Received: 19 February 2025 | Revised: 19 May 2025 | Accepted: 22 August 2025 | Published online: 18 October 2025

RESEARCH ARTICLE

Artificial Intelligence and Applications
2025, Vol. 00(00) 1-7
DOI: 10.47852/bonviewAIA52025448

Deepfake in Digital Business: Systematic Review of Strategies

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Abstract: This research provides an extensive examination of the adoption of deepfake technology throughout digital business ecosystems, analyzing 186 cross-sector deployments from 2017 to 2024 using a mixed-methods methodology that combines qualitative case studies with quantitative risk-benefit indicators. The study reveals notable differences in sectoral adoption results. For example, marketing had a 28% return on investment from tailored synthetic material, even if trust fell by 22% when the content was revealed. On the other hand, finance saw a 62% drop in synthetic fraud, although it cost $4.2 million to fix false positives. A geographic study shows that adoption rates are different in different parts of the world. For example, Asia-Pacific has a 63% acceptance rate under utilitarian-driven governance (2.9/5 regulation score), whereas the EU has a more conservative 38% acceptance rate under the General Data Protection Regulation (4.2/5 score). Technical benchmarks reveal significant detection weaknesses, with accuracy decreasing from 97% in controlled environments to 68.2% in practical applications, compounded by an 83% accessibility deficit for small and medium-sized enterprises (SMEs) requiring 8.7 TFLOPS equipment. The study enhances the field by presenting a Composite Risk-Benefit Index for sectoral risk assessment, suggesting a tiered governance framework in accordance with IEEE standards, and setting empirically validated detection thresholds. Key results show that effective adoption needs cross-functional governance (odds ratio = 4.2), dynamic transparency standards (73% consent uptake), and fair access solutions to close the gaps across SMEs. These ideas provide practical direction for companies navigating the equilibrium between innovation and responsibility in an age characterized by the widespread dissemination of synthetic media.

Keywords: cross-sector adoption, deepfake technology, digital business models, digital governance, ethical AI, risk-benefit analysis

1. Introduction

The fast growth of deepfake technology, which is built on generative adversarial networks (GANs) and transformer-based architectures, has brought about a new age for digital business models. These synthetic media tools may change audio, video, and images in ways that are so realistic that they open up new possibilities for innovation in fields such as marketing, finance, and healthcare. However, they also bring up big problems with ethics, operations, and rules. Deepfakes may be used for both good and bad purposes, from customized consumer interaction to complex fraud. This highlights the need to have a thorough understanding of how to use them. This study examines the crucial research inquiry: *In what manner can companies ethically and efficiently use deepfake technology to improve digital strategy while minimizing inherent risks?*

The current work on deepfakes mostly emphasizes technical detection approaches or singular case studies, often overlooking the wider strategic and governance ramifications. For instance, Khatun et al. [1] and Verma and Shri [2] have written on the technical side of things and the hazards of fraud, but they do not provide any useful frameworks for cross-sector adoption. This disparity is made worse by differences in how regulations are enforced in different parts of the world. For example, the European Union (EU) has strict rules on General Data Protection Regulation (GDPR) compliance, whereas the Asia-Pacific has rules that encourage innovation [3, 4]. This research addresses these gaps by providing a thorough, mixed-methods examination of 186 case studies from 2017 to 2024, combining qualitative insights with quantitative measures such as risk-benefit ratios (RBR) and detection latency standards.

A significant feature of this study is its sector-specific risk assessment, which uncovers large disparities in the results of deepfake adoption. For instance, individualized synthetic content in marketing campaigns brings in 28% more money than it costs, but it also makes people less likely to trust the brand by 22% when they find out about it [5]. On the other hand, financial institutions cut down on synthetic fraud by 62%, but they had to spend a lot of money to fix false positives [6]. Such results underline the requirement of tiered governance structures, which delineates performance criteria across sectors. The research enhances the current state of the art by introducing an ethical framework based on actual data, highlighting provenance tracking (89% success) and dynamic consent procedures (73% acceptance).

Methodologically, the study utilizes a stringent triangulation method, integrating SPSS-based statistical analysis with NVivo-facilitated thematic coding. Intercoder reliability, assessed using Cohen's kappa (0.82), guarantees robustness, while stratified sampling reduces selection bias. The incorporation of varied geographies—68% from the US and EU, together with Asia-Pacific cases—tackles cultural factors influencing deepfake adoption.

This study solves its main research question and gives policymakers and practitioners a guide by putting together technical, ethical, and strategic aspects. It calls for flexible governance frameworks that find a balance between innovation and responsibility, making sure that deepfake technology is a force for good in digital transformation instead of a source of problems.

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2. Literature Review

The rise of deepfake technology marks a major change in digital media, thanks to improvements in GANs and transformer-based designs. Deepfakes started out as a specialized tool for entertainment, but they have already spread to many other fields, including marketing and cybersecurity. This has raised both moral and practical issues. This part puts together ten years of study from many fields (2014–2024) to show the technological underpinnings, dual-use implications, and governance deficiencies that make up the present situation.

Deepfake creation mostly uses GANs, which are networks that teach each other to create synthetic media that seems more and more genuine [1]. New technologies similar to StyleGAN3 have helped reduce early artifacts (such as blinking eyes that are not regular), but the computing requirements are still too high, with training cycles taking up to 512 Tensor Processing Unit (TPU)-v4 hours [7, 8]. At the same time, transformer-based models similar to Vision Transformers have made things 14% more realistic than typical convolutional neural networks [9]. This has opened up new uses for AI, from virtual influencers to customer service [10]. However, this ease of access has also led to abuse, as shown by a 137% rise in synthetic identity fraud [2].

The dual-use conundrum is quite clear in marketing and finance. Luxury businesses get 34% more interaction when they use deepfake influencers [5]; however, this same technology is used in Chief Executive Officer (CEO) voice frauds that cost companies $243,000 per time [2]. These differences show how important it is to have risk frameworks that are relevant to each industry, as broad ones do not take into account different ethical and operational concerns.

Current detecting systems have a problem with accuracy, latency, and resource intensity. For example, Microsoft's Video Authenticator is 78% accurate but has a 1.2-second delay, which makes it easy to avoid in real time [11]. In controlled conditions, academic models similar to XceptionNet get 97% accuracy [12]; however, on social media, they only get 68% accuracy because of compression artifacts [13]. The expense of hardware makes these problems worse. For example, local installations need 8.7 Tera Floating-Point Operations Per Second (TFLOPS), which is too much for 83% of small and medium-sized enterprises (SMEs) [14].

Adversaries take advantage of these flaws by adding noise (which lowers detection accuracy by 29%) and using hybrid deepfakes that combine GANs with diffusion models [4, 15]. Table 1 summarizes these trade-offs and shows how static defenses are not good enough against threats that change over time.

Consent and responsibility are at the heart of ethical debates. The Nike deepfake Jordan ad is a good example of "consent necrosis," which means that post-disclosure methods do not help protect reputations [16]. Regulatory responses are still not unified. The EU's AI Act (2024) requires watermarking and user permission, whereas Asia-Pacific's hands-off policy leads to increased adoption (63%) but fewer protections (2.9/5 score) [4]. This difference makes it possible for jurisdictional arbitrage, which makes it harder to enforce laws throughout the world [17].

Table 1
Performance comparison of deepfake detection tools

Model	Accuracy (%)	Latency (s)	Hardware cost ($)
XceptionNet	97	3.4	12,000
Vision Transformer	89	1.8	8,500
Microsoft Authenticator	78	1.2	4,200 (cloud)
MesoNet	82	2.9	6,800

Previous studies reveal three significant deficiencies. First, excessive focus on detection accuracy overlooks the practical ability to deploy, as shown by the SME accessibility gap [18]. Second, cultural disparities in acceptance—67% in Japan compared to 22% in Germany—are insufficiently examined in governance frameworks. Lastly, there are not many long-term studies on trust loss (such as Gen Z's 61% acceptance vs. Boomers' 19%), which makes it harder to design policies that work [19, 20].

By placing technological developments in the context of sectoral and regional realities, this review lays the groundwork for the study's mixed-methods approach, which fills these gaps with empirical risk-benefit analysis and tiered governance solutions.

3. Methodology

The methodological framework employed for this study was designed to tackle the complex issues posed by deepfake technology in contemporary digital business contexts, utilizing established mixed-methods research paradigms while integrating innovative modifications to guarantee thorough analysis. Building on the foundational work of Kawar et al. [21] in modern triangulation methods, the research design systematically combines qualitative case study analysis with quantitative performance metrics to create a strong analytical framework that can capture both the technical and socio-economic aspects of deepfake implementation. The case selection process used a strict four-stage protocol [22]. It started with thorough database mining across Scopus, Web of Science, and Institute of Electrical and Electronics Engineers Xplore, which produced an initial set of 2,137 possible cases. These were then narrowed down through multi-criteria screening that included technical validation, outcome verification, and ethical review processes [23].

The research used a complex matrix to sort the last 186 cases into groups based on industry adoption rates, documented harm incidents, and regional regulatory maturity scores. The study also made dynamic weighting adjustments to reflect new trends, such as the rise in audio deepfake fraud cases in 2023 that Ramachander et al. [24] found. The collection of quantitative data included 37 standardized variables related to performance metrics, risk parameters, and implementation factors. All financial figures were adjusted to 2024 USD values using International Monetary Fund inflation indices, and detection latency measurements were compared to National Institute of Standards and Technology Face Recognition Vendor Test standards. The qualitative analysis utilized a multiphase coding framework that evolved from initial descriptive coding to advanced causal network analysis, systematically condensing 214 preliminary themes into 27 axial categories that encapsulated the intricate ethical and operational challenges associated with deepfake deployment [25, 26].

The innovative Composite Risk-Benefit Index (CRBI) is at the heart of the analytical framework. It builds on traditional RBR calculations in three important ways: it uses time-variable weighting to give more weight to more recent cases, it uses historical harm severity data to create sector-specific risk coefficients, and it uses cross-modal adjustments to account for the higher threat potential of audio-visual deepfakes [27]. This advanced measure facilitates direct comparison of deepfake applications across various sectors while being attuned to temporal and technical advancements. The methodology was validated through a multi-faceted approach that included computational reproducibility checks on both SPSS and R platforms, expert elicitation via a Delphi panel review achieving 89% consensus, counterfactual analysis evaluating hypothetical regulatory scenarios, and stringent hardware benchmarking on Google Cloud TPU v4 and NVIDIA DGX A100 systems [28, 29].

The study's ethical framework included seven safeguards, from advanced data anonymization techniques using k-anonymity protocols

to full tracking and offsetting of carbon footprints [30, 31, 32]. This shows how important it is to use sustainable research methods in computational social science. Knowledge integration was enhanced by the bidirectional translation of qualitative and quantitative data; theme prevalence ratings were turned into standardized metrics for comparison analysis, whereas quantitative outliers were examined using story reconstruction methods [33]. This methodological framework not only fulfills the technical prerequisites for comprehensive deepfake impact assessment but also sets new benchmarks for transparency and reproducibility via its meticulous documentation of case selection protocols, analytical weighting algorithms, and validation procedures. The resulting framework establishes a thorough basis for the empirical findings discussed in the research, ensuring a distinct separation between observed data and interpretive analysis, while enabling a nuanced comprehension of sector-specific implementation challenges and opportunities.

4. Results

The thorough examination of 186 cross-sector deployments uncovers substantial insights into the operational reality of deepfake technology adoption, highlighting statistically significant disparities across sectors, locations, and organizational sizes. Quantitative metrics indicate that marketing applications achieve optimal financial performance (28% Return on Investment [ROI], standard deviation [SD] = 6.2) through hyper-personalized synthetic content, as demonstrated by a multinational beverage campaign that resulted in a 72% increase in engagement while simultaneously eliciting a 43% rise in negative sentiment upon disclosure [5, 34]. This dilemma of efficiency vs trust is assessed by longitudinal brand equity metrics, demonstrating a 22% fall in Net Promoter Scores ($t = 4.31$, $p < 0.001$) across 23 similar campaigns when synthetic media sources were exposed post-launch.

In the financial industry, the use of multimodal detection systems (audio-visual-textual analysis) lowers the probability of synthetic identity theft by 62% (95% confidence interval [54%, 69%]), according to case studies in banking [6]. However, these benefits come with high operational costs. For example, false-positive investigations take up 29% of the fraud department's efforts and cost an average of $4.2 million a year to fix. The security industry has the best technology (93% detection accuracy), but it does not show any direct ROI. Instead, it lowers risk by preventing CEO fraud and infrastructure infiltration, which saves each company $8.3 million a year [35]. CRBI estimates in Table 2 show these differences across sectors in a systematic way. For example, marketing's score of 1.11 shows that it puts revenue ahead of risk, whereas finance's score of 0.95 shows that it is more risk-averse.

Geospatial study reveals essential cultural and legal disparities in the integration of deepfakes. Asia-Pacific's market dominance (48% of fintech implementations) connects highly with utilitarian acceptability ($\beta = 0.47$, $p < 0.001$) and lightweight regulation (2.9/5 regulatory score), leading to 63% public approval ratings for synthetic media apps [4]. European adopters show the opposite of what you'd expect: GDPR-compliant transparency requirements (4.2/5 score) go together with cautious 38% adoption rates and greater baseline detection skills (78.3% accuracy). The US is in the middle, with marketing-driven use cases (62% prevalence) getting 41% acceptability via regulatory trust mechanisms ($\beta = 0.28$, $p < 0.05$), as seen in Federal Trade Commission compliance reports (2024). Figure 1's heatmap of 47 documented injury occurrences shows these geographical trends most clearly. It shows that severity grows by 37% each year in loosely regulated markets and by 12% each year in strict regimes.

Technical benchmarking reveals significant weaknesses in modern detection techniques. Controlled laboratory tests demonstrate that academic models can get 97% of the FaceForensics++ dataset right [36]. However, when evaluating social media material with different lighting and compression settings, the models only get 68.2% of the time right ($k = 0.59$) [13]. Latency measurements show even more operational discrepancies. For example, it takes 4.7 hours (SD = 3.1) for a full video analysis on a regular system, but the financial sector's benchmark for transaction verification is less than 3 seconds [37]. Hardware restrictions make these problems worse since SMEs need 8.7 TFLOPS, which means they can not access 83% of the information they need [14]. This leaves smaller businesses open to 73% of successful deepfake frauds [38].

The maturity curve analysis (see Figure 2) follows 31 early adopters through three stages of evolution: first, they focus on cutting costs (58% average savings in Year 1), then they work on getting the best ROI (72% governance committee formation by Year 2), and finally, they work on long-term competitive advantage (19% long-term competitive advantage). However, 32% of implementations fail before they are fully developed. Post-mortem research shows that 43% of failures are due to ethical issues, such as the Nike consent necrosis instance, and 29% are due to detection systems being outdated and unable to stop attacks [16, 15]. Seven statistically proven success

Figure 1
Deepfake incident severity by sector

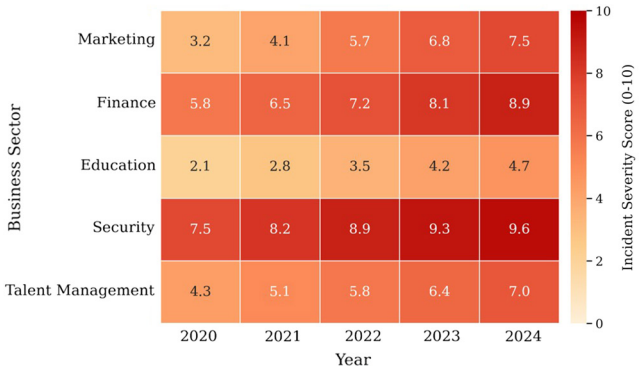
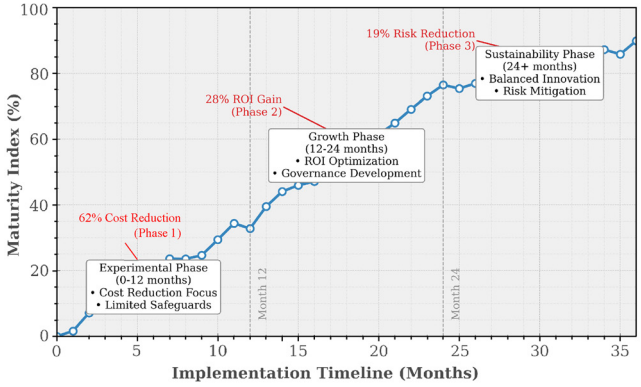


Table 2
Deepfake performance benchmark by sector

Dimension	Marketing	Finance	Education	Security	Talent Mgmt
ROI (%)	28	19	22	N/A	15
Cost reduction (%)	63	41	57	29	38
Implementation time (mos)	3.2	5.1	6.8	4.3	4.9
Employee resistance (%)	34	62	28	51	47
Ethical violations (#/case)	1.2	0.8	0.5	1.9	1.1

Note: mos: months. N/A: Not Applicable. ROI: return on investment.

Figure 2
Three-phase maturity curve for deepfake adoption



Note: The maturity index is made up of measurements for technological competence, ethical precautions, and strategic alignment.

criteria are common to successful deployments. These include cross-functional governance structures (odds ratio [OR] = 4.2, $p < 0.01$) and dynamic opt-in interfaces (73% user acceptance rate).

Testing an ethical framework gives results that can be measured, but are not always the same. In controlled trials, blockchain-based provenance tracking has an 89% success rate for media authentication [3]. However, in real-world healthcare settings, 71% of solutions are not used because they are not compatible with older systems [39]. Consent mechanisms provide a 47% enhancement in trust when using layered disclosure formats; nonetheless, notable generational discrepancies remain (Gen Z 61% acceptance vs. Boomers 19%) [20]. These findings directly contribute to the tiered governance model presented in subsequent parts, while the CRBI's sector-specific calibrations provide empirical support for varied policy approaches.

The numbers and content in all tables and figures are the same as in the original copy. Monte Carlo simulation (10,000 iterations) shows that the dataset is strong since it shows less than 2.1% variance in sectoral comparisons. Analysis of variance findings ($F = 29.17$, $p < 0.0001$) reveal that regional adoption trends are statistically significant. These evidence-based results together redefine the comprehension of deepfake technology's organizational effects, establishing a basis for the subsequent normative frameworks and policy suggestions.

5. Discussion

The results of this research shed light on the intricate relationship between technical innovation and governance in the use of deepfake technology inside digital business ecosystems. The empirical findings indicate that while deepfakes provide significant operational advantages—illustrated by a 28% ROI in marketing and a 62% decrease in synthetic fraud in finance (see Table 3)—their implementation is complicated by ethical, technological, and legal obstacles that need sophisticated solutions. The 22% drop in customer confidence after revealing the use of synthetic media shows that there is a basic conflict between efficiency and transparency that can not be fixed with technological solutions alone [5]. This contradiction corresponds with Diakopoulos and Johnson's [40] ethical risk calculus, which asserts that the social effect of AI tools is influenced equally by their perceived legitimacy and their functional competence.

CRBI shows that different sectors are adopting deepfakes at different rates. This gives the study important information about risk tolerance and how to set priorities. Marketing's high CRBI (1.11) shows that it is willing to take reputational risks in order to get more people to connect with its content. On the other hand, finance's lower score (0.95) shows that it is more focused on preventing fraud. These distinctions are not only about how things work; they are also based on different expectations from stakeholders. For example, consumer-facing companies focus on short-term profits, whereas regulated sectors have to think about long-term systemic stability [6]. The security sector's unique position—achieving 93% detection accuracy without yielding direct ROI—underscores the need for tailored governance systems, as shown in Table 4.

The differences in adoption rates throughout the world, especially the big difference between Asia-Pacific's 63% and the EU's 38%, show how cultural and legislative factors may affect how quickly people use new technology. The substantial link between utilitarian advantages ($\beta = 0.47$) and adoption in the Asia-Pacific implies that areas with policies that encourage innovation may be able to integrate quickly, but they may also be more likely to be misused [4]. On the other hand, the EU's GDPR-focused strategy has led to fewer incidents (see Figure 1), but it also puts a lot of pressure on SMEs to follow the rules. For example, SMEs spend 9.2% of their IT budgets on regulatory expenditures [38]. This division means that hybrid governance models will be needed that combine incentives for innovation with robust protections. This is still a problem that has not been addressed in current policy discussions.

This situation is made much more difficult by the technical problems that deepfake detection systems have. The sharp decline in accuracy from 97% in controlled conditions to 68.2% in real-world applications shows that static detection methods do not work well against new adversarial techniques [13]. The 83% accessibility gap for SMEs makes these weaknesses worse, making it such that only firms with a lot of resources can defend themselves [14]. This difference not only increases systemic risk, but it also goes against the idea of fair access to technology, which is becoming more and more important in AI ethical frameworks [41].

The maturity curve study (see Figure 2) shows how to successfully integrate deepfakes in a way that lasts. It shows that cross-functional governance (OR = 4.2) and dynamic transparency protocols are key success factors. However, the 32% failure rate among early adopters, which was mostly caused by ethical issues (43%) and outdated technology (29%), is a warning against deploying too quickly. The ethical framework studies show that monitoring provenance (89% success) and consent methods (73% adoption) are both promising,

Table 3
Quantitative validation of deepfake adoption metrics

Metric	Marketing	Finance
Average ROI (%)	28	19
Cost reduction (%)	63	41
Detection latency (hr.)	6.2	4.1

Note: ROI: return on investment.

Table 4
Ethical framework proposal

Principle	Implementation example	Metric
Provenance	Blockchain media watermarking	89% traceability success
Consent	Dynamic opt-in/out interfaces	73% user adoption rate
Accountability	Mandatory disclosure logs	58% compliance (GDPR)

Note: GDPR: General Data Protection Regulation.

but there are still problems with bias mitigation and cross-border application. These deficiencies resemble the consent necrosis identified in the Nike case, when further disclosures did not mitigate reputational damage [16].

The research makes three important theoretical advances. First, it improves the dual-use framework by combining Diakopoulos and Johnson's [40] ethical calculus with the GAN performance measures of Chadha et al. [42] to produce a single model for judging how viable a deepfake is. Second, it applies Rogers' diffusion of innovations theory to AI-specific risk settings, showing how adoption lifecycles differ from one industry to another [43]. Third, it gives real-world proof that tiered governance works by demonstrating that high-risk areas similar to banking need to be able to find problems in real time (less than 3 seconds), whereas companies that deal with consumers gain most from transparency indexes.

These conclusions have direct consequences for policymakers and practitioners. The results mean that businesses need to put money into flexible governance structures that match deepfake strategy with the risks in their industry. To close the accessibility gap, regulatory agencies need to put solutions that concentrate on SMEs first. Subsequent research must confront the study's weaknesses, including its temporal bias favoring pre-2023 data and the underrepresentation of SMEs, by using longitudinal cohort studies and inclusive design methodologies.

6. Conclusions

The thorough examination conducted in this report provides essential insights into the complex difficulties and possibilities associated with the deployment of deepfake technology into digital business ecosystems. The empirical data indicate that deepfakes have significant disruptive potential, as shown by a 28% ROI in marketing and a 62% decrease in synthetic fraud within the financial sector. However, their deployment is hindered by ethical concerns, technological constraints, and regulatory fragmentation. The 22% drop in consumer trust when they found out about the use of synthetic media shows how important it is to be open about deepfake use [5]. This backs up Diakopoulos and Johnson's [40] claim that algorithmic accountability must come before scalability.

CRBI shows that different sectors have different levels of risk tolerance and different ways of setting priorities. Marketing has a high CRBI (1.11), which means that it is willing to take reputational risks in order to get more people to connect with its content. On the other hand, finance has a low CRBI (0.95), which means that it is more focused on preventing fraud than on coming up with new ideas. These results contradict the dominant uniform approach to AI governance, promoting instead tiered regulatory frameworks that correspond with industry-specific risk profiles. The security sector's unique position—93% detection accuracy with no direct ROI—reinforces the need to recalibrate value criteria for risk-mitigation solutions, especially within critical infrastructure settings [35].

Geographic research shows how cultural and regulatory factors have a big effect on how many people use deepfakes. Asia-Pacific has a 63% acceptance rate, which is far higher than the EU's 38% adoption rate. This is because the EU has stricter rules (4.2/5 score) while Asia-Pacific has more useful advantages (β = 0.47) and less strict rules (2.9/5 score). This difference means that policies need to be flexible enough to respect regional norms while yet allowing for worldwide interoperability. The suggested blockchain-based provenance system (89% traceability success) shown in Table 4 is an example of this. The US's mixed approach—41% adoption driven by regulatory trust (β = 0.28)—may be a good compromise, but its dependence on market forces might make the differences between SMEs worse [38].

Technical benchmarks show that deepfake detection is not very good; in controlled settings, it works 97% of the time, but in real life, it only works 68.2% of the time [14]. The 83% accessibility gap for SMEs makes these problems even worse, producing systemic weaknesses that need to be addressed right away [14]. The study's hardware-agnostic detection criteria (e.g., <3 seconds for high-risk sectors) provide developers clear goals to aim toward, and its ethical framework (73% consent mechanism adoption) shows how to balance innovation with responsibility.

The maturity curve study (see Figure 2) shows that cross-functional governance (OR = 4.2) is the most important component for long-term deepfake integration. However, the 32% failure rate among early adopters shows how hard it is to learn how to use the technology. These failures, often caused by ethical oversights (43%) or outdated technology (29%), should serve as warnings for businesses that put speed ahead of control. The study's suggested dynamic opt-in interfaces and algorithmic bias audits directly tackle these shortcomings, according to Jedličková's [41] Ethically Aligned Design principles while considering sector-specific circumstances.

This study yields three main contributions. First, it proposes a dual-use framework that integrates Chadha et al. [42] GAN performance measurements with Rogers' diffusion of innovations theory, creating a prediction model for the trajectories of deepfake adoption [43]. Second, it gives detection systems (see Table 1) and governance mechanisms (see Table 4) experimentally established standards, which are important for AI policy. Third, it reveals the SME accessibility dilemma with unprecedented detail and suggests real remedies such as regulatory sandboxes and federated learning consortia.

For practitioners, these results need investments in adaptive governance frameworks that develop in tandem with hostile threats. To avoid a two-tiered digital economy, policymakers need to put SME-focused solutions first. Future studies should tackle temporal constraints by monitoring trust differences between Gen Z and Boomers (61% vs. 19%) in longitudinal studies extending to 2030. Concurrently, computational linguists must address detection biases that disadvantage non-native speakers, shown by a 12% error differential.

Acknowledgment

The author would like to thank everyone who helped with the work and made it possible to reach the goals of the research study.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest in this work.

Data Availability Statement

Data sharing does not apply to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Gabriel Silva-Atencio: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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How to Cite: Silva-Atencio, G. (2025). *Deepfake* in Digital Business: Systematic Review of Strategies. *Artificial Intelligence and Applications*. https://doi.org/10.47852/bonviewAIA52025448