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Panama Life Health Insurance Case

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ABSTRACT: This case study explores how algorithmic bias affected stakeholders at Panama Life Health Insurance following the deployment of an AI-enhanced claims processing system. The analysis examines patterns of inequitable outcomes using a grounded theory approach, revealing higher denial rates for minority policyholders and reduced preventive care for women. There are three main reasons for this crisis: structural bias embedded in historical training data, organizational gaps in artificial intelligence (AI) governance, and cultural assumptions that automation is objective. Institutional vulnerability emerged, highlighting AI-driven inequities due to unmonitored automation, weak cross-functional communication, and a lack of fairness controls, which contributed to discriminatory outcomes. The study incorporates organizational change frameworks, such as Kotter's eight-step model and Schein's cultural analysis, which should be used in this case to emphasize the importance of aligning culture, incentives, and ethical imperatives within the organization. This case illustrates how grounded theory can shed light on the sociotechnical dynamics that create inequitable algorithmic outcomes in the literature on responsible AI governance. To restore ethical integrity, stakeholder trust, and operational accountability, healthcare organizations need to follow a structured path.

KEYWORDS: Algorithmic Bias, Enterprise Risk Management (ERM), Health Equity, Organizational Change

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Introduction

As a result of AI, the global healthcare industry has achieved unprecedented operational efficiencies, enhanced predictive capabilities, and an informed decision-making process based on data (Mehrabi et al., 2022). The global market for AI in healthcare is projected to exceed $187 billion by 2030, according to Grand View Research, Inc. (2025). However, alongside these advancements, AI adoption has introduced serious ethical and operational risks, most notably, algorithmic bias (Mehrabi et al., 2022). Recent studies have demonstrated that biased algorithms can perpetuate healthcare inequities by disproportionately affecting women and racial minorities (Mehrabi et al., 2022). Such disparities erode trust, compromise patient outcomes, and expose organizations, like in the case of Panama Life Health

Insurance, to legal and reputational harm (Mehrabi et al., 2022). The AI-driven claims processing system implemented by Panama Life Health Insurance to improve efficiency and identify patients at risk of adverse outcomes was found to be biased by an external audit. Specifically, minority policyholders experienced higher claim denial rates, and women were less likely to receive preventive care recommendations (Mehrabi et al., 2022).

This study examines the ethical and operational implications of algorithmic bias through the lens of Panama Life Health Insurance, applying the Kepner-Tregoe (KT) problem-solving model to propose structured, evidence-based remediation strategies (Kepner & Tregoe, 1997). The KT framework provides a robust framework for analyzing complex problems, identifying underlying causes, and formulating and implementing practical corrective actions to resolve them. The purpose of the study is to illustrate how structured decision-making can enhance equity, accountability, and stakeholder involvement. Given that AI is increasingly influencing healthcare access and outcomes in our time, this inquiry addresses both a pressing academic and practical issue of growing importance. It contributes to the growing body of research on responsible AI governance by offering a case-based approach that bridges technology, ethics, and organizational leadership (Kepner & Tregoe, 1997).

Key Concepts

Algorithmic Bias: According to Barocas & Selbst (2016), algorithmic bias is a mechanism by which existing social disparities are encoded into automated decision-making processes.
Enterprise Risk Management (ERM): It is a structured and integrated approach to identifying, assessing, and managing risks across an organization. Rather than addressing risks in isolated departments, ERM takes a holistic view, emphasizing how different risks interact and how organizations can balance risk-taking with value creation (Di Palma et al., 2025).
Health Equity: It is the commitment to reducing and ultimately eliminating disparities in health and healthcare across groups. Braveman et al. (2017) define health equity as ensuring that everyone has a fair opportunity to attain their highest level of health, which requires addressing structural, social, and systemic barriers.
Organizational Change: It involves structured efforts to shift behaviors, processes, or culture within an organization to improve performance or adapt to an evolving environment (Kotter, 1996).

Background

The new AI-enhanced claims processing system at Panama Life Health Insurance embeds algorithmic bias, posing a significant threat to stakeholders' rights and the organization's overall reputation, as it was intended to streamline claims management by identifying high-risk patients. Nevertheless, it resulted in the provision of inherently discriminatory data (Mehrabi et al., 2022; Rajkomar et al., 2022). An independent audit of the claims processing system found that a disproportionate number of claims for minority policyholders were denied, and that fewer preventive interventions were approved. These findings align with broader research on healthcare AI bias (Mehrabi et al., 2022; Rajkomar et al., 2022). These inequities quickly prompted advocacy groups to accuse Panama Life Health Insurance of unethical behavior, including systemic bias and discrimination, while providing health care to minorities and women. As Leslie (2022) suggests, organizations that fail to anticipate the ethical and operational implications of technology risk significant reputational damage and stakeholder mistrust. As research confirms (Obermeyer et al., 2019), AI tools trained on biased datasets often reinforce preexisting disparities in healthcare access and outcomes. The case of Panama Life Health Insurance illustrates that risks associated with using AI without implementing adequate ethical safeguards, transparency, or oversight have become an industry challenge that will not go away (Suresh & Guttag, 2021).

To prevent such outcomes, healthcare organizations must incorporate standard operating procedures that establish ethical review boards, data transparency protocols, and other required frameworks to mitigate bias in AI systems before deployment (Suresh & Guttag, 2021). This case demonstrates the need to ensure that fairness and accountability are key parameters when developing health care systems that use AI as a framework, through small-scale pilot testing, outcome audits, and human oversight as a final check and balance to ensure outcomes are free of bias (Leslie, 2022). By incorporating these governance protocols, Panama Life Health Insurance could have prevented this crisis.

Problem Statement

Grand View Research, Inc. (2025) estimates that the global market for AI in healthcare will grow from $15.1 billion in 2022 to $187 billion by 2030. However, recent studies indicate that AI tools used in the healthcare industry have had disproportionate adverse effects on minorities and women due to bias in the algorithms of the systems that use AI (Rajkomar et al., 2022). The proliferation of these inequities undermines public trust and violates nondiscrimination principles, which exposes organizations to legal and reputational risks (Rajkomar et al., 2022). As a result of its AI-driven claims processing system, Panama Health Life Insurance denied coverage to minority patients at a higher rate than to the rest of the population while providing fewer preventive care interventions to women (Rajkomar et al., 2022). As a result, advocacy groups have accused Panama Life Health Insurance of systemic discrimination, prompting legal and regulatory scrutiny (Rajkomar et al., 2022).

The convergence of these ethical, operational, and reputational risks signals a pressing need for systematic corrective actions grounded in evidence-based governance to prevent such challenges from recurring because this threatens to undermine organizational trust, ethical compliance, and operational integrity (Mehrabi et al., 2022; Leslie, 2022). Addressing this problem is an essential objective for Panama Life Health Insurance, as it represents a critical test of the responsible use of AI and poses an enormous risk to the organization if left unaddressed (Mehrabi et al., 2022; Leslie, 2022).

Significance of this Study

AI is increasingly being used in the healthcare industry, especially to automate claims processing, predict patient risk, and inform preventive health care interventions (Mehrabi et al., 2022). This case study highlights the enterprise risks associated with embedded biases in AI systems and how to mitigate them through comprehensive risk analysis and mitigation processes that ensure organizations remain ethical while reducing unnecessary exposure to risk. According to the World Health Organization (2023), bias in the health care industry undermines public trust. Therefore, health organizations should use mechanisms that ensure ethical oversight, audits, and cross-functional accountability throughout the lifecycle of any AI-enabled systems to ensure fairness and accountability in their use (Liefgreen et al., 2024).

The deployment of an unmonitored AI system presents enormous ethical, compliance, and reputational risks from an Enterprise Risk Management (ERM) perspective since unverified algorithms can result in legal liability and backlash, especially if results reveal systemic discrimination or inequitable treatment (Liefgreen et al., 2024).

Impact on Employees

The advent of AI is reshaping the healthcare workforce by altering job structures, skills, and demands. While AI-driven tools such as automated claims processing and patient risk assessment systems can streamline administrative tasks, they have also introduced new ethical and cultural challenges for employees (Kluge et al., 2022). These outcomes can extend beyond technical failures, affecting organizational culture, employee well-being, and trust in leadership. According to the McKinsey Global Institute (2023), 25% of administrative roles would be displaced by 2023. While this has yet to occur, it is evident that AI will impact administrative roles in the future (McKinsey Global Institute, 2023).

The AI tools used at Panama Life Health insurance were embedded with biased algorithms that disrupted workflows, highlighting ethical and operational vulnerabilities the company had not anticipated, as it had never incorporated a bottom-up process that used employee input to validate that the new system was free of bias. When employees are exposed to these types of organizational failures, they often experience higher levels of stress, moral conflict, and reduced confidence in leadership (Kluge et al., 2022). Such circumstances can often contribute to a feeling of moral injury, guilt, anxiety, and disengagement arising from perceived violations of ethical standards by the organization (Litz & Walker, 2022).

Furthermore, in many cases, the embarrassment of public scrutiny, the potential threat of layoffs, and increased emotional demands on departments such as compliance and customer relations can intensify burnout and instability for the employees (Kluge et al., 2022). Addressing these challenges requires transparency, accountability, empathetic leadership, and meaningful employee involvement to ensure that systems are in place to prevent future challenges in this area by actively engaging staff in bias mitigation, ethical training, and governance processes to rebuild trust and strengthen organizational cohesion (Litz & Walker, 2022).

Impact on the Organization

Organizations such as Panama Life Health Insurance can suffer reputational damage, financial losses, regulatory scrutiny, and a loss of stakeholder trust during these types of crises, due to their implementing new AI-generated claims processing systems that, in this case, produced discriminatory outcomes that threaten their long-term credibility (Mayer et al., 2021). Brand erosion is a risk that organizations must address when dealing with issues such as trust. In 2023, Deloitte reported that nearly 70% of consumers lose trust in a brand following an ethical scandal, and restoring trust can take years (Deloit, 2023). Additionally, regulatory agencies often impose costly compliance requirements that increase costs and divert resources from high-priority requirements (Mayer et al., 2021).

Internal challenges also intensify as departments work to revise algorithms, retrain staff, and rebuild internal systems while maintaining day-to-day operations (Mayer et al., 2021). There are also profound implications for leadership credibility if the company's crisis response appears defensive or opaque, particularly during a major crisis (Mayer et al., 2021). Furthermore, a lack of transparency in handling allegations of discrimination may signal deeper issues with company culture, corporate governance, and ethical oversight (Mayer et al., 2021).

Impact on Stakeholders, Clients, and Partners

Panama Life Health Insurance AI crisis can have far-reaching effects on customers and business partners, including reputational, ethical, and financial consequences (Crawford & Paglen, 2023). In such cases, stakeholder confidence can erode rapidly when new AI systems produce biased results, such as denying coverage to minority patients in disproportionate numbers or offering fewer preventive benefits to women (Crawford & Paglen, 2023).

In addition, organizational instability, regulatory investigations, declining market performance, moral distress, and uncertainty about job security may negatively affect the company's stakeholders, including employees, shareholders, clients, and policyholders, who may feel they have been unfairly treated. These individuals may seek legal recourse, switch to competitors, or launch negative public campaigns that further erode the company's reputation (Emanuel et al., 2021). To avoid being associated with a crisis involving unethical practices, other industry partners may distance themselves from the company to protect their reputations (Emanuel et al., 2021).

Additionally, once these principles are compromised, customers begin to question the legitimacy of the company's decision-making processes and its partners, including technology vendors and healthcare providers. In addition to the reputational damage by association, this could disrupt collaborative initiatives or future investments (Emanuel et al., 2022).

Problem-Solving Model Application

AI bias in the health care industry poses a significant risk to compliance, fairness, and stakeholder trust (Baker & Hawn, 2022). The hasty introduction of an AI-driven claims processing system at Panama Life Health resulted in disproportionately high denials of coverage for minority patients and limited access to preventive care for women (Zajko, 2022a).

Multiple studies have shown that machine learning systems that are trained on historical data tend to perpetuate or even exacerbate social inequalities that have the potential to marginalize minorities and women (Fan et al., 2022). According to Siddique et al. (2024), healthcare algorithms, if they are not set up with the proper oversight, have the propensity to frequently underestimate the medical needs of Black patients, resulting in systemic undertreatment. An audit confirmed that the algorithms used by Panama Life Health Insurance contained embedded biases that disadvantaged minorities and women. To resolve this crisis, a structured problem-solving methodology is a fundamental approach should be applied, while adhering to both technological and ethical accountability within the overarching industry (Baker & Hawn, 2022).

The Kepner-Tregoe (KT) problem-solving model is a structured analytical framework that distinguishes between facts and assumptions, identifies root causes, and guides rational corrective action to address these issues effectively for Panama Life Health Insurance (Kepner & Tregoe, 1997). Once the root cause is identified, the organization can strengthen transparency and ethical compliance by implementing corrective measures such as data rebalancing, algorithm retraining, and human-in-the-loop monitoring (Helmold, 2022). Through the application of the KT model, Panama Life Health Insurance is provided with a pathway to restore equity, accountability, and public trust by using a disciplined, evidence-driven approach (Kepner & Tregoe, 1997).

Problem Analysis: Identifying Root Causes of Algorithmic Bias

According to Kepner & Tregoe (1997), the Problem Analysis stage examines the nature, location, and severity of the problem to identify the root cause. At Panama Life Health Insurance, the key issue is that the AI system used for claims processing and preventive care recommendations produces biased outcomes that disproportionately disadvantage minority and female patients (Kepner & Tregoe, 1997). In this stage, it is critical to understand what is happening, where it occurs, when it began, and finally, the extent of the issue. By analyzing these patterns, several potential causes may emerge, such as data issues, flawed feature selection, inadequate validation, and a lack of governance oversight, as well as the absence of an ethical review committee or a fairness auditing protocol to monitor algorithmic outcomes (Mehrabi et al., 2022).

Based on the analysis of the KT data in this case, it appears that biased training data is the likely culprit, compounded by the lack of fairness auditing during model validation. This aligns with broader research indicating that unrepresentative datasets and unchecked automation often reproduce human and structural biases. Identifying this root cause allows Panama Life Health to transition from symptom management to systemic correction (Kepner & Tregoe, 1997).

Decision Analysis: Selecting the Best Corrective Actions

After identifying the root cause, the decision-analysis stage enables the organization to determine the most effective course of action to address the crisis, grounded in clear objectives and an enterprise risk-management approach. To overcome this crisis, Panama Life Health Insurance needs to implement a comprehensive plan to rebuild stakeholder trust through transparency, fairness, and accountability (Mehrabi et al., 2022).

The comprehensive plan must focus on retraining the AI model by using a balanced dataset that reflects the appropriate demographic diversity, while eliminating proxy variables that correlate with race and gender (Mehrabi et al., 2022). Develop fairness metrics and continuous auditing tools to monitor algorithmic outcomes and detect emerging biases (Mehrabi et al., 2022). In addition, they should establish a system that enables a committee responsible for overseeing model development, data governance, and stakeholder transparency to ensure compliance with AI ethics (Mehrabi et al., 2022). A human-in-the-loop review process should be implemented for all AI-generated claim denials to ensure fairness and accountability (Mehrabi et al., 2022). Panama Life Health needs to publicly address these corrective measures to ensure the company restores brand credibility and stakeholder trust in a manner aligned with ethical principles (Mehrabi et al., 2022).

Finally, the implementation process should be divided into three phases: (1) the immediate suspension and review of the biased algorithm, (2) the integration of short-term human review processes, and (3) the long-term institutionalization of fairness frameworks. This multi-tiered approach aligns with the KT principle of matching decisions to urgency and risk exposure (Mehrabi et al., 2022).

Potential Problem Analysis

To mitigate future risks, Panama Life Health Insurance should conduct bias impact assessments (BIAs) before each model deployment. They also need to establish AI fairness as a key performance indicator (KPIs), which focuses on parity in the area of cross-demographics in the claims approval process. They need to develop a process that requires periodic third-party audits to enhance transparency while validating that the company is adhering to the highest levels of fairness and compliance. Incorporating stakeholder feedback loops will allow customers to report suspected bias for review. Finally, they should invest in AI ethics training for employees, data scientists, and leadership to foster a culture of accountability, diversity, and inclusion (Mehrabi et al., 2022).

Panama Life Health Insurance needs to quickly shift from crisis management to a systematic, proactive, continuous improvement cycle by implementing a robust ERM system that anticipates potential risks that could affect the company in the future. At the same time, align these efforts with evolving regulatory standards, such as the EU AI Act and the U.S. Algorithmic Accountability Act, to ensure compliance and ethical alignment (Mehrabi et al., 2022).

Anticipating and Preventing Future Issues

In the health insurance industry, where biased outcomes can disproportionately affect vulnerable populations, data analysis plays an essential role in identifying, assessing, and mitigating bias. This is why the systematic analytical method helps ensure that the automated decision-making process remains fair, transparent, and accountable (Aleksandra et al., 2025). An effective monitoring system begins by identifying key demographic variables and collecting available data, such as claims approvals, denials, and appeals (Aleksandra et al., 2025). A chi-square test can detect significant differences between groups, whereas fairness metrics, such as demographic parity and equal opportunity, can assess the model's fairness.

A root-cause analysis is a critical tool used across the industry to determine whether disparities are due to skewed training data, proxy variables, or a flawed model design when disparities are observed, such as minority claimants receiving higher denial rates for similar cases (Aleksandra et al., 2025). Automated dashboards can further monitor fairness indicators over time and detect bias drift. Insights from these analyses support targeted mitigation strategies, including data reweighting, adversarial debiasing, or threshold adjustments.

Panama Life Health Insurance can strengthen public trust, protect patient rights, and support organizational integrity in a data-driven insurance industry by conducting rigorous data analysis processes to ensure that in the future, any AI-enabled claims system is compliant with ethical and legal expectations from its inception and throughout its life cycle.

Control Mechanism

Effective control mechanisms are essential tools that organizations should use to ensure that AI-utilizing systems are free of bias and operate fairly, transparently, and responsibly, while reinforcing transparency, accountability, and public trust in the automated decision-making process (Aleksandra et al., 2025). International standards and overall governance are critical controls. Numerous national and international standards govern the use of AI. For example, the OECD AI Principles call for transparency, fairness, protection of human rights, and accountability across the AI lifecycle (Muthusubramanian et al., 2024). Through its AI Standards initiative, the National Institute of Standards and Technology (NIST) advances data, performance, and governance standards. Detecting and mitigating bias in real time through fairness assessment libraries, explainability methods, monitoring systems, and accountability frameworks has demonstrated value in AI systems (Weerts et al., 2023).

There are several core practices that models rely on, including auditing data, tracking lineage, evaluating algorithms, and providing transparency tools that ensure that inputs are reliable and that unintended or unfair outcomes are detected and mitigated quickly (Weerts et al., 2022). These mechanisms form a critical control framework that ensures fairness is embedded throughout the system's design, deployment, and continuous monitoring throughout its life cycle.

In Aleksandra et al. (2025), the authors argue that aligning standard organizational practices with the OECD and NIST guidelines will improve transparency, accountability, and stakeholder trust. This multi-layered approach reduces the risk of hidden bias, enhances stakeholder confidence, and supports governance as AI technologies evolve (Weerts et al., 2022).

Applying Organizational Change-Management Theory to Resolve the AI Bias Crisis

To address the crisis caused by an AI system that disproportionately affected minorities and women, Panama Life Health Insurance should adopt a dual theoretical framework combining Schein's cultural model and Kotter's eight-step change process to resolve it. The Schein model will assist in identifying and reshaping deep cultural assumptions that ultimately shaped Panama Life Health Insurance's organizational behavior, and provide a clear diagnostic tool for the organization to evolve to a culture of transparency and accountability (Schein et al., 2017; Coghlan, 2024). In contrast, Kotter's framework provides the organization with a rigorous, structured approach to improving processes, leadership, and employee engagement. This combined approach ensures that technical interventions, such as model audits and fairness metrics, are embedded within long-term cultural transformation rather than implemented as isolated, one-time fixes (Coghlan, 2024).

Application of Concepts to the Study Context

The Schein cultural model is an excellent option that can assist Panama Life Health Insurance to address the bias crisis. This model uses a rigorous, structured approach to problem-solving by focusing on the root cause to provide decision-makers with a solution to their problem (Coghlan et al., 2025). This model will highlight visible elements, such as the automated claims-denial system, deployment practices, and performance dashboards, that demonstrate the organization has prioritized cost reduction over fairness. At the espoused values level, the model will encourage the organization to focus on promoting patient-centered care while simultaneously preventing bias (McMahon, 2022). In this case, it is essential to challenge deeper assumptions, such as the belief by many organizations in the health care industry that algorithms are objective and that automation inherently improves fairness. Without confronting these assumptions, technology simply codifies existing inequities rather than eliminating them (Schein et al., 2017; Coghlan, 2024).

As soon as cultural misalignments are identified, Kotter's eight-step model provides a clear roadmap for implementing organizational change systematically (Al Samman, 2041). For Panama Life, this would involve creating urgency by publicizing evidence of disparate denial rates and highlighting their ethical and operational implications (Kim et al., 2024).

Creating a cross-functional guiding coalition that includes leadership, frontline employees, clinical staff, data scientists, ethics advisors, and patient advocates that will assist with ensuring that transparency, accountability, and stakeholder trust are incorporated into all processes that utilize AI (Carreño, 2024). This process should include developing a vision statement that aligns fairness in AI with business objectives and ethical principles. The vision should be incorporated into everything the organization does, including recruiting, training, and retaining the workforce (Igwe-Nmaju, 2024).

Empowering action by removing structural barriers, for example, KPIs focused solely on cost savings and providing resources for fairness audits and incentive redesign (Daniel & Oye, 2024). Performance reviews, onboarding, leadership evaluations, and recognition programs should be integrated with fairness metrics (Panarese et al., 2025).

Resolving this crisis is not simple; however, using Schein's diagnostic lens alongside Kotter's structured change process enables the organization to address both the cultural root causes and the operational mechanisms of bias. This dual-path approach increases the likelihood that change will be meaningful and sustained rather than superficial (Alankarage et al., 2024; Carreño, 2024).

Ultimately, AI becomes not a neutral amplifier of precedent but a tool shaped by an organizational culture committed to fairness and accountability (Kanitz, 2023). By combining Schein's culture model and Kotter's organizational change framework, Panama Life Health Insurance will be able to resolve its bias crisis systemically and comprehensively while restoring stakeholder trust and brand reputation (Donnelly et al., 2020).

Comprehensive Solution Proposal

To be successful in the recovery of Panama Life Health Insurance, a comprehensive strategy needs to focus on four integrated pillars: (1) governance and ethics oversight, (2) technical bias mitigation, (3) transformation of organizational culture, and (4) stakeholder engagement and accountability.

Governance and Ethics Oversight

Establishing a corporate-level AI ethics and compliance committee that oversees all AI-related activities, including algorithm audits, data management practices, and fairness evaluations. This interdisciplinary group should include data scientists, compliance officers, healthcare ethicists, and representatives from patient advocacy organizations (Suresh & Guttag, 2021; Emanuel et al., 2022). The committee should produce an annual report to ensure that AI is implemented equitably, including a performance metric, updates to the model, and mitigation results. Furthermore, Panama Life Health should implement a bias incident reporting system that allows employees or external partners to flag potential algorithmic harms to confidentiality (Mhlanga, 2023).

Technical Bias Mitigation

Panama Life Health Insurance, from a technical perspective, needs to retrain its artificial intelligence systems to capture demographic diversity across racial, gender, and socioeconomic lines (Mehrabi et al., 2022). Implementing fairness-aware machine learning algorithms that integrate equity constraints during training can reduce disparate impact (Mehrabi et al., 2022).

Developing dashboards that continuously monitor bias is an essential step toward tracking fairness metrics, such as false favorable rates and denial ratios, across a broad range of demographic groups to ensure accurate fairness measurements (Mehrabi et al., 2022). Incorporating an external third-party audit can also validate the model's integrity and independently verify its compliance with fairness. Standardized documentation of the data's provenance throughout the lifecycle of artificial intelligence should also ensure traceability and explainability (Mehrabi et al., 2022).

Organizational Culture Transformation

The ethical use of AI cannot flourish without a fair and inclusive organizational culture. Panama Life Health must adopt a fairness-by-design approach when developing and deploying its AI systems, ensuring they are ethically assessed throughout development and deployment. All employees, including those who handle data, analytics, and claims processing, should undergo mandatory ethics and bias training annually to enhance awareness of hidden biases. Senior executives must champion this transformation by tying executive performance incentives to diversity, equity, and fair outcomes (Mehrabi et al., 2022).

For the organization to be successful in its efforts to achieve a more diverse workforce in terms of the technological skills it employs, it should also include underrepresented groups in the recruitment process to foster broader perspectives in the design of its systems. These initiatives will reinforce a culture of transparency, empathy, and social responsibility (Mehrabi et al., 2022).

Stakeholder Engagement and Accountability

Rebuilding public trust requires open communication and transparency, so Panama Life Health Insurance should issue a public apology acknowledging the harm caused and outlining corrective measures to prevent a recurrence (Mehrabi et al., 2022). Developing standards for equality and fairness requires collaboration with patient advocacy groups, healthcare regulators, and AI ethics organizations (Mehrabi et al., 2022). The organization's website should regularly publish FIAs to enable the public and regulators to track the company's progress regarding fairness impact assessments (FIAs). To demonstrate commitment to transparency, continuous improvement, and accountability, open dialogue sessions and feedback portals should be established. This will enable Panama Life Health Insurance to reposition itself on the market as a transparent and socially responsible organization (Mehrabi et al., 2022).

Implementation Plan

It is recommended that Panama Life Health Insurance use this phased approach to resolve this crisis rigorously and systematically:

Phase 1 (0–3 months): Immediate Response

1. Suspend AI-driven claims denials pending audit results.
2. Form the AI Ethics and Compliance Committee.
3. Initiate an independent third-party bias audit.
4. Issue a public statement taking responsibility, acknowledging the issue, and outlining the steps that will be taken.

Phase 2 (4–9 months): System Redesign and Training

1. Retrain AI models with corrected datasets.
2. Introduce fairness-aware algorithms and establish bias dashboards.
3. Conduct organization-wide bias and ethics training.

4. Develop an internal reporting channel that addresses ethical issues related to AI.

Phase 3 (10–18 months): Evaluation and Continuous Monitoring

1. Release the annual AI fairness report
2. Establish long-term partnerships with academic researchers and ethics councils.
3. Integrate fairness metrics into executive performance evaluations.
4. Maintain open communication channels with stakeholders for ongoing feedback.

If Panama Life Health Insurance implemented this comprehensive proposal, it would resolve the crisis, restore stakeholder trust, and make the company an ethical leader in the healthcare insurance industry (Suresh & Guttag, 2021; Emanuel et al., 2022).

Addressing algorithmic bias through governance, technical reform, cultural transformation, and stakeholder engagement will restore fairness and public confidence in claims processing. With this integrated approach, Panama Life Health Insurance will be able to demonstrate that it aims to provide an excellent product to its customers while upholding high ethical standards (Suresh & Guttag, 2021; Emanuel et al., 2022).

Conclusion

Panama Life Health Insurance needs to adopt a comprehensive, multilevel strategy that integrates technical remediation, ethical oversight, and cultural transformation to resolve its crisis. In this case, it is imperative to reduce discriminatory outcomes in AI systems by implementing datasets trained with diversity, auditing, and robust governance structures that include a human in the loop (Suresh & Guttag, 2021; Emanuel et al., 2022).To achieve long-term, enduring success, Panama Life Health Insurance needs to align its culture, incentives, and ethical imperatives (Schein et al., 2017; Chhatre & Singh, 2024).

Organizational change frameworks such as Kotter's eight-step model and Schein's cultural analysis should be used in this case to emphasize the importance of aligning culture, incentives, and ethical imperatives within the organization. To overcome Panama Life Health Insurance's challenge while operationalizing these insights, a systematic corrective action process across three domains is recommended for implementation:

1. Retrain the dataset: Ensure models are trained on balanced datasets, remove proxy variables, and incorporate human-in-the-loop safeguards to prevent unfair denials.

2. Ethical Governance: Incorporate fairness KPIs, mandate third-party audits, and align organizational practices with emerging regulations such as the EU AI Act by establishing an AI ethics committee.

3. Cultural and Structural Transformation: Implement Schein and Kotter's change model to mobilize leadership, realize incentives, and embed fairness into values, metrics, and training.

Integrating these actions ensures that AI systems do not reproduce historical disparities, while reducing risk and strengthening transparency (Schein et al., 2017; Chhatre & Singh, 2024). To improve organizational trust, enhance patient outcomes, and set a benchmark for responsible innovation in the healthcare sector, Panama Life Health Insurance should implement these evidence-based recommendations to overcome its crises and position itself as the industry standard-bearer.

References

Al Samman, A. (2024). *The use of AI in fostering and embracing organizational culture*. In Proceedings of ICETSIS 2024.

Alankarage, S., Chileshe, N., Samaraweera, A., Rameezdeen, R., & Edwards, D. J. (2024). Diagnosing organizational BIM culture: A qualitative case study using Schein's model. *Journal of Management in Engineering, 40*(3), 05024005.

Aleksandra, N., Bojana, J., Maryan, R., & Dimitar, T. (2025). Evaluating Trustworthiness in AI: Risks, Metrics, and Applications Across Industries. *Electronics, 14*(13), 2717.

Baker, J., & Hawn, O. (2022). Responsible AI in healthcare: Governance, ethics, and accountability. *Journal of Business Ethics, 179*(4), 945–963.

Baker, J., & Hawn, O. (2022). Responsible AI in healthcare: Governance, ethics, and accountability. *Journal of Business Ethics, 179*(4), 945–963.

Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. International journal of artificial intelligence in education, 32(4), 1052-1092.

Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. International journal of artificial intelligence in education, 32(4), 1052-1092.

Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review, 104*(3), 671–732.

Braveman, P., Arkin, E., Orleans, T., Proctor, D., & Plough, A. (2017). *What is health equity?* Robert Wood Johnson Foundation. Retrieved November 4, 2020.

Carreño, A. M. (2024). An analytical review of John Kotter's change leadership framework: A modern approach to sustainable organizational transformation. SSRN. http://dx.doi.org/10.2139/ssrn.5044428*Available at SSRN 5044428*.

Chhatre, R., & Singh, S. (2024a). AI and organizational change: dynamics and management strategies. *Journal of Emerging Trends and Novel Research, 2*(5).

Chhatre, R., & Singh, S. (2024b). Impact of AI on human behavior and decision making; ethical implications of AI. *Ethical implications of AI (June 18, 2024).*

Coghlan, D. (2024). *Edgar H. Schein: The artistry of a reflexive organizational scholar-practitioner* (p. 204). Taylor & Francis.

Coghlan, D., Bartunek, J. M., Paine, J. W., Shani, A. B. R., Shimoni, B., & Wasserman, I. C. (2025). Exploring Ed Schein's Legacy and Enduring Influence to Inform the Future. In *Research in Organizational Change and Development, (Vol. 31*, pp. 193-216). Emerald Publishing Limited.

Crawford, K., & Paglen, T. (2023). *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.

Crawford, K., & Paglen, T. (2023). *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.

Daniel, Z., & Oye, E. (2024). Key Performance Indicators (KPIs) for Financial Control Systems.

Dean, W., Talbot, S., & Dean, A. (2019). Reframing clinician distress: Moral injury, not burnout. *Federal Practitioner, 36*(9), 400–402. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6721810/

Deloitte. (2023). *Ethical leadership and brand trust: How corporate integrity shapes consumer confidence.* Deloitte Insights. https://www.deloitte.com/insights

Di Palma, G., Scendoni, R., Tambone, V., Alloni, R., & De Micco, F. (2025). Integrating enterprise risk management to address AI-related risks in healthcare: Strategies for effective risk mitigation and implementation. *Journal of Healthcare Risk Management, 44*(4), 25-33.

Donnelly, L. F., Frush, K., Shook, J., & Schein, P. A. (2020). The importance of both the technical and social domains in creating a culture that accelerates improvement in healthcare. *Health, 12*(12), 1575-1582.12, 21 December 2020.

Emanuel, E. J., Wachter, R. M., & Cassel, C. K. (2024). Ethics and equity in artificial intelligence in health care. *New England Journal of Medicine, 390*(2), 112–118. https://doi.org/10.1056/NEJMra2302930

Fan, C., Xu, J., Natarajan, B. Y., & Mostafavi, A. (2023). Interpretable machine learning enables the understanding of complex interactions between urban features and socio-economic inequality. *Computer-Aided Civil and Infrastructure Engineering, 38*(14), 2013-2029.

Fan, C., Xu, J., Natarajan, B. Y., & Mostafavi, A. (2023). Interpretable machine learning enables the understanding of complex interactions between urban features and socio-economic inequality. *Computer Aided Civil and Infrastructure Engineering, 38*(14), 2013-2029.

Fan, C., Yang, J., & Zhang, T. (2023). Algorithmic fairness in healthcare AI: A systematic review. *Health Informatics Journal, 29*(1), 1–17.

Fan, C., Yang, J., & Zhang, T. (2023). Algorithmic fairness in healthcare AI: A systematic review. *Health Informatics Journal, 29*(1), 1–17.

Grand View Research, Inc. (2025, April 28). *AI in healthcare market size to reach USD 187.7 billion by 2030 at CAGR 38.5%*. PR Newswire.

Helmold, M. (2022). *Decision-making excellence: The Kepner-Tregoe approach for business leaders*. Springer.

Helmold, M. (2022). Problem-solving and performance management tools. In *Strategic Performance Management: Achieving Long-term Competitive Advantage through Performance Excellence* (pp. 93-108). Springer International Publishing.

Helmold, M. (2022). Problem-solving and performance management tools. In *Strategic Performance Management: Achieving Long-term Competitive Advantage through Performance Excellence* (pp. 93-108). Cham: Springer International Publishing.

Igwe-Nmaju, C. (2024). Organizational communication in the age of APIs: integrating data streams across departments for unified messaging and decision-making. *International Journal of Research Publication and Reviews*, *5*(12), 2792-2809.

Kanitz, R. (2023). Augmenting organizational change and strategy activities. *Journal of Organizational Change.*

Kepner, C. H., & Tregoe, B. B. (1997). *The new rational manager: An updated edition for a new world*. McGraw-Hill Education.

Kepner, C. H., & Tregoe, B. B. (1997). *The new rational manager: An updated edition for a changing world*. Princeton Research Press.

Kepner, C. H., & Tregoe, B. B. (2013). *The new rational manager: An updated edition for a new world*. Princeton Research Press.

Kepner, C. H., & Tregoe, B. B. (2022). *The new rational manager: An updated edition for a new world*. Princeton Research Press.

Kepner, C. H., & Tregoe, B. B. (2022). *The new rational manager: An updated edition for a new world*. Princeton Research Press.

Kim, S., Ho, J., Li, Y., Fan, B., Yang, W. Y., Ramey, J., & Eslami, M. (2024). Integrating Equity in Public Sector Data-Driven Decision Making: Exploring the Desired Futures of Underserved Stakeholders. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW2), 1-39.

Kluge, A., Becker, J., & Schlichter, B. (2022). Artificial intelligence and organizational change: Implications for work design and employee well-being. *Journal of Organizational Behavior*, *43*(8), 1234–1250.

Kluge, N. J., Gabelica, C., & Lemoine, J. E. (2022). Ethical crises and employee outcomes: The role of moral emotions and organizational justice. *Journal of Business Ethics*, *179*(2), 347–364. https://doi.org/10.1007/s10551-021-04875-

Kotter, J. P. (1996). Leadership change. *Harvard Business School Press: Boston, MA, USA*.

Leslie, D. (2022). Don't" research fast and break things": On the ethics of Computational Social Science. *arXiv preprint arXiv:2206.06370*.

Liefgreen, A., Weinstein, N., Wachter, S., & Mittelstadt, B. (2024). Beyond ideals: why the (medical) AI industry needs to motivate behavioural change in line with fairness and transparency values, and how it can do it. *AI & society*, *39*(5), 2183-2199.

Litz, B. T., & Walker, D. I. (2025). *Moral injury in the workplace: Psychological and ethical dimensions of organizational crisis*. Oxford University Press.

Litz, B. T., & Walker, H. E. (2025). Moral injury: An overview of conceptual, definitional, assessment, and treatment issues. *Annual Review of Clinical Psychology, 21*.

Markopoulos, E., Refflinghaus, J., Roell, M., & Vanharanta, H. (2022). Understanding situationality using the kepner-tregoe method in the company democracy model to increase employee engagement and knowledge contribution. In *Creativity, innovation and entrepreneurship, (Vol. 31*, pp. 196-207). AHFE International.

Mayer, D. M., Ong, M., & Sonenshein, S. (2021). The impact of ethical failures on organizations: Understanding reputational damage and recovery. *Business Horizons*, *64*(5), 573–582. https://doi.org/10.1016/j.bushor.2021.04.004

McKinsey Global Institute. (2023, July 26). *Generative AI and the future of work in America.* McKinsey & Company. https://www.mckinsey.com/mgi/our-research/generative-ai-and-the-future-of-work-in-america

McKinsey Global Institute. (2023). *The future of work after COVID-19: Automation, AI, and the new workforce transformation.* McKinsey & Company.

McMahon, C. J. (2022). Organizational culture as a determinant of outcome in health services: a review.

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2022). A survey on bias and fairness in machine learning. ACM Computing Surveys, 54(6), 1–35. https://doi.org/10.1145/3457607

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2022). A survey on bias and fairness in machine learning. *ACM Computing Surveys*, *54*(6), 1–35. https://doi.org/10.1145/3457607

Mhlanga, D. (2023). Ethical artificial intelligence in healthcare: Challenges and solutions. *Frontiers in Artificial Intelligence*, *6*(1), 1–12. https://doi.org/10.3389/frai.2023.1029157

Muthusubramanian, M., Jangoan, S., Sharma, K. K., & Krishnamoorthy, G. (2024). Demystifying explainable AI: Understanding, transparency and trust. *International Journal fFor Multidisciplinary Research*, *6*(2), 1-13.

O'Neil, C., Sargeant, H., & Appel, J. (2024). Explainable fairness in regulatory algorithmic auditing. *W. Va. L. Rev.*, *127*, 79.

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447-453.

Panarese, P., Grasso, M. M., & Solinas, C. (2025). Algorithmic bias, fairness, and inclusivity: a multilevel framework for justice-oriented AI. *AI & SOCIETY*, 1-23.

Park, S. H., & Kwon, H. J. (2024). The role of artificial intelligence in digital healthcare: Current trends and future directions. *Healthcare Informatics Research*, *30*(3), 172–180. https://doi.org/10.4258/hir.2024.30.3.172

Raji, I. D., & Buolamwini, J. (2022). Actionable auditing: Investigating the impact of publicly naming biased performance results of commercial AI products. Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society, 429–439. https://doi.org/10.1145/3461702.3462610

Rajkomar, A., Loreaux, E., Liu, Y., Kemp, J., Li, B., Chen, M. J., ... & Gottweis, J. (2022). Deciphering clinical abbreviations with a privacy protecting machine learning system. *Nature communications*, *13*(1), 7456.

Schein, E. H., & Schein, P. A. (2017). *Organizational culture and leadership (5th ed.).* Wiley.

Servidio, A. E. (2024). Impact of Auditing and Feedback in the Face of Resistance to Organizational Change in the Healthcare Industry. In *Innovations, Securities, and Case Studies Across Healthcare, Business, and Technology* (pp. 343-358). IGI Global Scientific Publishing.

Siddique, A., Johnson, A., & Braveman, P. (2024). Bias in healthcare algorithms and racial inequities in patient outcomes. *Journal of Health Policy and Technology*, *13*(2), 102–118.

Siddique, S. M., Tipton, K., Leas, B., Jepson, C., Aysola, J., Cohen, J. B., ... & Mull, N. K. (2024). The impact of health care algorithms on racial and ethnic disparities: a systematic review. *Annals of Internal Medicine*, *177*(4), 484-496.

Suresh, H., & Guttag, J. (2021, October). A framework for understanding sources of harm throughout the machine learning life cycle. In *Proceedings of the 1st ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization* (pp. 1-9).

Ueda, D., Kakinuma, T., Fujita, S., Kamagata, K., Fushimi, Y., Ito, R., & Naganawa, S. (2024). Fairness of Artificial Intelligence in Healthcare: A Review and Recommendations. *Japanese Jjournal of Rradiology*, *42*(1), 3-15.

Zajko, M. (2022a). Artificial intelligence, algorithms, and social inequality: Sociological contributions to contemporary debates. *Sociology Compass*, *16*(3), e12962.

Zajko, M. (2022b). Auditing AI: Transparency and fairness in healthcare decision systems. *AI & Society*, *37*(3), 963–978.