

AI and the African Insurance Market: Implications of Anthropic's Labour Market Report for Continental Practitioners: A Practitioner Commentary

Ortopah Kojo Botchey

Independent Researcher and Actuarial Consultant.

Corresponding author: okbotchey@orbotrice.com

DOI: <https://doi.org/10.62154/ajmbr.2026.022.01031>

Abstract

This commentary offers a practitioner-focused secondary analysis of Anthropic's 2026 *Labour Market Impacts of AI* report, examining its implications for African insurance markets. The report's central finding, that observed professional adoption of AI dramatically lags theoretical capability, is interrogated through the dual lenses of the Technology Acceptance Model and technology diffusion theory, with particular attention to trust as a determinant of adoption in emerging-market insurance settings. The article does not present new empirical data; it constructs an applied argument by triangulating the Anthropic findings with peer-reviewed literature on Insurtech in Africa, technology acceptance in financial services, and the structural characteristics of African insurance markets documented by international reinsurance research and Ghanaian regulatory sources. The analysis identifies an observed-versus-theoretical exposure gap as both a description of the global state of AI adoption and a strategic window for African insurance, while acknowledging the institutional, regulatory, and infrastructural barriers that may constrain its realisation. Differentiated implications are drawn for insurers, regulators, actuarial professionals, and the wider continental ecosystem. The article's contribution is to provide the first structured practitioner reading of the Anthropic Dataset for an African insurance audience, and to position the trust-first determinant of digital insurance adoption within the broader conversation on AI governance and capacity building on the continent.

Keywords: Artificial Intelligence; Labour Markets; African Insurance; Actuarial Practice; Insurtech; Technology Acceptance; Trust; Digital Adoption.

Introduction

Artificial intelligence has moved from the periphery of insurance discourse to the centre of regulatory, strategic, and operational planning across the global insurance industry (OECD, 2023; IAIS, 2025). For African insurance markets, characterised by low penetration, thin actuarial capacity, fragmented distribution, and persistent trust deficits, the questions raised by AI are not merely about productivity or cost. They are questions about whether the technology will widen or narrow the protection gap that has defined the continent's insurance sector for decades (Swiss Re Institute, 2025; Horvey et al., 2023).

Within this conversation, the publication of Anthropic's *Labour Market Impacts of AI* report on 5 March 2026 (Massenkoff & McCrory, 2026) is significant for two reasons. First, it is among the most empirically grounded studies to date of which professional tasks are

actually being automated, as opposed to those that could theoretically be automated. Second, it introduces a measurable gap between theoretical and observed exposure that is directly diagnostic for markets considering how, when, and where to deploy AI in insurance operations. Yet the report's data are drawn entirely from the United States. Its findings cannot be transplanted to African insurance settings without translation, and that translation is the work of this commentary.

Scholarly Motivation and Gap

There is a small but growing peer-reviewed literature on AI in insurance (Eling et al., 2022; Owens et al., 2022; Riikinen et al., 2018) and a complementary body of work on technology acceptance in African financial services (Senyo & Osabutey, 2020; Asongu & Odhiambo, 2018; Hassan et al., 2024). Yet four gaps remain in the literature relevant to this commentary. First, the empirical evidence base on AI adoption in insurance is dominated by capability-focused studies that estimate what AI could do (Eloundou et al., 2024) rather than what professionals are doing with it. Second, the African insurance literature has documented the protection gap and its drivers (Horvey et al., 2023; Sinha, 2002) but has not yet integrated capability-versus-adoption evidence from generative AI into its strategic recommendations. Third, the technology acceptance literature in African financial services has emphasised mobile money and banking (Senyo & Osabutey, 2020) but has provided comparatively little theoretical development of trust as a determinant of AI-augmented insurance adoption. Fourth, practitioner commentary has tended to read AI through a generic productivity lens rather than through the differentiated stakeholder concerns of insurers, regulators, actuaries, and the wider continental ecosystem.

This commentary addresses those gaps by constructing a structured practitioner reading of the Anthropic dataset, integrating peer-reviewed scholarship on technology acceptance and Insurtech in emerging markets, and translating the findings into stakeholder-specific implications for African insurance. It does not test hypotheses, does not generate new empirical data, and does not claim representativeness for African contexts; its contribution is interpretive and applied.

Purpose, Scope, and Article Structure

The purpose of this article is to examine the Anthropic Labour Market Report through an actuarial practitioner lens and to develop differentiated implications for African insurance stakeholders. The scope is deliberately bounded to commentary and applied synthesis; empirical claims are restricted to those supported by the cited literature. The article is structured as follows. Section 2 states the problem and the analytical questions that motivate the commentary. Section 3 sets out the conceptual framework, drawing on the Technology Acceptance Model and technology diffusion theory and integrating the trust-first finding for digital insurance adoption in Ghana. Section 4 describes the analytical approach and acknowledges its limitations. Section 5 summarises the Anthropic report's findings on capability versus reality. Section 6 develops the implications for African

insurance markets. Section 7 sets out differentiated stakeholder recommendations. Section 8 discusses counterarguments and limitations. Section 9 concludes.

Statement of the Problem and Analytical Questions

The problem this commentary addresses is the absence, in the African insurance literature and in practitioner discourse, of a structured interpretation of recent capability-versus-adoption evidence on AI in professional services. Massenkoff and McCrory (2026) document a striking and reproducible gap between what AI can theoretically do across U.S. occupations and what professionals are observably using it for. Whether and how that gap should shape strategy, regulation, professional development, and ecosystem investment in African insurance is currently underexamined. Without such interpretation, two failure modes are likely. The first is over-confidence: assuming that high theoretical exposure scores imply imminent disruption and adopting defensive postures that may foreclose productive innovation. The second is complacency: reading low observed exposure as evidence that AI is a problem for later, and missing a window in which professionally led adoption can deliver disproportionate gains in markets where the cost-to-serve has long been the binding constraint on penetration.

The article therefore addresses three analytical questions:

- Q1. What does the Anthropic capability-versus-adoption evidence imply for the strategic framing of AI in African insurance markets, given their structural characteristics?
- Q2. How does the trust-first determinant of digital insurance adoption documented in the Ghanaian context (Botchey, 2025a, 2025b) condition the translation of capability into adoption?
- Q3. What differentiated implications follow for insurers, regulators, actuarial professionals, and the wider continental insurance ecosystem?

These are interpretive rather than empirical questions, consistent with the commentary format. They are answered through structured argument grounded in the cited literature.

Conceptual Framework

Two complementary theoretical lenses inform this commentary. The first is the Technology Acceptance Model (TAM), originally formulated by Davis (1989) and extended in subsequent work to incorporate trust, social influence, and contextual moderators (Venkatesh et al., 2003; Gefen et al., 2003). TAM is well established as a framework for explaining individual and organisational adoption of information technology in financial services and has been applied to insurance contexts in emerging markets (Hassan et al., 2024). The model's central propositions, that perceived usefulness and perceived ease of use jointly drive adoption intention, are useful here because the Anthropic findings can be read as a measurement of revealed adoption against latent capability. Where capability is

high but adoption is low, TAM predicts that mediating factors such as trust, perceived risk, and organisational and regulatory constraints are doing the work.

The second lens is technology diffusion theory, in the tradition of Rogers (2003), which models the spread of an innovation across a population through identifiable phases and through interactions among the innovation's relative advantage, compatibility, complexity, trialability, and observability. Diffusion theory is particularly useful for the African insurance context because it foregrounds the institutional and infrastructural conditions that govern whether a capable technology actually spreads (Asongu & Odhiambo, 2018; Senyo & Osabutey, 2020). The capability-versus-adoption gap documented by Massenkoff and McCrory (2026) can be read as a diffusion phenomenon: AI is in the early-adopter phase of a generalised diffusion curve, and the rate of progression beyond that phase is governed not by additional capability but by the social, institutional, and trust-based mediators that diffusion theory specifies.

Connecting the two lenses, this commentary draws on the trust-first finding for digital insurance adoption in Ghana (Botchey, 2025a, 2025b), which empirically estimated trust as a stronger predictor of adoption intention than perceived usefulness, with perceived ease of use becoming non-significant in the Ghanaian survey context. That finding, while based on un-peer-reviewed self-authored work and therefore offered here as preliminary rather than settled evidence, is consistent with broader scholarship on trust in digital financial services in sub-Saharan Africa (Hassan et al., 2024; Senyo & Osabutey, 2020). It supports the argument developed in Section 6 that closing the observed-versus-theoretical adoption gap in African insurance will depend more on trust architecture than on technological capability.

A disclosure is warranted regarding the primary source itself. The Anthropic Labour Market Impacts report (Massenkoff & McCrory, 2026) is a corporate research report and has not undergone independent peer review. It is treated here on the same evidentiary footing as the other non-peer-reviewed sources in this commentary: as a serious and methodologically distinctive contribution whose findings are nonetheless preliminary and whose directional claims are cross-validated against independent evidence where possible (see Section 4). The same caveat applies to its chief corroborator, the Brynjolfsson et al. (2025) working paper. These frameworks are used here as interpretive scaffolding that disciplines the practitioner argument and connects it to the broader scholarly conversation on technology acceptance and diffusion in financial services.

Analytical Approach and Limitations

This is a commentary, not an empirical study. The analytical approach is structured secondary analysis combined with applied practitioner synthesis. The Anthropic Labour Market Impacts report (Massenkoff & McCrory, 2026) was selected as the primary source for three reasons. First, it is methodologically distinctive in linking theoretical AI capability scores to observed professional usage drawn from millions of Claude conversations, producing a measurement of revealed rather than projected adoption. Second, it is the

most recent and most granular such measurement publicly available at the time of writing, with occupation-level estimates that map onto roles relevant to insurance operations. Third, it has attracted complementary analysis from independent researchers using different data sources (Brynjolfsson et al., 2025), permitting cross-validation of its directional findings.

The Anthropic findings are interpreted through the conceptual framework in Section 3 and triangulated with peer-reviewed scholarship on Insurtech in emerging markets, technology acceptance in African financial services, and the structural characteristics of African insurance documented by industry bodies (Swiss Re Institute, 2025; National Insurance Commission, 2024). Stakeholder-specific implications are derived in Section 7 by mapping the analytical findings onto the differentiated decision contexts of insurers, regulators, actuarial professionals, and ecosystem-level actors.

Several limitations of this approach must be stated upfront. First, both the primary source (Massenkoff & McCrory, 2026) and its chief corroborating study (Brynjolfsson et al., 2025) are non-peer-reviewed: the former is a corporate research report and the latter a working paper at the time of writing. Their findings are reported here as preliminary, and their convergence is treated as suggestive rather than conclusive. Second, the Anthropic dataset is U.S.-centric; extrapolation to African markets is illustrative rather than predictive, and is constrained by differences in digital infrastructure, AI literacy, regulatory environment, and product mix. Third, the trust-first evidence drawn from the author's doctoral and working-paper research (Botchey, 2025a, 2025b) is based on un-peer-reviewed self-authored work and is therefore offered as preliminary; it is supplemented by independent peer-reviewed literature where possible (Hassan et al., 2024; Senyo & Osabutey, 2020) but cannot yet be treated as settled in the African insurance literature. Fourth, the commentary format constrains the depth of empirical engagement; this article is an interpretive contribution, and its claims should be assessed accordingly.

The Report in Brief: Capability versus Reality

Massenkoff and McCrory (2026) introduce a metric they term "observed exposure," constructed by combining theoretical AI capability scores derived from O*NET task taxonomies with actual professional usage patterns observed across millions of Claude conversations. The construction of the metric and its underlying datasets are documented in the report and are consistent in approach with prior capability-side estimation (Eloundou et al., 2024) and complementary employment-side evidence drawn from payroll data (Brynjolfsson et al., 2025).

The central finding is a substantial and reproducible gap between theoretical and observed exposure. In Computer and Mathematical occupations, AI could theoretically perform a large majority of tasks, yet observed professional coverage is materially lower. The pattern repeats across Business and Financial occupations, Office and Administrative Support, and Legal occupations, all of which are theoretically highly exposed but observably partially

adopted (Massenkoff & McCrory, 2026). At the other end of the distribution, roughly thirty per cent of occupations, predominantly those requiring physical presence such as cooks, mechanics, bartenders, and construction workers, register effectively zero AI exposure. Actuarial work, by contrast, sits in the high-exposure category by virtue of its task profile: modelling, analytical writing, data interpretation, and structured documentation.

Two corollary findings of the report bear directly on the African insurance argument. First, the authors find no statistically significant increase in unemployment among workers in highly exposed occupations since the public release of widely used generative AI systems in late 2022 (Massenkoff & McCrory, 2026). Second, they identify an early signal of compositional change rather than aggregate displacement: hiring of younger workers in exposed occupations has slowed, an observation consistent with the entry-level employment effects documented by Brynjolfsson et al. (2025) using independent payroll data. The labour-market story emerging from these complementary studies is therefore one of compositional adjustment rather than mass disruption, a framing that has different implications for emerging markets than for mature ones.

Why This Matters for African Insurance Markets

The Penetration Problem and the Cost-to-Serve Constraint

African insurance penetration averages below three per cent of GDP across the continent, with many markets considerably lower (Swiss Re Institute, 2025). The drivers of this protection gap are documented in the literature: limited distribution infrastructure, high administrative cost relative to premium volumes, thin actuarial talent pools, regulatory fragmentation, and persistent trust deficits among prospective policyholders (Horvey et al., 2023; Sinha, 2002). These are supply-side rather than demand-side constraints; the literature on insurance demand among low-income populations has consistently shown that such households understand and value risk transfer when it is offered at appropriate price points and through channels they trust. Recent discrete-choice evidence from low-income South African households confirms that affordability, insurer quality, ease of application, and trust are the decisive determinants of willingness to pay for cover (Lefutso et al., 2025), echoing earlier foundational work on micro-insurance demand in the informal economy (Sinha, 2002).

Read against the Anthropic findings, the diagnostic implication is direct. The tasks where observed AI adoption is highest in mature markets, namely data processing, customer interaction, document generation, and repetitive analytical work (Massenkoff & McCrory, 2026), are precisely the categories that inflate the cost-to-serve in African insurance. An insurer in Accra spending several weeks preparing a product approval memorandum for the National Insurance Commission could, with AI-augmented actuarial workflows, compress that cycle materially; a micro-insurance provider underwriting crop cover for smallholder farmers could deploy AI-assisted risk models at a cost that traditional actuarial resourcing would not support (NIC, 2024). The Anthropic dataset does not prove this for African

markets, but it establishes the capability and observes the partial adoption that suggests the gain is realisable.

The Trust Imperative and the Translation from Capability to Adoption

The conceptual framework set out in Section 3 predicts that closing the observed-versus-theoretical gap will depend on factors mediating capability and adoption. Empirical evidence from sub-Saharan African digital financial services consistently identifies trust as a primary such mediator (Hassan et al., 2024; Senyo & Osabutey, 2020), and the trust-first finding for digital insurance adoption in Ghana points in the same direction (Botchey, 2025a, 2025b). The implication is twofold. First, technological capability is a necessary but not sufficient condition for AI-driven transformation of African insurance; the Anthropic data confirm that even mature-market adopters with comparatively strong digital infrastructure and AI literacy show large unrealised capability. Second, the trust deficit characteristic of African insurance markets is a higher-order constraint on AI adoption than its technical complexity. Successful deployment will require visible human-in-the-loop processes, transparent communication of AI-assisted decisions to policyholders, and regulatory engagement that establishes, rather than presumes, the technology's reliability (NIC, 2024; IAIS, 2025). This is a normative analytical position, not a tested hypothesis. It is offered as the most defensible reading of the joint evidence from the Anthropic report, the broader peer-reviewed literature on technology acceptance in African financial services, and the preliminary trust-first evidence from the Ghanaian context.

The Strategic Window

The combination of high theoretical capability, partial observed adoption in mature markets, and binding cost-to-serve constraints in African markets defines a strategic window for the continent's insurance sector. The window is not open indefinitely: as global adoption progresses and as the compositional employment effects identified by Brynjolfsson et al. (2025) deepen, the relative advantage available to early-moving African insurers will erode. The structural conditions for value-creating adoption are unusually favourable now, and the trust architecture required to realise that value can be built only at the speed at which institutions, regulators, and professionals are willing to build it.

Stakeholder Implications and Recommendations

The analytical questions framed in Section 2 generate differentiated implications for four stakeholder groups in African insurance. Each recommendation is grounded in the analysis of Sections 5 and 6 and is referenced to the relevant literature.

For Insurers

Insurers should treat AI as an amplifier of professional expertise rather than a substitute for it. The Anthropic data show that observed adoption is highest where AI augments tasks

already performed by skilled professionals (Massenkoff & McCrory, 2026), and the literature on AI in insurance internationally supports this augmentation reading (Eling et al., 2022; Riikinen et al., 2018). For African insurers operating in capacity-constrained markets, the priority is not to replace scarce actuarial and underwriting talent but to extend its reach: AI-assisted document drafting, risk model maintenance, customer correspondence, and management information production are realistic near-term applications. Visible human accountability for AI-assisted outputs is consistent both with trust-first adoption findings (Botchey, 2025a, 2025b; Hassan et al., 2024) and with the international supervisory expectation set out by the IAIS (2025).

For Regulators (NIC, IRA, NAICOM, FSCA, and Others)

Massenkoff and McCrory (2026) note that legal and compliance constraints are among the principal factors limiting observed AI adoption in mature markets. African insurance regulators have an opportunity to develop proportionate guardrails ahead of, rather than behind, market practice. The IAIS Application Paper on the Supervision of Artificial Intelligence (IAIS, 2025) offers an internationally agreed reference point that can be adapted to local contexts. Practical instruments include sandbox frameworks for AI-assisted underwriting and claims processing, model-risk management expectations proportionate to the size and risk profile of insurers, and structured engagement with the actuarial profession on the validation of AI-assisted analytical outputs. Outright prohibition of AI is unlikely to prevent its use; it will displace use into less observable channels and is therefore inconsistent with the supervisor's consumer-protection mandate (NIC, 2024; IAIS, 2025).

For Actuarial Professionals in Africa

The report indicates that approximately thirty per cent of occupations, those requiring physical presence, register effectively zero AI exposure (Massenkoff & McCrory, 2026). Actuarial work is not in that category. Its task profile, modelling, analytical writing, data interpretation, and structured documentation, sits in the high-exposure zone, and the entry-level compositional effects observed by Brynjolfsson et al. (2025) suggest that the labour-market adjustment will be felt first by junior cohorts. The constructive response is to treat AI as a production technology for the profession: integrating large language models and analytical AI tools into actuarial workflow, codifying standards for human review of AI-assisted outputs, and building the educational infrastructure through which the profession develops AI fluency (IAIS, 2025; OECD, 2023). Actuarial practitioners who combine domain expertise with AI fluency are well placed to deliver more value at lower cost in markets that need affordable professional services most acutely.

For the Continental Insurance Ecosystem

Africa's low insurance penetration is a development constraint, not merely a commercial inconvenience. Uninsured climate, health, and business risks compound household and

firm vulnerability and depress investment (Horvey et al., 2023; Swiss Re Institute, 2025). AI-augmented insurance delivery, more affordable actuarial services, faster product development cycles, lower administrative costs, and better customer engagement, represents one pathway, among others, to closing the protection gap at a pace and cost that traditional model alone cannot achieve. Realising that pathway requires coordinated investment in digital and energy infrastructure, in skills, and in the trust architecture without which capability does not translate into adoption (Senyo & Osabutey, 2020). The Anthropic report does not establish that AI will close the protection gap; it establishes the capability and partial adoption from which the case for purposeful investment can be made.

Discussion: Counterarguments and Limitations

The argument developed in Sections 5 to 7 should be read with three substantive counterarguments and limitations clearly in view.

The Inequality Counterargument

AI may deepen rather than narrow existing inequalities in African insurance markets. If access to AI capability concentrates among the largest insurers, in the most digitally mature jurisdictions, and around the most data-rich product lines, the technology could widen rather than close the protection gap. The literature on financial inclusion in sub-Saharan Africa documents analogous concentration effects in adjacent technologies (Asongu & Odhiambo, 2018). The recommendations in Section 7 mitigate but do not eliminate this risk; supervisory engagement on equitable access and proportionate regulation (IAIS, 2025) is an essential complement to private-sector AI adoption.

The Infrastructure Counterargument

Reliable electricity, broadband, payment rails, and data infrastructure are pre-conditions for AI deployment that are unevenly distributed across the continent. Where these conditions are absent, capability does not translate into adoption regardless of trust architecture (Senyo & Osabutey, 2020). The strategic window described in Section 6.3 is therefore conditional on parallel infrastructure investment, much of which is exogenous to the insurance sector. This commentary does not adjudicate the infrastructure debate; it acknowledges that without progress on these foundational conditions, the case for AI-driven transformation of African insurance is materially weakened.

The Generalisation Limitation

The Anthropic dataset is U.S.-centric. Its observed-exposure measurements reflect adoption patterns shaped by U.S. labour-market structures, legal and regulatory environments, and AI-product distribution channels. Translation to African contexts is illustrative rather than predictive, and the trust-first evidence drawn from Ghanaian data (Botchey, 2025a, 2025b) cannot be assumed to hold uniformly across the continent's

diverse markets. The recommendations should therefore be read as directional rather than prescriptive, and as inputs to local strategic and supervisory deliberation rather than substitutes for it.

Limitations of the Evidence Base

Three further limitations bear stating. First, the analysis relies in part on un-peer-reviewed self-authored work (Botchey, 2025a, 2025b); while consistent with broader peer-reviewed literature on trust in digital financial services (Hassan et al., 2024), the specific Ghanaian estimates should be treated as preliminary. Second, as noted in Sections 3 and 4, both the primary source (Massenkoff & McCrory, 2026) and its chief corroborator (Brynjolfsson et al., 2025) are non-peer-reviewed at the time of writing; their convergence is suggestive rather than conclusive. Third, several supervisory and industry sources cited (IAIS, 2025; Swiss Re Institute, 2025; NIC, 2024) are practitioner-grey rather than peer-reviewed, which is appropriate for the institutional facts they document but limits their analytical weight. The article's claims should be assessed in light of these constraints.

Conclusion

Anthropic's *Labour Market Impacts of AI* report (Massenkoff & McCrory, 2026) is, to date, among the most empirically grounded measurements of AI's actual penetration into professional work. Its central finding, that observed adoption substantially lags theoretical capability, deserves a careful, conditional reading in African insurance contexts. The argument advanced in this commentary is that the gap between capability and adoption defines a strategic window for the continent's insurance sector, but that the realisation of that window is not technologically determined. It depends on trust architecture, supervisory engagement, professional development, and infrastructure investment, each of which is documented in the literature as a binding constraint in its own right. The article therefore resists two equally tempting framings. It declines the techno-optimism that reads high theoretical capability as a forecast of imminent transformation. It also declines the techno-pessimism that reads structural constraints as evidence that the question can be deferred. The more accurate reading is that capability is necessary but not sufficient, that the constraints documented in the African insurance literature (Horvey et al., 2023; Senyo & Osabutey, 2020; Swiss Re Institute, 2025) are real and binding, and that the speed at which they are addressed will determine whether AI narrows or widens the protection gap. *The question is not whether AI will transform African insurance. It is whether African insurance institutions, regulators, and professionals can build the trust architecture and absorptive capacity through which capability becomes adoption, quickly enough to matter, carefully enough to last.*

That is a practitioner question, a regulatory question, and a research question. This commentary contributes only to the first of those, and only as far as a structured reading of one important dataset will permit. Empirical work on AI adoption in African insurance, on the trust mediators specific to this product class and these markets, and on the regulatory

designs that prove proportionate in practice is the next step. The author hopes this article serves as a useful input to that agenda.

References

- Asongu, S. A., & Odhiambo, N. M. (2018). Information asymmetry, financialisation, and financial access. *International Finance*, 21(3), 297–315. <https://doi.org/10.1111/inf.12136>
- Botchey, O. K. (2025a). Consumer technology acceptance in digital insurance adoption: Evidence from Ghana [Unpublished doctoral thesis]. SBS Swiss Business School. (Non-peer-reviewed.)
- Botchey, O. K. (2025b). Trust, infrastructure, and digital insurance adoption in Ghana: Evidence for institutionally contingent technology acceptance hierarchies [Working paper]. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=6240918 (Non-peer-reviewed working paper.)
- Brynjolfsson, E., Chandar, B., & Chen, R. (2025). Canaries in the coal mine? Six facts about the recent employment effects of artificial intelligence [Working paper]. Stanford Digital Economy Lab. <https://digitaleconomy.stanford.edu/publications/canaries-in-the-coal-mine/> (Non-peer-reviewed working paper.)
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Eling, M., Nuessle, D., & Staubli, J. (2022). The impact of artificial intelligence along the insurance value chain and on the insurability of risks. *The Geneva Papers on Risk and Insurance – Issues and Practice*, 47(2), 205–241. <https://doi.org/10.1057/s41288-020-00201-7>
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science*, 384(6702), 1306–1308. <https://doi.org/10.1126/science.adj0998>
- Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51–90. <https://doi.org/10.2307/30036519>
- Hassan, M. K., Rabbani, M. R., & Mohd. Ali, M. A. (2024). Trust in digital financial services: A systematic review and research agenda for emerging markets. *International Journal of Bank Marketing*, 42(3), 521–548. <https://doi.org/10.1108/IJBM-09-2023-0501>
- Horvey, S. S., Odei-Mensah, J., & Moloi, T. (2023). Insurance penetration and inclusive economic growth in sub-Saharan Africa: Evidence from panel linear and nonlinear analysis. *International Economic Journal*, 37(4), 618–645. <https://doi.org/10.1080/10168737.2023.2251027>
- International Association of Insurance Supervisors. (2025). Application paper on the supervision of artificial intelligence. IAIS. <https://www.iais.org/>
- Lefutso, D., Ogundeji, A. A., Danso-Abbeam, G., & Nyam, Y. S. (2025). Low-income households' willingness to pay for flood risk insurance in South Africa. *Progress in Disaster Science*, 25, 100403. <https://doi.org/10.1016/j.pdisas.2024.100403>
- Massenkoff, M., & McCrory, P. (2026). Labour market impacts of AI: A new measure and early evidence. *Anthropic Research*. <https://www.anthropic.com/research/labor-market-impacts> (Non-peer-reviewed corporate research report.)
- National Insurance Commission. (2024). Annual report 2024. National Insurance Commission, Ghana. <https://nicgh.org/>
- Organisation for Economic Co-operation and Development. (2023). The impact of artificial intelligence on the labour market. OECD Publishing. <https://doi.org/10.1787/08785bba-en>
- Owens, E., Sheehan, B., Mullins, M., Cunneen, M., Ressel, J., & Castignani, G. (2022). Explainable artificial intelligence (XAI) in insurance. *Risks*, 10(12), 230. <https://doi.org/10.3390/risks10120230>

- Riikkinen, M., Saarijärvi, H., Sarlin, P., & Lähteenmäki, I. (2018). Using artificial intelligence to create value in insurance. *International Journal of Bank Marketing*, 36(6), 1145–1168. <https://doi.org/10.1108/IJBM-01-2017-0015>
- Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
- Senyo, P. K., & Osabutey, E. L. C. (2020). Unearthing antecedents to financial inclusion through FinTech innovations. *Technovation*, 98, 102155. <https://doi.org/10.1016/j.technovation.2020.102155>
- Sinha, S. (2002). *Strength in solidarity: Insurance for women workers in the informal economy*. International Labour Organization.
- Swiss Re Institute. (2025). sigma No. 2/2025: World insurance in 2025: A riskier, more fragmented world order. Swiss Re Institute. <https://www.swissre.com/institute/research/sigma-research/sigma-2025-02-world-insurance-riskier-fragmented-world.html>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>