Is There a Digital Premium in M&A?

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Abstract

We examine whether digital orientation, a firm's strategic focus on integrating digital technologies and capabilities, drives mergers and acquisition (M&A) activity and outcomes. While prior research links digital orientation to higher firm value, less is known about whether corporate decision-makers treat it as an acquirable and transferrable strategic asset. Using a digital scoring methodology based on 10-K textual analysis we find that firms with higher digital orientation are more likely to become both acquirers and targets in M&A deals, while they also receive higher acquisition premiums and complete transactions more quickly. We further document that acquirers of digitally more oriented targets experience measurable post-deal increases in their own digital orientation. Our findings suggest that digital capabilities are priced in the market for corporate control and can be transferred across firms through M&A, positioning digital orientation as an important driver of corporate investment behavior.

Keywords: Digital, mergers, acquisitions, takeover likelihood, offer premia

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1. Introduction

The digital transformation of the global economy is fundamentally reshaping 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 et al., 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). Prior research has shown that digitally active firms tend to be more highly valued by the market (Chen and Srinivasan, 2023) and that a clear digital business strategy leads to superior financial performance (Bharadwaj et al., 2013). Moreover, firms with more advanced digital capabilities have been found to exhibit resilience during periods of macroeconomic stress (Gaspar et al., 2024) and closer alignment with investor expectations (Zhai, Yang & Chan, 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 DO 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 may reflect broad market expectations and investor perceptions. M&A transactions involve direct resource allocation by corporate decision-makers, informed by internal assessments of strategic fit and long-term synergistic gains. Studying M&A

activity therefore allows us to examine whether firms view digital orientation as a value-driving strategic capability that can be acquired to enhance firm performance and competitive position. If so, we would expect digital orientation to influence the likelihood of deal participation, the deal premia, the time to deal completion, and post-deal outcomes of transactions, including whether digital capabilities are transferred to the acquiring firm.

While several strands of the finance literature have examined the role of intangibles and innovation in shaping corporate investment decisions (Bena and Li, 2014; Makri et al., 2010; and Peters and Taylor, 2017) these studies often rely on proxies such as patent counts or R&D intensity. Such measures, however, capture only specific facets of innovation and may not reflect the integrated and dynamic nature of digital transformation. Digital orientation encompasses a broader set of embedded attributes, such as a firm's technological infrastructure, data-driven capabilities, digital culture, and external interfaces. These attributes can play a pivotal role in corporate investment decisions such as M&A by enabling better opportunity recognition and signalling of strategic fit but also by shaping post-acquisition integration and value realization. To that end, our study contributes by highlighting how digital orientation, beyond traditional innovation inputs, can serve as a critical determinant of firm behavior in the market for 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 and Seiler, 2017; Gaspar et al., 2023) and applies a curated bag-of-words method tailored to capture explicit statements about digital orientation. Our DO measure captures four interrelated dimensions identified by 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, non-technology firms from 2000 to 2022 and link these scores to a comprehensive M&A dataset. Our empirical analysis is guided by the following interrelated questions: Are firms with stronger digital orientation more likely to be acquired or to initiate acquisitions? Do they receive higher premiums or complete deals more quickly? And does acquiring a more digitally active firm lead to observable changes in the acquirer's own 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 non-tech 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' propensity to engage in M&A and their likelihood of being selected as acquisition targets. Digitally mature firms may be more attractive acquisition targets since digital skills can be transferred via acquisitions.[1] At the same time, they may also be better equipped, both operationally and strategically, to pursue acquisitions themselves. 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 when targeted in an acquisition deal. A one standard deviation increase in target DO is associated with an average increase of $40m in the deal premium. These findings suggest that acquirers place meaningful value on digital capabilities, treating them as strategically important components of target

[1] Prior research shows that digital capabilities can be transferred via acquisitions (Mallette and Godard, 2018; Hanelt et al., 2021).

firm valuation and further support the view that digital orientation acts as a non-financial value driver in high-stakes capital allocation decisions.

Third, we find that greater digital orientation leads to 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. These results are consistent 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 stronger when the target is more digitally mature than the acquirer, indicating that acquirers are able to internalize meaningful capability upgrades through these transactions.

Our study reframes digital orientation as a transferable, strategic asset that shapes firm behavior in the market for corporate control. Specifically, our findings make three key contributions. First, we extend the growing literature on the role of digital transformation by showing that digital orientation is not only recognised by capital markets as value-enhancing, but also materially influences corporate investment behavior and managerial decision making in the context of M&As. Second, we contribute to the literature on M&A and strategic capabilities by demonstrating that digital orientation is a distinct, non-financial factor that helps explain acquisition behavior and outcomes, beyond traditional innovation proxies like patents and R&D (Bena and Li, 2014; Peters and 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 capital allocation 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.

The remainder of this study is structured as follows: Section 2 describes the data, methodology and summary statistics. Section 3 presents our empirical findings on digital orientation and acquisition likelihood. Section 4 provides the results on deal valuation and deal execution effects of digital orientation. Section 5 presents robustness tests to validate our findings and address potential endogeneity concerns. Section 6 concludes the study.

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., non-technology[2] firms listed on the NYSE, NASDAQ, and AMEX exchanges with share codes 10 or 11, spanning the years 2000 to 2022. We exclude firms in utilities

[2] We exclude technology firms from our analysis to avoid sector-specific heterogeneity in digital usage. These firms are identified using the classification approach of Chen and Srinivasan (2023), which is based on 4-digit SIC and NAICS codes corresponding to industries such as computers, electronics, communications, data processing, and internet services.

(SIC codes 4900–4999) and financials (SIC codes 6000–6999) due to their distinct regulatory and reporting environments. Firms are included only if they have a 10-K filing for a given year. The final firm-year panel comprises 34,117 firm-year 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 11,656 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.

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 (2021), Chen and Srinivasan (2023), and Zareie et al. (2024), resulting in a comprehensive set of 268 digital-related terms (see Appendix II). This dictionary captures four dimensions of digital orientation (Kindermann, 2021): digital technologies, digital architecture configuration, digital capabilities, and digital ecosystem coordination. The dictionary includes 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 to digital term selection is motivated by two considerations. First, foundational digital terms signal early-stage digitalization efforts, which remain relevant throughout the entire sample period. Second, even when such terms come to reflect routine operations, they help trace the trajectory of firms' digital evolution over time. For each year, we count the frequency of digital terms in the Business Description section of 10-Ks and assign a digital score to each firm-year observation 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 within that year. This ranking approach accommodates temporal variation in digital discourse and allows comparability across time periods without imposing strict frequency cutoffs.

[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. The timeline also highlights key inflection points. Early surges (e.g., in 2001) are driven by foundational terms such as "internet protocol" and "sensor," coinciding with broader corporate digitization and the dot-com recovery. The launch of major digital platforms in 2006, such as Amazon Web Services and the first iPhone is followed by a jump in total digital language, including the introduction of terms like "cloud," "real-time," and "analytics" in subsequent years.

The financial crisis of 2007–2009 marks a temporary decline, likely due to reduced digital investment. From 2010 onward, adoption accelerates with new terms such as "social media" (2011), "apps" (2012), and "cyber" (2013) entering regular corporate use, followed by the emergence of more sophisticated terminology such as “blockchain,” “machine learning,” and “artificial intelligence” in the mid-2010s. The sharp acceleration from 2020 to 2022 aligns with the COVID-19 pandemic, which catalyzed digital adoption across industries, alongside increased prevalence of terms such as “AI,” “cloud platform,” and “digital platform”. Red dashed lines in Figure 1 mark the entry years of new top 50 digital terms, often coinciding with inflection points in broader technological or economic shifts. Together, these may indicate a quantitative increase in digital discourse and/or a qualitative shift toward more strategic and complex digital themes over time.

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 ratios averages 3.09, with lower valuation for targets (2.26) and higher valuations for acquirers (3.26). Cash reserves account for 19% of total assets, with slightly higher levels among targets (20%) than acquirers (12%). Stock returns exhibit marked dispersion. The average abnormal return is 7.63% for the full sample, but 0.96% for targets and +15.84% for acquirers. Leverage ratios are similar across groups, averaging 24%. Fixed asset ratios are slightly lower for acquirers (22%) relative to targets and the overall sample (26%). Industry concentration, measured by the Herfindahl Index, shows slightly higher values for acquirers (0.24) than for targets (0.21).

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%. Acquirer CARs around the announcement date are near zero on average across all roles, while synergy gains, measured as combined acquirer and target abnormal returns weighted by market cap average 4.3%, with a median of 2.8%. Competitive bidding is observed in 2% of all deals but is more common among matched target deals (12%). Hostile takeovers are virtually absent in the sample. Diversifying acquisitions account for 47% of the sample, indicating that nearly half of the transactions involve parties from different industries. While withdrawn deals represent 3% of all transactions, the proportion rises to 17% among deals involving matched target firms. The average time to deal completion is approximately 117 days in the deal sample.

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 (Harford, 1999; Powell and Yawson, 2007; Cornett, Tanyeri, and

Tehranian, 2011). Targets, in contrast, tend to be smaller, and exhibit weaker performance, making them more attractive for acquisition due to potential value creation through restructuring (Powell and 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 and Rousseau, 2002). We also observe that target shareholders receive substantially higher premiums, averaging over 30%, whereas acquirer announcement returns are close to zero, echoing the well-documented asymmetry in deal value distribution (Alexandridis et al., 2013, Masulis and Simsir, 2018). In our sample, all-cash deals account for 22%, all-stock deals for 15%, and the majority involve mixed payments, with cash comprising about 60% of the consideration. This pattern is consistent with recent evidence showing that mixed, cash-heavy payment structures have become the dominant form in M&A transactions (de Bodt, Cousin, and Officer, 2022).

Table 2 presents descriptive statistics for target and acquirer firm-years by digital orientation. Panel A reports target firm-year summary statistics and Panel B those for acquirers, grouped by digital score quintiles. We show whether high-digital targets and acquirers share distinct characteristics compared to their low-digital counterparts, and whether digital intensity is systematically associated with firm characteristics such as firm size, profitability, cash holdings, and market valuation.

[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. Notably, target firms in the highest digital quintile are smaller and less profitable on average, while high-digital acquirers maintain relatively strong fundamentals but tend to be more asset-light. These patterns suggest that digital maturity may be associated with common structural traits such as flexibility, liquidity, and growth orientation, on both sides of the M&A transaction.

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 (Palepu, 1986; Powell & Yawson, 2007; Cornett, Tanyeri and Tehranian, 2011; Mavis et al., 2020). Higher ROA and abnormal returns signal strong performance, making firms more likely acquirers, while underperformers are more likely targets (Palepu, 1986; Powell and Yawson, 2007; Cornett, Tanyeri and Tehranian, 2011; Mavis et al., 2020). High cash may support acquisitions or deter takeovers, depending on perceived utilization (Harford, 1999; Powell and Yawson, 2007; Cornett, et al., 2011; 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 and Rousseau, 2002). Leverage has a mixed effect enabling restructuring opportunities or deterring deals due to risk (Powell and Yawson, 2007; Bhanot et al., 2010). Industry concentration (Herfindahl Index) may encourage acquisitions for consolidation but is moderated by regulatory constraints (Powell and Yawson, 2011; Cornett et al., 2011). We also include the industry median digital score to control for sector-level digital intensity. 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, and 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 Targets to Acquirers

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 test this channel by examining whether acquiring a target with higher digital orientation leads to an improvement in the acquirer's own digital score. We start by defining the dummy variable *Digital Score Difference 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* Score *Difference* as the difference between the target's and acquirer's digital scores measured prior to the deal, calculated as *Target Digital Score* minus *Acquirer Digital Score*.

[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. We define the dependent variable in Appendix 1 Panel B and control variables in Appendix I Panel C. As reported in Table 5, acquiring a more digitally mature target leads to a statistically significant improvement in the acquirer's digital orientation. One standard deviation increase in *Digital Score Difference* is associated with an 8% increase in the acquirer's 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 Digital Alignment Between Acquirers and Targets

In this section, we examine whether firms tend to acquire targets whose level of digital orientation aligns with their own. To that end, a positive association between the digital scores of acquirers and those of targets would suggest that digital orientation is not only a strategic capability but also a factor shaping acquirer–target matching dynamics.

To test this, we estimate an ordered probit regression where the dependent variable is the target firm's digital score, and the primary independent variable is the digital score of the acquirer.

[Please Insert Table 5 About Here]

The results in Table 5 reveal a statistically significant and positive association between acquirer and target digital scores. Specifically, a one standard deviation increase in the acquirer's digital score is associated with a higher probability that the target falls into a more digitally oriented category. This finding suggests that firms with greater digital orientation are more likely to acquire similarly oriented targets, while lower-digital firms tend to acquire targets that also exhibit lower digital orientation.

Taken together with our prior results on post-deal capability transfer (Section 3.3), this evidence implies that digital orientation is not randomly distributed across transactions. Instead, firms tend to select acquisition partners whose digital profiles mirror their own, reflecting an underlying alignment in strategic capabilities. This alignment may arise from synergies in systems, processes, or strategic priorities that facilitate integration and reduce frictions during post-merger execution.

4. Valuation and Execution Effects of Digital Orientation

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 Is there a 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 calculate target premia over 66-day $(-63, 2)$ and 190-day event window $(-63,126)$. 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. The observed relationships with control variables are consistent with prior work showing that smaller firms (Moeller et al., 2004), firms with lower cash reserves (Masulis and Simsir, 2018), and those with higher leverage (Powell and Yawson, 2007) tend to receive higher premiums. These results provide strong support for the idea that digital capabilities are explicitly valued in the market for corporate control. Acquirers appear willing to pay a premium to acquire firms with digital capabilities, reinforcing the role of DO as a strategic, non-financial asset.

4.2 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 and 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 et al., 2018, Chang 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, digital alignment, acquisition premia, deal completion time, and post-acquisition digital score changes using these randomly assigned placebo digital scores. Across all specifications, the coefficients on the placebo digital scores are statistically insignificant. These findings reinforce the interpretation that the documented effects of digital orientation on M&A outcomes reflect economically meaningful relationships rather than random variation or noise. We report the results for the relationship between random digital scores and acquisition likelihood in Table 8, and those for the relationship between target premia and randomly assigned target digital scores in Table 9. Results of additional analyses using random digital scores for targets and acquirers are presented in Appendix III.

[Please Insert Table 8 and 9 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 introduce a two-year lag instead of a one-year lag between the digital score and M&A activity to ensure our results are not driven by short-term fluctuations in digital disclosures. The results remain qualitatively similar, indicating that the predictive power of digital orientation is not limited to short-term cycles. Second, we construct an alternative digital orientation score using the Term Frequency – Inverse Document Frequency (TF – IDF) methodology as in Loughran and McDonald (2011). This approach adjusts raw word counts by down-weighting common terms and giving greater emphasis to less frequent, more distinctive terms in each year. The TF–IDF score helps mitigate concerns that our findings are driven by generic or overused digital language. When we replace the baseline score with the TF–IDF version in our key regressions, the results remain consistent with our baseline findings. Third, we limit our analysis to the period 2012-2022 to examine whether our results hold in a more recent and digitally intensive period. This subsample reflects a decade during which digital language became widespread and firms' digital strategies were more developed. The findings remain robust in this restricted window, indicating that the effects of digital orientation are not confined to earlier stages of digital transformation. Fourth. to further address concerns about endogeneity and potential selection bias, we conduct a propensity score matching (PSM) analysis. We begin by constructing a dummy variable equal to one for firm-years with digital word counts above the sample mean, and zero otherwise. We then estimate a probit regression using firm characteristics as predictors of high digital orientation and use the estimated propensity scores from this regression to match treated and control firms using radius matching with the three closest neighbours. We re-estimate the probit regressions for target and acquirer likelihood on the matched sample, using the high-digital dummy as the main regressor. The results remain consistent with our main findings, suggesting that our estimates are not driven by observable differences in firm characteristics captured by the control variables.

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, leveraging digital capabilities for strategic growth. We further show that acquirers tend to match with targets that exhibit similar levels of digital orientation, suggesting that firms consider digital compatibility when selecting acquisition partners. We also validate that the acquisition of a target with a 1-point higher digital score improves digital score of the acquirer by 0.2, meaning that acquisitions are effectively shaping digital orientation of industries. Higher digital scores are associated with increased target premia, reflecting market optimism toward digital-oriented firms, which are perceived as innovative, resilient, and well-positioned for future growth. Our estimates indicate that targets in the highest digital score group receive $40mm more premia on average. This digital premium implies that acquirers are willing to pay materially more for firms with strong digital capabilities treating digital orientation as a valuable strategic asset. Additionally, DO affects deal execution, as firms with higher digital scores experience shorter periods between the announcement and closing of a deal. Taken together, our findings suggest that digital orientation is a material factor shaping who participates in M&A activity, how firms are valued, who they choose to acquire and how efficiently transactions are completed. Our study highlights the growing importance of digital orientation as a non-financial strategic capability that influences corporate investment decisions.

APPENDIX I

Variable Definitions

Panel A: Summary Statistics	
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 (Common shares outstanding (csho) * price at calendar year-end +1) / (Common equity (ceq)) or if ceq is not available, (Common shares outstanding (csho) * price at calendar year-end) / (Total assets (at) - Total liabilities (lt))
Leverage	Debt-to-Assets ratio calculated as Total debt (dt) / Total assets (at) using CCM data
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
Percentage of Stock	Value paid in stock divided by total deal value taken from LSEG Eikon. Mean and median are calculated for observations where the sum of Percentage of Stock and Percentage of Cash are equal to or higher than 80.
Percentage of Cash	Value paid in cash divided by total deal value taken from LSEG Eikon. Mean and median are calculated for observations where the sum of Percentage of Stock and Percentage of Cash are equal to or higher than 80.
Target Premium	Target Cumulative Abnormal Returns with an event window of (-63,2) around deal announcement date, calculated using Eventus, based on CRSP data. Premiums are winsorized at 1%, 99% level.
Acquirer CAR	Acquirer Cumulative Abnormal Returns with an event window of (-2,2) around deal announcement date, calculated using Eventus, based on CRSP data. Acquirer returns are winsorized at 1%, 99% level.
Synergy Gains	5-day window cumulative abnormal returns of target and acquirer weighted by calendar year-end market values
Competition	Percentage of deals with more than one bidder
Hostile	Percentage of hostile deals
Diversification	Deals between two firms with different 2-digit SIC codes divided by total number of deals calculated in percentage
Withdrawn	Percentage of deals withdrawn
Days to Completion	Days between Date Announced and Date Effective. Calculated for observations where both the target and acquiror are public firms and Deal Status is "Completed".
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 HoldAbnormal 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 Digital Score	Difference between *Acquirer Digital Score* before and after the deal

Panel C: Control Variables for Firm Valuation and Acquisition Likelihood	
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	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 (Common shares outstanding (csho) * price at calendar year-end +1) / (Common equity (ceq)) or if ceq is not available, (Common shares outstanding (csho) * price at calendar year-end) / (Total assets (at) - Total liabilities (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 Growth	Calculated as change in the firm's sales (sale) over the previous two years as in Cornett, Tanyeri and Tehranian (2011) data using CCM data
Sales Growth	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 Digital Score	Difference between *Acquirer Digital Score* before and after the deal
Random Digital Score	A score of 1 to 5 randomly assigned to each firm-year while keeping the distribution of scores the same for each year,

Panel D: Control Variables for Target Returns and Other Tests

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.
Digital Score Difference Dummy	Dummy variable equal to 1 if the pre-deal target digital score is higher than the acquirer digital score and 0 otherwise
Digital Score Difference	Pre-deal difference between the target digital score and the acquirer digital score
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
Random Digital Score	A score of 1 to 5 randomly assigned to each target and/or acquirer while keeping the distribution of scores the same for each year

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

APPENDIX III

Robustness Test - Randomized Digital Scores

Appendix III presents the results of placebo tests using randomly assigned digital scores for both targets and acquirers, instead of the computed digital scores. In Column 1, we replicate the analysis of digital skill transfer from targets to acquirers (originally reported in Table 4), in column 2, we repeat the digital alignment test between acquirers and targets (from Table 5), in columns 3 and 4 we replicate the analysis of the relationship between digital scores and days to completion, originally presented in Table 7, all based

	Acquirer Digital Score Improvement (1)	*Target Digital Score (2)*	*Days to Completion (3)*	*Days to Completion (4)*
Target Digital Score			-1.513	
			(-0.862)	
Acquirer Digital Score		-0.015		1.605
		(-0.406)		(0.904)
Relative Digital Orientation	0.015			
	(0.878)			
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	474	504	445	441
R-sq	0.029	0.076	0.299	0.218

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Figure 1 – Evolution of Total and Average Digital Word Count Over Time Highlighting Key Technological and Economic Events

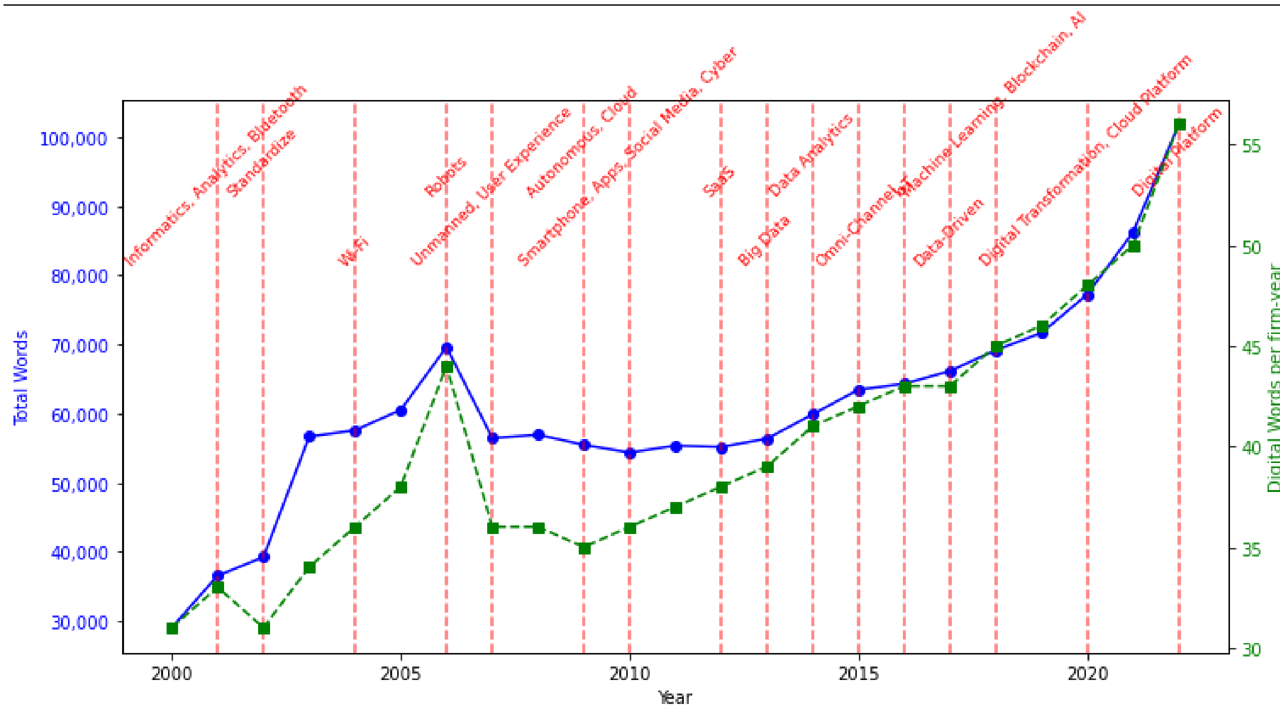

TABLE 1

Summary Statistics

Table 1 Panel A reports summary statistics for our sample of all firms from CRSP Compustat merged database. Each observation represents a firm-year from 2000 to 2022. All firms are US headquartered, non-technology, listed in NYSE, Amex and Nasdaq with revenues over $1 million. Digital scores are estimated based on digital word counts from Loughran Mcdonald Software Repository of 10-K reports. 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 acquirors with US origin. Acquiror sample represent Completed and Withdrawn control deals from SDC with public, non-tech, US origin acquirors that can be matched with our initial firm-year sample and targets with US origin. We merge target and acquiror 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. ***, ** and * denote significance at 1%, 5% and 10% level, respectively.

Panel A: Firm Characteristics

		All Firm-Years	Targets	Acquirors
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	3,918.46	1,666.96	7,230.77
	median	712.23	380.35	1,516.20
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
Sales Shock	mean	0.12	0.12	0.11
	median	0.08	0.08	0.07
Leverage	mean	0.24	0.24	0.24
	median	0.20	0.20	0.22
Herfindahl Index	mean	0.22	0.21	0.24
	median	0.16	0.16	0.18

Panel B: Deal Characteristics

		All Firm-Years	Targets	Acquirors
Number of observations		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	84.63	80.68	84.40
	median	100.00	100.00	100.00
Target Premium (%)	mean	34.43	33.21	38.20
	median	27.64	27.58	30.11
Acquirer CAR (%)	mean	0.64	0.02	0.90
	median	0.33	0.10	0.50
Synergy gains (%)	mean	4.46	4.28	4.28
	median	3.47	2.62	2.62
Competition	mean	0.02	0.12	0.01
	median	0.00	0.00	0.00
Hostile	mean	0.00	0.01	0.00
	median	0.00	0.00	0.00
Diversification	mean	0.47	0.56	0.45
	median	0.00	1.00	0.00
Withdrawn	mean	0.03	0.17	0.02
	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 Sample Statistics by Digital Orientation Quintile

Table 2 reports statistics on firm characteristics for the sample of targets (Panel A) and acquirers (Panel B) by digital score quintile. Digital score quintile breakpoints are derived from the full firm-year sample described in Table 1. The table also reports p-values from difference tests between quintiles 5 and 1. Definitions for all variables are in Appendix I.

Panel A Target Sample Statistics by Digital Orientation Quintile

		Low Digital Score (1)	(2)	(3)	(4)	High Digital Score (5)	Difference (p-value) '(5-1)
Firm_Size_($_million)	mean	2,153.64	2,075.56	1,984.58	1,498.95	1,386.15	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 (1)	(2)	(3)	(4)	High Digital Score (5)	Difference (p-value) '(5-1)
Firm_Size_($_million)	mean	6,984.50	8,256.95	6,146.02	8,282.63	5,605.73	0.02
	median	1,341.88	1,651.73	1,388.17	1,398.60	1,182.60	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 Acquirer Likelihood in Panel B. We use our Digital Score as a measure of digital activity. We define Target/Acquirer 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: Acquirer Likelihood*		
	Public Acquirers (1)	Public Acquirers (2)	All Acquirers (3)	Public Targets (1)	Public Targets (2)	All Targets (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 and control variables in Appendix I. We control for year and industry fixed effects. ***, ** and * denote significance at 1%, 5% and 10% level, respectively.

	(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 R^2	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.

	(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 R^2	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.

	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	1,408	1,406	1,448	1,448
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 ran on a filtered deal sample where deal status is "Completed" and both the target and acquiror are public firms.

	(1)	(2)	(3)	(4)
Target Digital Score	−6.910**	−6.099**		
	(−2.478)	(−2.249)		
Acquirer Digital Score			−7.301**	−7.331**
			(−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

Digital Orientation and Acquisition Likelihood with Randomly Assigned Digital Scores

Table 8 reports results of probit regression analysis of Target Likelihood in Panel A and Acquiror Likelihood in Panel B with the main independent variable *Random Digital Score*. We randomly reassign digital scores across firms within each year to create the Random Digital Score variable and address endogeneity concerns. We define Target/Acquirer dummy variables that take the value of 1 if a firm−year observation was included in our SDC Target/Acquirer 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: Acquirer Likelihood*		
	Public Acquirers (1)	Public Acquirers (2)	All Acquirers (3)	Public Targets (1)	Public Targets (2)	All Targets (3)
Random Digital Score	0.016	0.014	0.011	0.015	0.014	0.006
	(1.383)	(1.240)	(1.268)	(1.377)	(1.210)	(1.015)
Firm Size		−0.020*	−0.077***		0.249***	0.148***
		(−1.845)	(−8.866)		(21.726)	(27.975)
ROA		0.127	−0.007		0.158	0.648***
		(1.237)	(−0.089)		(1.123)	(9.847)
Cash Reserves		0.470***	0.002		0.197*	−0.416***
		(4.921)	(0.026)		(1.696)	(−7.500)
M/B		−0.009**	−0.009***		0.005*	0.003*
		(−2.546)	(−3.425)		(1.672)	(1.657)
Stock Return		−0.213***	−0.206***		−0.001	0.019
		(−9.539)	(−11.788)		(−0.039)	(1.492)
Leverage		0.169**	0.207***		−0.142	−0.323***
		(2.064)	(3.256)		(−1.462)	(−7.085)
Herfindahl Index		−0.080	−0.027		−0.409***	0.037
		(−0.664)	(−0.303)		(−3.158)	(0.696)
Sales Shock		−0.016	−0.029		0.175	0.031
		(−0.093)	(−0.211)		(1.029)	(0.366)
Intercept	−2.016***	−2.169***	−1.545***	−1.819***	−3.544***	−1.931***
	(−8.366)	(−7.840)	(−7.514)	(−8.972)	(−13.877)	(−14.702)
Industry Digital Score		0.043	0.046		0.006	−0.084***
		(0.884)	(1.258)		(0.133)	(−3.741)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	33,776	33,447	33,683	33,639	33,311	33,787
Pseudo R-sq	0.033	0.054	0.050	0.033	0.131	0.085

TABLE 9

Digital Orientation and Digital Premia with Randomly Assigned Digital Scores

Table 9 presents the results of probit regression analysis examining the relationship between Target Random Digital Score and Target Premiums. We randomly reassign digital scores across firms within each year to create the *Random Digital Score* variable and address endogeneity concerns. 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.

	Premium (−63,2)	Premium (−63,126)	SDC Premium	Premium (Offer Price/Stock Price)
Random Digital Score	−0.002	−0.003	0.000	0.001
	(−0.305)	(−0.298)	(0.015)	(0.061)
Firm Size	−0.031***	−0.047***	−0.059***	−0.059***
	(−4.492)	(−5.149)	(−6.302)	(−7.282)
FCF	−0.007	−0.001	−0.357***	−0.339***
	(−0.107)	(−0.009)	(−4.243)	(−4.589)
M/B	0.004	0.003	0.005	0.004
	(1.482)	(0.832)	(1.321)	(1.215)
Leverage	0.156***	0.158**	0.127*	0.030
	(3.163)	(2.462)	(1.920)	(0.515)
All Cash	0.111***	0.091***	−0.099***	−0.133***
	(4.365)	(2.756)	(−2.880)	(−4.386)
All Stock	−0.145***	−0.135***	−0.146***	−0.185***
	(−3.764)	(−2.722)	(−2.815)	(−4.064)
Competition	0.023	0.093*	0.012	−0.123***
	(0.698)	(1.860)	(0.271)	(−3.161)
Diversification	−0.054**	−0.043	−0.004	−0.019
	(−2.340)	(−1.433)	(−0.129)	(−0.707)
Acquirer Public Status	0.117***	0.140***	0.073**	0.015
	(4.676)	(4.294)	(2.148)	(0.487)
Intercept	0.507***	0.575***	0.907***	0.914***
	(3.171)	(2.885)	(4.168)	(4.784)
Industry Digital score	−0.003	−0.013	−0.049	0.005
	(−0.094)	(−0.332)	(−1.202)	(0.130)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,408	1,252	1,448	1,448
Adj. R-sq	0.111	0.096	0.111	0.144