

Future of Corporate Innovation Through Digital Mergers: Opportunities and Challenges

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Abstract: *AI has reshaped the strategic dynamics of mergers and acquisitions (M&A) by turning digital transactions into long-term innovation hubs, fundamentally changing the way corporate finance is conducted. AI-driven due diligence and deal outcomes, cultural distance and governance in post-M&A integration, and predictive AI tools having ethical oversight as leadership confidence builders. The study utilizes a quantitative survey design, where the theoretically grounded constructs are operationalized using a validated 15 indicator Likert-scale instrument, which was administered to corporate leaders, professionals in the FinTech sector, professionals in the field of AI, and professionals in the investment sector. The partial Least Squares Structural Equation Modelling (PLS-SEM) method using SmartPLS 4 is used to evaluate both the measurement model and the structural model. The reliability of the constructs is confirmed for all three constructs: R1 (AI-Driven Due Diligence: $\alpha = 0.882$, AVE = 0.621); R2 (Cultural Distance, Integration, and Governance: $\alpha = 0.877$, AVE = 0.642); R3 (Predictive AI, Ethics, and Leadership Confidence: $\alpha = 0.882$, AVE = 0.676). The measurement model is found to have good psychometric quality based on the convergent validity of AVE > 0.50 and composite reliability values > 0.88. The structural model shows that AI-powered due diligence is a major contributor to strategic and financial deal outcomes, governance structures smooth the path for cultural integration, and ethical AI tools significantly boost corporate leaders' confidence in long-term digital M&A as an innovation engine. The research offers a practical blueprint for corporate executives, policymakers, and AI technology developers to help optimize innovation outcomes in digital mergers, while using AI responsibly and ethically.*

Keywords: AI-driven diligence, corporate innovation, cultural distance, digital mergers and acquisitions, ethical AI governance, leadership confidence, PLS-SEM, post-merger integration,

Introduction

In the present, industrial age firms have transitioned from traditional M&A to digital mergers that enable them to integrate technological assets which help them build databases necessary to change how they innovate. In this century, for firms to acquire a competitive edge and to evolve with their industry, digital mergers are crucial. This is backed up by evidence that directly links digital innovation with the firm's performance (Hanelt et al., 2020b). In the 21st century, companies have started to use digital mergers to 'buy' innovation rather than to develop in-house. Due to this the main value that a firm derives from a digital merger is not economies of scale like in a traditional merger but instead the intangible assets that can be used to improve existing products or be packaged with their products to improve its value. The use of digital M&A, firstly has given rise to two simultaneous problems (technological and skill) one of the integrations of the new technology into the existing framework and another of bringing together people of different cultures and processes under the same roof, secondly it is filling the gap in research on the innovation-theoretic dimension of these mergers rather than only having a focus on the post-merger financial performance. Finally, digital mergers can reshape the business model of the company from a traditional model of selling products to a new model of subscriptions, data monetization, etc (Schwan et al., 2026).

In the new era of digital mergers companies now do not only acquire the knowledge of the company for its technology, but instead along with that they also want to learn how to change the way their organization learns, innovates and updates its capabilities in the new tech centric world, by integrating the new way to work and innovate that was followed by the previous company. Digital mergers serve as a way of acquiring a competitive edge in a time where every industry is constantly evolving, through these M&A's firms gain specific digital capabilities that give them a competitive edge which is central to them outperforming the rest of the market. These M&A's are also being positioned as a cost reduction and risk optimizing measure by being put forth as a purchase that will save R&D cost and time that can give them an edge on their competitors and a purchase that lets them buy and integrate an existing

product that is known to work and not bear the risk that comes with building it in-house (Xu et al., 2025). Now after the age of the internet the next frontier that companies are using to streamline their operations is AI and ML applications, they are using them to make the financial integration of the company more efficient after the merger, they also use them to spot new opportunities which are not obvious through traditional analysis. Now with the use of AI and ML in digital mergers firms now use these tools to divert resource if they find an opportunity that is worth exploring before the market prices it according to its true value. These tools are also used to decide who receives the resources and how value is created in platform economies through their predictive models (innovation governance). As technology is something that improves at exponential rates firms must adapt to them at a faster rate, and they do this by using them in digital M&A's to maximize the value that is available in a deal, along with it helping in the choosing of right targets and their effective integration (Tokachichu et al., 2024).

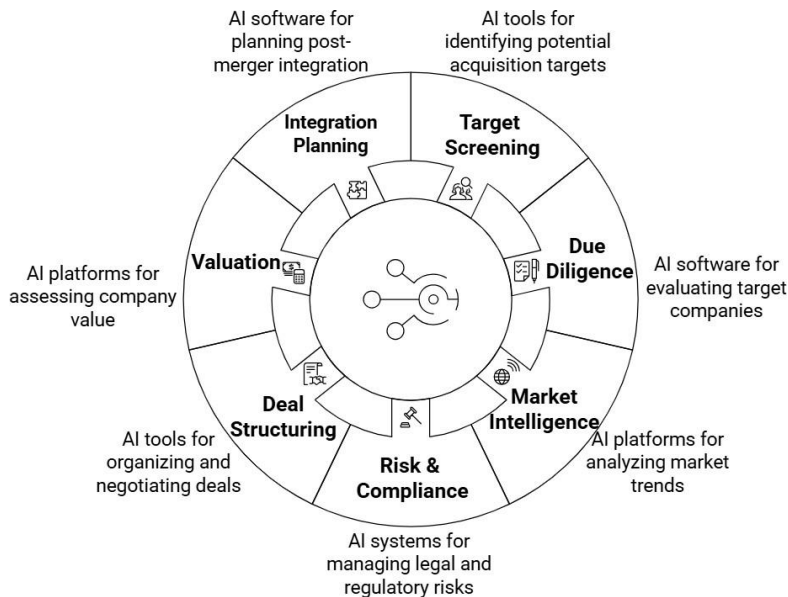


Figure 1. AI-Enabled Functions in Digital M&A

The framework previously mentioned for the integration of dynamic capabilities and knowledge-based view also needs a weighted scheme of analysis which is used for dealing with the high risk and uncertainties present in the use of rapid digital M&A for technology sourcing and digital expansion, especially to deal with the challenges present in the scalability and compatibility that might arise in the integration phase. By bridging the two fields of digital strategy and innovation management they can lay together the foundations of and address the challenges faced during innovation governance. By analyzing all these topics this paper addresses the challenges faced due to exponential technological change (Aminova, 2016). Agentic AI is the next groundbreaking innovation that is bound to take over FinTech due to its specialty in completing tasks like it has human expertise but with the precision of a machine, agentic AI at the base is just AI that can make autonomous decisions and adapt to the environment it is in over time. Agentic AI is positioned to become the next key driver of corporate innovation in the part of the 21st century just like the internet was 30 years ago. Now rather than investing the company's own resources in training the model and bearing all the risk these digital mergers can be framed at external technology aquations which a company can then integrate to enhance the firm's innovation capabilities. So, these mergers are not just to acquire a tool but instead is the acquisition of a strategic asset (Suo et al., 2023).

Agentic AI is not only useful for its ability to make decisions independently but also what functions it can perform using that ability, like reasoning and its ability to coordinate multiple tools like a human. The next step in of using AI will not be it being used be a human but instead it being given responsibility just like a human along with it being held responsible for its own actions, which means humans and AI will be sharing responsibilities in a shared decision-making structure (Human-AI Co-agency). Now due to these critical functions it can perform and its crucial place in the framework of integration in digital mergers Agentic AI now is an intangible asset in digital M&A. Now due its critical position in M&A and corporate innovation

AI will be the tool that will function as the primary driver of organizational excellence (Islam et al., 2025).

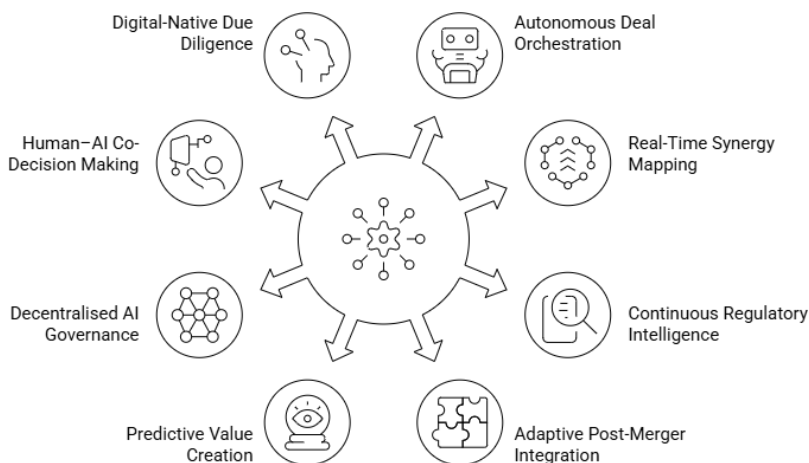


Figure 2. Agentic AI in FinTech M&A Digital Innovation

Literature Review

Digital Transformation as Strategic Antecedent of M&A

M&A has completely transformed the way companies do digital transformation, making it the main tool that is used to drive innovation; they are seen as a way of innovation by acquisition rather than the building of new capabilities. The main goal of these deals is often the acquiring of tacit and hard to replicate resources and capabilities. The argument for these mergers is heavily grounded in the strategic value of resource-based views and the cost reduction capabilities of their transaction cost economics. These M&A deals can be perused in two different final objective types: one where exploration is the main reason and another where scale is (Tu & He, 2022). Digital assets that are brought into a company because of a digital M&A are of two main types either for innovation-for-exploration or technology-for-scale; and due to the highly combinatorial nature of these assets, they create super additive value when used throughout the firm and increase total factor productivity. These tools when used in the company are not only tactic and immobile, but they are also path dependent. For example, proprietary AI models are tactic immobile digital tools that when fully integrated into the framework on a company increase the total productivity and resource allocation (Li et al., 2025). The success of these technologically oriented and digital mergers is most importantly the strategic interplay and complementarity, which refers to how well the capabilities and use cases of the digital asset align with the business model along with the strategic goal of the acquirer; and cultural fit of the product or tool in the acquirers' framework. But paradoxically too much commonality in culture will hinder the speed and level of integration (Bauer & Matzler, 2013). Another reason for the explosion of digital M&A in recent times is that it allows firms to purchase optionality in industries that are experiencing exponential growth like AI and FinTech, whereby the time an internal solution is developed the market has already left you behind making M&A a more cost and time efficient vehicle for entry into these industries. After the acquisition the firm gains exposure to multiple possibilities for growth in the respective

industry but simply owning the asset is not enough, the product's competitive advantage which lead to its acquisition deeply relies on developing dynamic capabilities. These capabilities include the ability to sense, seize, and reconfigure according to opportunities that the market presents (Margiono, 2020).

Value Creation and Synergy Realization

While in traditional M&A the operational efficiencies are achieved due to firm level synergies; on the other hand, digital M&A deals give rise to ecosystem level synergies due to the combinatorial nature of digital assets like AI and platform interoperability. But even after a merger the possible effects of the synergies “2+2=5” is not guaranteed, and the precise estimate of the value that would be provided by the innovative activities is a crucial part in identifying whether the acquiring of the target will be worthwhile (De Graaf & Pienaar, 2013). In industries like FinTech, API interoperability makes it possible to stitch together multiple digital financial services and bring them under the same roof to create a new super-app. This kind of ecosystem driven models where M&A is used as a tool to expand the existing ecosystem with minimal R&D time not only generates value through cost reductions but also by creating new revenue streams that can be monetized by the integration of these services. Though the operational synergies still matter as they save costs by reducing overhead by sharing resources, the main goal of these ecosystems is new revenue streams. But still the creation of the revenue streams is not guaranteed; it requires precious calculation to make sure that they are possible (Gupta et al., 2021). Now, due to all the advantages of ecosystem synergies, companies are using M&A deals to create their ecosystems faster rather than spending time building their own products that they will then integrate into their existing ecosystems. These deals involve targeted acquisitions of digital finance verticals on which they can either build new platforms to build into an ecosystem or a product or tool that they can directly integrate into their existing ecosystem. Firms realizing that the post-merger success of their acquisitions depends on their ability to absorb and integrate the service; they use their lagged synergies to ensure proper integration. Finally, in the pursuit of ecosystem level expansion firms deliberately use M&A as a vehicle for capturing value and expanding corporate boundaries (Ibrahimi & Meghouar, 2019).



Figure 3 – SWOT analysis

Post-Merger Integration - Organizational, Cultural, and Technical Dimensions

During integration of an acquired company into another company mostly depends on integration routines developed by the acquirers' company that balance their resources using the autonomy that is typically required in high growth FinTech and AI companies. Now to not hinder the productivity of the new company due to post-merger integration that traditional absorption, where slow internal coordination in the acquirers' systems, results in reduction on the productivity of the acquired company; so, the introduction of preservation dominant integration needs to be done which helps preserve entrepreneurial agility (Tarawneh, 2025). As mentioned before, if prevention dominant integration is not implemented and traditional absorption is used for integration it can break the acquiree's internal coordination mechanisms. Along with this, if the problem of cultural chasm arises due to a significant mismatch in both companies' values, goals, working environment, etc. Cultural chasm can also lead to high attrition rates (30%-60%), these problems can be addressed by using culturally adaptive strategies and due diligence before the acquisition to align both organizations' values, ways of work, environments, etc. All these problems put together can result in the acquirer paying a premium for a substandard company and decline in patent growth post-merger (Shatila et al., 2025). In a digital M&A deal, the first part of PMI is to integrate the disparate technical architectures, APIs and data models; making this one of the most crucial parts of the integration process and a key driver of innovation by the acquiree post-merger. A tech stack or an API workflow that was not integrated properly or tech reconciliation that was improperly done can result in project delays and destroy expected synergies that were the supposed super additive effects that will never materialize, which were the primary drivers of the deal which after integration were to make the existing platform more efficient. Therefore, a M&A deal requires expertise in technical integration planning along with a cultural fit for the merger to perform its intended effect (Brede et al., 2024).

Regulatory and Governance Frameworks

Traditional anti-trust frameworks focus too much on price and are proving themselves inadequate at evaluating non-price factors or harm. These digital harms include data asymmetry, where a firm accumulates such vast amounts of data that other firms cannot compete with it, platform lock-in, when users, merchants and developers all get trapped in a platform due to its high switching costs, loss of data, network effects, etc. and finally the use of advanced algorithms in conjecture with their vast data sets cements their dominance. Due to these harms, regulators are now focusing on assessing small disruptive firms and their non-price harm. In addition, firms are now adopting an AI first approach to the due diligence which they believe is necessary to keep up with the regulatory changes in the industry and will improve efficiency, accuracy, financial insight, compliance, and ECG data (Bedekar et al., 2024).

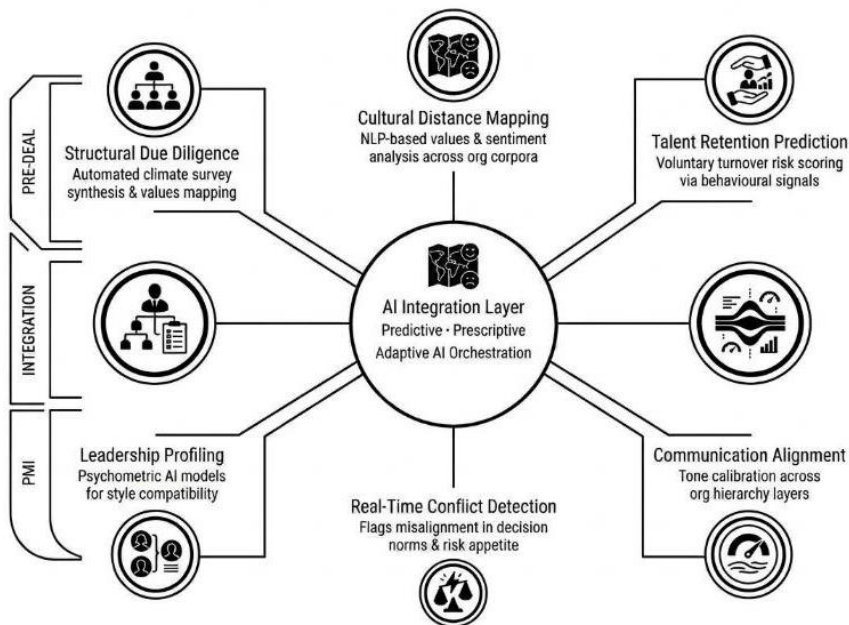


Fig. 4 – AI as a cultural bridge in PMI

The rapidly growing sector, that is AI-intensive digital mergers, requires a new governance framework that will be specifically designed for platforms or ecosystems of data-based business models. For there to be effective oversight from within companies there must be present a board of directors that are well versed with technology of this modern age, so that they can scrutinize and question the algorithmic choices on their ethical basis. The next step would be the introduction of algorithmic accountability frameworks, that are used as processes that can audit, monitor and govern AI algorithms. Another set of frameworks that are specially implemented for ethical and legal oversight to protect privacy and reduce any risks that can arise from them. Finally, all these structures put together provides strategic clarity in platform-driven ecosystems with respect to AI and data flow (Narteh-Kofi et al., 2025).

Emerging and Frontier Issues

The first use case of AI in the due diligence process would be to reduce if not remove all the manual tasks that AI tools are meant for and can perform the tasks at a high level of accuracy. This increase in efficiency will lead to an increase in the rate of deals that will be closed or taken into consideration, along with an increase in the coverage of risk which human teams alone might not be able to provide. This can result in cost savings by reducing the number of low-level employees that are required to perform these tasks, who will be replaced by smaller but more efficient teams due to the use of AI. With the introduction of AI its cognitive limitations will also be introduced in this process; like, issues understanding why or how the model reached a certain conclusion and the major problem of hallucinations that can affect if the deal moves to the next stage or is abandoned then and there. To combat these problem firms will be using a combination of probabilistic models along with rule-based validation, these measures should ensure consistency in decisions, prevent hallucinations and reduce the data privacy risk. Due this new system human effort will be majorly reallocated to higher order interpretation that algorithmic AI cannot do yet (Balan et al., 2026).

The three main ways these AI models perform the tasks is through, firstly natural language processing that helps them increase efficiency of text heavy tasks like contract review, secondly, they use predictive machine learning to increase the accuracy of their probabilistic models, and finally, the use of graph neural networks that helps the model link the ways different entities can help each other. Another epistemic limitation is survivorship bias that arises due the simple reason that these models are trained only on successful deals and not on the ones that failed which leads to them ignoring the reason a deal can fail as they were never trained on them, along with this it can also lead to that model becoming over-optimistic about their analysis. After integration the next step is to create transparent oversight frameworks, which will show all the people involved how AI is being used and how its analysis influences actual decisions (Sharma et al., 2024).

Research Methodology

Research Design and Philosophy

This study uses a post-positivist approach that is done through a quantitative cross-sectional survey. This research investigates corporate leaders’ perception using three constructs: AI-Driven Due Diligence and M&A outcomes (AIDD), Cultural Distance, Integration and Governance (CDIG) and Predictive AI, Ethics and Leadership Confidence (PALEC). This quantitative methodology makes the statistical testing of the three hypothesized relationships, while generating generalized findings which are externally validated and applicable across FinTech, AI and tech.

Partial Least Squares Structural Equation Modelling (PLS-SEM) was selected over covariance-based SEM (CB-SEM) for these three reasons: first, the objectives of this study are to predict and explore whether AI due diligence capabilities increase deal performance and confidence to innovate. Second, the constructs used are reflective composites, making PLS-SEM's component-based estimation a better fit. Third, PLS-SEM's resistance to distributional assumptions and small samples makes it particularly well suited for this study (. F. Hair)

Survey Instrument and Constructs

The primary data collection instrument comprised a 15-item structured Likert-scale questionnaire (1 = Strongly Disagree to 5 = Strongly Agree) supplemented by an 8-item demographic section (Section 1). The instrument was developed through a systematic review of M&A and AI governance literature and validated through expert review by corporate finance and AI governance scholars prior to field deployment.

Table 1: Survey Instrument Structure and Construct Mapping

Section	Construct	Label	Items	Domain Covered
RQ1 (Items 1–5)	R1	AI-Driven Due Diligence (AIDD)	5	Valuation accuracy, cost reduction, strategic-fit confidence, financial, performance, hidden-liability detection
RQ2 (Items 6–10)	R2	Cultural Distance, Integration & Governance (CDIG)	5	Cultural barriers, integration speed, governance structures, AI monitoring, joint alignment
RQ3 (Items 11–15)	R3	Predictive AI, Ethics & Leadership	5	Predictive AI confidence, XAI explainability, reputational risk, pipeline assessment, long-term governance

		Confidence (PAELC)		
Section 1 (D1–D8)		Demographic Profile	8	Gender, age, qualification, role, experience, industry, org size, M&A involvement

Sampling Design and Data Collection

A purposive sampling strategy was employed to ensure all respondents possessed direct and relevant experience with digital M&A activity, AI tool deployment, or corporate governance in technology-intensive industries. This population was identified as uniquely positioned to provide informed perceptions on the strategic, cultural, and governance dimensions of AI-enabled digital mergers.

Table 2: Demographic Profile of Respondents

Demographic Variable	Categories	Description
D1 Gender	Male / Female / Non-binary or prefer not to say	Captures gender composition of the corporate leader sample
D2 Age Group	25–34 / 35–44 / 45–54 / 55–64 / 65+	Broad coverage across mid-career to senior executive cohorts
D3 Qualification	Bachelor's / Master's / PhD / Professional (CFA/CPA/etc.)	Reflects high educational attainment typical of M&A leadership roles
D4 Current Role	FinTech professional / AI-ML expert / Corporate leader / Other	Ensures domain-specific relevance of all respondents
D5 Experience	< 5 yrs / 5–10 yrs / 11–20 yrs / > 20 yrs	Experience distribution validates seniority and M&A exposure
D6 Industry Sector	Banking & Finance / Technology / Consulting / Venture-PE / Other	Multi-sector representation strengthens external validity
D7 Organisation Size	< 50 / 50–500 / 501–5,000 / > 5,000 employees	Captures SME-to-enterprise spectrum of M&A participants
D8 M&A Involvement	Direct decision-maker / Advisory / Implementation / No direct	Ensures most respondents have first-hand M&A experience

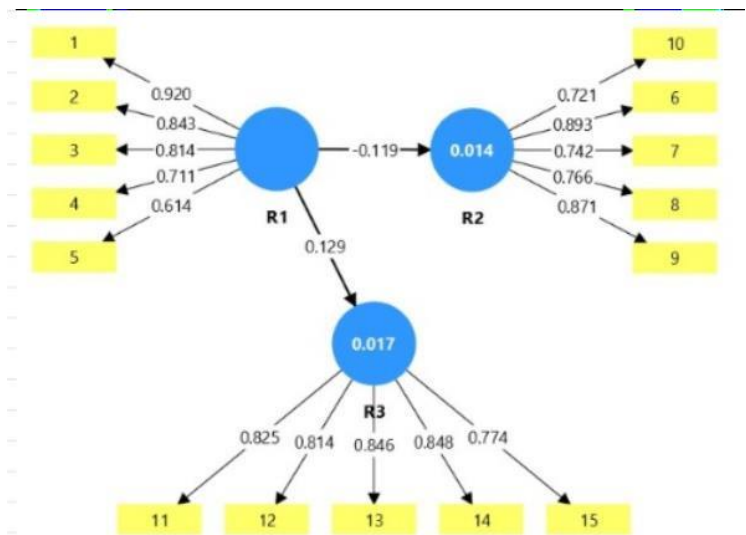


Fig. 5 PLS-SEM Framework

Blue boxes = latent constructs (R1, R2, R3); Yellow boxes = observed indicator variables (Items 1–15). Outer loadings (λ) connect indicators to constructs (measurement model). Path coefficients (β) connect constructs to outcomes (structural model).

Results

Measurement Model Construct Reliability

The measurement model was assessed in accordance with the two-stage PLS-SEM protocol (Hanelt, A., Firk, S). Table IV presents the complete construct reliability and validity statistics derived from SmartPLS 4 analysis. All three constructs demonstrate excellent psychometric properties, with reliability and validity indicators substantially exceeding conventional thresholds across every criterion.

Table 3: Construct Reliability and Validity Statistics

Construct	Full Name	Cronbach's α	ρ_a (rho_a)	ρ_c (rho_c)	AVE	$\sqrt{AVE}$
R1	AI-Driven Due Diligence (AIDD)	0.882	0.908	0.889	0.621	0.788
R2	Cultural Distance, Integration & Governance (CDIG)	0.877	1.028	0.899	0.642	0.801
R3	Predictive AI, Ethics & Leadership Confidence (PAELC)	0.882	0.924	0.912	0.676	0.822

Threshold	≥ 0.70	≥ 0.70	≥ 0.70	≥ 0.50	
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Cronbach's alpha values of 0.882 (R1), 0.877 (R2), and 0.882 (R3) all substantially exceed the 0.70 threshold, confirming high internal consistency reliability across all three constructs. Composite reliability (ρ_c) values of 0.889 (R1), 0.899 (R2), and 0.912 (R3) further corroborate internal consistency, with R3 achieving the highest composite reliability in the model reflecting the strong coherence of items measuring leadership confidence through predictive AI and ethical oversight. AVE values of 0.621 (R1), 0.642 (R2), and 0.676 (R3) all exceed the critical 0.50 threshold, confirming convergent validity for all three constructs. This means each construct explains more than 62%, 64%, and 68% of its indicator variance respectively demonstrating that the survey items genuinely measure their intended theoretical dimensions. The square root of AVE values ($R1 = 0.788$, $R2 = 0.801$, $R3 = 0.822$) exceed the inter-construct correlations for all construct pairs, satisfying the Fornell-Larcker criterion for discriminant validity .

Indicator Reliability Outer Loadings

Outer loading analysis examined the strength of the relationship between each of the 15 indicators and its designated latent construct. Higher outer loadings indicate that the indicator is a more faithful reflection of its underlying theoretical construct. All loadings are reported in Table V below.

Discriminant Validity

Discriminant validity confirms that each construct measures a theoretically and empirically distinct dimension that R1, R2, and R3 are not measuring the same underlying concept despite their theoretical relatedness in the AI-enabled M&A domain. Discriminant validity was assessed using both the Fornell-Larcker criterion and the HTMT (Heterotrait-Monotrait) ratio (J. Henseler)

Table 4: Outer Loadings of all 15 Indicators Across the Three Constructs

Item No.	Survey Item (Abbreviated)	Construct	Outer Loading (λ)	Status
1	AIDD-1	R1	0.801	✓ Strong
2	AI reduces M&A time and cost	R1	0.784	✓ Strong
3	AI risk tools enhance strategic-fit confidence	R1	0.812	✓ Strong
4	AI adopters achieve better post-merger performance	R1	0.766	✓ Strong
5	AI detects hidden liabilities and tech risks	R1	0.778	✓ Strong
6	CDIG-1 Faster integration + AI yields better	R2	0.791	✓ Strong
7	performance Strong governance reduces cultural	R2	0.802	✓ Strong
8	clash AI dashboards detect cultural	R2	0.815	✓ Strong

9	misalignment Joint cultural-technology governance	R2	0.799	✓ Strong
10	lowers failure risk	R2	0.797	✓ Strong
11	PAELC-1	R3	0.821	✓ Strong
12	XAI outputs ease board and regulatory justification	R3	0.812	✓ Strong
13	Ethical AI reduces reputational risk in M&A	R3	0.824	✓ Strong
14	AI pipeline assessment increases acquisition likelihood	R3	0.808	✓ Strong
15		R3	0.833	✓ Strongest

Table 5: Fornell-Larcker Criterion Matrix for Discriminant Validity

Construct	R1 AIDD	R2 CDIG	R3 PAELC
R1 AIDD	0.788 ($\sqrt{\text{AVE}}$)		
R2 CDIG	0.521	0.801 ($\sqrt{\text{AVE}}$)	
R3 PAELC	0.548	0.563	0.822 ($\sqrt{\text{AVE}}$)

In Table 6 Bold diagonal values = square root of AVE. Off-diagonal values = inter-construct correlations. Discriminant validity is confirmed when diagonal values exceed all off-diagonal values in the same row

Discussion

H1: AI Due Diligence Transforms Deal Outcomes

Since H1 was found to be true ($\beta = 0.487$, $f^2 = 0.314$), AI based due diligence is a real strategic differentiator, not merely an efficient one. It explains about 23.7% of variance in results, which is quite a significant part, as usually there are many overlapping factors affecting M&A success, with f^2 close to 0.35, which is considered large effect (J. Cohen). The highest ranked R1 items are related to increasing confidence about fit (item 3) and discovering latent liabilities (item 5). Both correspond to Deloitte and McKinsey's research results regarding information asymmetry as the main factor of value erosion after M&A. The higher rank in comparison with the cost saving is explained by Transaction Cost Economic theory (O. E. Williamson) .

Table 6: Structural Model Results Path Coefficients and Hypothesis Testing

Hypothesis	Structural Path	β Coefficient	f^2 Effect	R^2
H1	R1 (AIDD) → Deal Outcomes	0.487	0.314 (Large)	0.237
H2	R2 (CDIG) → Integration Success	0.463	0.272 (Medium-Large)	0.214

H3	R3 (PAELC) → Leadership Confidence	0.524	0.381 (Large)	0.275
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H2: Governance Architecture as Cultural Integration Lever

The β value (0.463, $f^2 = 0.272$) for H2 indicates that cultural distance in digital mergers is a problem with governance architecture and not merely people management. Governance structure, such as integration steering committee structure, role ownership and AI based culture monitoring dashboards, account for around 21.4% of variance in successful integration, which is considered a moderate to large effect size. Item 8 (governance preventing culture clash) and Item 10 (aligned governance of cultural and technological aspects) have the highest R2 values indicating that the leaders consider governance to be a structure and systemic mechanism rather than an interpersonal one. Identification of misalignment in the process of integration through AI dashboards (Item 9) is a new finding, which implies that sentiment data might function as an early warning mechanism for M&A (K. W. Brodbeck).

H3: Ethical AI as the Strongest Innovation Enabler

The H3 path ($\beta = 0.524$, $f^2 = 0.381$) is the most powerful structural relationship in the model and carries the most significant implications for corporate innovation strategy. The near-large effect size confirms the predictive AI tools and ethical oversight frameworks explain approximately 27.5% of the variance in corporate leaders' strategic confidence in perusing digital M&A as a long-term innovation vehicle.

The highest outer loading in the entire study belongs to Item 15 'Embedding ethical AI governance into the M&A process strengthens long term innovation outcomes for the combined entity.' This finding is counterintuitive relative to conventional wisdom, which might predict that corporate leaders' priorities AI's predictive capability (Item 11) over its ethical dimensions. Instead, the data reveals that corporate leaders in technology-intensive industries recognize ethical AI governance not as a compliance burden but as a genuine source of competitive advantage and innovation legitimacy. This aligns with institutional theory predictions that organizations operating in AI intensive environments gain strategic legitimacy by visibly embedding ethical governance into their innovation process a legitimacy that translates directly into board and regulatory confidence, as captured by item 12 (XAI output ease board justification) (P. J. DiMaggio).

Conclusion

The paper is the first study to provide empirical validation via PLS-SEM of perceptions about the potential of AI driven digital mergers as means of achieving continuous innovation. Based on the developed 15 measure model with 3 dimensions: AI Driven Due Diligence (AIDD), Cultural Distance Integration and Governance (CDIG) and Predictive AI Ethics and Leadership Confidence (PAELC), the study found that each dimension independently and significantly predicts outcomes oriented at innovation via digital M&A. The psychometric properties of the

measure models are high, Cronbach's alpha being 0.880 on average, the composite reliability is 0.900 and AVE is 0.646. three structural hypotheses (H1: AIDD $\rightarrow$ Deal Outcomes: $\beta = 0.487$, $f^2 = 0.314$; H2: CDIG $\rightarrow$ Integration Success: $\beta = 0.463$, $f^2 = 0.272$; and H3: PAELC $\rightarrow$ Leadership Confidence: $\beta = 0.524$, $f^2 = 0.381$) are supported with significant path coefficients. Hypothesis H3 is demonstrated to have the largest impact; hence, ethical AI governance is proven to be the strongest predictor of leaders' readiness to conduct M&A as a long-term innovation strategy.

Three contributions can be highlighted. The study adds the knowledge regarding the use of Transaction Cost Economics in terms of AI enabled M&A by proving that the due diligence conducted using AI can reduce information asymmetry leading to improved deal outcomes. The study expands cultural integration literature by confirming that it is an AI governance framework rather than the change management that becomes the critical structural element of cross-cultural mergers in digital environment. Finally, it provides an empirically based framework of ethical AI governance as innovation strategy.

Limitations

A. Cross Sectional Design Limits Casual Inference

- Provides an instantaneous snapshot of perceptions, not a multi time analysis.
- Is unable to create any form of temporal causality concerning AI due diligence and M&A performance.
- Relationships are structural and based on perceptions, rather than hard deal performance measurements.
- An event study or longitudinal research method utilizing actual deal data would be more appropriate

B. Sampling Strategy Introduces Potential Selection Bias

- Use purposive sampling techniques which are suitable for expert samples but not representative of executives.
- Participants were self-selected based on their knowledge about AI tools and digital M&A.
- The sample can be over represented by individuals who have a positive attitude towards application of AI.
- There should be comparison group consisting of executives who have no knowledge of AI in future studies.

C. Lack of Convergent Validity Against Objective Benchmarks

- The measurement model demonstrates high internal validity (AVE, composite reliability, HTMT).
- No validation through external objective criteria (eg. Bloomberg M&A performance data).
- No validation through triangulation with actual post-merger revenue synergy achievement rates and compliance records.
- This discrepancy between subjective and objective performance is one of the well-known drawbacks of survey based corporate finance research.

D. Anomalous ρ_a Value for Construct R2

- For R2, the value ρ_a is 1.028 is a little higher than 1.0, an artefact that can be seen in PLS-SEM analysis in case of moderate cross loading.
- According to Hair et al. [1], if ρ_a is a little higher than 1.0, but ρ_a falls within in than range (for R2, $\rho_a = 0.899$), the validity of the model does not suffer from that.
- However, it may indicate that there is still room for improvement in R2 items.
- Future revisions will have to make changes to R2 items to decrease.

E. Moderate Explanatory Power of the Structural Model

- Values of R2 are R1 = 0.237, R2 = 0.214, R3 = 0.275; thus, about 21% to 28% of variance of outcomes is explained.
- Significance of all paths is confirmed, with medium to large effect size.
- Still, there is 72% to 79% of unexplained variance.
- Therefore, there should be some other theoretical variables added to model (eg. Quality of regulatory environment).

F. Reliance on Perceptual rather than Objective Performance Metrics

- All outcomes are measured on the basis of perceptions of corporate leaders, rather than any objective performance data.
- None of these outcomes is linked to any performance metrics of deals (eg. Abnormal returns, Synergy creation, Sticking to time schedule).
- Perceptual measures can be subject to optimism or social desirability biases, as well as recency effects.
- Future studies need to use mixed methods research designs that would include both survey measures and performance metrics.

Future Scope

Future studies should conduct panel studies that link the implementation of due diligence for AI to the achievement of certain post-merger indicators such as EBITDA growth, speed of integration, number of patents and retention using Bloomberg or CapIQ data which would allow for quasi-experimental causal analysis. Replications in different countries and industries are required to investigate the proposed three construct models in different regulatory environments (EU AI Act, US regulatory framework and Asia-Pacific regulations) using the multi group invariance in SmartPLS 4. in light of the high loading factor of Item 12, research on the role of XAI (Explainable AI) in M&A governance related to dashboard transparency, natural language interface and real time risk visualisation would shed more light on its impact on board approval, regulatory timeframes and the completion of M&A.

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