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Managing spillover crises in the age of generative AI

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Abstract The rapid development of generative artificial intelligence (generative AI) has marked a significant shift in how organizations operate and innovate. While generative AI offers new opportunities, it also entails new risks that can escalate into crises. These crises are not always limited to the organization where they originate but can spill over to other organizations in the same sector, causing broader reputational consequences. In this article, we investigate such spillover crises in the age of generative AI. We build on Laufer and Wang's crisis spillover model and extend it to generative-AI-related contexts. Specifically, we identify five types of spillover crises associated with generative AI and illustrate them using real-world cases that highlight how reputational damage can extend beyond a single firm and affect others in the industry. We propose a strategic framework to help organizations identify the risk of spillover crises, and we offer prescriptive guidance for avoiding, mitigating, or responding to spillover crises when they occur.

1. Spillover crises in the age of generative AI

The rapid development of generative artificial intelligence (generative AI) technologies has marked a significant shift in how organizations innovate and deliver value (Kaplan & Haenlein, 2020). From AI-generated content in marketing and journalism to autonomous decision-making systems in the hiring process and healthcare, generative AI has rapidly transitioned from experimental novelty to core business infrastructure that has been widely adopted across different sectors (Holmström, 2022). As this trend intensifies, risks sparked by generative AI failures are unavoidable, and they may not always be confined to the organization where the incident originated. However, they can

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result in crisis spillover, adversely impacting other organizations in the same sector (Chang & Rim, 2024; Laufer & Wang, 2018).

For example, in 2023, *Sports Illustrated* faced public backlash following the discovery of AI-generated articles that were published using fake author profiles. Although the crisis only involved *Sports Illustrated*, the resulting uproar quickly spread to other media outlets, triggering industry-wide scrutiny of editorial authenticity (Salam, 2023). In the same year, Levi Strauss announced its use of AI-generated virtual models, causing widespread concerns about the displacement of human labor in the fashion industry and adversely impacting other brands (Savage, 2024). In both cases, the reputational damage spread beyond the directly impacted organization, illustrating the phenomenon of industry-level crisis spillover in the age of generative AI.

Laufer and Wang (2018, p. 174) defined *crisis spillover* risks as arising when "consumers make assumptions of guilty by association," and proposed a model based on the accessibility—diagnosticity framework from the field of psychology. Further, Wang and Laufer (2024) argued in their crossdisciplinary review article that the crisis spillover phenomenon is increasingly relevant in an era where organizations are increasingly dependent on digital technologies. In this article, we investigate how generative-AI-induced crises can lead to crisis spillover effects across organizational boundaries. Our contributions are fourfold. First, in Section 2, we extend the crisis spillover model proposed by Laufer and Wang (2018) to an under-researched area of great importance in the age of generative AI (i.e., generative-AI-related crises). Then in Section 3, we identify five types of spillover crises associated with generative AI, and we use real-world examples to explain how such crises can affect other generative-AI-integrated organizations that are not always directly involved in the crisis. Next, we propose a strategic framework for companies to protect themselves if they are at risk of a generative AI spillover crisis. Finally, we offer strategies for practicing managers to effectively avoid, mitigate, and respond to spillover crises.

2. Revisiting the crisis spillover model

In their *Business Horizons* article, Laufer and Wang (2018) explained that crisis spillover occurs when a crisis triggers broader awareness to stakeholders beyond the organization experiencing the crisis and is perceived as diagnostic of an issue that affects a shared category (e.g., industry or organizational type). Their perspective is derived from the accessibility—diagnosticity framework (Feldman & Lynch, 1988; Roehm & Tybout, 2006)[2], which is highly relevant for understanding spillover risks in the age of generative AI. For example, when AI-generated content misleads consumers or an algorithm demonstrates bias, the public may infer that these are not isolated incidents but rather structural issues intrinsic to the technology or the organizations deploying it (De Freitas, 2025). When companies share one or more of the risk factors associated with shared categories (e.g., industry, organizational type, country of origin, or positioning strategy), they are more likely to experience guilt by association (Laufer & Wang, 2018; Wang & Laufer, 2024).

In the digital age—in which information spreads rapidly, and public narratives coalesce online—the risk of being judged as guilty by association has only intensified (Laufer & Wang, 2024). For example, consider the role of industry as a crisis spillover factor: A crisis involving the displacement of human labor at one fashion company may activate broader concerns about bias in all fashion brands using generative AI systems. The Levi Strauss scandal mentioned earlier illustrates this kind of crisis spillover effect, and organizational type further complicates matters. For example, nonprofits that leverage generative AI to increase operational efficiency may be lumped together if one is implicated for privacy violations, even if others adhere to stringent data ethics. For instance, when the NGO EyesOnOpenAI challenged OpenAI over transparency in its nonprofit governance, many observers began to question public trust not just in OpenAI but in nonprofit-led AI initiatives broadly, worrying that nonprofit structures may mask profit motives or lax oversight (Johnson, 2025). As Laufer and Wang (2018) and Wang and Laufer (2024) argued, comparable organizational missions and perceived motivations can amplify the accessibility of a crisis. In addition, the same country of origin may shape public expectations about corporate behavior and technical standards due to high accessibility via a shared category. For example, a generative-AI-related scandal at a Silicon Valley firm around privacy could spill over to other American

[2] In this framework, *accessibility* refers to how easily consumers can recall and associate the focal firm with the one experiencing the crisis. In other words, this occurs when an organization shares a common category like an industry or organizational type. *Diagnosticity*, on the other hand, occurs when the attributes of the crisis are perceived as indicative of a category-wide problem. In other words, there is a perceived fit between the crisis type and the category.

technology companies due to preexisting beliefs about US firms prioritizing innovation over data security (Maher & Singhapakdi, 2017). This was illustrated when Italy's privacy watchdog fined OpenAI for ChatGPT's violations in collecting users' personal data, resulting in broader concerns in Europe of OpenAI and other American technology companies' privacy violations (Zampano, 2024).

Perhaps equally subtle—yet insidious—is the dimension of strategic positioning argued by Laufer and Wang (2018) as a key crisis spillover factor. For example, when organizations publicly align their brand with values like trust, transparency, or digital innovation, they increase the likelihood of being perceived as other companies with a comparable positioning strategy. This is especially relevant in the context of generative AI. Increasingly, companies across sectors are positioning themselves as generative-AI-driven or generative-AI-enhanced, framing the adoption of generative AI as a marker of technological leadership and a differentiating factor in their industry (De Freitas, 2025). While this alignment may yield reputational benefits under normal conditions, it also introduces a shared identity that heightens accessibility in the event of a crisis. In other words, organizations that prominently market their use of generative AI may find themselves lumped together in public perception when one firm faces scrutiny. As such, the crisis no longer appears isolated. Instead, it reinforces a broader concern about the risks or ethics of generative AI adoption, increasing the spillover potential to competing companies that share a generative AI positioning strategy. For example, after the FTC sued Air AI for advertising exaggerated business outcomes tied to its generative AI tools, media coverage and public commentary began assessing not just Air AI but many generative AI firms making similar growth or earnings claims (Drayton, 2025). This raised trust issues across companies with a similar strategic positioning.

According to the crisis spillover model (Laufer & Wang, 2018; Wang & Laufer, 2024), the spillover effect becomes particularly pronounced when companies share multiple risk factors like being in the same industry and pursuing the same positioning strategy around generative AI (e.g., generative-AI-driven or generative AI-enhanced). In such cases, their perceived interconnectedness creates a cognitive shortcut for consumers, media, and stakeholders to draw guilt-by-association conclusions. As Laufer and Wang (2018) suggested, the more nodes of similarity between organizations in the public's mindset, the higher the accessibility and the greater the risk of crisis spillover effects.

3. Generative-AI-related crises with spillover risks

While accessibility or belonging to a shared category is a key component in determining whether a crisis will spill over, it is not sufficient on its own (Laufer & Wang, 2018). The potential for crisis spillover also depends on diagnosticity. As noted earlier, this refers to whether the attributes of a specific crisis are perceived as symptomatic of a broader category-level problem (Feldman & Lynch, 1988; Roehm & Tybout, 2006). A crisis perceived as highly diagnostic signals to stakeholders that the issue is not a one-off failure but reflects systemic flaws in the underlying technology or organizational practices that impact a broader category. As such, we identified five types of generative-AI-related crises that are high in diagnosticity and pose elevated spillover risks for AI-integrated organizations: (1) authenticity/integrity, (2) labor displacement, (3) technical failure, (4) data security and privacy, and (5) discrimination/bias (see Table 1). We focused on these five types of risks because they mirror the immediate concerns executives and stakeholders raise when it comes to generative AI adoption. According to Kunz and Wirtz (2024), companies are expected to take responsibility for digital practices across the board (i.e., failures in areas like authenticity, privacy, or bias are quickly seen as systemic weaknesses rather than isolated errors). Bowen (2024) also found that without clear ethical standards (e.g., relating to labor displacement, technical bias, or failure), many stakeholders assume that firms will pursue any technological possibility unless proven otherwise. This mindset makes crises in these domains especially dangerous. They not only damage the company directly involved but also signal to the market and the public that other companies belonging to the same category (e.g., in the same industry) may be at risk. Thus, the five aforementioned areas carry heightened spillover potential since they touch on widely shared concerns about how generative AI is used responsibly in business. Each crisis type is described in Sections 3.1.—3.5. using real-world examples to show how high diagnosticity amplifies guilt by association beyond the initial focal organization for a generative-AI-related crisis.

A key factor in the diagnosticity of these spillover risks is the perception by stakeholders that generative AI solutions are homogeneous (De

Table 1. Types of generative-AI-related crises with spillover risks and response strategies

Crisis types	Description	Examples	Strategies for avoiding the spillover crisis	Strategies for mitigating the negative consequences of the spillover crisis	Strategies for responding to spillover crisis
Authenticity/ integrity	Related to content trustworthiness and the erosion of credibility when using generative AI	*Sports Illustrated* was exposed for using fake author profiles for AI-generated articles, prompting sector-wide scrutiny of editorial authenticity in journalism.	Avoidance requires clear disclosure of generative AI use and rigorous fact-checking to protect content credibility.	Mitigation depends on rapid audits and reinforcing human editorial oversight to restore confidence.	Response should distance the organization from unethical practices associated with the use of AI (e.g., the lack of disclosure) and emphasize transparency around the use of AI to its stakeholders.
Labor displacement	Employment risk associated with the use of generative AI	Levi Strauss' use of AI-generated models caused a public backlash about labor displacement and raised concerns about job losses at other fashion brands.	Avoidance requires upfront communication about workforce transformation and investment in reskilling.	Mitigation involves engaging employees and highlighting how AI complements rather than replaces human work.	Response should frame the incident as specific to the focal firm, deny parallels with its own employment policies, and emphasize that AI assists employees with productivity but does not replace them.
Technical failure	Highlights how technical failure in one company can spill over to others in the industry and emphasizes concerns regarding the perceived reliability of generative AI tools	A self-driving car failure (operated by Cruise, a robotaxi subsidiary of General Motors) that injured a pedestrian led to broader distrust in autonomous vehicle safety.	Avoidance rests on rigorous testing, external certification, and cautious rollouts before full deployment.	Mitigation requires immediate suspension of flawed systems, transparent reporting, and compensation for those affected.	Response should emphasize that the AI-related technical issue is unique to the affected company and describe the different technologies or processes that it uses to differentiate itself from the company experiencing the crisis.

(*continued on next page*)

Table 1 (*continued*)

Crisis types	Description	Examples	Strategies for avoiding the spillover crisis	Strategies for mitigating the negative consequences of the spillover crisis	Strategies for responding to spillover crisis
Data security/ privacy	Related to concerns over the use of data that is provided by organizations when using generative AI	New Zealand's government ministry banned staff use of generative AI tools due to data leak concerns, fueling broader scrutiny of generative AI adoption in public administration.	Avoidance relies on privacy-by-design practices and clear rules for data handling.	Mitigation includes quickly updating protocols, publishing transparency reports, and seeking expert validation.	Response should distance the firm by clarifying it does not use the same AI tools or practices, deny exposure to the same vulnerabilities, and highlight strict proprietary safeguards.
Discrimination/ bias	Reflects systemic bias and structural inequality concerns in HR practices, extending beyond the organizations directly involved when using generative AI	Amazon's generative AI tool penalized female candidates, and Workday was sued for generative AI-based hiring discrimination, raising systemic concerns about bias across the employment tech sector.	Avoidance requires fairness testing, diverse training data, and ethical oversight during system design and use.	Mitigation can be achieved via corrective model adjustments and inclusive stakeholder dialogue.	Response should explicitly reject association with discriminatory practices and highlight distinct fairness protocols that set the firm apart (e.g., emphasizing training AI tools on more diverse data sets when compared with the company experiencing the crisis).

Freitas, 2025). Unlike solutions involving people, which are considered varied and heterogeneous, generative AI solutions are seen as sharing similar characteristics (Longoni et al., 2022), making generative-AI-related crises more prone to spillover to other generative-AI-integrated organizations.

3.1. Authenticity/integrity crises

Generative-AI-related crises that adversely impact the perceived *authenticity (integrity)* of an organization's communications erode public trust (Deptula et al., 2025). In the 2023 *Sports Illustrated* example, the company was criticized for publishing AI-generated articles under fabricated author identities (Salam, 2023). Although the media company claimed editorial oversight, the crisis triggered a wave of skepticism about the legitimacy of AI-generated content across the entire journalism industry. Other media companies (e.g., *BuzzFeed*) that incorporated generative AI faced scrutiny, not necessarily because of their practices but because the crisis at *Sports Illustrated* was perceived to be industry-wide.

Another example of how a crisis related to authenticity and integrity can spill over to other organizations is the use of AI-generated images by the Ai Yixing Public Welfare Service Center in Chengdu, China, for donation appeals in 2024 (Huang, 2024). The organization was criticized for presenting computer-generated images of beneficiaries as though they were real people, raising concerns that donors were being misled about the impact of their contributions. Although the crisis

initially centered on this single organization, it quickly ignited a broader debate about whether other charities might also be fabricating or exaggerating their appeals with generative AI tools. Journalists and watchdog groups began scrutinizing the fundraising materials of other charitable organizations in China, questioning whether they too might be misrepresenting reality (Huang, 2024). In this way, a localized generative-AI-related crisis for one organization became a sector-wide challenge, amplifying concerns about authenticity and integrity across charities in China and undermining public trust in donation campaigns overall.

These examples satisfy the two key conditions of the accessibility—diagnosticity framework. Accessibility is high because the affected organizations share strong categorical similarities with others in their sectors (e.g., media companies or nonprofit charities), making it easy for stakeholders to cognitively form a link. Diagnosticity is also high, as both crises tap into foundational societal concerns related to generative AI use, including credibility and transparency that are viewed as systemic rather than isolated. According to the crisis spillover model, when a single organization's crisis is perceived as reflective of industry-wide practices or ethical blind spots, the reputational harm will likely spill over to similar organizations. In media companies and nonprofit organizations, for example, the convergence of shared missions, communication methods, and public-facing narratives amplifies the potential for guilt by association, making authenticity/integrity crises a high risk for spillover in the age of generative AI.

3.2. Labor displacement crises

Like authenticity/integrity crises, those involving the perceived *displacement of human labor* by generative AI often result in societal debates over the future of work (Chen et al., 2022; Chhibber et al., 2025). As a result, these crises are highly diagnostic as well. One example is Levi Strauss' 2023 announcement to collaborate with Lalaland.ai to introduce AI-generated fashion models in its advertising campaigns (Savage, 2024). While the company framed the move as a step toward inclusivity and efficiency, critics accused the company of attempting to lower costs by hiring fewer models, particularly among underrepresented groups in the fashion industry (Greene, 2024). The controversy quickly extended beyond Levi's to other fashion brands like Target, Kohl's, and fast-fashion giant Shein, as it raised normative concerns about the ethics of AI-driven visual communication.

Another illustrative case arose in the customer service sector. In 2023, major corporations (e.g., British Telecom) announced plans to replace significant portions of their call-center workforces with generative-AI-powered chatbots (Sweney, 2023). While these companies promoted the technology as improving efficiency and reducing wait times, unions and employees denounced the move as a cost-cutting strategy that sacrificed jobs and service quality. Public backlash intensified when customers complained about the inability of generative AI chatbots to resolve complex issues, amplifying concerns that generative AI adoption would both degrade consumer experience and accelerate large-scale labor displacement. As with the Levi Strauss case, criticism extended well beyond the companies directly involved. Other companies like Vodafone were affected, which fueled broader debates about the ethical and economic implications of automating frontline service roles across industries.

According to Laufer and Wang's (2018) crisis spillover model, accessibility in these cases is driven by shared public narratives around digital transformation in fashion and customer service. Diagnosticity is high because the backlash was not merely about Levi's or the telecommunications companies' choices, but rather the broader fears of automation displacing human creativity and labor. Further, it was considered an industry trend rather than an isolated act. The positioning of many fashion brands and service providers as progressive and customer-oriented further amplified their similarity in the public's mind.

3.3. Technical failure crises

The third crisis type we identify is *technical failure*. Crises stemming from such failures of generative AI systems often signal systemic design flaws or a premature rush to deployment of generative AI tools (Kaplan & Haenlein, 2020), making them highly diagnostic. A good example of this type of crisis is the damage suffered by an autonomous vehicle company operated by Cruise, a robotaxi subsidiary of General Motors, after one of its cars failed to recognize a pedestrian at night, causing a serious injury (De Freitas, 2025). Although the incident involved a single vehicle, public attention quickly expanded to include other self-driving tech firms, particularly those using similar large language model (LLM)-driven perception models. Media outlets highlighted similarities in the underlying generative AI

systems across companies, while experts pointed to the black box nature of machine learning as a structural weakness rather than a firm-specific error. The failure was perceived not as an isolated incident but as evidence that generative-AI-based systems may be fundamentally ill-equipped to handle complex cases in real-world environments. The spillover effect from this crisis led to regulatory delays and a drop in the stock prices of competing firms like Waymo and Zoox, even though they did not experience any safety incidents. Moreover, cities that had been negotiating pilot projects with other robotaxi providers temporarily suspended approvals, and insurance companies like Swiss Re reconsidered liability frameworks for autonomous driving. This reinforced the impression that the Cruise accident was indicative of an industry-wide fragility in generative AI deployment.

Another example of a spillover crisis regarding a technical failure that happened in the higher education sector (Staton, 2023). Following widespread adoption of generative-AI-based detection tools meant to flag ChatGPT-assisted plagiarism, universities in the UK—including Cambridge and other leading UK universities—encountered alarming false positives, especially among nonnative English-speaking students. In one widely publicized case, a student was falsely accused of using AI to write a philosophy paper, only to later be cleared after weeks of reputational damage to the university and emotional distress to the student. A major factor in the spillover effect of the crisis to other universities was the use of generative AI detection tools. Generative AI tools are perceived by stakeholders to be homogeneous, so crises may spill over to other universities, even if they used other types of generative AI tools to identify plagiarism. The narrative quickly shifted from isolated implementation flaws to a broader question of whether universities were blindly outsourcing judgment to unproven generative AI.

In these two cases, like the previous ones, the accessibility—diagnosticity framework offers a powerful explanation of how these crises spilled over to other firms. Accessibility is high because the implicated organizations share common categories with the organizations experiencing the crisis: industry and the deployment of generative AI. Diagnosticity is also high, since both crises cast doubt on the core functionality and maturity of generative AI technologies themselves. This occurs because stakeholders view these failures as emblematic of broader issues, as generative AI solutions are considered part of the same technological ecosystem.

3.4. Data security/privacy crises

Crises involving generative AI and *data governance* frequently evoke concerns about surveillance and institutional accountability (Prahl & Goh, 2021), making them diagnostic of organizational control or lack thereof. In 2023, New Zealand's Ministry of Business, Innovation and Employment banned the use of ChatGPT and other generative AI tools by staff, citing concerns over data leaks and third-party access to sensitive information (Cardwell, 2023). Although the move applied to a specific government body, it fueled broader discussions about the risks of integrating generative AI tools into administrative and enterprise systems without robust security protocols at other government ministries.

In the same year, Samsung faced a crisis when engineers inadvertently input sensitive source code and confidential meeting notes into ChatGPT while troubleshooting errors (Ray, 2023, May 2). These disclosures, although unintentional, immediately raised alarms about how easily proprietary corporate data could be shared with external generative AI systems outside of a company's control. In response, Samsung swiftly banned the internal use of ChatGPT and similar tools while exploring the development of in-house generative AI solutions. The case did not remain confined to Samsung; rather, it triggered broader anxieties across the technology sector about the risk of unmonitored employee interactions with public generative AI platforms, reinforcing fears that any firm allowing such practices might face comparable breaches of confidentiality and intellectual property.

With data security and privacy crises, diagnosticity is high because the incident raises red flags about systemic data vulnerability, suggesting that any organization using similar tools may be exposed to comparable threats. Meanwhile, accessibility stems from similarities in institutional type (e.g., government bodies, corporations, or nonprofits) using third-party generative AI systems, often under similar assumptions of trust. When one prominent organization publicly bans or discredits a generative AI tool, other adopters are cognitively clustered as facing the same risks, leading to a spillover in stakeholder concern even when no direct incident has occurred elsewhere. The Samsung case further demonstrates that even when the original breach is limited to one organization, stakeholders quickly generalize the perceived vulnerabilities to the wider industry, which amplifies the spillover effect. Once again,

the perceived homogeneity of generative AI solutions by stakeholders increases the likelihood that a spillover effect will occur.

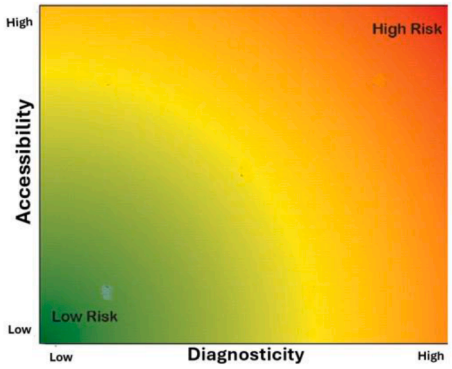
3.5. Discrimination/bias crises

Finally, crises involving *algorithmic bias*—particularly in hiring and resource allocation—are an area of key concern. For example, Amazon's discontinued AI recruitment tool was found to penalize women based on historical training data, systematically downgrading résumés that included terms like "women's chess club captain" (Dastin, 2018). In addition, Workday was recently sued for alleged racial and disability discrimination by its resume-screening algorithms, with plaintiffs claiming that qualified candidates were unfairly excluded from hiring pools and raising questions about the opacity of third-party AI tools used in human resources (Wiessner, 2024). Both cases damaged the reputation of the firms involved and evoked widespread concern about systemic discrimination embedded in generative-AI-based decision-making across the sector, particularly in contexts involving fairness and equity.

Diagnosticity in these cases is high, as stakeholders interpreted such failures as structural (i.e., reflecting the biases and blind spots of the teams from the same industry designing and deploying these tools). Accessibility is heightened when multiple firms in the sector use similar tools (e.g., algorithmic resume screening), especially in regulated domains like employment or finance. As Laufer and Wang (2018) noted, when public narratives coalesce around a few high-profile failures in one sector, other companies in the sector are pulled into the same reputational narrative—even those with better controls. The result is a heightened risk of sector-wide trust erosion and crisis spillover, especially in industries already scrutinized for lack of diversity and inclusivity.

In summary, identifying these five high-diagnosticity crisis types has practical value for organizational risk and crisis communication strategies. While accessibility determines whether an organization can be perceptually linked to another's crisis, diagnosticity shapes the intensity and breadth of reputational spillover (Laufer & Wang, 2018; Wang & Laufer, 2024). Each crisis type triggers distinct stakeholder concerns—credibility, labor norms, system reliability, governance integrity, and social justice—which widens resonance. Recognizing these distinctions enables firms to anticipate potential crisis spillover risks and tailor responses strategically. Thus, understanding diagnosticity empowers organizations to more precisely assess spillover risks and craft nuanced communication strategies for resilience in a generative-AI-intensive ecosystem.

Figure 1. The severity of crisis spillover risks



We recommend managers begin identifying potential spillover risks based on the accessibility—diagnosticity framework. The 2x2 matrix in Figure 1 can be used to guide the severity of this risk. If organizations are facing spillover risks that fall into the five types identified in this article, managers should be especially vigilant. After identifying the most vulnerable areas, managers should collect data to assess whether spillovers are occurring. As Laufer and Wang (2018) pointed out, gathering data from the news media and social media accounts that mention a generative-AI-related crisis can provide strong evidence for managers of a potential spillover effect.

4. Responding to AI spillover crises

When the spillover risk is high based on the accessibility—diagnosticity framework, and an organization has confirmation of spillover from the news media or social media, it is important for the organization to protect itself. According to Laufer and Wang (2018), an effective strategy to manage a spillover crisis is to differentiate the company from the organization experiencing the generative-AI-related crisis. A good example involves crises associated with discrimination and bias like ChatGPT, which has been accused of providing biased results to prompts (West, 2023). Claude, a competitor of ChatGPT, differentiated itself by stating that Claude is trained using a constitutional approach that is more transparent, interpretable, and aligned with human values (De Freitas, 2025).

When developing a response to a spillover crisis involving generative AI, an effective differentiating strategy will typically involve a discussion

around proprietary algorithms, safety measures, and human oversight (Prahl & Goh, 2021). These differentiating factors can be incorporated in an organization's response to highlight differences between the organization directly impacted by the crisis and others adversely impacted by a spillover effect (Chang & Rim, 2024; De Feitas, 2025). In Table 1, we list examples of differentiation strategies that can be used with the different types of generative-AI-related crises with spillover risks.

The importance of differentiation cannot be overstated when it comes to mitigating generative AI-related spillover risks. As discussed in Sections 1—3, spillover occurs because organizations are perceived to share technological infrastructures, ethical blind spots, or operational similarities. Therefore, differentiation for preventing, mitigating, and responding to spillover crises serves as a communicative tool to weaken both accessibility and diagnosticity in the public imagination (Feldman & Lynch, 1988; Roehm & Tybout, 2006). By clearly articulating how one's system, governance structures, or human oversight differs, companies can reframe their positioning in ways that reduce the perceived similarity to the organization involved in the generative-AI-related crisis.

A good example involves Clearview AI, which experienced a privacy breach back in February 2020. Clearview is a facial recognition company with a database of billions of photos scraped from social media and the web. In response to the crisis, several companies issued denials, including Bank of America: "We're not a client of Clearview." A Bank of America spokesperson further stated, "We haven't been a client, we didn't stop being a client, and we never were a client." (Mac et al, 2020). This is an example of how a company can differentiate itself by emphasizing that it does not use an AI system involved in a crisis.

When developing a differentiation strategy, it is important to ensure that it is crisis-specific, corresponding directly to the five categories of generative-AI-related crises identified in Table 1. For authenticity and integrity crises, differentiation requires proactive transparency. Organizations should emphasize early disclosure of generative AI use and clear labeling to demonstrate that they do not engage in deceptive practices (Deptula et al., 2025). For labor displacement crises, firms should highlight how generative AI is used to augment rather than replace human workers, aligning with broader narratives of employee empowerment and inclusivity (Chen et al., 2022; Chhibber et al., 2025). For technical failures, differentiation strategies should stress alternative systems, enhanced safety checks, and human-in-the-loop safeguards (Kaplan & Haenlein, 2020). In cases of data security and privacy crises, companies can highlight their proprietary protocols, stronger encryption, or selective partnerships with trusted providers to reduce diagnosticity (Prahl & Goh, 2021). Finally, for discrimination and bias crises, differentiation should focus on diverse training datasets, continuous auditing, and human oversight that ensures fairness in outcomes (Longoni et al., 2022).

The response strategies illustrated in Table 1 are examples of key points that should be communicated during spillover crises in the age of generative AI. However, simply claiming differentiation is not enough. Instead, companies must provide evidence, for example, in the form of technical documentation or third-party endorsements. This evidence-based communication reinforces credibility (Coombs, 2007) and helps stakeholders distinguish between firms to reduce the likelihood of guilt by association (Laufer & Wang, 2018). Crisis communication must shift from generic assurances to tailored narratives that speak directly to stakeholder concerns tied to each crisis type (Laufer & Wang, 2018; Wang & Laufer, 2024).

Further, differentiation should be both reactive and anticipatory. As we highlighted, diagnosticity increases when stakeholders perceive systemic flaws (Chang & Rim, 2024). By engaging in proactive disclosure and participating in self-regulatory initiatives, companies can build reputational buffers before a crisis occurs. For example, sector-wide commitments to transparency or fairness can reduce the diagnosticity of any single organization's failure, thus lowering the chances of spillovers. This aligns with Barnett and King's (2008) insight that collective self-regulation can make reputational boundaries between organizations more visible, acting as good fences against crisis contagion.

In addition, differentiation should be understood as a dynamic, ongoing process rather than a one-off response. This is aligned with the dynamic process addressed by the crisis READINESS framework[3] (Jin et al., 2024; Jin et al., 2025; Voges et

[3] The READINESS framework (Jin et al., 2024; Jin et al., 2025) defines READINESS as a multidimensional construct that goes beyond traditional notions of preparedness or resilience. It comprises three interrelated dimensions: (1) multilevel efficacy, which includes self-efficacy at the individual level, collective efficacy at the team level, and organizational efficacy at the systemic level; (2) mindset, which emphasizes emotional leadership, mental adaptability, and a proactive orientation toward risks and crises; and (3) dynamic process, which views READINESS as an ongoing, adaptive process of learning and responding within complex and evolving crisis environments.

al., 2024). As stakeholder expectations evolve and as generative AI tools permeate, companies must continuously adapt their communicative positioning. This involves monitoring social media narratives, engaging with watchdog groups, and remaining sensitive to emerging concerns (e.g., regarding authenticity, integrity, privacy, and fairness; Holmström, 2022). Differentiation is as much about sustained dialogue with stakeholders as it is about technological safeguards.

To conclude, managing generative AI spillover crises requires organizations to operationalize differentiation in ways that directly correspond to the five generative-AI-induced crisis types. Effective communication must emphasize both preventive measures and reactive strategies, supported by credible evidence and continuous stakeholder engagement. An effective response can reassure stakeholders that the spillover crisis is not related to the organization and help prevent negative consequences like reputational damage, negative word-of-mouth, or a decline in sales. By integrating differentiation into their broader crisis communication frameworks, companies can prevent guilt by association and preserve stakeholder trust in the age of generative AI.

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