Is There a Digital Premium in M&A?

Z. Ancel Ilaslan, G. Alexandridis, C. Mavrovitis

Abstract

We examine whether digital orientation, a firm's strategic focus on integrating digital technologies and capabilities, drives mergers and acquisitions (M&As). Our study shows that firms with higher digital orientation are more likely to become acquisition targets and acquirers, command higher deal premiums, complete deals more quickly, and transfer digital capabilities post-acquisition. These findings suggest digital orientation is a transferrable strategic asset valued in corporate control markets.

Alexandridis and Ancel Ilaslan are from ICMA Centre, Henley Business School. Mavrovitis is from Surrey Business School. Corresponding author's e-mail: zeynep.ancelilaslan@henley.ac.uk

1. Introduction

The digital transformation of the global economy is fundamentally altering how firms operate and compete in the face of growing digital disruption. Corporate investment in digital technologies has surged in recent years (Deloitte, 2024; Gartner, 2024). Existing research highlights that digital transformation can enhance firm performance (Westerman & McAfee, 2012) and contribute to more flexible, adaptive organizational structures (Hanelt et al., 2021).

Digital orientation (DO), the extent to which firms embed digital technologies and data-driven thinking across strategic and operational domains as part of a deliberate strategic direction, has emerged as a critical organizational capability (Kindermann et al., 2024). Existing studies demonstrate that firms with higher digital activity enjoy higher market valuations (Chen & Srinivasan, 2023) and a clear digital business strategy leads to superior financial performance (Bharadwaj et al., 2023). Moreover, DO has been associated with greater firm resilience during periods of macroeconomic stress (Gaspar et al., 2024) and closer alignment with investor expectations (Zhai et al., 2022). However, most of this evidence focuses on market-based outcomes. While investors appear to reward digital maturity, it is less clear whether corporate decision-makers recognize digital orientation as a transferrable, strategic capability when making high-stakes investment decisions.

To address this gap, we examine whether digital orientation influences firm behavior in the context of mergers and acquisitions (M&As), a setting where firms make high-stakes investment decisions that reveal how they value strategic capabilities. Unlike equity market responses, which reflect investor sentiment and expectations, M&A transactions involve direct resource allocation by corporate decision-makers, informed by internal due diligence and assessments of long-term synergistic gains. Studying M&A activity therefore allows us to test whether firms view digital orientation as a transferrable capability they are willing to acquire in order to enhance their own performance, competitiveness, or long-term value. If so, we would expect digital orientation to influence the likelihood of deal participation, the pricing, speed, and post-deal outcomes of those transactions, including whether digital capabilities are transferred to the acquiring firm.

While several strands of the finance literature explore how intangibles and innovation shape corporate investment activity (Bena & Li, 2014; Makri et al., 2010; Peters & Taylor, 2017), digital orientation encompasses a broader set of embedded attributes, such as infrastructure, organizational culture, and customer-facing technology, that may not be captured by conventional measures like patents or R&D intensity. Our study sits at the intersection of digital transformation and M&A, offering new insights into how complex, non-financial capabilities influence capital reallocation and corporate control.

We develop a novel, firm-level measure of digital orientation using dictionary-based textual analysis of the Business Description section of 10-K filings. This approach builds on prior work using textual methods to infer firm-level traits (Friberg & Seiler, 2017; Gaspar et al., 2024) and applies a curated bag-of-words method tailored to capture explicit statements about digital orientation. Our DO measure captures four interrelated dimensions as in (Kindermann et al., 2021): digital architecture, digital capabilities, digital technologies, and digital ecosystems, allowing us to assess both the structural and strategic aspects of digital orientation. We compute annual DO scores for a large panel of U.S. publicly listed firms from 2000 to 2022 and link these scores to a comprehensive M&A dataset. Our empirical analysis addresses a series of interrelated questions: Are firms with stronger digital orientation perceived as more attractive candidates in the market for corporate control? Do such firms tend to pursue dealmaking more actively? Is digital maturity reflected in acquisition premiums or deal timelines? And does the acquisition of a digitally mature firm lead to observable changes in the acquiring firm's digital orientation?

Our results provide robust evidence of the strategic value of digital orientation in M&A markets. Overall, we observe a systematic and positive relationship between firms' digital maturity and their involvement in, and outcomes from, M&A activity. Firms with higher DO scores are more likely to participate in M&A activity, both as targets and acquirers.

First, we find that a one-standard-deviation increase in a firm's DO score is associated with a 13% higher likelihood of being acquired, and a 10% greater likelihood of becoming an acquirer. These results suggest that digital orientation influences firms' participation in the market for corporate control on both sides. Digitally mature firms may be more attractive acquisition targets since digital skills can be transferred via acquisitions (**Hanelt2020**; Mallette & Goddard, 2018). At the same time, such firms may also be better equipped, both operationally and strategically, to pursue acquisitions themselves due to reduced information asymmetry (Tu & He, 2022). Their digital orientation may support more effective due diligence, integration planning, and post-deal execution, making acquisition a more viable and lower-risk growth strategy.

Second, we find a strong positive association between a firm's digital orientation and the offer premium it receives. A one standard deviation increase in target DO translates to additional value of $40 million. This digital premium persists after controlling for growth opportunities, profitability, and other firm fundamentals. The result suggests that acquirers place meaningful value on digital capabilities, treating them as strategically important components of target firm valuation. This provides further support for the premise that digital orientation functions as a non-financial value driver in high-stakes investment decisions.

Third, we find that greater digital orientation is associated with faster deal execution. Specifically, a one-standard-deviation increase in the target's digital orientation score is associated with a reduction of approximately 8 days in deal completion time, while the same increase in the acquirer's score shortens the period by about 9 days. This observation aligns with insights from industry sources, which suggest that digital tools such as cloud-based platforms, SaaS systems, and secure data-sharing technologies can reduce complexity during the M&A process (Accenture, 2021).

Fourth, we find strong evidence of post-deal digital capability transfer. When the target is more digitally oriented than the acquirer, the acquiring firm increases its own digital capabilities by an average of 8% post-acquisition. This suggests that digital capabilities, though often considered intangible and firm-specific, can be transferred through acquisition. The effect is strongest when the target is more digitally mature than the acquirer, indicating that acquirers are able to internalize meaningful capability upgrades through these transactions. Our findings make three key contributions. First, we extend the growing literature on digital transformation and firm value by showing that digital orientation is not only recognized by capital markets, but also materially influences real corporate investment behavior. Second, we contribute to the literature on M&A and strategic capabilities by identifying digital orientation as a distinct, non-financial value driver that helps explain acquisition outcomes, beyond traditional innovation proxies like patents and R&D (Bena & Li, 2014; Peters & Taylor, 2017). In doing so, we link a strategic, firm-level capability commonly examined in the digital strategy literature to core financial decisions, demonstrating that digital orientation influences real investment behavior through the M&A channel. Third, our paper contributes empirical evidence on the post-acquisition transfer of digital capabilities. We show that acquiring firms exhibit increases in their own digital orientation when the acquirer initially lags the target firm in digital orientation. Taken together, our findings suggest that digital orientation is an important strategic capability that influences corporate investment behavior and acquisition outcomes in an increasingly digital economy.

Our study has several practical implications. It shows that going digital is not merely operational; when it is coupled with a strategic direction, digital orientation influences firms' market positioning and the market for corporate control. Digitally oriented firms are more likely to act as acquirers, attract acquisition offers, and command higher deal premiums, highlighting the importance for executives to invest in and clearly communicate their digital strategies. These dynamics carry broader policy implications that underpin successful digital transformation across sectors. Key among them are investments in digital infrastructure, regulatory capacity, and workforce skills, which create the enabling conditions for firms to develop and deploy strategic digital capabilities (World Bank, 2020). Equally important is a coordinated, cross-sectoral approach to innovation and taxation that supports inclusive and competitive digital economies (OECD, 2020). In sectors central to digital infrastructure, such as telecommunications, policy becomes more directly consequential. In sectors central to digital infrastructure, such as telecommunications, policy becomes more directly consequential. Preserving competition among mobile network operators is critical, as evidence shows that markets with more MNOs typically offer more affordable and innovative services, underscoring the need for policymakers to scrutinize consolidation efforts that may reduce competition (OECD, 2020). Finally, a common framework for measuring and disclosing digital capabilities is needed. Standardized disclosure can help investors and stakeholders evaluate firms' true digital readiness and avoid risks such as AI washing. Uniform reporting would also improve market transparency and accountability as digital transformation accelerates.

2. Data and Methodology

2.1 Firm and Deal Sample

We construct our dataset by integrating three primary sources: (i) the CRSP Compustat Merged (CCM) database for firm-level financial and market data, (ii) the SDC Platinum database for M&A transactions, and (iii) the Loughran and McDonald 10-K repository for firm annual (10-K) reports. These sources allow us to assemble both a firm-year panel and a deal-level sample to investigate the relationship between firms' digital orientation (DO) and their M&A activity and outcomes.

Our firm-year panel consists of U.S. firms listed on the NYSE, NASDAQ, and AMEX exchanges with share codes 10 or 11, spanning the years 2000 to 2022. Following (Chen & Srinivasan, 2023), we exclude technology firms to avoid sector-specific heterogeneity in digital language usage. We also exclude firms in utilities (SIC codes 4900–4999) and financials (SIC codes 6000–6999) due to differing regulatory environments. Firms are included only if they have a 10-K filing for a given year. The final firm-year panel comprises 34,117 observations.

Our deal-level sample is drawn from SDC and includes M&A transactions between 2001 and 2023 in which both the target and acquirer are U.S.-based. We focus on transactions classified as either completed or withdrawn and exclude privatizations, repurchases, exchange offers, self-tenders, recapitalizations, and spin-offs. We further restrict the sample to control acquisitions, where the acquirer's ownership increases from below 50% to 50% or more. Deals in which neither party can be matched to our firm-year sample are dropped. The final sample includes 12,647 M&A transactions: in 11,174 deals, only the acquirer is matched; in 962 deals, only the target is matched; and in 511 deals, both parties are matched.

2.2 Measure of Digital Orientation

We quantify digital orientation using a firm-level digital score derived from annual 10-K filings. For each filing matched to our firm-year panel, we extract the "Business Description" section, typically bounded by the headings "Item 1. Business," "Item 1A. Risk Factors," or "Item 2. Properties," while accounting for variation in textual structure across filings.

This section provides detailed descriptions of the firm's core products, services, markets, and strategic direction, making it well-suited for assessing digital orientation.

To construct our digital dictionary, we integrate term lists from (Kindermann et al., 2021), (Chen & Srinivasan, 2023), and (Zareie et al., 2024), resulting in a comprehensive set of 268 digital-related terms (see Appendix II). In line with (Kindermann et al., 2021), we categorize these terms under four dimensions of digital orientation: digital technologies, digital architecture configuration, digital capabilities, and digital ecosystem coordination. The dictionary captures both basic terms (e.g., "data," "internet," "platform") and advanced terminology (e.g., "AI," "robotics," "cloud"), allowing us to map a broad spectrum of digital terms.

Our comprehensive approach is motivated by two considerations. First, foundational digital terms signal early-stage digitalization efforts, which remain relevant throughout the 2000-2023 period. Second, even when such terms come to reflect routine operations, they help trace the trajectory of firms' digital evolution over time.

For each firm-year, we count the frequency of digital terms in the Business Description and assign a digital score by ranking firms into quintiles based on their annual word counts. Each firm-year receives a score from 1 (lowest) to 5 (highest), reflecting its relative digital orientation in that year. This ranking approach accommodates temporal variation in digital discourse.

[Please Insert Figure 1 Around Here]

Figure 1 illustrates the evolution of digital terminology in corporate disclosures over time. The solid line represents the aggregate count of digital terms across all firm-year observations, while the dotted line shows the average per firm-year. Both series exhibit a sustained upward trajectory, reflecting the growing prominence of digital themes in firm narratives. From 2000 to 2022, the compound annual growth rate (CAGR) of total digital word use is approximately 6%, underscoring the increasing integration of digital strategy and language in public reporting.

2.3 Sample Statistics

In addition to our digital score, we include a set of firm-level control variables commonly used to explain target and acquirer abnormal returns. These variables capture firm size, performance, valuation, financial flexibility, and industry conditions, characteristics shown to influence the likelihood of participating in M&A either as a bidder or a target.

Table 1 reports the summary statistics for the key variables in our analysis. Panel A provides descriptive statistics based on the firm-year, target and acquirer sample, while Panel B focuses on observations related to M&A transactions at the deal level.

[Please Insert Table 1 About Here]

Panel A summarizes the characteristics of 34,117 firm-year observations in our sample. The average firm has total assets of approximately $3.9 billion, with a median of $712 million. Target firms are notably smaller, with a mean size of $1.7 billion and a median of $380 million, while acquirers are larger, averaging $7.2 billion in assets (median: $1.5 billion). Profitability, measured by ROA, averages 3% for the overall sample, with target firms at 1% and acquirers at 9%. In terms of valuation, the market-to-book ratio averages 3.09 across the sample, with lower valuation for targets (2.26) and higher valuations for acquirers (3.26).

Panel B reports statistics for 12,610 M&A transactions drawn from our deal-level sample. In 11,656 of these, the acquirer can be matched to our firm-level panel; in 1,464 deals, the target is matched; and in 511 deals, both parties are matched. On average, cash is the dominant form of payment, comprising 84.6% of deal value (median: 100%), while stock comprises 14.2% on average. Deal premiums average 34.4%.

The descriptive statistics presented in Table 1 align closely with established findings in the M&A literature. Acquirers are generally larger than targets, consistent with the notion that resource-rich firms are more likely to participate in deals (Cornett et al., 2011; Harford, 1999; Powell & Yawson, 2007). Targets tend to be smaller and exhibit weaker performance, making them more attractive for acquisition due to potential value creation through restructuring (Powell & Yawson, 2007). Firms with higher market-to-book ratios are more likely to act as acquirers, while those with lower valuations tend to be targets receiving higher premiums (Jovanovic & Rousseau, 2002).

Table 2 presents descriptive statistics for target and acquirer firm-years by digital orientation. Panel A reports summary statistics for target firm-years and Panel B for acquirer firm-years, across digital score quintiles. Digital scores range from 1 (low) to 5 (high) and are based on firm-specific digital word counts derived from 10-K filings.

[Please Insert Table 2 About Here]

Across both panels, higher digital orientation is associated with lower leverage and higher cash reserves, suggesting that digitally oriented firms tend to be more liquid and less reliant on debt financing. In addition, market-to-book ratios increase with digital score, implying greater investor expectations and potential growth orientation.

3. Digital Orientation and Acquisition Likelihood

This section examines whether digital orientation (DO) predicts a firm's likelihood of participating in M&A activity, either as an acquirer or a target. If DO functions as a transferable strategic asset, firms with higher digital maturity should be more likely to engage in M&A – both by attracting acquisition offers and by initiating deals themselves.

[Please Insert Table 3 About Here]

3.1 Digital Orientation and Target Likelihood

To test our hypothesis that DO increases the likelihood of becoming a target, we create a dummy dependent variable that equals one if the firm is listed as a target in our M&A sample in the subsequent year, and zero otherwise. Using probit regressions, we regress this target indicator on the lagged digital score and a set of firm-level controls.

As shown in Table 3 Panel A, the coefficient on *Digital_Score* is positive and statistically significant at 1% level. A one standard deviation increase in DO is associated with a 13% increase in the probability of being acquired. This finding supports the hypothesis that acquirers value digital capabilities and are more likely to target firms that exhibit stronger digital orientation.

We control for firm size, profitability (ROA), cash holdings, leverage, annual adjusted abnormal returns, market-to-book (M/B) ratio, and industry concentration, as these have been shown to influence M&A activity. Larger firms are less likely to be targets but more likely to acquire due to scale benefits and fewer financial constraints (Cornett et al., 2011; Mavis et al., 2020; Powell & Yawson, 2007). Higher ROA and abnormal returns signal strong performance, making firms more likely acquirers, while underperformers are more likely targets (Cornett et al., 2011; Mavis et al., 2020; Powell & Yawson, 2007). High cash may support acquisitions or deter takeovers, depending on perceived utilization (Cornett et al., 2011; Harford, 1999; Mavis et al., 2020). M/B captures valuation and growth potential: high M/B firms are more likely to acquire, while low M/B firms are attractive targets (Jovanovic & Rousseau, 2002). Leverage has a mixed effect—enabling restructuring opportunities or deterring deals due to risk (Bhanot et al., 2010; Powell & Yawson, 2007). Industry concentration (Herfindahl Index) may encourage acquisitions for consolidation but is moderated by regulatory constraints (Cornett et al., 2011; Powell & Yawson, 2007). We also control for digital intensity of industries using industry median digital scores. Control variable results are broadly consistent with prior studies; smaller firms, firms with lower M/B, lower excess returns and higher leverage are more likely to become targets.

3.2 Digital Orientation and Acquirer Likelihood

We use a similar approach to test whether DO predicts acquirer activity. The dependent variable is a dummy variable equal to one if the firm is an acquirer in the subsequent year. We use probit regressions with lagged DO and control variables.

The results in Table 3 Panel B show that the digital score is positively associated with acquirer likelihood and statistically significant at the 1% level. A one standard deviation increase in DO raises the probability of initiating an acquisition by 10%. This suggests that digital orientation not only makes more attractive targets but also enables firms to be more effective acquirers.

Among the control variables, larger firms, firms with higher ROA, firms with lower leverage are more likely to become acquirers. Higher digital orientation may help reduce information asymmetries and facilitate more effective due diligence and integration. We also include the industry median DO score and industry fixed effects to account for time-varying digital characteristics and industry-specific factors. Acquirers in highly concentrated industries are less likely to make acquisitions, although the effect is not significant across all specifications.

Overall, these findings confirm that digital orientation is a significant predictor of M&A activity. Firms with higher DO scores are more likely to be acquisition targets, reflecting the perceived value of their digital capabilities. In addition, firms with higher DO scores are also more likely to initiate acquisitions, consistent with the strategic advantages associated with digital maturity.

3.3 Digital Skill Transfer from Target to Acquirer

If digital orientation reflects a strategic capability, then acquiring a more digitally mature firm should enable capability transfer to the acquirer. In this section, we test whether digital skills can be transferred through acquisitions by examining changes in the acquirer's digital orientation following a deal.

Acquirers acquire firms with higher DO level because the digital skills are transferable, and they become more acquisitive due to the qualities these digital skills bring to the firm such as lower information asymmetry. We confirm this channel by showing that the acquisition of a target with higher digital orientation levels improves the DO level of the acquirer. We start by defining the dummy variable *Relative_Digital_Orientation_Dummy*, which takes the value of 1 if the *Target_Digital_Score* exceeds the *Acquirer_Digital_Score* prior to the transaction, and 0 otherwise. Additionally, we define *Digital_Orientation_Difference* as the difference between the target's and acquirer's digital scores measured prior to the deal.

[Please Insert Table 4 About Here]

Our dependent variable is the year-over-year change in the acquirer's digital score, *Improvement_in_Acquirer_Digital_Score*. We also include firm-level controls and fixed effects. As reported in Table 4, acquiring a more digitally mature target leads to a statistically significant improvement in the acquirer's digital orientation. One standard-deviation increase in *Digital_Orientation_Difference* results in an 8% increase in their digital score post-acquisition on average. This evidence supports the view that digital orientation can be partially transferred across organizations through M&As.

3.4 Target Digital Orientation

In this section, we test whether acquirers systematically prefer targets with higher digital orientation, consistent with the notion that firms seek to acquire digital capabilities they do not possess internally. If acquirers value digital maturity as a strategic asset, we would expect a positive relationship between the digital scores of acquiring and target firms.

[Please Insert Table 5 About Here]

As shown in Table 5, acquirer digital orientation is positively and significantly associated with the digital score of the target. Specifically, a one-unit increase in the acquirer's digital score is associated with a higher probability of selecting a target from a more digitally mature quintile. The result supports the view that acquirers exhibit a preference for targets whose digital capabilities complement or exceed their own.

Taken together, Sections 3.3 and 3.4 show that acquirers not only experience measurable improvements in their digital orientation following the acquisition of a more digitally mature target, but they appear to actively select such targets in the first place. The positive relationship between acquirer and target digital scores suggests that firms pursue digital capabilities intentionally, rather than acquiring them incidentally.

4. Digital Orientation, Digital Premia and Days to Completion

Having established that digital orientation influences M&A participation and target selection, in this section, we examine whether digital maturity is priced into deals and whether it influences the efficiency of deal execution. Specifically, we assess whether digital orientation is associated with higher acquisition premiums for targets, and shorter time to completion.

4.1 Digital Orientation and Digital Premium

We first test whether digital orientation is priced into M&A deals by examining whether more digitally mature targets receive higher acquisition premiums. If digital capabilities are valued by acquirers, we would expect them to pay higher premiums compared to acquiring non-digitally mature firms.

Our dependent variables include various measures of target premium. Specifically, we follow (Schwert, 2000) and (Eaton et al., 2019) and calculate target premia over 66-day (-63, 2) and 108-day event windows (-105, 2). We also calculate the ratio of the offer price to the target's stock price four weeks prior to announcement as used by (Alexandridis et al., 2010).

[Please Insert Table 6 About Here]

As shown in Table 6, the target's digital score is positively and significantly associated with acquisition premiums across all measures. A one standard deviation increase in the digital score leads to a 10.3% increase in the premium paid, translating to approximately $40 million in additional value. This digital premium persists after controlling for firm size, cash holdings, leverage, and other fundamentals. The observed relationships are consistent with prior work showing that smaller firms (Moeller et al., 2004), firms with lower cash reserves (Masulis & Simsir, 2018), and those with higher leverage (Powell & Yawson, 2007) tend to receive higher premiums. These results provide strong support for the hypothesis that digital capabilities are priced in the market for corporate control.

4.2 Digital Orientation and Deal Completion Time

Finally, we examine whether digital orientation influences the speed at which deals are completed. If digital orientation enables more efficient due diligence, better information exchange, or smoother coordination, we expect deals involving more digitally oriented firms to close more quickly.

We regress the number of days between deal announcement and completion on the digital scores of the acquirer and target, using our deal sample.

[Please Insert Table 7 About Here]

The results in Table 7 confirm our expectations. A one standard deviation increase in the target's digital score reduces time to completion by approximately eight days, while a one standard deviation increase in the acquirer's score reduces it by nine days. These effects represent roughly a 7-9% reduction in the typical deal time. The coefficients of the control variables complement prior findings on deal timing, where cash deals are executed more quickly (Luypaert & De Maeseneire, 2014).

This evidence suggests that digital orientation improves not only the strategic fit, but also the transactional efficiency, by facilitating smoother and faster execution.

5. Robustness Tests

5.1 Placebo Test – Randomized Digital Orientation Assignment

To address endogeneity concerns and validate the causal interpretation of our results, we conduct a placebo test by randomly reassigning digital scores across firms within each year, similar to (Wang & Yin, 2018), (Zhang et al., 2021), and (Chowdhury et al., 2025). This procedure preserves the empirical distribution of digital orientation but breaks any systematic link between a firm's true digital strategy and its M&A activity.

If the observed relationships between digital intensity and M&A outcomes are driven by spurious correlations or unobserved firm characteristics unrelated to digital capabilities, similar results would be expected under the randomized assignment. We replicate our baseline regressions for target and acquirer likelihood, target and acquirer DO relation, target premiums, deal completion time and acquirer DO improvement using these randomly assigned digital scores. Across all specifications, the coefficients on the placebo digital scores are statistically insignificant.

[Please Insert Table 8 About Here]

5.2 Other Robustness Tests

To ensure the reliability of our findings, we perform a series of other robustness checks to address alternative explanations, methodological concerns, and potential biases.

First, we re-estimate our key models for target and acquirer likelihood, as well as for target and acquirer abnormal returns, using a two-year lag instead of a one-year lag. The results remain qualitatively similar.

Second, we construct an alternative digital score using the Term Frequency–Inverse Document Frequency methodology of (Loughran & Mcdonald, 2011). This accounts for both the frequency and rarity of terms used in each document.

Third, we restrict our analysis to a narrower time window from 2012-2022 to test robustness in a more digitally intensive era. Results remain consistent, suggesting the effect is not time-bound.

We also apply a propensity score matching (PSM) approach. A dummy variable equals one for firm-years with above-average digital word counts. Using probit regression, we match treated and control firms on observable characteristics. Regression results on the matched sample remain consistent, confirming robustness to selection bias.

6. Conclusion

We find that digital orientation influences M&A dynamics in a nuanced way. A one standard deviation increase in a firm's digital score raises its likelihood of receiving an acquisition offer in the following year by 13% and its likelihood of pursuing an acquisition by 10%. This highlights how digital orientation not only enhances a firm's attractiveness as an acquisition target, but also empowers it to act as an acquirer.

We also validate that acquiring a target with a one-point higher digital score increases the acquirer's score by 8%. This suggests that acquisitions actively shape the digital orientation landscape. Targets with higher digital scores command $40 million more in premiums on average. The results confirm that acquirers value digital capabilities in pricing.

Finally, deals involving more digitally mature firms close faster, suggesting digital orientation enhances both strategic fit and operational execution. In summary, digital orientation plays a central role in determining who participates in M&A, how deals are valued, and how efficiently they are completed.

Appendix I: Variable Definitions

Panel A:Summary Statistics

Variable	**Description**
Digital_Score	A score of 1 to 5 calculated based on digital word count. Textual analysis is used to calculate digital word count on firm 10-K reports.
Firm_Size	Firm asset size in $ millions (at) taken from CRSP Compustat merged database (CCM).
Return_on_Assets_(ROA)	Calculated as Operating income after depreciation (oiadp) / Total assets (at) using CCM data.
Cash_Reserves	Calculated as Cash and Short-term Investments (che) / Total assets (at) using CCM data.
Stock_Return	One-year stock return calculated in Eventus using value-weighted CRSP index as a benchmark.
Market-to-Book	Market-to-Book calculated using CCM data: (csho $\times$ year-end price +1) / (ceq), or if ceq is missing, (csho $\times$ year-end price) / (at $-$ lt).
Leverage	Debt-to-Assets ratio calculated as Total debt (dt) / Total assets (at) using CCM data.
Sales_shock	Absolute difference between firm and industry 2-year median sales growth.
Herfindahl_Index	Sum of squared market shares of all firms in same 3-digit SIC, divided by total assets in the same 3-digit SIC and year (from CCM).
Percentage_of_Stock	Value paid in stock / Total deal value from LSEG Eikon. Computed when sum of stock and cash is 80%.
Percentage_of_Cash	Value paid in cash / Total deal value from LSEG Eikon. Computed when sum of stock and cash is 80%.
Target_Premium	Target CAR with a window of (-63,2) around deal announcement, from Eventus, based on CRSP. Winsorized at 1%, 99%.
Acquirer_CAR	Acquirer CAR with window of (-2,2) around deal announcement, from Eventus, based on CRSP. Winsorized at 1%, 99%.
Synergy_Gains	5-day cumulative abnormal returns for target and acquirer, weighted by market value.
Competition	Percentage of deals with more than one bidder.

Hostile	Percentage of hostile deals.
Diversification	Percentage of deals between firms in different 2-digit SIC industries.
Withdrawn	Percentage of deals withdrawn.
Days_to_Completion	Number of days between announcement and effective date, based on completed deals with public firms.
Panel B: Dependent Variables	
Target_Likelihood	A dummy variable that takes the value of 1 if the firm received an offer in year t+1, and 0 otherwise.
Acquirer_Likelihood	A dummy variable that takes the value of 1 if the firm made a bid in year t+1, and 0 otherwise.
Change_in_Digital_Score	Calculated as the difference in digital score for each CIK in consecutive years.
Target_Digital_Score	A score of 1 to 5 calculated based on digital word count. Target digital score is based on digital word count of firm 10-K report for the previous year that the deal took place.
Acquirer_Digital_Score	A score of 1 to 5 calculated based on digital word count. Acquirer digital score is based on digital word count of firm 10-K report for the previous year that the deal took place.
Target_Premium_(-63,2)	Target Buy and Hold Abnormal Returns with an event window of (-63,2) around Date Announced calculated using WRDS Event Study tool, based on CRSP data.
Target_Premium_(-63,126)	Target Buy and Hold Abnormal Returns with an event window of (-63,126) around Date Announced calculated using WRDS Event Study Tool, based on CRSP data.
SDC_Premium	Target premium calculated by SDC as stock price of target 1 month prior to Date Announced divided by Offer Price, winsorized for 0 to 2.
Premium_(OfferPrice/Stock_Price)	Target premium calculated as Offer Price from SDC divided by stock price of target 1 month prior to Date Announced from CRSP, winsorized for 0 to 2.
Target_CAR	Target Cumulative Abnormal Returns with an event window of (-1,1), (-2,2), and (-3,3) around Date Announced, calculated using WRDS Event Study tool based on CRSP data.
Days_to_Completion	Number of days between Date Announced and Date Effective in SDC.

Improvement_in_Acquirer_DO	Difference between Acquirer_Digital_Score before and after the deal.
Panel C: Acquisition Likelihood Control Variables	
Firm_Size	Log of firm asset size (at) from CCM.
Return_on_Assets_(ROA)	Calculated as Operating income after depreciation (oiadp) / Total assets (at) using CCM data.
Cash_Reserves	Calculated as Cash and Short-term Investments (che) / Total assets (at) using CCM data.
Stock_Return	One-year return calculated in Eventus using value-weighted CRSP index as a benchmark.
Market-to-Book	Market-to-Book calculated using CCM data: (csho × price at calendar year-end +1) / (ceq), or if ceq is not available, (csho × price at calendar year-end) / (at – lt).
Firm_Age	The difference between financial year and the year firm went for an IPO.
Leverage	Debt-to-Assets ratio calculated as Total debt (dt) / Total assets (at) using CCM data.
Sales_shock	Absolute difference between firm and industry 2-year median sales growth.
Herfindahl_Index	Sum of squared market shares of all firms sharing the same 3-digit SIC code, divided by total assets in the same 3-digit SIC code and year, using CCM sales (sale) and total assets (at) data.
Days_to_Completion	Number of days between Date Announced and Date Effective in SDC.
Improvement_in_Acquirer_DO	Difference between Acquirer_Digital_Score before and after the deal.
Panel D: Other Control Variables	
Firm_Size	Log of firm asset size from CCM for the financial year-end preceding the deal announcement.
FCF	Net cash flow from operating activities (oancf)/Total assets (at) for the financial year-end preceding the deal announcement.
Market-to-Book	Market-to-Book of Target/Acquiror calculated using CCM data for the financial year-end preceding the deal announcement.
Leverage	Debt-to-Assets ratio calculated as Total debt (dt) / Total assets (at) using CCM data for the financial year-end preceding the deal announcement.

All_Stock	A dummy variable which takes the value of 1 if Percentage of Stock from Refinitiv Eikon is equal to 100%.
All_Cash	A dummy variable which takes the value of 1 if Percentage of Cash from SDC is equal to 100%.
Competition	A dummy variable that takes the value of 1 if Number of Bidders in SDC is higher than 1.
Diversification	A dummy variable that takes the value of 1 if 2-digit SIC code of target and acquiror are different and 0 otherwise.
Industry_Digital_Score	Annual median digital score by industry based on 2-digit SIC code.

Appendix II: Digital Dictionary

3-d print	computer	developer	graphical user interface
5G	computer vision	device	green computing
advanced communication	connected factory	DevOps	GUI
advanced manufacturing	connectivity	digital	hardware
advanced technology	control system	digital currency	heterogeneous data
AI	converged infrastructure	digital device	high-speed
algorithm	conversational AI	digital logistics	high-tech
analytical tool	cryptocurrency	digital marketing	home page
analytics	customer intelligence	digital platform	human cloud
API	customizable	digital revolution	hybrid cloud
app	cyber	digital strategy	image recognition
app-based	cyber physical system	digital technology	image understanding
artificial intelligence	cyber space	digital transformation	industrial internet
artificial reality	cybernetics	digital twin	industry 4.0
augmented reality	cyber-physical systems	digitalize	informatics
automate	data	digitize	information integration
automation	data analytics	distributed computing	information management
autonomous	data architecture	drone	information security
autonomous driving	data capture	e-business	information system
autonomous technology	data integration	e-catalog	information technology
bandwidth	data lake	e-commerce	in-memory computing
big data	data mining	e-learning	insurtech

biometric	data monetization	edge	integrated solution
blockchain	data network	edge computing	intelligent automation
bluetooth	data processing system	electronic	intelligent cloud
bot	data science	e-mobility	intelligent equipment
broadband	data service	energy management system	intelligent media
business intelligence	data transmission	engineer	intelligent pattern
chief digital officer	data visualization	enterprise cloud	intelligent recommendation
chief information officer	database	enterprise management system	intelligent system
CIO	data-driven	enterprise resource planning	interface
cloud	data-dependent	ERP	internet
cloud based	data-driven	e-procurement	internet of things
Cloud collaboration	data-enabled	e-publishing	internet protocol
Cloud computing	data-intensive	e-service	IoT
cloud deployment	decentralized finance	evolutionary AI	IP
cloud enablement	deep learning	evolutionary computing	IT infrastructure
Cloud manufacturing	deep reinforcement learning	facial recognition	IT solution
cloud platform	design in the cloud	fintech	IT system
cognitive computing	designer	fintech platform	LAN
compute	desktop	functionality	legaltech
local area network	peer-to-peer protocol	smart content	text mining
machine learning	personalized customization	smart contract	traceable material
marketing automation	phone	smart data	transparent data
metadata	process automation	smart device	transparent factory

metaverse	product lifecycle management	smart factory	ubiquitous
mobile	programmable	smart healthcare	UI
mobile internet	programmer	smart home	unmanned
mobile payment	proprietary algorithm	smart investment	user experience
multi-channel	quantum computing	smart transportation	user interface
natural language processing	real-time	smartphone	UX
network infrastructure	recognition algorithm	social media	virtual
network service	remote monitoring	social technology	virtual agent
network standard	resource planning system	software	virtual assistant
neural network	robot	software-as-a-service	virtual design
new economy	robotic process automation	speech recognition	virtual factory
newsfeed	robotics	speech translation	virtual machine
NFC	SaaS	standardize	virtual production
NLP	self-driving	streaming	virtual reality
office automation	self-learning	supply chain management system	virtualization
omni-channel	semantic recognition	suptech	voice recognition
online	semantic search	tablet	web
open banking	sensor	technologist	web-based
open source	sentiment analysis	technology platform	web 3.0
operating intelligence	serverless computing	telematics	website
operating system	smart	telemedicine	wi-fi
P2P protocol	smart cloud terminal	text analysis	wireless

References

Accenture. (2021). Digitizing mergers and acquisitions [Available at: https://www.accenture.com/gb-en/insights/strategy/digitizing-mergers-acquisitions].

Alexandridis, G., Petmezas, D., & Travlos, N. G. (2010). Gains from mergers and acquisitions around the world: New evidence. *Financial Management*, *39*(4), 1671–1695. https://doi.org/10.1111/j.1755-053X.2010.01122.x

Bena, J., & Li, K. (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance*, *69*(5), 1923–1960.

Bhanot, K., Mansi, S. A., & Wald, J. K. (2010). Takeover risk and the correlation between stocks and bonds. *Journal of Empirical Finance*, *17*(3), 381–393. https://doi.org/10.1016/j.jempfin.2009.10.006

Bharadwaj, A., El Sawy, O., Pavlou, P., & Venkatraman, N. (2023). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, *37*(2), 471–482.

Chen, W., & Srinivasan, S. (2023). Going digital: Implications for firm value and performance. *Review of Accounting Studies*, *29*(2), 1619–1665.

Chowdhury, M., Aram, M., Javadi, S., & Nejadmalayeri, A. (2025). Geopolitical risk and corporate capital structure [Article 102796, Online First]. *Journal of Corporate Finance*. https://doi.org/10.1016/j.jcorpfin.2025.102796

Cornett, M., Tanyeri, B., & Tehranian, H. (2011). The effect of merger anticipation on bidder and target firm announcement period returns. *Journal of Corporate Finance*, *17*(3), 595–611.

Deloitte. (2024). Focusing on the foundation: How digital transformation investments have changed in 2024 [Available at: https://www2.deloitte.com/us/en/insights/topics/digital-transformation/where-are-organizations-getting-the-most-roi-from-tech-investments.html].

Eaton, G., Liu, T., & Officer, M. (2019). Rethinking measures of mergers & acquisitions deal premiums. *Journal of Financial and Quantitative Analysis*, 1–30.

Friberg, R., & Seiler, T. (2017). Risk and ambiguity in 10-ks: An examination of cash holding and derivatives use. *Journal of Corporate Finance*, *45*, 608–631.

Gartner. (2024). Gartner survey reveals that only 48% of digital initiatives meet or exceed their business outcome targets [Available at: https://www.gartner.com/en/newsroom/press-releases/2024-10-22-gartner-survey-reveals-that-only-48-percent-of-digital-initiatives-meet-or-exceed-their-business-outcome-targets].

Gaspar, J.-M., Wang, S., & Xu, L. (2024). Digitalization and the performance of non-technological firms: Evidence from the covid-19 and natural disaster shocks. *Journal of Corporate Finance*, *89*, 102670.

Hanelt, A., Firk, S., Hilebrandt, B., & Kolbe, L. (2021). Digital m&a, digital innovation, and firm performance: An empirical investigation. *European Journal of Information Systems*, *30*(1), 1–24.

Harford, J. (1999). Corporate cash reserves and acquisitions. *The Journal of Finance*, *54*(6), 1969–1997.

Jovanovic, B., & Rousseau, P. (2002). The q-theory of mergers. *American Economic Review*, *92*(2), 198–204.

Kindermann, B., Beutel, S., Garcia de Lomana, G., Strese, S., Bendig, D., & Brettel, M. (2021). Digital orientation: Conceptualization and operationalization of a new strategic orientation. *European Management Journal*, *39*(5).

Kindermann, B., Schmidt, C., Fengel, F., & Strese, S. (2024). Expanding the boundaries of digital orientation research: Scale development and validation. *Journal of Business Research*, *185*, 114895.

Loughran, T., & Mcdonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, *66*(1), 35–65.

Luypaert, M., & De Maeseneire, W. (2014). Antecedents of time to completion in mergers and acquisitions. *Applied Economics Letters*, *22*(4), 299–304.

Makri, M., Hitt, M., & Lane, P. (2010). Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal*, *31*(6), 602–628.

Mallette, F., & Goddard, J. (2018). Why companies are using m&a to transform themselves, not just to grow [Harvard Business Review. Available at: https://hbr.org/2018/05/why-companies-are-using-ma-to-transform-themselves-not-just-to-grow].

Masulis, R., & Simsir, S. (2018). Deal initiation in mergers and acquisitions. *Journal of Financial and Quantitative Analysis*, *53*(6), 2389–2430.

Mavis, C. P., McNamee, N. P., Petmezas, D., & Travlos, N. G. (2020). Selling to buy: Asset sales and acquisitions. *Journal of Corporate Finance*, *62*, 101587.

Moeller, S. B., Schlingemann, F. P., & Stulz, R. M. (2004). Firm size and the gains from acquisitions. *Journal of Financial Economics*, *73*(2), 201–228. https://doi.org/10.1016/j.jfineco.2003.07.002

OECD. (2020). *Going digital integrated policy framework*. https://www.oecd.org/en/publications/going-digital-integrated-policy-framework_dc930adc-en.html

Peters, R., & Taylor, L. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, *123*(2), 251–272.

Powell, R., & Yawson, A. (2007). Are corporate restructuring events driven by common factors? implications for takeover prediction. *Journal of Business Finance & Accounting*, *34*(7-8), 1169–1192.

Schwert, W. (2000). Hostility in takeovers: In the eyes of the beholder? *The Journal of Finance*, *55*(6), 2599–2640.

Tu, W., & He, J. (2022). Can digital transformation facilitate firms' m&a: Empirical discovery based on machine learning. *Emerging Markets Finance and Trade*, 1–16.

Wang, Y., & Yin, S. (2018). Ceo educational background and acquisition targets selection. *Journal of Corporate Finance*, *52*, 238–259. https://doi.org/10.1016/j.jcorpfin.2018.08.013

Westerman, G., & McAfee, A. (2012). The digital advantage: How digital leaders outperform their peers in every industry [Available at: https://ide.mit.edu/sites/default/files/publications/TheDigitalAdvantage.pdf].

World Bank. (2020). *The effects of digital-technology adoption on productivity and factor demand: Firm-level evidence from developing countries* (Report) (Accessed: 2025-05-12). World Bank. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/829161595512126439/the-effects-of-digital-technology-adoption-on-productivity-and-factor-demand-firm-level-evidence-from-developing-countries

Zareie, M., Attig, N., El Ghoul, S., & Fooladi, I. (2024). Firm digital transformation and corporate performance: The moderating effect of organizational capital. *Finance Research Letters*, *61*, 105032.

Zhai, H., Yang, M., & Chan, K. (2022). Does digital transformation enhance a firm's performance? evidence from china. *Technology in Society*, *68*, 101841.

Zhang, C., Kandilov, I., & Walker, M. (2021). Direct flights and cross-border mergers & acquisitions [Article 102063]. *Journal of Corporate Finance*. https://doi.org/10.1016/j.jcorpfin.2021.102063

TABLE 1
Summary Statistics

Panel A reports summary statistics for our firm-year sample from CRSP Compustat merged database from 2000 to 2022. All firms are US headquartered, non-technology, listed in NYSE, Amex and Nasdaq with revenues over $1 million. Targets and acquirors in this sample are identified using deal sample from SDC. A firm-year is included in Panel A Targets or Acquirors if the firm is included as a target or acquiror in SDC deal sample in the following year.
Table 1 Panel B presents summary statistics for our deal sample. Our target sample is from SDC Completed and Withdrawn control deals sample from 2001 to 2023 with public, non-tech, US origin targets that can be matched with our initial firm-year sample and acquiror sample is generated similarly for acquirors. We merge target and acquirer samples to find our all deal sample and remove duplicate deals where both the target and acquiror are public, non-tech firms with US origin. Description of all variables are given in Appendix I.

Panel A. Firm Characteristics

Variable		**Firm-Years**	**Targets**	**Acquirers**
Number of observations		34,117	1,464	11,656
Digital_Score	Mean	3.01	3.19	3.17
	Median	3.00	3.00	3.00
Firm_Size ($ million)	mean	3,918	1,667	7,231
	median	712	380	1,516
ROA	mean	0.03	0.01	0.09
	median	0.07	0.06	0.10
Cash_Reserves	mean	0.19	0.20	0.12
	median	0.10	0.10	0.07
Stock_Return_ (%)	mean	7.63	0.96	15.84
	median	-3.63	-11.84	4.87
M/B	mean	3.09	2.26	3.26
	median	2.06	1.67	2.38
Leverage	mean	0.24	0.24	0.24
	median	0.20	0.20	0.22
Sales_Shock	mean	0.12	0.12	0.11
	median	0.08	0.08	0.07
Herfindahl_Index	mean	0.22	0.21	0.24
	median	0.16	0.16	0.18

Panel B. Deal Characteristics

Variable		**All Deals**	**Targets**	**Acquirers**
Number of deals		12,610	1,464	11,656
Percentage_of_Stock_(%)	mean	14.15	18.57	14.22
	median	0.00	0.00	0.00
Percentage_of_Cash_(%)	mean	84.60	80.08	84.86
	median	100.00	100.00	100.00
Target_Premium_(%)	mean	34.43	36.02	38.00
	median	27.64	27.58	30.81
Acquirer_CAR_(%)	mean	0.64	0.02	0.90
	median	0.33	0.10	0.01
Synergy_gains_(%)	mean	4.46	2.62	4.82
	median	0.00	0.00	0.00
Competition	mean	0.37	0.28	0.40
	median	0.00	0.00	0.00
Diversification	mean	0.43	0.65	0.40
	median	0.00	1.00	0.00
Withdrawn	mean	0.10	0.07	0.10
	median	0.00	0.00	0.00
Days_to_Completion	mean	116.62	119.96	113.82
	median	95.00	100.00	90.00

TABLE 2
Target and Acquirer Statistics by Digital Orientation Quintile

Table 2 Panel A reports target firm-year sample and Panel B reports acquirer firm-year sample by Digital Score. We use CRSP Compustat merged database for financial statement data and Loughran Mcdonald database for 10-K reports. We assign a digital score from 1 to 5 based on digital word count of firm-years within a year. Digital words are listed in Appendix II. Last column represents the p-value results of the statistical tests for the significance of the difference between the means and medians of the highest digital score group and lowest digital score group for each variable. Definitions of all variables are in Appendix I.

Panel A Target Sample Statistics by Digital Orientation Quintile

		Low Digital Score				High Digital Score	
Variable		(1)	(2)	(3)	(4)	(5)	Difference (p-value) '(5-1)
Firm_Size_($_million)	mean	2153.64	2075.56	1984.58	1498.95	1386.15	0.07
	median	424.08	517.06	399.85	416.37	234.39	0.00
ROA	mean	0.06	0.03	-0.02	0.00	-0.04	0.00
	median	0.08	0.06	0.05	0.06	0.05	0.00
Cash_Reserves	mean	0.11	0.12	0.23	0.23	0.28	0.00
	median	0.06	0.06	0.12	0.12	0.22	0.00
M/B	mean	1.83	1.93	2.58	2.48	2.42	0.10
	median	1.54	1.49	1.70	1.64	2.00	0.00
Stock_Return_(%)	mean	-8.63	-17.59	-27.40	-19.26	-34.78	0.00
	median	-10.94	-6.98	-22.95	-14.88	-24.65	0.05
Leverage	mean	0.27	0.29	0.25	0.24	0.16	0.00
	median	0.25	0.26	0.21	0.19	0.06	0.00
Fixed_Asset_Ratio	mean	0.35	0.35	0.26	0.21	0.13	0.00
	median	0.29	0.29	0.18	0.13	0.10	0.00
Herfindahl_Index	mean	0.25	0.23	0.19	0.20	0.19	0.00
	median	0.18	0.17	0.14	0.16	0.13	0.00

Panel B Acquirer Sample Statistics by Digital Orientation Quintile

		Low Digital Score				High Digital Score	
Variable		(1)	(2)	(3)	(4)	(5)	Difference (p-value) '(5-1)
Firm_Size_($_million)	mean	6984.50	8256.95	6146.02	8282.63	5605.73	0.02
	median	1341.88	1651.73	1388.17	1398.60	1182.60	0.00
ROA	mean	0.09	0.10	0.09	0.09	0.07	0.00
	median	0.10	0.10	0.10	0.10	0.09	0.00
Cash_Reserves	mean	0.10	0.11	0.12	0.14	0.20	0.00
	median	0.06	0.07	0.07	0.08	0.13	0.00
M/B	mean	2.81	3.18	2.90	3.51	3.55	0.00
	median	2.00	2.27	2.24	2.47	2.57	0.00
Stock_Return_(%)	mean	2.42	6.29	3.82	7.15	3.52	0.61
	median	2.86	2.87	3.76	5.48	3.03	0.00
Leverage	mean	0.24	0.26	0.26	0.24	0.19	0.00
	median	0.22	0.25	0.24	0.21	0.16	0.00
Fixed_Asset_Ratio	mean	0.30	0.27	0.25	0.20	0.13	0.00
	median	0.25	0.20	0.18	0.14	0.10	0.00
Herfindahl_Index	mean	0.28	0.25	0.23	0.23	0.21	0.00
	median	0.22	0.19	0.19	0.18	0.15	0.00

TABLE 3
Digital Orientation and Acquisition Likelihood

Table 3 reports results of probit regression analysis of Target Likelihood in Panel A and Acquiror Likelihood in Panel B. We use our Digital Score as a measure of digital activity. We define Target/Acquiror dummy variables that take the value of 1 if a firm-year observation was included in our SDC Target/Acquiror sample for the specific year. We define control variables in Appendix I. We winsorize all control variables at 1% and 99% level. We control for year and industry FEs. ***, ** and * denote significance at 1%, 5% and 10% level, respectively.

	Panel A: Target Likelihood			***Panel B: Acquiror Likelihood***		
	Public Acquirors		**All Acquirors**	***Public Targets***		**All Targets**
Variable	(1)	(2)	(3)	(1)	(2)	(3)
Digital_Score	0.050***	0.038***	0.025**	0.039***	0.047***	0.047***
	(3.680)	(2.664)	(2.222)	(2.908)	(3.177)	(6.748)
Firm_Size		-0.023**	-0.079***		0.246***	0.145***
		(-2.077)	(-9.038)		(21.413)	(27.288)
ROA		0.152	0.011		0.193	0.689***
		(1.478)	(0.132)		(1.362)	(10.400)
Cash_Reserves		0.429***	-0.026		0.142	-0.477***
		(4.420)	(-0.328)		(1.202)	(-8.465)
M/B		-0.009***	-0.009***		0.005	0.002
		(-2.636)	(-3.517)		(1.582)	(1.425)
Stock_Return		-0.213***	-0.205***		-0.000	0.019
		(-9.516)	(-11.749)		(-0.011)	(1.549)
Leverage		0.174**	0.213***		-0.131	-0.322***
		(2.128)	(3.352)		(-1.352)	(-7.064)
Herfindahl_Index		-0.070	-0.030		-0.424***	0.021
		(-0.580)	(-0.323)		(-3.249)	(0.396)
Sales_Shock		-0.034	-0.038		0.154	0.022
		(-0.201)	(-0.272)		(0.905)	(0.263)
Intercept	-2.222***	-2.313***	-1.447***	-2.230***	-3.903***	-1.820***
	(-5.878)	(-5.794)	(-6.121)	(-5.881)	(-8.737)	(-11.779)
Industry_Digital_Score		0.033	0.032		-0.011	-0.105***
		(0.677)	(0.865)		(-0.225)	(-4.643)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	33,733	33,405	33,662	33,618	33,290	33,787
Pseudo R-sq	0.034	0.054	0.050	0.034	0.133	0.087

TABLE 4

Improvement in Acquirer Digital Skills

Table 4 presents the results of ordered probit regression analysis examining the relationship between Acquirer_Digital_Score_Improvement with pre-deal Digital_Orientation_Difference and Digital_Orientation_Difference_Dummy. Deals included in this analysis are between public, US, non-tech targets and acquirors that can be matched with our initial CCM sample. We define dependent variables in Appendix I Panel B and control variables in Appendix I Panel D. We control for year and industry fixed effects. ***, ** and * denote significance at 1%, 5% and 10% level, respectively.

Variable	(1)	(2)	(3)	(4)
Digital_Orientation_Difference_Dummy	0.355***	0.372***		
	(2.660)	(2.705)		
Digital_Orientation_Difference			0.166***	0.167***
			(3.825)	(3.733)
Acquirer_Firm_Size		-0.051		-0.050
		(-1.087)		(-1.070)
Target_Firm_Size		0.035		0.038
		(0.785)		(0.854)
Acquirer_FCF		1.563*		1.455
		(1.767)		(1.637)
Acquirer_Leverage		0.022		0.031
		(0.057)		(0.081)
Acquirer_M/B		-0.009		-0.011
		(-0.597)		(-0.733)
All_Stock		0.426**		0.425*
		(1.964)		(1.953)
All_Cash		0.337**		0.326**
		(2.198)		(2.119)
Competition		-0.009		-0.020
		(-0.039)		(-0.086)
Diversification		-0.124		-0.150
		(-0.863)		(-1.040)
Industry_Digital_Score		-0.097		-0.101
		(-0.904)		(-0.942)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	483	474	483	474
Pseudo R2	0.105	0.123	0.115	0.131

TABLE 5

Target's Digital Orientation

Table 5 presents the results of ordered probit regression analysis examining the relationship between Target Digital Score and Acquirer Digital Score. Deals included in this analysis are between public, US, non-tech targets and acquirors that can be matched with our initial CCM sample. We define control variables in Appendix I. We control for year and industry FEs. ***, ** and * denote significance at 1%, 5% and 10% level, respectively.

Variable	(1)	(2)	(3)	(4)
Acquirer_Digital_Score	0.251***	0.250***	0.260***	0.272***
	(5.312)	(5.182)	(5.360)	(5.398)
Target_Firm_Size		0.029		0.019
		(0.747)		(0.400)
Target_FCF		-1.050***		-1.079***
		(-3.207)		(-3.140)
Target_M/B		0.009		0.010
		(0.753)		(0.818)
Target_Leverage		-0.886***		-0.855***
		(-3.348)		(-3.186)
Acquirer_Firm_Size			0.022	0.025
			(0.656)	(0.626)
Acquirer_FCF			-0.053	0.217
			(-0.074)	(0.282)
Acquirer_M/B			0.011	0.014
			(0.887)	(1.093)
Acquirer_Leverage			-0.060	0.054
			(-0.176)	(0.149)
All_Stock				0.165
				(0.913)
All_Cash				0.104
				(0.784)
Competition				0.006
				(0.032)
Diversification				-0.081
				(-0.582)
Target_Industry_Digital_Score		0.599***		0.630***
		(7.899)		(7.903)
Acquirer_Industry_Digital_Score				-0.260
				(-1.519)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	510	507	509	506
Pseudo R2	0.174	0.191	0.177	0.195

TABLE 6
Digital Orientation and Digital Premia

Table 6 presents the results of probit regression analysis examining the relationship between Target Digital Score and Target Premiums. All variables are winsorized at 1% and 99% level except Premium (Initial Offer Price/Price 4 weeks prior) and SDC Premium. These variables are winsorized at 0 to 2. All stock, Competition and Diversification are dummy variables. Descriptions for all variables are given in Appendix I. ***, ** and * denote significance at 1%, 5% and 10% level, respectively.

Variable	Premium (-63,2)	Premium (-63,126)	SDC Premium	Premium (Offer Price/Stock Price)
Digital_Score	0.024***	0.022**	0.023**	0.023*
	(2.608)	(2.025)	(2.075)	(1.852)
Firm_Size	-0.030***	-0.028***	-0.059***	-0.062***
	(-4.340)	(-3.390)	(-7.230)	(-6.594)
FCF	-0.001	0.092	-0.317***	-0.319***
	(-0.009)	(1.250)	(-4.283)	(-3.779)
M/B	0.004	0.001	0.005	0.005
	(1.399)	(0.348)	(1.509)	(1.454)
Leverage	0.154***	0.137**	0.065	0.148**
	(3.146)	(2.370)	(1.112)	(2.242)
All_Cash	0.102***	0.105***	-0.137***	-0.095***
	(4.014)	(3.487)	(-4.498)	(-2.748)
All_Stock	-0.149***	-0.169***	-0.203***	-0.153***
	(-3.853)	(-3.695)	(-4.422)	(-2.939)
Competition	0.013	0.030	-0.113***	0.038
	(0.411)	(0.771)	(-2.913)	(0.862)
Diversification	-0.056**	-0.078***	-0.019	-0.005
	(-2.366)	(-2.797)	(-0.688)	(-0.168)
Acquirer_Public_Status	0.114***	0.156***	-0.001	0.055
	(4.583)	(5.289)	(-0.040)	(1.625)
Intercept	0.478**	0.472*	0.749***	0.762***
	(2.340)	(1.952)	(3.034)	(2.708)
Industry_Digital_score	-0.013	-0.017	-0.037*	-0.052**
	(-0.756)	(-0.842)	(-1.762)	(-2.182)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1408	1406	1448	1448
Adj. R-sq	0.121	0.113	0.145	0.114

TABLE 7

Days to Completion

Table 7 reports OLS regression results on Target and Acquirer Digital Score's relation to days between deal announcement and deal completion. This test is run on a filtered deal sample where deal status is "Completed" and both the target and acquiror are public firms.

	Panel A: Target Digital Score		*Panel B: Acquirer Digital Score*	
Variable	(1)	(2)	(3)	(4)
Digital_Score	-6.910**	-6.099**	-7.301**	-7.331**
	(-2.478)	(-2.249)	(-2.380)	(-2.440)
Firm_Size		13.836***		3.134
		(6.756)		(1.524)
FCF		-12.612		-33.949
		(-0.678)		(-0.748)
M/B		-0.421		-0.172
		(-0.609)		(-0.231)
Leverage		7.677		14.826
		(0.512)		(0.699)
All_Cash		-36.385***		-48.906***
		(-5.184)		(-5.877)
All_Stock		14.556		17.591
		(1.421)		(1.463)
Competition		6.893		20.395
		(0.493)		(1.233)
Diversification		9.971		6.835
		(1.388)		(0.824)
Intercept	280.555***	209.895***	285.488***	292.439***
	(4.009)	(3.265)	(4.069)	(4.188)
Target_Industry_Digital_Score		-1.714		
		(-0.376)		
Acquirer_Industry_Digital_Score				-14.990
				(-1.430)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	448	443	448	441
Adj. R-sq	0.188	0.358	0.187	0.285

TABLE 8

Robustness Test – Randomized Digital Scores

Table 8 Panel A presents the results of probit/OLS regression analysis examining the relationship between randomly assigned digital scores to targets and acquirers. We replicate the same analysis in Table 3 (Digital Orientation and Acquisition Likelihood), Table 4 (Improvement in Acquirer Digital Skills), and Table 5 (Target's Digital Orientation) by randomly assigning digital scores while keeping the distribution of scores fixed.

Table 8 Panel B presents the results of probit/OLS regression analysis examining the relationship between randomly assigned digital scores to targets and acquirers. We replicate the same analysis in Table 6 (Digital Orientation, Digital Premia) and Table 7 (Days to Completion) by randomly assigning digital scores while keeping the distribution of scores fixed.

Panel A Variable	Target Likelihood - All Acquirers	Target Likelihood - Public Acquirers	Acquirer Likelihood - All Targets	Acquirer Likelihood - Public Targets	Acquirer Digital Score Improvement	Target Digital Score
Target_Digital_Score	0.011	0.014	0.006	0.014		
	(1.268)	(1.240)	(1.105)	(1.210)		
Acquirer_Digital_Score						-0.015
						(-0.406)
Relative_Digital_Orientation					0.015	
					(0.878)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	33,683	33,447	33,036	33,311	474	504
Adj/Pseudo R-sq	0.050	0.054	0.086	0.131	0.029	0.076

Panel B Variable	Target Premium (-63,2)	Target Premium (-63,126)	SDC Premium	Premium (Offer-Price/Stock Price)	Days to Completion Target DS	Days to Completion Acquirer DS
Target_Digital_Score	-0.004	-0.008	-0.001	-0.001	-1.513	
	(-0.652)	(-0.892)	(-0.138)	(-0.104)	(-0.862)	
Acquirer_Digital_Score						1.605
						(0.904)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,417	1,262	1,448	1,448	445	441
Adj/Pseudo R-sq	0.173	0.184	0.143	0.111	0.299	0.218