COSO[6] principles, for instance) and, in the particular case of the financial sector, is defined by the European Banking Authority as "the current or prospective risk to the institution's earnings, own funds or liquidity arising from damage to the institution's reputation"[7]. Reputational risk has not traditionally been regarded as a prime risk, but the already discussed factors, together with the amount of high-loss and even bankruptcy cases due to reputational events in recent years, are drawing the attention of regulators, large financial institutions and corporations to this risk.

Although regulations have attempted to lay down requirements for identifying, measuring and managing this risk, the inherent difficulty of this task has meant that at present the level of regulatory development and standardization is lower for this risk than for others. In any case, regulators and supervisors continue to work towards incorporating reputational risk into the strategic risk management processes of corporations and financial institutions[8].

This is also reflected in the fact that companies are developing reputational risk management frameworks, still incipient in most cases, which in their most advanced form cover all relevant risk management areas: governance, three lines of defense organization, policies and procedures, data and models, scenario analysis and stress testing, reporting and limits, and particularly communication, given the nature of this risk.

Traditionally, organizations have tried to measure reputational risk from information obtained through indices, surveys, qualitative analysis, etc. To this must be added at least three new components: i) the exponential growth of immediately available data (e.g. data from social networks and useful digital press sources); ii) the development of artificial intelligence and machine learning techniques such as natural language processing and deep neural networks, aimed at data processing, content interpretation or sentiment analysis; and iii) the availability of low cost, mass processing capabilities[9].

All this marks a turning point in reputational risk measurement: possibilities that were previously unfeasible are now feasible at a reasonable cost. There are now tools for identifying and labeling potentially harmful news, sentiment analysis models, reputational risk measurement tools, and scorecards with KRIs for internal management.

In this context, this study aims to provide a comprehensive view of reputational risk management. The study is divided into three sections, which are intended to:

- Describe the context for and regulations on reputational risk.
- Present the components of a reputational risk management framework.
- Examine the use of quantitative techniques applied to reputational risk management using advanced artificial intelligence and machine learning methods.

Finally, the document intends to illustrate how all these components are being implemented in practice in large corporations and global financial institutions.

[1] Benjamin Franklin (1706-1790), American politician, writer and scientist, considered to be one of the founding fathers of the United States.
[2] The Economist Intelligence Unit. (2019) and The Economist Intelligence Unit. (2005).
[3] Environmental, Social and Governance.
[4] Gomez-Trujillo, A.M., Velez-Ocampo, J. and Gonzalez-Perez, M.A. (2020).
[5] According to the Oxford English Dictionary (2020).
[6] COSO (2018).
[7] "Reputational risk" means the current or prospective risk to the institution's earnings, own funds or liquidity arising from damage to the institution's reputation. Guidelines on common procedures and methodologies for the SREP and supervisory stress testing. EBA (2018).
[8] For example, the EBA has included reputational risk under operational risk in its SREP guidelines (2018), and the ECB has included it in its ICAAP and ILAAP guidelines as well as in its guidelines on climate and environmental change risks.
[9] Management Solutions (2020).

Executive summary

"What can be said, can be said briefly"
Wittgenstein[10]

This section aims to summarize the main conclusions reached on reputational risk management, which are expanded in later sections of this document.

Reputational risk background and regulation

1. Numerous scientific studies support that there is a causal link between reputation and a negative impact on revenue, operating margin, liquidity, share value, cost of capital, etc. There are also positive reputational events, but studies suggest that their impact is not symmetrical (i.e. it is less pronounced than for negative events).

2. Stakeholders (customers, suppliers, employees and investors) are the mechanism for transmission between reputational events and negative impacts.

3. Some of the main causes of negative reputational impacts include operational events (fraud, lawsuits, sanctions, environmental crimes ...), company behavior (business practices, management team integrity, mass layoffs, employee satisfaction, inadequate crisis management, transparency ...), and unexpected financial results.

4. All studies on the subject agree on the need to identify, measure, manage and mitigate reputational risk, meaning "the current or prospective risk to the institution's earnings, own funds or liquidity arising from damage to the institution's reputation"[11,12].

5. Some organizations[13] emphasize that reputation risk is manageable, and have tried to identify which elements affecting reputation are endogenous and can be managed. Some of these elements are: corporate governance, ethical management, employee skills and competencies, corporate culture, risk management and control, company viability and sustainability, prudent and responsible business practices, customer satisfaction, regulatory compliance, contagion risk management, proper crisis management, and transparency.

6. Many regulatory bodies emphasize the need for organizations to explicitly incorporate this risk into their management frameworks. For example, COSO highlights its interconnection and impacts on other risks, and, in the financial sphere, the Financial Stability Board, the Basel Committee, the European Commission, the European Banking Authority (EBA) and the European Central Bank (ECB) coincide in pointing out the significance of this risk and its potential impact on organizations, and require its active management at different levels of detail.

7. In Europe, the most detailed regulation takes place is in the financial industry and is possibly the one published by the EBA, which lays down[14] that reputational risk must be supervised, and this requires analyzing internal and external risk factors, qualitative and quantitative indicators (for which it gives examples), and assessing the significance of this risk and its links with other risks. For its part, the ECB requires that reputational risk be incorporated into the ICAAP[15] and the ILAAP[16].

Elements of a reputational risk framework

8. Given the importance of reputation, intimately connected to trust and key to achieving sustainable growth, and partly also due to regulatory requirements, corporations from different industry sectors are developing reputational risk management frameworks. These frameworks are underpinned by a set of principles and are structured into five blocks: i) definition and objectives, ii) organization, governance and policies; iii) measurement methodologies, iv) reputational risk map, and v) integration into the business-as-usual.

[10] Ludwig Wittgenstein (1889-1951), Austrian-British philosopher, mathematician, linguist and logician.
[11] EBA (2018).
[12] Other definitions (Honey, G., 2009) identify reputational risk as the difference between stakeholder expectations and the organization's actual performance.
[13] Hong Kong Monetary Authority. (2008).
[14] EBA (2018), section 6.4.3.
[15] ECB (2018a), paragraph 65.
[16] ECB (2018b), paragraph 61.

9. The first block covers defining the key reputational risk issues for the organization and setting the medium and long-term objectives and the roadmap for managing this risk. For this, it is essential to determine i) the internal and external risk factors that can lead to events that might impact reputation; ii) the sources for observing reputation and conducting active, ongoing and comprehensive listening (press, reports, blogs, social networks, etc.); iii) the information classification mechanisms for content discrimination intelligence; and iv) the quantitative methodologies for impact analysis.

10. Three lines of defense for reputational risk need to be identified in organizations. This includes describing their roles and responsibilities and updating the necessary policies in the organization. The first line of defense lies with the business and support areas directly engaged with stakeholders, and with the communication area; the second line of defense is provided by the Risk function supported by the Compliance function; and the third line of defense is Internal Audit.

11. As with any other significant risk, it is key for the Board of Directors and Senior Management to be involved in the active management of reputational risk, as well as to adapt the governance structure (committees). This involves updating the corporate governance policy as well as the risk management policies and control framework.

12. As for methodologies, reputation measurement has traditionally been based on listening to and processing information from the media and social networks, and on conducting surveys. This has been done using traditional methodologies such as the development of reputation indicators (internal or external, such as RepTrak, FTSE4Good or DJSI) and the analysis of surveys (e.g. the reputation quotient or the SPIRIT model).

13. The most advanced methodologies are based on the analysis of mass amounts of news from the media, social networks, blogs, etc. using machine learning and artificial intelligence techniques, specifically natural language processing (NLP). These techniques are applied in five phases: information extraction, text mining, topic modeling, sentiment analysis and impact estimation.

14. In short, the methodologies described are intended to quantify and thereby provide an objective assessment of reputational risk in order to make it easier for the organization to manage it, which involves observing, interpreting, analyzing and evaluating reputational events that may have an impact on the organization.

15. The fourth block in the framework, the reputational risk map, makes it possible to monitor risks and anticipate their impact on the organization's reputation, and therefore on its revenue, capital and liquidity. This map is based on a set of indicators and metrics that are used for monitoring the value of an organization as perceived by its stakeholders, which enables the organization to manage and mitigate any risks.

16. It is necessary to integrate an organization's reputational risk management framework into the business-as-usual for control to be effective. For this, the organization needs to i) develop management tools, such as incorporating reputation risk into the risk appetite; designing and monitoring

anticipatory management metrics with objectives and limits, designing and implementing internal reputational risk reporting, and preparing reputational contingency plans; ii) strengthen the role of its reputational risk control function; iii) embed reputation into the organization's strategic processes: budgeting, capital and liquidity planning, and iv) promote a corporate culture of reputational risk awareness and management, with special focus on the first line of defense and the involvement of Senior Management.

Quantitative techniques applied to reputational risk

17. Using quantitative techniques for the objective assessment and management of reputational risk is particularly complex, since the appropriate data sources are mostly external, unstructured and without guarantees of quality or integrity.

18. There are artificial intelligence tools that use NLP techniques to manage reputational risk based on actively listening to social networks and the media[17,18].

19. These tools seek to answer a series of questions: i) what do the news and social networks say about my organization? – through active listening and text mining; ii) what are the key concepts in these news items? – through topic modeling techniques that use artificial intelligence and NLP; iii) to what extent do they impact my organization? – through econometric models and visualization techniques; and iv) How do they affect my key indicators including share value, income, deposits, etc.? – through analyzing their impact on these indicators.

20. The information used as a source is the corpus of news from the digital press, social networks, etc., which is pre-processed using text mining techniques. AI and NLP techniques are then used to identify the topics (recurring themes) present in the news, build time series from these topics, and determine their incidence (correlation) with any indicators that the organization wants to have explained (e.g. market value , income, sales, deposit inflows and outflows, etc.). This makes it possible to determine the influence of specific reputational events on an organization's indicators.

21. To illustrate how reputation risk is measured using advanced techniques, the described tools were used in a case study that sought to examine which reputational events had an impact on several major European financial institutions in 2018-2020 and how these events affected their share price, looking at mainstream digital economic press media.

22. For this, a digital press database was filtered to obtain xxx relevant news, on which the methodology was applied. More than 3,000 relevant topics were identified for the analysis period and a time series of their relative importance during that period was built.

23. Next, the impact of each topic on the selected variable was measured, this variable being the share value series for each organization after removing the market trend from it. In other words, we attempted to determine the magnitude of the rapid share price shocks resulting from reputational events, not so much the structural shift in share prices as a result of the aggregate market movement.

24. Share price movements are largely unrelated to market trends, but are instead explained by specific reputational events (share price movements of up to 5% in one day for these reasons were observed throughout the year). Some of the key topics with a positive influence on reputation were the "fight against climate change" (the bank announced a program on this matter) and "EU Court of Justice" (there was a ruling in favor of the bank), whereas topics with a negative influence included, notably, "net profit" (the bank´s performance was worse than expected) and "current account fees"(the bank announced an increase in fees). This shows that up to 5 percent of an organization´s capital is subject to very rapid fluctuations exclusively as a result of reputational events.

25. In view of the results of this study, our view is that an analysis of this nature can help not only to identify the main areas of focus of reputation management, but also to quantify their potential impacts in terms of income, capital, liquidity, etc., and therefore to make decisions about these areas and manage them appropriately.

[17]Following a R&D process of several years, Management Solutions and mrHouston have developed a comprehensive solution for the management and control of reputational risk that uses Natural Language Processing Artificial Intelligence to measure this risk based on information from media and social networks.

[18]mrHouston (mrhouston.net) is a technology solutions firm specializing in artificial intelligence and software development that develops R&D work within the European Social Fund, the CDTI and the Digital Enabling Technologies (THD) program of the Government of Spain.

Reputational risk context and regulation

"The way to gain a good reputation is to endeavor to be what you desire to appear"
Sócrates[19]

Nature of reputation and how it can be affected

Studies published by prestigious institutions estimate[20] that around 70% of the market value of companies comes from their intangible assets (such as patents, intellectual property, brand, innovation, quality of human resources and management team, or business relationships), and no more than 30% comes from tangible assets. The fact that most of these intangible assets are influenced by stakeholders' perception of organizations makes such organizations especially vulnerable to events that could damage their image, which has led to a growing concern for corporate reputation.

The question arises as to whether there is an actual causal link between an organization's reputation and sustainability. In other words, is the insight that damage to reputation leads to a worsening of financial performance true? And if so, how can an organization protect its reputation?

In recent years, numerous studies[21] have analyzed this insight, and the answer is unequivocal: regardless of the countries and the metrics analyzed, there is a significant causal link between reputational events, stakeholder reaction and a negative impact on revenue, operating margin, liquidity, share value and cost of capital.

Negative reputational impact causes include operational events (fraud, lawsuits, sanctions, environmental crimes...), corporate behavior (business practices, management team intergrity, massive layoffs, employee satisfaction, inadequate crisis management, transparency ...), and unexpected financial results.

The transmission mechanism between these reputational events and financial deterioration is none other than the stakeholders' reaction. This is because, before a reputational event[22]:

- Clients perceive the organization negatively, which reduces operating income and cash flows, diminishes loyalty and favors competitors.
- Suppliers and business partners can review their prices and other conditions, which drives up costs.
- Employees lose motivation and productivity, and there may be a departure to competitors.
- Investors and analysts review the organization's market value after estimating the potential impact of the reputational event. Their opinion of the organization's management team deteriorates, which also reduces share value. I addition, to protect their own reputation, they prefer not to be related to the organization, which can lead to complete divestment and therefore to decapitalization.

On the other hand, the scientific literature also confirms that there is a positive relationship[23] between reputation and good financial performance, although this relationship is not symmetric: on average, a negative event is more damaging to results than a positive event is beneficial.

All the above leads to a logical conclusion, reached by all studies on the subject: the need to measure, manage and mitigate reputational risk.

[19] Sócrates (470-399 a.C.),classical Greek philosopher, teacher of Plato, considered to be one of the founders of Western moral philosophy.
[20] Harvard Business Review (2007).
[21] Gatzert, N. (2015).
[22] Gatzert, N. (2015).
[23] Raithel, S. and Schwaiger, M. (2014).

Reputational risk: definition and sources

Risk has traditionally been defined as the possibility that an economic loss will occur due to some previous event, and has been quantified using measures such as value at risk (VaR), which incorporate estimates of the probability that a loss will be incurred and of the amount of that loss. However, the intangible nature of reputational risk, as well as its ability to trigger other risks (e.g. liquidity or market), makes it difficult for such risk to be included in this traditional definition.

Definition of reputational risk

Although there are different definitions of reputational risk, all of them highlight the importance of identifying the sources of risk, as well as their intangible nature. The COSO risk management framework, a reference in all industries, considers reputational risk as part of ESG risks and defines it as[24]:

> *"Unacceptable differences between how an organization wants and needs to be perceived and how it is actually perceived".*

The financial sector in particular, whose business is based on trust as a fundamental intangible asset, has tried to rigorously address the definition of this risk.

On the one hand, the revised Basel II accord published in 2009 by the Basel Committee on Banking Supervision (BCBS) contains specific guidelines within Pillar 2 in relation to this risk[25], including a definition of reputational risk:

> *"The risk arising from negative perception on the part of customers, counterparties, shareholders, investors, debt-holders, market analysts, other relevant parties or regulators that can adversely affect a bank's ability to maintain existing, or establish new, business relationships and continued access to sources of funding (e.g. through the interbank or securitisation markets)".*

This definition is elaborated on in the Basel guidelines on step-in risk – understood as the risk that a bank decides to provide financial support to an unconsolidated entity that is facing financial stress[26], beyond its contractual obligations or in the absence of them. These guidelines point out that step-in risk is also a potential source of reputational risk and identify liquidity risk as one of the affected risks, recognizing that "reputational risk can affect a bank's liabilities, since both market confidence and a bank's ability to finance its business are closely related to its reputation"[27]. However, the BCBS explicitly mentions that reputational risk is different from operational risk[28], as the latter includes legal risk but excludes both strategic and reputational risk. This definition, which applies to any industry and organization type (going beyond the regulatory requirements of the financial sector), is therefore based on a drop in the value of an organization's intangibles.

At the European level, as previously mentioned, the European Banking Authority (EBA) has defined reputational risk as[29]:

> *"The actual or expected risk to an institution's profits, equity, or liquidity arising from damage to the institution's reputation".*

The EBA recognizes that this risk is more significant for large institutions, particularly for those with listed shares or debt, and for those that operate on interbank markets. However, the EBA classifies it as a subtype of operational risk, unlike the BCBS classification. In any case, it clarifies that the outcome of a bank's reputational risk assessment should be incorporated into its business model analysis and liquidity risk assessment.

[24] COSO (2018).
[25] BCBS (2009), paragraph 47.
[26] BCBS (2017), paragraph 14.
[27] BCBS (2009), paragraph 52.
[28] BCBS (2011), paragraph 10.
[29] EBA (2018).

The reputational impact of the Covid-19 vaccine

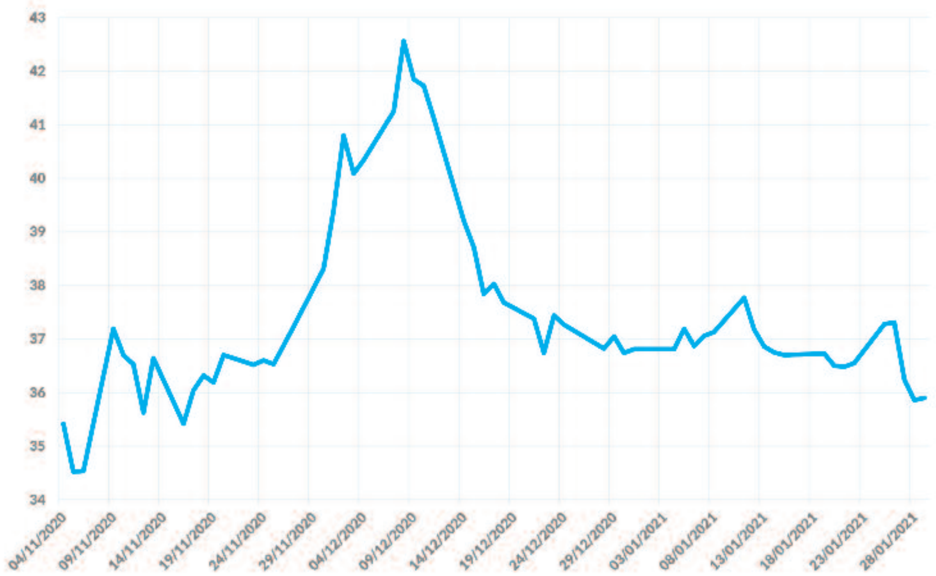
The crisis generated due to the new coronavirus discovered at the end of 2019 has put the focus of people's attention on the pharmaceutical companies tasked with developing a vaccine quickly, safely and effectively. This has meant that any announcement by pharmaceutical companies and any news in the media has resulted in very significant impacts on the capitalization of pharmaceutical companies.

As an example, Figure 1 shows the capitalization of US pharmaceutical company Pfizer, developer of one of the two main new RNA messenger generation vaccines. You can see the reputational impact of the news by or about the company in November and December 2020.

As can be seen, the share price movements resulted from news released by the company, but also by the competition and the media, and even by strong investors such as Warren Buffett.

- 9/11/2020. Pfizer's market capitalization rises by more than 7% in one day, after announcing that its Covid-19 vaccine is 90% effective.
- 12/11/2020. It is reported that the CEO of Pfizer has sold more than 60% of his shares in the company, causing the company's shares to drop by almost 3%.
- 13/11/2020. Europe confirms the contract to buy Pfizer's vaccines, which partially offsets the negative reputational impact of the CEO's share sales.
- 16/11/2020. Moderna announces that its vaccine is 94.5% effective, resulting in a 3% decrease in Pfizer's market capitalization.
- 17/11/2020. Warren Buffett announces that they will increase their investment in the pharmaceutical companies that are developing the vaccine. This announcement increases Pfizer's market capitalization by almost 2%.
- 18/11/2020. Pfizer makes a new announcement increasing its vaccine's effectiveness from 90% to 95%, which boosts its market capitalization by almost 1%.
- 27/11/2020 al 02/12/2020. Pfizer's market capitalization goes up by 9.5% due to announcing that is has applied for its vaccine to be authorized by the FDA and the European Union, that the United Kingdom has approved it and that vaccination will commence a week later.
- 09/12/2020 al 22/12/2020. After a week of share price increases due to previous announcements, vaccination in the United Kingdom began on December 8. On December 9, news of adverse reactions began to emerge, reducing Pfizer's market capitalization by 12%. This was not stopped by the United States, Canada and the European Union approving the vaccine, which occurred in that period.
- 23/12/2020. Pfizer's market capitalization rose by almost 2% after the Company announced a second agreement with the US government to supply an additional 100 million doses.
- 11/01/2021 al 19/01/2021. There appeared to be a downward trend in the company's share value as a result of a slowdown in the distribution of the vaccine and a possible link, later denied, with some deaths after the injection, which caused the share value to drop by 2.8%

Figure 1. Pfizer´s market capitalization between November 2020 and January 2021.



The Boston Federal Reserve[30] notes that reputational losses can materialize when shareholders infer that there may be direct negative consequences for future cash flows, and identifies several consequences of reputational risk: i) loss of current or future customers; ii) loss of employees or managers within the organization – or increased hiring costs; iii) reduction of current or future business partners; iv) increased costs of funding through credit or capital markets; and (v) increased costs from regulation, fines, or other penalties.

Other definitions focus on the risk that certain events will occur: the OECD echoes the definition of the Canada Revenue Agency (CRA)[31], identifying reputational risk not only as any event that could damage stakeholder trust, but also any event that could damage respect for an organization. In this definition, reputational risk would be more closely related to operational risk.

Finally, some academic studies[32] identify reputational risk as the difference between stakeholder expectations and the organization's actual performance. Thus, reputation risk arises when the organization is not capable of meeting stakeholder expectations (Figure. 2), as this can lead to a lack of liquidity and a fall in the organization's share price[33]. This view implies that stakeholder expectations should be measured against the same areas of performance these expectations are about (for example, expectations about dividends, products, corporate management, ethical standards, etc.), using consistent metrics that produce a quantitative value that can be transposed to a financial impact[34].

Sources of reputation risk

The growing interest in corporate reputation analysis has resulted in numerous studies attempting to identify the sources of reputational risk. Some key potential sources are the organization's strategic positioning and performance, conflict of interest management, individual professional conduct, the compliance system and incentive systems, leadership, and corporate culture[35].

Some institutions have tried to identify a broad set of elements that affect reputation and that organizations can manage. By way of illustration, the Hong Kong Monetary Authority (one of the few that has issued specific guidance on this matter) points out 12 areas that can potentially lead to reputation risk[36]:

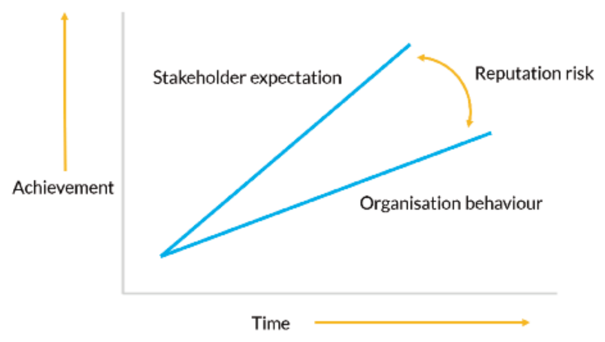
1. Corporate governance – which shows the Board's ability to steer the business and manage the associated risks.

2. Management team integrity and ethics.

3. Employees' skills and competencies, motivation and satisfaction with how the organization provides for their needs.

[30]Perry, J. and Fontnouvelle, P. (2005).
[31]OECD (2020).
[32]Honey, G. (2009).
[33]Corporate Reputation Forum (2011).
[34]Scandizzo, S. (2011).
[35]Walter, I. (2008).
[36]Hong Kong Monetary Authority (2008).
[37]Honey, G. (2009).

Figura 2. Interpretation of reputation risk as the difference between stakeholder expectations and actual company performance[37]



4. Corporate culture – including ethical standards and responsible behavior, compliance with legislation, and mechanisms to protect and defend reputation.

5. The risk control and management system in place to safeguard the value of the organization's assets and capital position.

6. The organization's financial viability and sustainability, as well as the strength of its financial position.

7. Business practices, whether they are responsible, honest and prudent.

8. Customer satisfaction, including fair treatment, accurate information, the provision of suitable and efficient services, proper claims management, and the absence of malpractice.

9. Compliance with legislation and regulatory requirements.

9. 10. Effective management of contagion risk and of any information that may spread among stakeholders, even if it is untrue.

11. Proper crisis management (and development of business continuity plans).

12. Transparency and the organization's ability to satisfy stakeholders' needs for information.

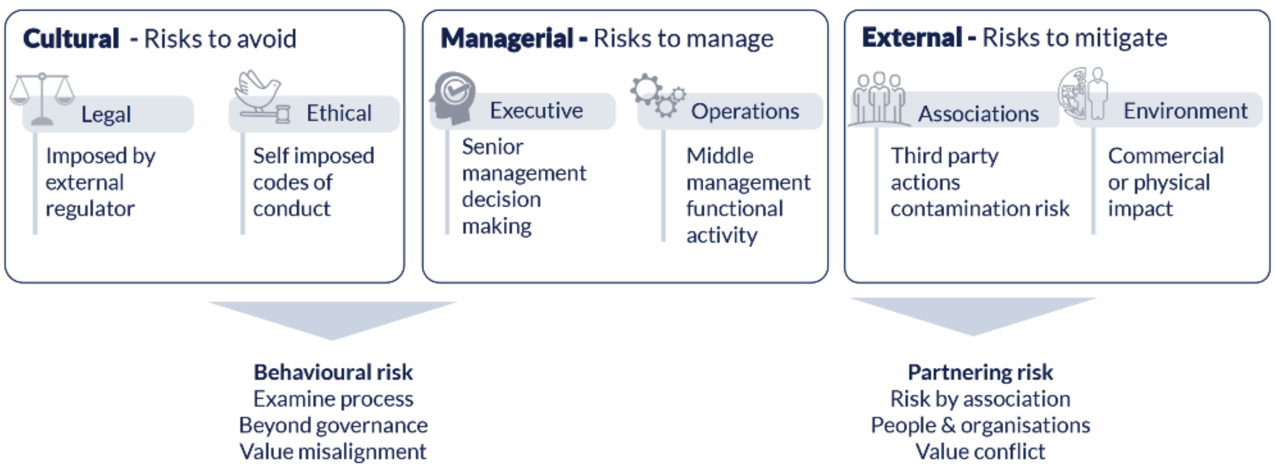
In an effort to grasp the diversity of reputational risk sources, some organizations have classified these sources to be able to measure and mitigate reputational risk. For example, the OECD classifies[38] reputational risk sources into external (such as system hacks) and internal (such as poor customer service or fraud), and this classification forms part of the criteria used to assess the maturity of an organization's reputational risk management framework.

Other approaches classify reputational risk sources into three groups[39] (Fig. 3): i) Cultural (related to codes of conduct and legal risk as well as self-imposed ethical standards), ii) Management and operational (linked to financial objectives, customer satisfaction and product behavior), and iii) External (related to the services provided by the organization or to the environment).

Finally, some studies[40] have tried to find statistical correlations to identify sources of reputational risk by analyzing empirical data on operational losses. Upon analyzing the correlation for a group of financial institutions, these studies concluded that, for operational losses, there is a positive correlation between a fall in reputation and i) the level of risk assumed by an organization, ii) the level of profitability, and iii) the size of the organization. On the other hand, a negative correlation is observed between a fall in reputation and i) the level of intangibles, and ii) the organization's market capitalization. The correlation observed is different depending on the business area that incurs the operational loss.

[38] OECD (2020).
[39] Corporate Reputation Forum (2011).
[40] Fiordelisi, F., Soana, M. G., and Schwizer, P. (2013).
[41] Honey, G. (2009).

Figure 3. Three reputational risk source groups[41].



Regulatory context

Many regulatory authorities emphasize the need for organizations to explicitly include this risk in their management frameworks, no matter which definition of reputational risk they use:

1. The COSO[42] risk management framework considers reputational risk as part of ESG risks and emphasizes the need to analyze its interconnection with other risks (operational, climate, etc.).

2. The FSB states[43] that reputation risk should be part of an organization's risk management framework and risk appetite statement, albeit in a qualitative way.

3. The Basel Committee states[44] that, despite the difficulties in measuring reputation risk, the financial industry is expected to develop management techniques for all aspects of this risk. In fact, the reviewed Basel II framework explicitly includes this requirement, establishing that it should be incorporated into the management processes of other types of risk (credit, liquidity, market or operational), and should be adequately addressed in the liquidity contingency and ICAAP[45] plans. Firms are also expected to improve their stress testing methodologies to capture the effects of reputational risk[46].

4. In Europe, the CRD emphasizes[47] the potential impact of reputational risk on liquidity, and states that methods for managing funding positions should factor in any potential reputational impact. This requirement is also detailed in the CRR, which specifies[48] that firms must take particular account of any significant damage to their reputation when evaluating liquidity outflows.

5. The EBA also states[49] that reputational risk analysis results should be considered as part of the business model analysis (BMA) and liquidity analysis, since it may have an impact on reduced profits and on loss of confidence in the bank by investors, depositors or interbank market participants.

   This requirement has led the EBA to incorporate reputational risk into the supervisory activity of the relevant authorities. Thus, in its SREP guidelines, the EBA includes a reputational risk analysis section, establishing that "supervisory authorities must assess the reputation risk to which financial institutions are exposed, taking advantage of their understanding of financial institutions´ governance, business model, products and the environment in which they operate"[50].

[42]COSO (2018).
[43]FSB (2013).
[44]BCBS (2006).
[45]BCBS (2009).
[46]BCBS (2019).
[47]PE y CE (2013a), article 86, paragraph 4.
[48]PE y CE (2013a), article 420.
[49]EBA (2018).
[50]EBA (2018), section 6.4.3.

These guidelines specify that reputational risk supervision should cover the following:

a. Analysis of internal and external factors that may be a source of reputation risk for the institution.

b. Analysis of qualitative and quantitative indicators such as: the number of sanctions received, advertising campaigns and consumer association initiatives that may damage reputation, consumer complaints, negative events associated with the financial sector as a whole, financing of industries or people that can damage reputation (arms trade financing, deals with countries with embargoes, financing of people on sanction lists, etc.), as well as other market indicators (rating or share price falls, etc.).

c. Analysis of the significance of reputation risk and its connection with other risks (mainly credit, market, operational and liquidity), using the assessment of these risks to identify any potential secondary effects in any direction (from reputation to other risks and vice versa).

5. Similarly, the European Central Bank establishes that reputational risk must be included in the risk inventory for ICAAP[51] and ILAAP[52].

6. Last, reputation risk management is covered by regulatory requirements associated with specific matters such as:

i) the FSB's requirement that compensation to Senior Management should be adjusted to factor in all types of risks, including those that are difficult to measure (such as liquidity, reputation and cost of capital)[53];

ii) the BCBS's statement that money laundering and terrorist financing risk management helps protect the reputation of banks and the national banking system[54];

iii) the EBA's requirement to analyze the impact that potential incidents on the part of payment providers[55] may have on reputation;

iv) the ECB's supervisory expectation that banks should factor in any potential loss of reputation resulting from the public, the bank's counterparties or investors associating the financial institution with adverse environmental or social impacts[56].

[51] ECB (2018a), paragraph 65.
[52] ECB (2018b), paragraph 61.
[53] FSB (2018).
[54] BCBS (2020).
[55] EBA (2017).
[56] ECB (2020).

Elements of an objective reputational risk framework

"You earn reputation by trying to do hard things well"
Jeff Bezos[57]

Given the growing importance of reputation in business performance and sustainability, organizations from different sectors are developing reputation risk[58] management frameworks, incorporating and sometimes going beyond regulatory requirements. These frameworks are usually approved at the highest level of an organization and include components that make it easier to identify, measure, control and manage this risk.

To build a reputation risk management framework aligned with best practices and international standards applicable to other risks[59], it is first necessary to establish a set of principles that will form the basis of the framework's structure and deployment. These principles revolve around[60]:

- ***Relevance:*** determining the importance of reputation risk with respect to other risks. This principle is subsequently cascaded down the risk map and the risk appetite framework.

- ***Responsibility:*** defining roles and responsibilities, as well as establishing accountability mechanisms.

- ***Scope:*** identifying the areas of the organization for which reputational risk will be measured. This will be the basis for determining the roles that will be involved in measuring the risk.

- ***Measurement:*** since reputation risk needs to be quantified, specific metrics need to be defined and later incorporated into processes such as goal setting as well as into monitoring and reporting systems.

Once these principles are defined, the key components of the reputational risk management framework can be developed. These components can be categorized into five blocks (Figure 4):

- Definition and objectives: conceptually defining the framework, factors and stakeholders affected.

- Organization, governance and policies: embedding reputational risk management into the governance and organizational structure of the risk function, assigning roles and responsibilities, and updating internal policies.

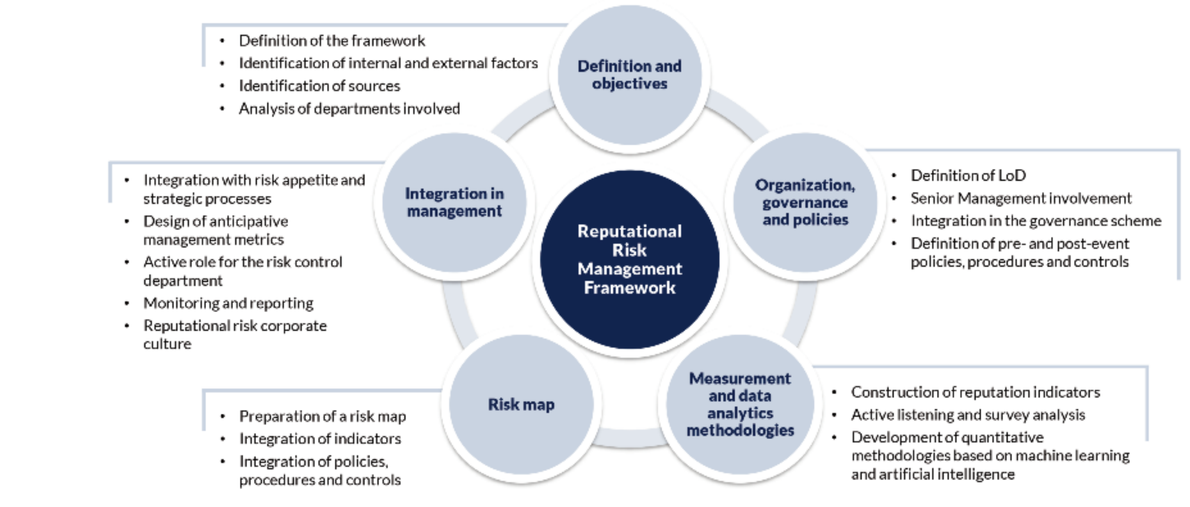
- Measurement methodologies: developing methodologies such as active listening, text mining, natural language processing, topic modeling, sentiment analysis, impact measurement, etc. to observe, interpret, analyze and evaluate reputation risk in an objective way.

- Reputation risk map: developing strategic and operational tools to monitor risk.

- Integration into the business-as-usual: integrating reputational risk in processes and tools that allow for adequate monitoring and reporting, with the appropriate level of aggregation at different levels in the organization.

[57]Jeffrey Preston Bezos n. (1964), founder and CEO of Amazon. According to Forbes, as of March 2021, he is on a par with Elon Musk as the world's richest person.
[58]For example, Deutsche Bank makes public its reputational risk management approach; see https://www.db.com/cr/en/concrete-management-of-reputational-risks.htm
[59]ISO (2018), section 5.4.
[60]A non-exhaustive list of examples of principles governing the definition of a reputational risk framework.

Figure 4. Elements of a reputational risk management framework



Definition and objectives

A reputation risk management framework begins with a set of definitions and objectives. First, what is meant by "reputation" and "reputation risk" needs to be defined, as this is essential for the framework to remain consistent when deployed throughout the organization.

Second, the objectives to be pursued need to be specified. Some examples include aspects such as: being aware of the corporate image among different stakeholders, having mechanisms for managing the corporate image, understanding the impact of reputation on the business and the income statement, analyzing how reputation risk relates to other risks, or determining the resilience of the organization to events that can lead to this risk materializing.

Third, a target operating model[61] needs to be designed. This model should outline the desired reputation risk management model and integrate the map of elements to be defined.

Once these definitions are formalized, the elements involved in measuring and managing reputation risk need to be identified. These elements can be represented in a relationship map that should include (Figure 5):

[61] Wijers, G., Liefers, R. & Halfhide, O. (2012).

Figure 5. Reputational risk management framework elements.

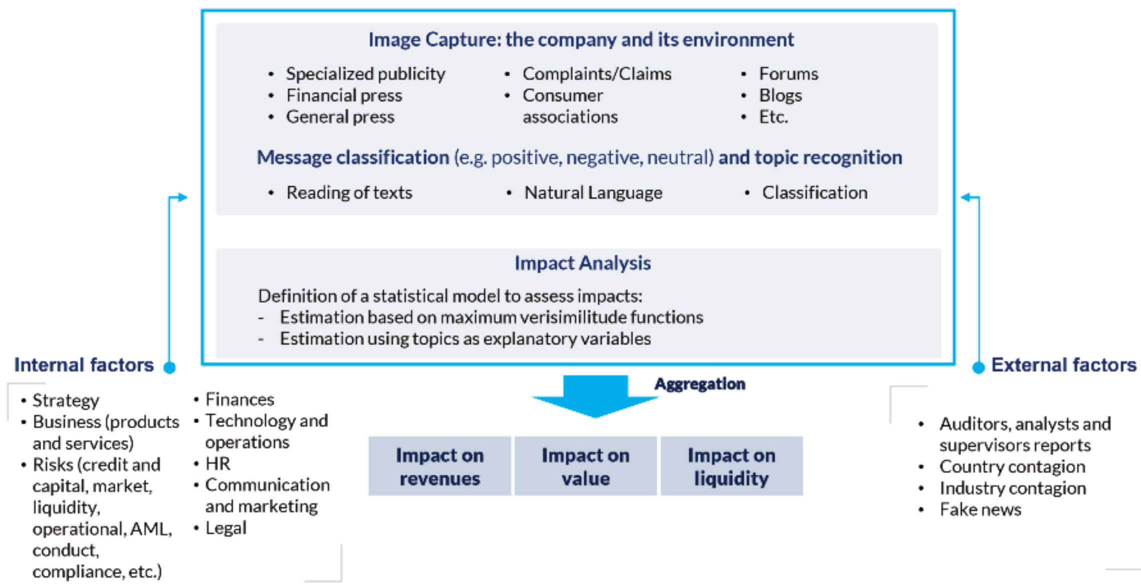
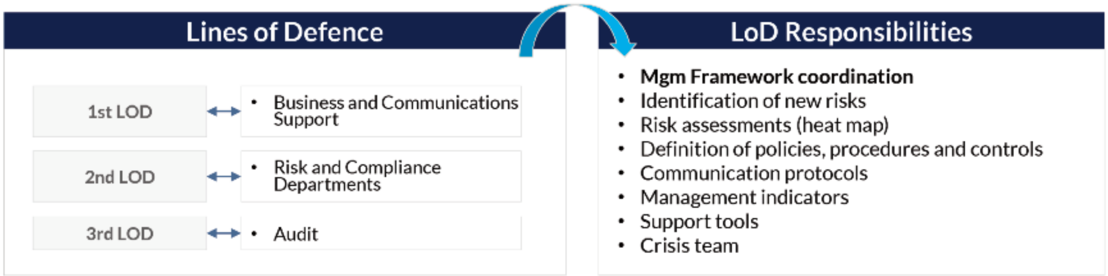


Figure 6. Definition and functions of the lines of defence for reputational risk management.



- Risk factors that can lead to events with an impact on reputation. These factors may have their origin in internal areas of the organization (such as the areas involved in strategy definition, design and marketing of products and services, measurement of risks associated with the business, or support areas such as Finance, Technology, Human Resources , etc.), but they can also have their origin in external elements that impact on the organization's reputation (such as other stakeholders, market sentiment, sectoral or regional contagion, false news, etc.).

- Sources for observing the organization's reputation (press, reports, blogs, social networks, etc.). Methods that allow active, ongoing and thorough monitoring of these sources need to be developed.

- Information classification mechanisms providing content discrimination intelligence.

- Quantitative analysis methodologies that can be used to measure reputational impact on factors such as company value, business turnover or liquidity.

Organization, governance and policies

As shown by different studies, good corporate governance affects stakeholder trust[62], therefore reputation risk should be a focal point of corporate governance[63]. Good practice would be to integrate reputation risk into a global risk management model based on three lines of defense[64] (LoD), specifying the responsibilities of each line and suitably updating the relevant policies (Figure 6). Thus:

- The first line lies with the business and support areas that carry out the organization's activities in direct relationship with customers, suppliers, etc., and the corporate communication area, which looks after the image that stakeholders have of the organization.

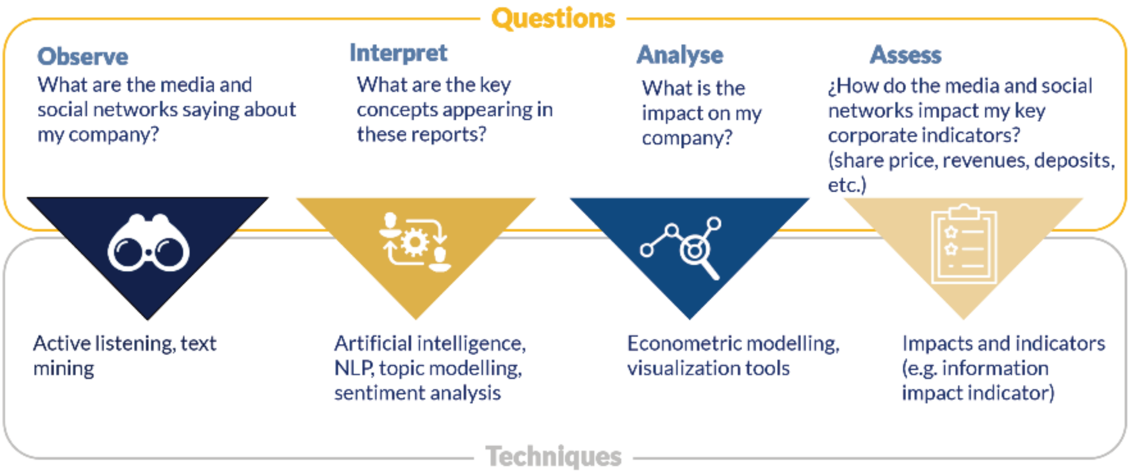
- The second line are the Risk functions, responsible for setting up action frameworks, defining measurement metrics and tolerance thresholds for this risk, and ensuring that the organization is resilient to reputational events. These functions are supported by the compliance function to ensure that the reputational risk management framework is observed.

- Finally, the third line is Internal Audit, who acts as the control of last resort and verifies both the reputational risk management framework and its proper implementation.

As with any other relevant risk, it is important to involve the Board of Directors and Senior Management in the active management of reputation risk[65], as well as to adapt the governance structure (committees) to ensure proper decision-making in this area. This usually involves updating the corporate governance policy as well as the risk management policies and the control framework. This update must include at least roles and responsibilities, measurement metrics and mechanisms, and monitoring and control procedures.

[62] Durán F. (2004).
[63] Hart, O. (1995).
[64] BCBS (2015).
[65] In the case of Spain, 93% of the companies that make up the Ibex 35 have already incorporated reputational risk management into their corporate risk management and compliance systems. For example, at BBVA the Permanent Executive Committee assists the Board of Directors in making decisions related to reputational risk, in addition to having specialized units both at regional and/or business level and at Group level.

Figure 7. Key points for reputational risk measurement.



Measurement methods

Measuring an organization's reputation has traditionally been based on listening to and processing information from media and social networks, as well as conducting surveys[66] in person, by phone or online. This has been done using traditional methods such as:

- The development and use of reputation indicators: building internal indices from information collected by the organization, or using external methodologies or indicators such as RepTrak[67] indices, FTSE4Good[68] indices or the Dow Jones Sustainability Index[69].

- The implementation of survey analysis methodologies such as the reputation quotient[70] methodology or the SPIRIT[71] model, which use statistical techniques (regression, factor analysis). These surveys aim to find out about how different stakeholders perceive specific aspects of the organization, such as whether they trust it, whether they are familiar with its products, how the organization compares with competitors in the eyes of customers, etc. With these procedures, it is possible to quantify concrete qualitative aspects and establish internal indices and metrics to monitor reputation.

Beyond these classical methodologies, advances in data accessibility, storage, and processing, as well as the development of advanced analytics and the intensive use of machine learning models, have led to more robust and efficient quantitative approaches.

These advanced methodologies support the entire reputation risk management and control cycle: observation, interpretation, analysis and evaluation (Figure 7).

Application of machine learning techniques

The most advanced methodologies are based on the intensive use, analysis and exploitation of large bodies of data using machine learning techniques focused on natural language processing[72] (NLP)[73]. These techniques allow the analysis of large volumes of media reports, social networks, specialist blogs and other digital resources to detect when a given industry or company are mentioned, and they are capable of identifying published content using topic modelling, as well as classification, usually based on a positive/negative/neutral mentions framework. This allows effective quantification of the impact of the information on specific business indicators.

The application of these methodologies can be conceptualized in five phases: data extraction, text mining, topic modelling, sentiment analysis and impact estimation (Figure 8).

[66] A current example of reputation surveys is the American Banker/RepTrack annual banking reputation survey, conducted through an online questionnaire on more than 14,000 people. Available at: https://www.americanbanker.com/news/bank-reputation-survey
[67] https://www.reptrak.com/reptrak/
[68] https://www.ftserussell.com/products/indices/ftse4good
[69] https://www.spglobal.com/esg/csa/indices/index
[70] Fombrun, C. J., Gardberg, N. A., and Sever, J. M. (2000).
[71] MacMillan, K., Money, K., Downing, S., & Hillenbrand, C. (2004).
[72] Jurafsky, D. and Martin, J.H. (2020)
[73] EBA (2020) refers to the use of text analytics techniques to extract valuable information from texts.

Classic methodologies: reputation quotient and the SPIRIT model

Reputation Quotient

The reputation quotient methodology was developed in the 1990s with the aim of creating a corporate reputation measure for strategic decision-making processes. It provides a rigorous methodology allowing comparison between companies even where they operate in different industries, and it includes a very broad range of stakeholders influenced by a firm's reputation. This methodology, which combines various earlier methods, is used to calculate the subject firm's rating based on a questionnaire consisting of 20 items grouped in six reputational classes, in which each item is scored between 1 (strongly disagree) and 7 (strongly agree).

Reputation quotient questionnaire[74]

Emotional appeal	• I have a good feeling about the company • I admire and respect the company • I trust the company
Products and services	• It backs its products and services • It develops innovative products and services • It offers high quality products and services • Its products and services offer a good quality-price ratio
Vision and leadership	• It displays excellent leadership • It has a clear vision of its future • It recognizes and acts on market opportunities
Workplace environment	• It is well run • It seems to be a good place to work • It seems to be a company that would have good employees
Social and environmental responsibility	• It supports good causes • It is an environmentally responsible company • It treats people well
Financial performance	• It has a strong profit record • It looks like a low-risk investment • It tends to do better than its competitors • It seems to have a strong growth outlook

This methodology is still widely used today as a jumping-off point to develop more company-specific measures, to address specific aspects and to focus on discrete stakeholder groups (e.g. investors or customers).

The SPIRIT model

The SPIRIT model is more specific than the reputation quotient, insofar as it proposes procedures and techniques for the analysis of the data generated. The name is an acronym of Stakeholder Performance Indicator, Relationship Improvement Tool, and it is a two-stage methodology:

- The first or SPI phase consists of a survey to obtain data, as in the case of the reputation quotient. In this case, the questionnaire consists of 16 items grouped in four categories analysing the company's past performance and the outlook for future performance. The questions are flexible and can be adapted to the context of the company, although the goal is always to understand the stakeholders' position towards the company in light of:
  - Their experience in relation to the company (e.g. customer service, product and service proposal).
  - Knowledge of the company obtained from external agents (e.g. press reports, legal disputes involving the company or pressure groups).
  - Positioning with regard to the company (e.g. cooperation, permanence, flight).
  - Perception of the company (e.g. trust, positive image).
- The second or RIT phase applies different statistical techniques to the SPI data obtained, including factorial analysis, Cronbach's alpha and regression analyses to ensure that results are robust and significant. These techniques are used to identify the key reputational drivers, whether positive or negative, allowing the business to take appropriate action.

Analysis of the data obtained from the questionnaires may be utilized as a decision-making tool, to benchmark the company to competitors or as an informational measure.

[74] Fombrun, C. J., Gardberg, N. A., and Sever, J. M. (2000).

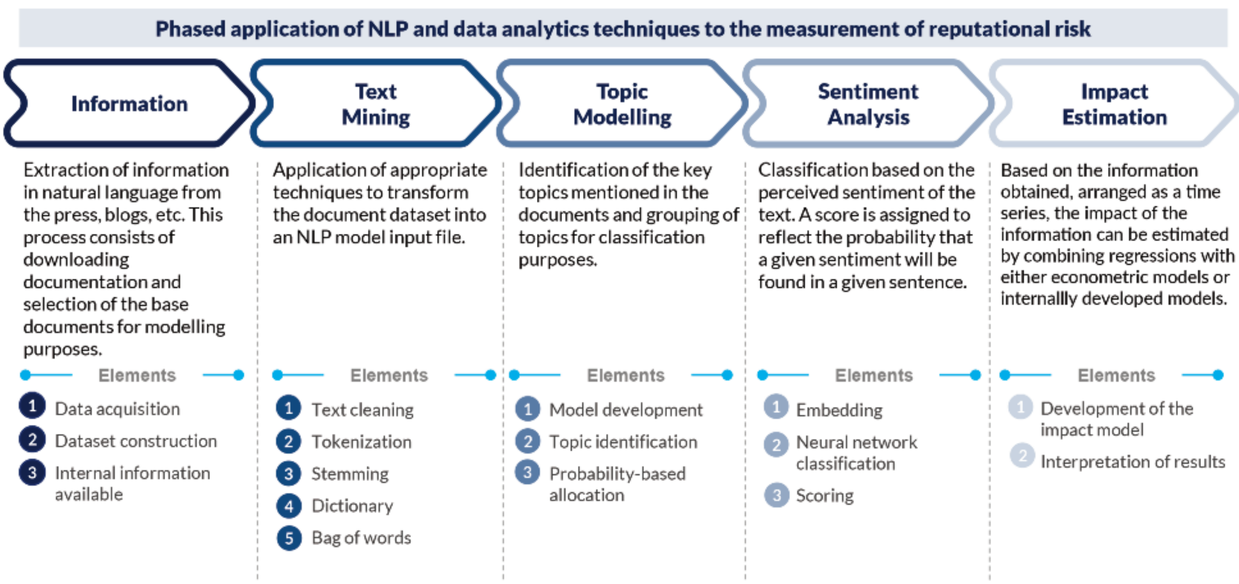
- **Data extraction**[75]**.** The first step consists of obtaining the data sets for analysis, which involves seeking external sources[76] like web pages, ,online news, blogs or social networks. A search is run, filtered according to the type of news reports analysed (business, politics, social, etc.), to obtain relevant information for the measurement of reputational risk. The depth and volume of the data will depend on the information sources consulted in this process.

- **Data mining**[77]. Cleaning and pre-processing the data is a common step in all advanced analytics practices, and it constitutes a key phase in the modelling process. In natural language processing, the pre-processing stage consists of the application of different filters to erase noise, redundant words and words that provide no information so as to obtain a structured text data set. The main techniques utilized comprise (i) text cleaning, which consists of the elimination of stop words, line breaks, punctuation signs or certain numbers of the document set; (ii) tokenization, which involves the creation of a marker or token for each word in the document set; (iii) lemmatization, reducing words to their base form; iv) dictionary, which consists of the allocation of a numerical identifier to each individual word; v) bag-of-words modeling of the probability that each word in the dictionary is in the document set.

- **Topic modelling.** Topic modelling is used to extract, compress and group data obtained from a document set by ideas and subjects. One of the first such models is based on TF-IDF type algorithms, which assign weightings to each term depending on frequency in each document. However, this model is not particularly useful when it comes to extracting the main topics contained in a text or establishing relationships between the different terms used. This led to further development utilizing probabilistic and Bayesian models like LDA[78], which allow topic extraction by modelling data generation based on probability distribution. Other more advanced models like DTM[79] are capable of extracting topics and analysing their behaviour over time. The basic idea behind these models is that a topic associated with a data set can be represented by means of a probability distribution for the words contained in a given dictionary[80], and that this text will in turn be made up of a specific topic distribution.

[75] Salton, G., and McGill, M. (1983).
[76] Mitchell R. (2018).
[77] Feldman, R., and Sanger, J. (2006).
[78] *Latent Dirichlet Allocation,* one of the most commonly used models. Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003).
[79] Dynamic Topic Modelling. Blei, D., and Lafferty, J. (2006).
[80] Mei, Q., Shen, X. and Zhai, C. (2007).

Figure 8. Phased application of NLP techniques to the measurement of reputational risk.



- **Sentiment analysis.** This analysis includes sentiment metrics when classifying opinions in order to improve the measure of the impact of these opinions on an organization's reputation. Different processes are used for this purpose, including (i) embedding (transforming each word into a numerical vector containing both the word itself and its context; (ii) neural network training (typically based on BERT or LSTM[81]) to enable the detection of patterns in relatively large data sequences; and (iii) sentiment scoring based on the characteristics extracted.

- **Impact estimation.** Finally, the impact of a given indicator's output or the output of a company management model (e.g. corporate value) is modelled. The estimation model used in this procedure must combine the NLP techniques developed in order to obtain the impact of reputational events.

Reputational risk map

The reputational risk map allows tracking of the principal impact risks affecting a company's reputation and, therefore, its results[82]. The aim of this technique is to obtain information to facilitate decision-making in order to strengthen perceptions of the entity's reputation and to mitigate the principal threats (Figure 9):

- The risk map is designed to identify the principal risk factors that could affect the corporate reputation and to allow their evaluation in terms of correlations, frequency of occurrence, severity of materialization and management policy.

- Indicators and metrics are defined to track the corporate reputation scores obtained for each stakeholder group, so as to allow analysis of the correlation and impact of both internal and external factors on the entity's reputation score.

[81] Staudemeyer, R. C., and Morris, E. R. (2019).
[82] For example, Groupe BPCE has proprietary reputational risk maps allowing it to spot risk events, classify them based on severity and undertake active management of the risks concerned (BCPE, 2019).

Figure 9. Strategic and operational tools used in the management of reputational risk.

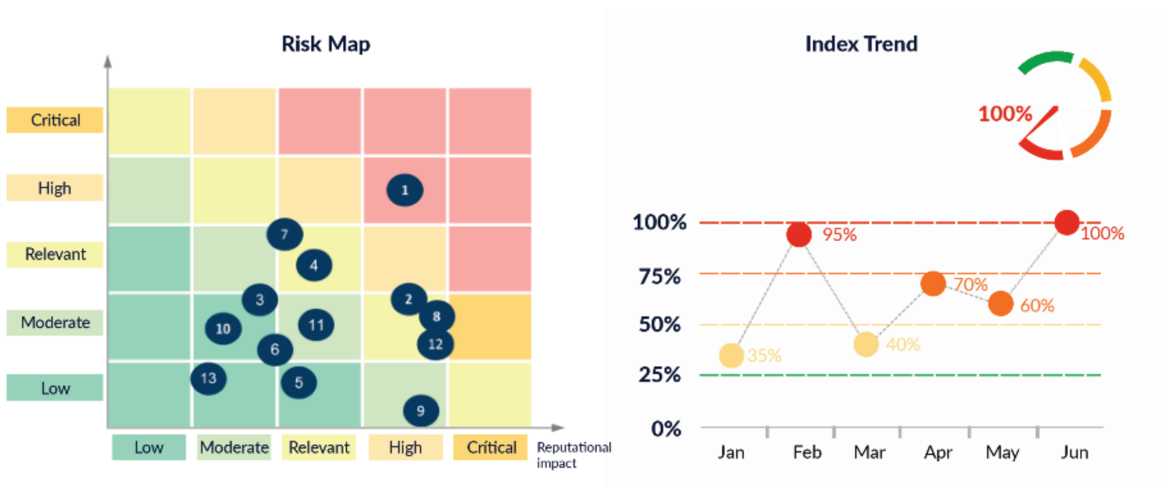


Figure 10. Management integration of reputational risk.

Management integration

Various different levers must be activated if reputational risk is to be integrated in management, ensuring careful consideration of the relevant factor in decision-making processes (Figure 10):

- Development of management tools to include factors such as: (i) the inclusion of reputational risk in the definition of risk appetite (including indicators and limits for the deterioration of internal and/or external reputational risk indices; (ii) design, implementation and tracking of anticipative management metrics (e.g. appearance of negative topics in the media) and definition of front line goals; (iii) development of an appropriate internal reporting system to provide an executive's eye view of reputational risk status and trends in different fields (business units, geographical units, division or department, etc.); or (iv) preparation of contingency plans to ensure the immediate adoption of measures wherever an adverse reputational event may occur.

- Active role for the reputational risk control function by assuring (i) participation in the assessments of the level of risk inherent in relevant transformation processes and in the organization's overall change management procedures; (ii) involvement in the management of specific risks (e.g. via the processes involved in the definition and approval of new products, cybersecurity management, etc.); or (iii) development of risk intelligence (e.g. encouraging the use of artificial intelligence techniques for pattern recognition, topic definition and analysis of the correlation of risks with corporate value).

- Consideration of reputation as a factor in the organization's strategic processes, including (i) budget processes, (ii) capital[83] and liquidity[84,85] planning processes, and (iii) simulations, scenario analysis and stress tests.

- Support for a corporate culture of reputational risk awareness to ensure (i) that the first line of defence is aware of risks, for example by identifying events that affect reputation and defining the associated communication flows; (ii) proper communication and training for both the first line of defence and the reputational risk department itself; or (iii) integration of additional "culture and behaviour" factors to involve Senior Management in the development of a value-based culture (honesty, personal responsibility, etc.) and its communication to stakeholders[86].

[83] ECB (2018a), para. 59.
[84] ECB (2018b), para. 57.
[85] Processes of this kind are known in the financial industry as Internal Capital Adequacy Assessment Processes (ICAAP) and Internal Liquidity Adequacy Assessment Processes (ILAAP), which are governed in both cases by specific regulations.
[86] Some regulators, such as the FCA in the UK, publish information of this kind online (FCA, 2018).

Quantitative techniques applied to reputational risk: a case study

"When you can measure what you are speaking about, and express it in numbers, you know something about it; but (…) when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind"
Lord Kelvin[87]

There is a tendency in the industry towards quantitative reputational risk management that is based on the collection of data and is not, therefore, solely qualitative or expert knowledge. This quantitative management involves continuous, active listening to the information published about a company or industry, which requires the use of NLP[88] techniques for interpretation and measurement given the volume of data concerned and the fact that it is expressed in natural language.

In this regard, the quantification of reputational risk is a peculiarly complex task, given that the data measured is drawn not from controlled, reliable, internal sources as in the case of other risks, but from unstructured external sources that usually offer scant guarantees in terms of quality or integrity.

As mentioned in the preceding section, the quantification of reputational risk allows effective management and control through the observation, interpretation, analysis and assessment of the factors involved employing objective criteria.

This section presents a case study of the quantification of certain reputational risk indicators applying these tools in order to illustrate the latest trends and potential of NLP techniques and topic modelling in the quantitative management of risk.

The calculations presented in this case study were made using the advanced reputational risk management tool[89, 90], which uses artificial intelligence and NLP techniques to measure reputational risk based on information obtained from the media and social networks.

In the following discussion we begin by describing the tool used and then go on to address the approach taken in the study and to summarize its main findings, and we end by explaining the key methodological issues in more detail from a technical standpoint.

An artificial intelligence tool applied to reputational risk

The tool is designed to calculate the impact that public information has on key corporate indicators (share price, sales, revenues, etc.) over time allowing active management of reputational risk aligned with regulatory requirements.

In other words, the tool seeks to provide answers to the following questions:

- What do the media and social networks say about my company?
- What are the key concepts appearing in the media?
- What is the impact on my company?
- How do the media and social networks impact my key corporate indicators (share price, revenues, deposits, etc.)?

[87] William Thomson, Lord Kelvin (1824-1907), was a British physicist and mathematician who is famous for his efforts to modernize physics and for inventing the Kelvin temperature scale.

[88] Natural Language Processing is a discipline in Artificial Intelligence and Linguistics concerned with the automated processing and analysis of large volumes of natural language.

[89] Developed by Management Solutions and mrHouston after a research and development program lasting several years.

[90] mrHouston (mrhouston.net) is a technological solutions firm specializing in artificial intelligence and software development, which carries out R&D work for the European Social Fund, Spain's Centre for Industrial and Technological Development and the Spanish Government's Enabling Digital Technologies program.

In outline, then, the solution:

- Is fed by a body of natural language texts such as digital press reports, mentions in social networks or online texts obtained from different websites, filtered for relevance;
- Pre-processes this corpus using data mining techniques, eliminating information lacking semantic value (prepositions, conjunctions, etc.), and it transforms it into word sets suitable for modelling;
- Obtains the semantic core, i.e. the concepts to which the words refer, from the texts using NLP topic modelling techniques, which allow definition of the topic concerned as recurring patterns in the appearance of groups of words together in a text. For example, if the words "bank", "services", "customers", "savings", "current accounts" and "loans" appear together in a news report, the topic will be identified as "banking";
- Uses the topics defined to build time series showing their importance over time, so that the specific days on which a given topic was relevant in terms of the number of mentions in the press or social media can be observed; and
- Calculates the correlation of the time series for the appearance of each topic with other time series provided by the user, so that it is possible to reckon the influence of a given topic (e.g. money laundering) on a given indicator (e.g. share price).

Applied to the quantification of reputational risk, this solution can determine the specific reputational events, defined by way of topics, that impact a company's performance over time, and to what extent.

One key feature of the tool is that it does not require any a priori information to identify the topics, i.e. it is not necessary to specify that the object is to establish the influence of a given item (e.g. the publication of stress test results) on reputation. The tool simply analyses the body of texts and automatically identifies the key topics using artificial intelligence.

Finally the tool is equipped with an interactive visualization layer (Figure 11) to make it easier to compare time series or to determine what specific news items have generated an increase in the importance of a topic on a given day, and in general to arrive at an intuitive understanding of the connection between topics and their impact on the time series analysed. Through this tool, the user is able to identify topics that impact on the reputation of the organization or of other organizations in the industry, and measure that impact.

Study approach and procedure

The case study is designed to show the procedure employed in the quantification of reputational risk by means of topic modelling using the tool described. Specifically, the tool analyses online reports appearing in the leading digital financial media to identify the reputational events that had an impact on various major European banks[91] over the period 2018-2020 and then goes on to quantify that impact.

To this end, a digital press provider was used as the data source and, after screening by articles related to the financial industry within the desired time window, the medium that covered

[91] For reasons of confidentiality, the banks cannot be named in this case study.

Figure 11. Representation of the time series for various firms.

European financial topics in greatest depth was selected from all other digital media, resulting in a corpus of over 3,000 news reports.

In other words, the reputational impact is measured in terms of the residual series remaining after eliminating the market trend in the share price.

For example, if a case of money laundering affecting a bank is reported in the news, the market reaction will be a sharp fall in its share price that will be differentially sharper than any fall affecting other entities. What this study seeks to quantify is precisely the size of this drop based on the trigger reputational event measured as the difference with respect to the central market trend.

Hence, the time series used to measure the impact of the reputational events observed for each bank analysed was constructed as follows:

- We take the time series (z_i) for the simple return on each bank's share price over the period of the analysis, which we will call the "share price" series.
- We take the time series (m_i) for the simple return on a stock market index of financial entities, which we will call the "market series"
- The time series used to measure the impact of the reputational events is the difference ($r_i = z_i - \beta m_i - \alpha$) between the first time series and a linear adjustment obtained using the second time series as the regressor, which we will call the "residual series".

In other words, the reputational impact is measured in terms of the residual series remaining after eliminating the financial market trend in the share price.

For example, if a case of money laundering affecting a bank is reported in the news, the market reaction will be a sharp fall in its share price that will be differentially sharper than any fall affecting other entities. What this study seeks to quantify is precisely the size of this drop based on the trigger reputational event measured as the difference with respect to the central market trend.

Figure 12 shows the residual series for one of the banks analyzed and the series showing the aggregate impact of the most influential topics. In this case, topics that had a positive influence included "fight against climate change" (the bank announced a program on this topic) and "EU Court of Justice "(there was a ruling in favor of the bank); whilst topics with a negative influence included "net profit" (the bank's performance was worse than expected) and "current account fees" (an increase in fees was announced).

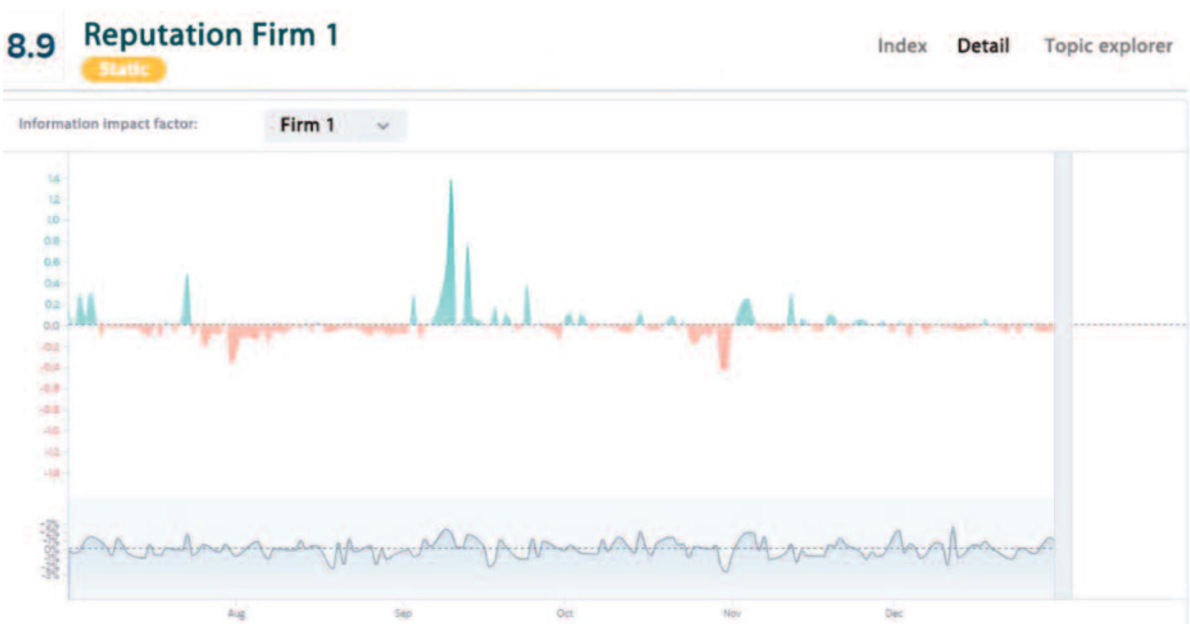
Thus, each of the topics shows a certain correlation with the residual series for each bank, which is to say it explains a certain percentage of movements in the share price that cannot be explained by reference to market trends.

Key findings

The key findings obtained from the case study are as follows

- Share price movements are largely unrelated to market trends, but are rather explained by specific reputational

Figure 12. Residual series from one of the firms analyzed (below) and from the impact of the topics on its reputation (above).



events (share price movements of up to 5% in the space of one day due to reputational impacts were observed from this study)[92].

- The most significant of these events are related to the organization's performance, climate change, legal disputes and pricing decisions (increased fees in this case).

- As may be observed, the reputational events with the greatest impact are both negative and positive, supporting the intuition that active reputation management can have a direct, positive impact on a firm's performance.

- Specifically, a non-stable fraction of each entity's capital, which can be up to 5% in light of our results, is exposed to very rapid fluctuations due solely to reputational events

Above and beyond the specific terms of this case study, it appears from the results obtained that an analysis of this nature can not only identify the key issues arising for reputation management but can also quantify them, allowing decision-making with regard to the factors concerned.

Finally, this study employs a series of hypotheses and assumptions, which will logically vary depending on the specific scenarios analysed. Key assumptions include the following:

- The identification of relevant topics is conditioned by the selection of an appropriate information source and an adequate set of news items, as well as the media presence of the companies analysed. The tool chosen determines which document series is selected for measuring the impact, and its quality.

- The time series explained are based on public information concerning the share price of each entity, and the study was designed to capture very short-term impacts. Companies supplement studies of this kind with internal series (e.g. daily sales, transactions, deposit in- and outflows) based on different frequencies as part of their reputational risk management procedures. This allows assessment of the impact of reputational events in other dimension and over periods established for management purposes.

- For the sake of simplicity and clarity, we used simple methodological assumptions in order to avoid the application of more complex techniques to identify market trends and trends in the fundamentals for each stock analysed, among other matters. The assumptions made would in all probability be more sophisticated in studies carried out for internal management purposes.

To conclude, news reports were transformed into topics applying recent advances in the field of NLP and their impact on a selection of major banks was then measured to confirm and quantify the influence of reputational events on the performance of each entity.

Despite the promise they hold out in the area of reputational risk management, further research into these methodologies and their application is still needed.

[92] A typical measure of the simple daily return (its standard deviation) in this study is 1%, of which the market is able to explain 40%, with residuals left at approximately 0.6%. On average, standard reputational events can explain around 25% of the daily fluctuations in the residual series, which leaves intrinsic fluctuations at 0.5%.

Methodology

Data mining

Pre-processing of the texts used is an essential step to obtain significant results, because it is here that the text is transformed into the kind of data that can be used in the model. The processes applied in this case were as follows:

- *Part-of-speech* (POS) *tagging*: this process converts the text into elements that the model algorithms can understand. In this case, each phrase was converted into a tuple formed by pairs (token[93], tag[94]).
- Elimination of superfluous elements for the semantics of the text, such as punctuation, numbers, symbols and stop words (words tagged as determiners, conjunctions, interjections and so on).
- Conversion to lower case.
- Lemmatization of the resulting tokens so as to reduce inflected words to their basic form.
- Elimination of tokens containing less than the minimum number of characteristics established or occurring less frequently than the threshold defined.
- Elimination of duplicate or near duplicate documents. Many articles vary by just a few words, and their duplicates should not be used in the analysis.

The tokens resulting from the pre-processing exercise comprise the dictionary utilized for the extraction of topics.

[93]Tokens are the elementary elements into which a text can be broken up (e.g. paragraphs, sentences, words, syllables).
[94]In the present case, tags are grammatical categories (noun, verb, article, etc.), although they may also include number, grammatical gender, time and other inflexions.

Automated topic tagging

A topic will usually be found in the presence of 5-10 keywords, i.e. words reflecting a higher probability $p(w_i \mid z_i)$. However, it may sometimes be difficult to infer a tag that encompasses all of these terms, which may also require manual work on the part of the analyst, introducing a propensity to subjectivity.

It is in this context that automated topic tagging comes in. The aim of this technique is to automatically assign one or more descriptive tags to represent each topic. This problem is relatively new and still the subject of research in the field of NLP.

The first paper to formulate the problem was published in 2007[95]. The authors propose a probabilistic approach to reach a solution in two steps: (i) identification of a set of candidate tags, and (ii) design of a relevance scoring function to measure the similarity between the tag and the topic.

This two-step approach constitutes the basis for the majority of subsequent proposals, which focus on enhancing the quality of the candidate tags (e.g. using external sources) or on the development of methodologies to select the best candidate tag (e.g. via supervised classification model training based on the characteristics of the tags).

In this context, a solution based on the use of graphs was used to identify[96]:

- Extraction of candidate tags.
- Creation of a link graph showing the semantic relations between the candidate tags in order to identify those which are relevant and eliminate redundant or less informative tags.
- Generalization of the resulting tags and combination with aggregation patters, where possible.

[95]Mei, Q., Shen, X. and Zhai, C. (2007).
[96]This methodology is based on Mehdad, Y., Carenini, G., Ng, R., and Joty, S. (2013).

Topic modelling

In order to assess the relationship between news items and market movements, each document must be reduced to a numerical vector using topic modelling techniques.

To begin with, a bag of words (BoW) was generated to represent each document as a set of words and frequencies. An alternative would have been to use TF-IDF (term frequency – inverse document frequency) transformation to measure the relevance of the words instead of their frequency, substituting word counts for TF-IDF scores for the complete document.

We then proceeded with topic modelling. Various algorithms can be used for this purpose[97]: including LSA, pLSA, NMF, LDA, BTM, DTM, cDTM and ATM, among others. In this case, we opted for a Latent Dirichlet Allocation or LDA, which is about representing documents as a distribution of topics, each of which is characterized by a given distribution of words. Using this method, a document can be broken down into a mixture of topics so that the fraction of its contents corresponding to each topic can be determined. Numerous libraries can be used for the application of this procedure, Although numerous libraries can be used for applying this procedure, for reasons of efficiency and to better control the interactions between the topics and the time series, we developed an exclusive model that is detailed later in this document.

After training the model with k topics, each document d of the corpus is represented by a k-dimensional vector $\theta_d=(\theta_{d,1},\theta_{d,2},\ldots,\theta_{dk})$. The terms of this vector may be interpreted as the probabilities associated with each topic, and their sum is therefore one.

As regards the time series, the purpose of the case study is to quantify the impact of news items on daily trends in market movements. To this end, we carried out a temporal aggregation to ensure the same granularity in each of the time series[98].

[97]Listed in chronological order of appearance in scientific circles.
[98]For more details on the impact calculation process, see Cendrero, J. et al. (2021).

A model combining topics and time series

A time series of numerical data and a sequence of texts in time order can often show a strong correlation. A paradigmatic example is the correlation between economic or political news and share price index movements[99,100]. Another example is the potential economic impact that reputational events published in the press and on social networks have on organizations. This correlation is examined in the study: quantifying reputational risk[101].

To analyze these types of correlations, text regression often takes a TF or TF-IDF[102] representation of documents as input to predict a time series[103]. A weight is obtained for each word in the vocabulary, thus determining each document's contribution to predicting the dependent variable. There are arguably two key downsides to this approach: first, there is a high risk of overfitting, since there are as many regressors as there are words in the vocabulary; second, outcome interpretability is poor.

Both problems can solved by using "Topics"[104,105], instead of words as the explanatory variables. Thanks to reduced dimensionality, the number of features needed to represent a document is much lower than the number of words, which leads to better performance due to reduced overfitting. Besides, themes contain greater semantic meaning than words, allowing better interpretation of results.

Topic modeling has become a standard technique for discovering the hidden structure of texts. A topic is defined as a probability distribution over a vocabulary of words. Consequently, a document made up of a large number of words from that vocabulary can be modeled as a probability distribution over a reduced number of topics, each representing[106] an underlying semantic theme.

Recent studies[107] have analyzed and developed a new combined model that takes a corpus of documents and a numerical time series as inputs, and produces a collection of topics that are specially tailored to act as regressors for the given time series together with the values of their regression coefficients. This model is intended to achieve the following three objectives:

- Automatically select only topics from the corpus showing a significant correlation with the time series, and discard those that are not correlated.
- Quantify the (positive or negative) impact of each chosen topic on the time series.
- Avoid overfitting by using appropriate regulators (Lasso/ElasticNet), and adjusting them by trying to predict the value of the time series on documents with dates not used in the training sample.

This model solves several of the limitations shown by other recently proposed models.

[99]Mahajan, A., Dey. L., and Haque, S. M. (2008).
[100]Pui Cheong Fung, G., Xu Yu, J., and Lam, W. (2002).
[101]Fombrun, C. J., Gardberg, N. A., and Barnett, M. L. (2000).
[102]Spärck Jones, K. (1972).
[103]Kogan, S., Levin, D., Routledge, B. R., Sagi, J. S., and Smith, N. A. (2009).
[104]Hofmann, T. (1999a).
[105]Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003).
[106]Hofmann, T. (1999a) y Hofmann, T. (1999b).
[107]Cendrero, J. et al. (2021).

Latent Dirichlet Allocation (LDA)

Latent Dirichlet Allocation[108] is one of the most commonly used topic modelling techniques. It is a Bayesian[109] version of the earlier pLSA (Probabilistic Latent Semantic Analysis), which applies probabilistic methods rather than breaking data down into singular values. More specifically, it consists of a 3-level hierarchical Bayesian model.

The basic assumptions made in the model are:

The documents are represented as a random mixture of topics, i.e. each document contains a mixture of topics.

The topics are characterised by a multinomial word probability distribution

For ease of understanding of the generation process, the notation utilized is as follows:

V is the total number of terms/words

D is the total number of documents

A document is a sequence of N words denoted by $w=\{w_1,w_2,\ldots,w_N\}$, where w_n refers to the nth word of the document

α is the Dirichlet distribution parameter in the distribution of topics by document

ξ is the Poisson distribution parameter that models the number of words N as a random variable

θ refers to the distribution of topics for the document

k is the number of topics

$z=\{z_1,z_2,\ldots,z_N\}$ is the sequence of topics associated with each word, where z_n denotes the topic associated with the nth word of the document

β is a matrix with dimensions $k \times V$, where $\beta_{ij}=P(w_j=1|z_i=1)$,), which is the probability that a word j is associated with topic i

Accordingly, for a fixed number of topics k and a vocabulary of V words, the generative process assumed by the model for each document is:

Choose N ~ Poisson(ξ)

Choose θ ~ Dir(α)

For each of the N words of the document ($i \in \{1, \ldots, N\}$):

Choose a topic z_i ~ Multinomial(θ)

Choose a word w_i de $P(w_i|z_i,\beta)$, being the multinomial distribution of words conditional upon the topic

In this generative model, the random variable N, may, for the sake of simplicity, be considered a constant set a priori, because the topic probabilities are independent of the variable's random nature. Meanwhile, the word probabilities are parametrized by the matrix β, the values of which are treated as fixed quantities to be estimated in first approximation.

Likewise, θ refers to the distribution of topics for a given document, following a Dirichlet distribution of the k-dimensional parameter α. This distribution is a multivariant generalization of the beta distribution and the conjugate of the multinomial distribution:

$$p(\theta|\alpha) = \frac{\Gamma(\sum_{i=1}^{k}\alpha_i)}{\prod_{i=1}^{k}\Gamma(\alpha_i)}\theta_1^{\alpha_1-1}\cdots\theta_k^{\alpha_k-1}$$

Figure 13 shows a graphic representing this generative model. The nodes represent the model parameters and the random variables, while the links represent the dependencies between them.

As may be observed, this is a 3-level hierarchical Bayesian model. The parameters α and β are found in the first level, as the variables relating to the level of the corpus. The second level is formed by variable θ, referring to the documents. Finally, the variables z and w make up the last level, which refers to the words.

The topic modelling technique described here is a problem of Bayesian inference. As such, the aim is to calculate the a posteriori distribution $P(\theta,\bar{z}|\bar{w},\alpha,\beta)$. However, the analytical calculate of this distribution is unviable. Hence, various different procedures must be used to approximate the distribution, including Gibbs sampling[110], the use of Markov Monte Carlo chains (MCMC)[111], and variational Bayesian methods[112].

[108] See Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003) for further information..

[109] Bayes theorem is used in Statistics to update probabilities via the inclusion of new data or events. It is expressed as the conditional probability of an event A depending on B:

$$P(A\backslash B) = \frac{P(B\backslash A)P(A)}{P(B)}, \quad P(A\backslash B) = \frac{P(A \cap B)}{P(B)}$$

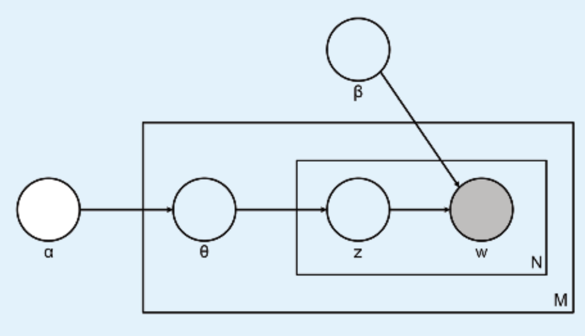
[110] Yildirim, I. (2012).

[111] Geyer, C. (2011).

[112] Tzikas, D.G., Likas, A.C. and Galatsanos, N.P. (2008).

[113] Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003).

Figure 13. Representation of the LDA[113]



Concluding remarks

"I think I'll leave it here"
Sir Andrew Wiles[114]

As explained above, reputation is a valuable intangible asset, and in this light firms have become increasingly interested in its measurement and management. Furthermore, the digital era has allowed ever greater and faster access to information, accelerating and enormously amplifying the reputational risks and thereby creating the need to enhance management in this area.

In heavily regulated industries, supervisors have increasingly stressed the need to learn more about reputational risks and to improve knowledge, measurement and management of the factors in play, which by their nature are tightly interwoven with other risks and involve all of an organization's multiple functions and departments.

In this context, organizations have begun to address the management of reputational risk by developing management frameworks to define governance and organizational structures, establish policies, design reputational risk maps and develop tools to allow risk tracking and effective management.

However, the quantitative management of reputational risk is extremely complex, given its intangible nature. To solve this problem, conventional measurement mechanisms have increasingly been supplemented by advanced models and analytics, bringing in machine learning, artificial intelligence and natural language processing techniques. These techniques allow processing of mass data extracted from news items, reports and communications produced in different formats, including unstructured information. However, results are highly dependent on the data used, and the selection of sources, data quality and currency are key aspects of the process. It is also essential to have in place effective procedures and robust models to allow the consistent extraction of patterns.

The development and use of these techniques still involve serious challenges in what remains an ongoing process. Many techniques are strongly reliant on the training language, which can be a major stumbling block for multinational organizations. Meanwhile, the results generated by the techniques used still require interpretation by a person, again reflecting the need to develop additional mechanisms (e.g. topic tagging techniques).

In any event, the expected trend is for the development of quantitative reputational risk management tools to continue in the future, as they gradually become established as essential elements in the risk management frameworks of large organizations.

[114] Sir Andrew Wiles (n. 1953), is a British mathematician who is famous for having proved Fermat's Last Theorem, a problem that had remained unsolved for more than 350 years. He used these words to conclude the public lecture at which he astonished the world in 1993.

References

Basel Committee on Banking Supervision (BCBS). (2006). Basel II: International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version.

Basel Committee on Banking Supervision (BCBS). (2009). Enhancements to the Basel II framework.

Basel Committee on Banking Supervision (BCBS). (2011). Principles for the Sound Management of Operational Risk.

Basel Committee on Banking Supervision (BCBS). (2015). Corporate governance principles for banks.

Basel Committee on Banking Supervision (BCBS). (2017). Guidelines Identification and management of step-in risk.

Basel Committee on Banking Supervision (BCBS). (2019). Principles for sound stress testing practices and supervision.

Basel Committee on Banking Supervision (BCBS). (2020). Guidelines Sound management of risks related to money laundering and financing of terrorism.

Blei, D., and Lafferty, J. (2006). Dynamic topic models. Proceedings of the 23rd international conference on Machine learning.

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent dirichlet allocation. The Journal of machine learning research, 3, 993-1022.

BPCE (2019). Grupo BPCE. Informe de Pilar III. 2019.

Cendrero, J. et al. (2021). Time Series Impact Driven by Topic Modeling, submitted. To request a draft, please send an email to izapata@mrhouston.net

COSO (2018). Enterprise Risk Management. Applying enterprise risk management to environmental, social and governance-related risks.

Curme, C., Zhuo, Y., Moat, H. S., and Preis, T. (2017). Quantifying the diversity of news around stock market moves. Chester Curme, Ying Daisy Zhuo, Helen Susannah Moat and Tobias Preis, Quantifying the diversity of news around stock market moves, Journal of Network Theory in Finance, 3(1), 1-20.

Durán F. (2004). Guía sobre el gobierno corporativo de las sociedades cotizadas. Manual de la empresa responsable.

European Banking Authority (EBA). (2017). EBA/GL/2017/10. Guidelines on major incident reporting under Directive (EU) 2015/2366 (PSD2).

European Banking Authority (EBA). (2018). EBA/GL/2014/13. Guidelines on common procedures and methodologies for the supervisory review and evaluation process (SREP) and supervisory stress testing.

European Banking Authority (EBA). (2020). BA/REP/2020/01. Final Report on Big Data and Advanced Analytics.

European Central Bank (ECB). (2018a). Guide to the internal capital adequacy assessment process (ICAAP)

European Central Bank (ECB). (2018b). Guide to the internal liquidity adequacy assessment process (ILAAP)

European Central Bank (ECB). (2020). Guide on climate-related and environmental risks

Feldman, R., and Sanger, J. (2006). Text Mining Preprocessing Techniques. In The Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data (pp. 57-63). Cambridge: Cambridge University Press.

Financial Conduct Authority (FCA). (2018). Transforming Culture in Financial Services.

Financial Stability Board (FSB). (2013). Principles for an Effective Risk Appetite Framework.

Financial Stability Board (FSB). (2018). Supplementary Guidance to the FSB Principles and Standards on Sound Compensation Practices.

Fiordelisi, F., Soana, M. G., and Schwizer, P. (2013). The determinants of reputational risk in the banking sector. Journal of Banking & Finance, 37(5), 1359-1371.

Fombrun, C. J., Gardberg, N. A., and Barnett, M. L. (2000). Opportunity Platforms and Safety Nets: Corporate Citizenship and Reputational Risk. Business and Society Review, 105(1):85–106.

Fombrun, C. J., Gardberg, N. A., and Sever, J. M. (2000). The Reputation Quotient SM: A multi-stakeholder measure of corporate reputation. Journal of brand management, 7(4), 241-255.

Foro de Reputación Corporativa. (2011). Reputación Corporativa. Introducción a la gestión de los riesgos reputacionales.

Gatzert, N. (2015). The impact of corporate reputation and reputation damaging events on financial performance: Empirical evidence from the literature. European Management Journal, 33(6), 485-499.

Geyer, C. (2011). Introduction to markov chain monte carlo. Handbook of markov chain monte carlo, 20116022, p.45.

Gomez-Trujillo, A.M., Velez-Ocampo, J. and Gonzalez-Perez, M.A. (2020). A literature review on the causality between sustainability and corporate reputation: What goes first?, Management of Environmental Quality, Vol. 31 No. 2, pp. 406-430.

Hart, O. (1995). Corporate governance: some theory and implications. The economic journal, 105(430), 678-689.

Harvard Business Review (2007). Reputation and its risks.

Hofmann, T. (1999a). Probabilistic Latent Semantic Analysis. In Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence, pages 289—-296, Stockholm, Sweden, 1999. Morgan Kaufmann Publishers Inc.

Hofmann, T. (1999b). Probabilistic Latent Semantic Indexing. Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 50–57, 1999.

Honey, G. (2009). A Short Guide to Reputation Risk. Gower, Abingdon.

Hong Kong Monetary Authority. (2008). Supervisory Policy Manual (SPM) RR-1 Guidance on Reputation Risk Management.

International Organization for Standardization (ISO). (2018). ISO 31000:2018. Risk management — Guidelines.

Jurafsky D. and Martin J.H. (2020). Speech and Language Processing.

Kogan, S., Levin, D., Routledge, B. R., Sagi, J. S., and Smith, N. A. (2009). Predicting Risk from Financial Reports with Regression. In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, number June, pages 272–280, Boulder, Colorado, 2009. Association for Computational Linguistics.

MacMillan, K., Money, K., Downing, S., & Hillenbrand, C. (2004). Giving your organisation SPIRIT: an overview and call to action for directors on issues of corporate governance, corporate reputation and corporate responsibility. Journal of General Management, 30(2), 15-42.

Mahajan, A., Dey. L., and Haque, S. M. (2008). Mining Financial News for Major Events and Their Impacts on the Market. In 2008 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, volume 1, pages 423–426. IEEE, 2008

Management Solutions. (2020). Auto Machine Learning, hacia la automatización de los modelos.

Mehdad, Y., Carenini, G., Ng, R., and Joty, S. (2013). Towards topic labeling with phrase entailment and aggregation. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (pp. 179-189).

Mei, Q., Shen, X. and Zhai, C. (2007). Automatic labeling of multinomial topic models. In Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 490-499).

Mitchell R. (2018). Web scraping with Python. O'Reilly Media.

Organisation for Economic Co-operation and Development (OECD). (2020). Forum on Tax Administration: Enhancing Reputational Risk Management.

Parlamento Europeo y Consejo de la Unión Europea (2013a). Directiva 2013/36/UE.

Parlamento Europeo y Consejo de la Unión Europea (2013b). Reglamento (UE) No 575/2013.

Perry, J. and Fontnouvelle, P. (2005). Measuring Reputational Risk: The Market Reaction to Operational Loss Announcements. SSRN eLibrary, 1-33.

Pui Cheong Fung, G., Xu Yu, J., and Lam, W. (2002). News Sensitive Stock Trend Prediction. In MS. Chen, P.S. Yu, and B. Liu, editors, Proceedings of the 6th Pacific-Asia Conference on Advances in Knowledge Discovery and Data Mining, volume 2336, pages 481–493, Berlin, Heidelberg, 2002. Springer-Verlag.

Raithel, S. and Schwaiger, M. (2014). The effects of corporate reputation perceptions of the general public on shareholder value. Strategic management journal, 36(6), 945-956.

Salton, G., and McGill, M. (1983). Introduction to modern information retrieval. McGraw-Hill.

Scandizzo, S. (2011). A framework for the analysis of reputational risk. The Journal of Operational Risk, 6(3), 41.

Spärck Jones, K. (1972). A statistical interpretation of term specificity and its application in retrieval. Journal ofDocumentation, 28(1):11–21, 1972.

Staudemeyer, R. C., and Morris, E. R. (2019). Understanding LSTM--a tutorial into Long Short-Term Memory Recurrent Neural Networks.

The Economist Intelligence Unit. (2005). Reputation: risk of risks.

The Economist Intelligence Unit. (2019). How to identify reputational risks.

Tzikas, D.G., Likas, A.C. and Galatsanos, N.P. (2008). The variational approximation for Bayesian inference. IEEE Signal Processing Magazine, 25(6), pp.131-146.

Walter, I. (2008). Reputational risk and conflicts of interest in banking and finance: the evidence so far. In Variations in Economic Analysis (pp. 75-97). Springer, New York, NY.

Wijers, G., Liefers, R., & Halfhide, O. (2012). Toward a successful Target Operating Model.

Yildirim, I. (2012). Bayesian inference: Gibbs sampling. Technical Note, University of Rochester.

Glossary

Sentiment Analysis: the set of methods, techniques and tools allowing the extraction of emotional meaning from natural language.

Bag of words: a technique that represents each document numerically based on the frequency with which each token appears.

Reputational quotient: standardized corporate reputation measure used to understand the perceptions of stakeholders via analysis of reputational categories.

ESG (Environmental, Social and Governance): criteria: a series of standards for the measurement of sustainability and the social impact of investments.

ICAAP (Internal Capital Adequacy Assessment Process): internal capital adequacy self-assessment process applied in the banking industry.

ILAAP (Internal Liquidity Adequacy Assessment Process): internal liquidity adequacy self-assessment process applied in the banking industry

KRIs (Key Risk Indicators): risk management metrics used to indicate the risk inherent in an activity.

LDA (Latent Dirichlet Allocation): one of the most commonly used topic modelling techniques.

Lemmatization: a technique used to reduce inflected works to their basic form.

Machine Learning: the field of computer science concerned with the development of techniques to enable a program to find patterns in a data set.

SPIRIT model (Stakeholder Performance Indicator, Relationship Improvement Tool): the series of procedures and techniques used to analyse the data obtained from surveys in order to identify key business drivers.

Natural Language Processing: a discipline in Artificial Intelligence and Linguistics concerned with the automated processing and analysis of natural language.

Stemming: technique used to reduce an inflected word to its root.

Stop words: words that lack any semantic meaning, such as determiners or prepositions.

Target Operating Model (TOM): description of an organization's target operating model.

TF-IDF: technique used to represent each document numerically taking into account the relevance of tokens and not just their frequency (i.e. penalizing tokens that appear in the majority of the documents analysed).

Tokenization: process of splitting a text up into its basic units, called tokens.

Topic modelling: unsupervised statistical model used to describe hidden categories or topics present in a given set of texts.

Our aim is to exceed our clients' expectations, and become their trusted partners

Management Solutions is an international consulting services company focused on consulting for business, risks, organization and processes, in both their functional components and in the implementation of their related technologies.

With its multi-disciplinary team (functional, mathematicians, technicians, etc.) of 2,500 professionals, Management Solutions operates through its 31 offices (15 in Europe, 15 in the Americas and 1 in Asia).

To cover its clients' needs, Management Solutions has structured its practices by sectors (Financial Institutions, Energy, Telecommunications and other industries) and by lines of activity (FCRC, RBC, NT), covering a broad range of skills - Strategy, Sales and Marketing Management, Risk Management and Control, Management and Financial Information, Transformation: Organization and Processes, and New Technologies.

The R&D department provides advisory services to Management Solutions' professionals and their clients in quantitative aspects that are necessary to undertake projects with rigor and excellence through the implementation of best practices and the continuous monitoring of the latest trends in data science, machine learning, modeling and big data.

Javier Calvo
Partner at Management Solutions
javier.calvo.martin@managementsolutions.com

Manuel Ángel Guzmán
Partner at Management Solutions
manuel.guzman@managementsolutions.com

Segismundo Jiménez
Supervisor at Management Solutions
segismundo.jimenez@managementsolutions.com

Nicolás Franco
Partner at mrHouston
nfranco@mrhouston.net

Ivar Zapata
Director AI at mrHouston
izapata@mrhouston.net

Management Solutions, Professional Consulting Services

Management Solutions is an international consulting firm whose core mission is to deliver business, risk, financial, organization, technology and process-related advisory services.

For further information please visit **www.managementsolutions.com**

Follow us at:

www.managementsolutions.com

Madrid Barcelona Bilbao La Coruña London Frankfurt Paris Amsterdam Copenhaguen Oslo Warszawa Zürich Milano Roma Lisboa Beijing New York Boston Atlanta Birmingham Houston San Juan de Puerto Rico San José Ciudad de México Medellín Bogotá Quito São Paulo Lima Santiago de Chile Buenos Aires