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# Fooled by the hype? The influence of technology hype on acquisition premiums in digital M&As

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ABSTRACT

Given the rapidly evolving nature of digital technologies, the valuation of digital target firms in mergers and acquisitions (M&As) is particularly uncertain and complex. Adopting a socio-cognitive perspective, we argue that the cognitive burden of processing complex and uncertain information surrounding a digital technology creates a susceptibility for managers to rely on easily accessible expectations and media claims about these technologies, consistent with an availability heuristic. Consequently, managers incorporate excessively optimistic expectations from technology hype into their valuation assessments, leading them to pay higher acquisition premiums. We further propose that in-depth digital technology knowledge among the top management and prior experience in acquiring digital target firms alleviate the cognitive burden of assessing digital target firms, thereby reducing managers' reliance on overly optimistic expectations associated with technology hype. Using a sample of digital M&As by S&P 1500 firms, we find support for these propositions. Additional analyses further reveal that digital M&As executed during hype phases generate lower post-acquisition returns than those completed outside hype phases. Overall, this study contributes to a better understanding of when and why heuristics may bias decision-making.

## 1. Introduction

Acquiring digital technology resources via mergers and acquisitions (i.e., digital M&As) has become a vital strategy for advancing incumbent firms' digital transformation (Boote et al., 2019; Hanelt et al., 2021a). Not surprisingly, digital M&As doubled their global value from 2012 to 2017 (Boote et al., 2019) and remain at the top of the M&A agenda of incumbent firms (Stafford et al., 2025). Digital M&As promise rapid access to emerging technologies and the knowledge required to deploy them at scale (Hanelt et al., 2021b). At the same time, digital technologies are largely intangible and evolve rapidly (Yoo et al., 2012), making the assessment of future prospects and synergies in digital M&As inherently uncertain and complex. These uncertainties arguably call for a diligent and cautious approach to digital M&As (Clarke et al., 2020). However, systematically higher acquisition premiums in digital M&As relative to traditional M&As, along with higher failure rates, cast doubt on whether such caution is actually exercised (Leroi et al., 2017). With

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awareness of the potential unfavorable consequences of excessive premiums (Haunschild, 1994; Krishnan et al., 2007), we aim to better understand why managers pay such excessive premiums in digital M&As and what helps to mitigate this behavior.

Prior research on acquisition premiums has highlighted that assessing the synergies and prospects of targets requires acquiring managers to screen and analyze vast amounts of technological, strategic, and financial information (Bauer and Friesl, 2024). This literature also points to a substantial asymmetry between the information needed for such assessments and readily available information (Hambrick and Hayward, 1997; Welch et al., 2020). To navigate this complex and uncertain environment, it has been well established that managers use heuristics in their information processing (Malhotra et al., 2015; Li and Haleblian, 2022). For instance, recent studies suggest that managers anchor their bids to recent peer transactions (Malhotra et al., 2015; Li and Haleblian, 2022) and that they interpret media news as social feedback and adjust their M&A decisions accordingly (Liu and McConnell, 2013; Steinbach et al., 2019). While these studies provide valuable insights into how managers use stakeholder signals as heuristics to make better-informed premium decisions, heuristics also introduce the risk of biased decision-making (Hodgkinson et al., 2023). However, little is known about when and how the use of heuristics may lead to biased premium decisions.

We introduce a socio-cognitive perspective tailored to the distinctive features of digital M&As to explain how satisficing and the availability heuristic lead to excessive premiums in digital M&As during periods of technology hype. Technology hype refers to overly optimistic or exaggerated claims about a technology's potential, maturity, and impact, often amplified via extensive media attention and widespread diffusion (Dedehayir and Steinert, 2016). Given the exaggerated nature of technology hype and its potential to quickly lead to disappointment (Fenn and Raskino, 2008), managers should cautiously approach these claims. However, managers of incumbent firms, who often lack detailed experience with focal digital technology, are forced to search for and interpret external information about a technology's potential. In this context, the considerable cognitive effort required to assess the vast information of a technology's potential, paired with a finite cognitive capacity, creates a tendency for individuals to settle for "satisfactory" information—the satisficing principle (Simon, 1956). Moreover, following the availability heuristic (Tversky and Kahneman, 1973), the easily accessible, salient, and optimistic media discourse during hype phases increases the likelihood that managers will incorporate this optimistic discourse in their assessment of a target's value. Consequently, we hypothesize that managers are likelier to pay inflated acquisition premiums during a phase of technology hype than in phases in which such hype is absent.

Following research on socio-cognitive processes (for an overview, see Vuori et al., 2024), we further suggest that managers' reliance on technology hype decreases when they are supported by more technology knowledge and experience. We argue that the background of a top management team (TMT) and the cumulative experience of an organization in the decision-making context are critical sources of such knowledge and experience. Specifically, a TMT's digital knowledge, which describes the skills and experiences of top managers in domains related to digital technologies (Firk et al., 2022), should enable a TMT to evaluate readily available and optimistic media discourse on a technology's potential more critically, making them less prone to relying on technology hype in its assessment of a digital target. Moreover, in firms with substantial experience with digital M&As, managers are likelier to be supported by dedicated approaches and routines for evaluating digital target firms, which likely exposes managers to more reflective and critical information about a technology, ultimately reducing their reliance on exaggerated claims during technology hype. Fig. 1 summarizes our research framework.

To test our hypotheses, we ran ordinary least squares (OLS) regressions on a sample of digital M&As conducted by S&P 1500 firms between 2004 and 2018. To capture technology hype, we developed an innovative measure that quantifies the nonlinear accumulation of optimistic media coverage about a technology. We find a significant positive relationship between technology hype and premiums, suggesting that, in situations of greater technology hype, managers are, on average, willing to pay higher premiums. We also find that the positive association between technology hype and acquisition premiums is attenuated when firms exhibit higher TMT digital knowledge and greater digital M&A experience, supporting our argument that technology-related knowledge and experience enable managers to better resist exaggerated claims on the potential of a technology. An additional analysis shows that digital M&As executed during a technology hype are associated with lower future value creation—both in terms of future Tobin's Q and Buy-and-Hold Abnormal Returns (BHARs) over three years. Overall, these findings highlight the joint importance of technology hype and technological knowledge and experience in driving the potential for the availability heuristic biasing premium decisions in digital M&As.

This study offers three major contributions to the academic literature. First, it contributes to the literature on heuristics and biases in managerial decision-making (Hodgkinson et al., 2023; Vuori et al., 2024) by integrating Simon's (1956) satisficing principle with Tversky and Kahneman's (1973) work on universal heuristics and by explaining how boundedly rational search processes can unfold as bias in a real-world setting. Second, it contributes to the research on M&A premiums. Whereas prior research has mainly viewed

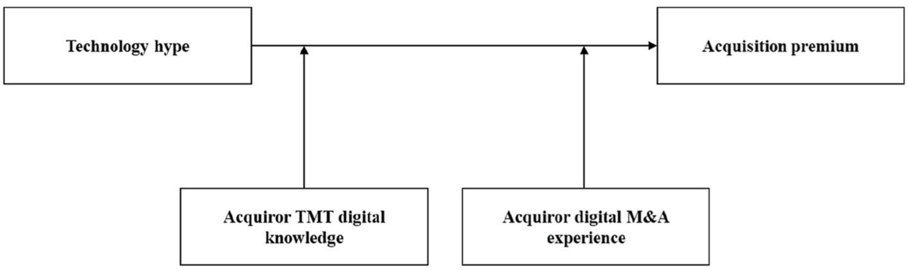


**Fig. 1.** Research framework.

heuristics as functional for setting M&A premiums (Malhotra et al., 2015; Li and Haleblian, 2022), we argue and illustrate how the distinctive features of digital M&As can bias M&A premiums during technology hype phases. Third, we contribute to the literature on digital transformation (Hanelt et al., 2021a; Verhoef et al., 2021) by integrating the separated streams of digital M&As (Hanelt et al., 2021b) and competencies in the TMT (Firk et al., 2022; Christofi, 2024) to create a better understanding of when and why digital expertise is particularly valuable for a firm's digital transformation. By highlighting the role of technology-related experience within the upper echelons in avoiding economically dysfunctional premium decisions during technology hype phases, this study also provides important practical insights for the composition of TMTs and decision-making in digital M&As.

## 2. Theory and hypotheses

### 2.1. Digital M&As and acquisition premiums

Acquiring digital competencies, technologies, and talent through M&As has been an increasingly relevant strategy for firms and an essential part of their digital transformations (Boote et al., 2019; Hanelt et al., 2021b). Digital M&As—that is, "acquisitions of (or mergers with) firms that intensely leverage digital technologies as critical elements of their business model" (Hanelt et al., 2021b, p. 3)—can provide firms with access to valuable resources, such as technologies, expertise, and customer bases (Leroi et al., 2017). Digital M&As also provide a way for incumbent firms to enter new markets or pivot their business models to better align with digital trends. However, despite these strategic opportunities, digital M&As are not without criticism. Scholars have raised concerns about the complexity and risk associated with these transactions, stemming largely from the unique characteristics of digital targets and the inherent difficulties in assessing their synergistic value (Cloodt et al., 2006; Heeley et al., 2007; Ransbotham and Mitra, 2010).

Most importantly, digital technologies are often intangible and embedded in complex, novel business models, which makes it difficult to assess their intrinsic value (Yoo et al., 2012). Moreover, their rapidly evolving nature (Bharadwaj et al., 2013; Huang et al., 2017) and the dynamic development of the business environment (e.g., supply, market demand, regulations) (Dedehayir and Steinert, 2016) make forecasting their development and economic potential highly uncertain. As a result, evaluating a digital target's technology and its strategic fit with an acquiring firm requires forward-looking judgments under considerable uncertainty (Chondrakis et al., 2021). Moreover, the full value of a digital target often materializes only in the long term and is contingent on successful integration into an acquirer's existing structures (Puranam and Srikanth, 2007; Ransbotham and Mitra, 2010; Chondrakis, 2016). This process demands competencies that are often underdeveloped in incumbent firms (Leroi et al., 2017). Consequently, digital M&As are inherently complex, not only due to the novel nature of the acquired assets but also because of the substantial knowledge gap between what is required and what is available for informed decision-making.

Despite the complexity and high risk involved, acquiring firms frequently pay substantial premiums for digital targets (Boote et al., 2019). Hewlett-Packard's (HP) acquisition of Autonomy, a data analytics company focused on processing unstructured data, provides an example of such a deal. In an attempt to transform HP's hardware-based business model into a software-driven business model, HP valued Autonomy and its data analytics capabilities at more than $11 billion, equaling a premium of about 60 % over Autonomy's market price. The deal turned out to rely on poor due diligence, ultimately resulting in severe long-term financial losses (Sayer, 2024).

High acquisition premiums in digital M&As are not exceptions; rather, they are common and have spawned numerous consultancy reports on the logics of digital deals (Boote et al., 2019; Clarke et al., 2020). However, academic research on this topic remains relatively limited. While prior studies have suggested that digital M&As can be an effective strategy for driving digital transformation (Hanelt et al., 2021b), less is known about the specific challenges involved, particularly when it comes to pricing a digital target. Therefore, this study seeks to explain whether and why managers may succumb to bias when setting acquisition premiums in digital M&As.

### 2.2. A socio-cognitive perspective on premiums in digital M&As

Prior research suggests that it is a natural socio-cognitive process for decision-makers to use heuristics when dealing with highly complex and uncertain information environments (Vuori et al., 2024). Heuristics are cognitive shortcuts or "rules of thumb that serve as potential aids to decision-making by focusing decision-makers' attention on particular aspects of information" (Hodgkinson et al., 2023, p. 1034). A common explanation for their use traces back to Simon's seminal work (1955, 1956), which suggests that decision-makers' bounded cognitive capacities do not allow them to process all available information in complex settings and that heuristics help mitigate their cognitive burden. Specifically, Simon (1955, 1956) introduced the satisficing principle, whereby decision-makers, instead of searching exhaustively for perfect information, accept the first satisfactory "alternative that meets their minimum requirements with respect to a given set of criteria" (Hodgkinson et al., 2023, p. 1040). The high information asymmetries in M&A decisions make it practically impossible to collect and interpret all relevant information (Sirower, 1997; Laamanen, 2007) and, thus, provide a context in which managers will naturally tend to satisfice.

While the satisficing principle describes how decision-makers terminate their search for information once a satisfactory option is identified, Tversky and Kahneman's (1974) heuristics-and-biases program describes how decision-makers navigate that search by emphasizing universal heuristics that prioritize easily retrievable or particularly vivid information. Heuristics, such as anchoring, representativeness, and availability, illustrate how individuals simplify complex judgements based on attributes that readily come to mind (see Kahneman and Frederick, 2002). For instance, a hiring manager may intuitively answer the challenging question of whether a job candidate possesses outstanding ability based on whether the candidate graduated from an elite university, as such institutions and their alumni are frequently praised in public discourse. The heuristic regulates the hiring manager's cognitive burden required for a fully informed decision by privileging salient, easily accessible cues, while the satisficing principle implies that the hiring manager ends the search once a candidate appears "good enough" to meet the job requirements. As such, integrating Tversky and Kahneman's universal heuristics with Simon's satisficing principle clarifies how decision-makers identify and select what they perceive as satisfactory within the limits of bounded search.

Simon (1955, 1956) as well as Tversky and Kahneman (1973, 1974) emphasized that heuristics are often functional, enabling decision-makers to arrive at effective "second-best" solutions under substantial uncertainty. However, these heuristics may also carry the risk of systematic bias. Prior research on heuristics in the M&A context largely aligns with the idea that heuristics enable individuals to functionally solve complex problems without the need to collect and process all information. For instance, managers anchor their acquisition bids to recent peer transactions (Malhotra et al., 2015; Li and Haleblian, 2022), use media coverage as social feedback (Gamache et al., 2019), and respond to media sentiment by either pursuing bolder moves when reinforced (Hayward et al., 2004) or abandoning deals facing criticism (Liu and McConnell, 2013). However, despite these valuable insights, little is known about when managers' use of heuristics shifts from being functional to biasing decision-making and how these cognitive traps might be avoided (Hodgkinson et al., 2023).

One heuristic that may catalyze a shift from functionality to bias in decision-making is the availability heuristic. The availability heuristic describes a socio-cognitive process in which individuals assess the probability of an event (such as success) by the ease with which instances can be brought to mind (Tversky and Kahneman, 1973). While its use does not necessarily yield biased estimates, it increases the risk of such if the imported (easily retrievable) information does not fit the actual environment but instead represents misconceptions or exaggerations. In the context of digital M&As, this is particularly relevant as the heuristic could be a gateway for incorporating technology hype into the assessment of digital M&As.

### 2.3. *Technology hype and premiums decisions in digital M&As*

Technology hype refers to a situation in which intense interest in an emerging technology is accompanied by unrealistically high expectations (Dedehayir and Steinert, 2016; Heupel et al., 2024). It often arises from media enthusiasm for a technology long before a technology's true capabilities have been demonstrated (Fenn and Raskino, 2008). This enthusiasm is fueled by the collectively constructed promises that innovators and other stakeholders circulate to secure resources and legitimacy, creating a self-reinforcing cycle of optimism (Borup et al., 2006). As implementation challenges emerge, the "hype phase" can quickly give way to disappointment and disillusionment (Fenn and Raskino, 2008). Because hype is at least partly engineered to influence investment decisions and rarely delivers on its promises, there are frequent calls that it should be approached with caution (Chowdhury and Marler, 2024).

However, given the complexity of pricing digital targets in M&A transactions, we argue that satisficing and the availability heuristic lead managers to incorporate the overly optimistic expectations embodied in technology hype into their assessments. Pricing digital targets requires managers to search for, process, and interpret vast amounts of information to estimate a target's technological value and synergistic potential. This task entails understanding a technology's potential, impact, maturity, and combinatorial value within an incumbent firm's operations or domain (Bauer and Friesl, 2024). Given that digital technologies evolve rapidly and often involve business logics that differ substantially from those in incumbent firms (Yoo et al., 2012; Bharadwaj et al., 2013), creating such an understanding is highly complex and requires considerable cognitive effort. The cognitive burden of assessing digital target firms is further amplified, as managers of incumbent firms often lack direct experience with the technologies and their associated business models. In line with the notion of satisficing, managers may (unconsciously) seek to avoid cognitive overload and regulate their cognitive burden when searching for the information needed to assess a digital target's technological value and synergistic potential. During periods of technology hype, overly optimistic and exaggerated claims about a technology are readily available and highly salient to managers. In this context, the availability heuristic makes managers susceptible to incorporating the overly optimistic information into their assessments. Hence, when a digital target's technology is subject to hype, managers are likelier to accept overly positive assessments of its technological value and synergies as "satisfactory" options, stop their information search, and set the acquisition price accordingly.

Taken together, we suggest that inflated assessments of a digital target's technology during periods of technology hype increase acquirers' willingness to pay higher acquisition premiums for such targets. We therefore hypothesize:

**H1**. *Technology hype is positively associated with the premium paid in digital M&As, such that M&As of target firms relying on hyped digital technologies are associated with higher premiums compared to M&As involving less hyped technologies.*

### 2.4. *The role of digital knowledge and experience with digital M&As*

Research on socio-cognitive processes suggests that managers are likelier to use heuristics when they lack detailed, experiential knowledge of the decision context (Tversky and Kahneman, 1974; Fiske and Taylor, 1991). While managers of established firms often lack direct experience with digital technologies and their associated business models, there is likely considerable variation in the depth of such knowledge and experience. Greater familiarity and experience with digital technologies reduce the cognitive effort required to search for, process, and interpret information about a target's technology and its value. Therefore, individuals who possess greater familiarity with digital technologies and who work in a context that provides valuable experience related to the evaluation of digital target firms may be less inclined to regulate their cognitive burden by using cognitive shortcuts in a biased manner. As such, the reliance on salient, easily accessible information in a phase of technology hype should be less pronounced when managers draw on relevant knowledge and experience.

***The role of TMT digital knowledge.*** Managers' knowledge influences how they interpret situational demands, sense opportunities, and evaluate potential decision-making options (Hambrick and Mason, 1984). Domain knowledge can make individuals intuitively process and evaluate information differently from individuals without such knowledge (Akinci and Sadler-Smith, 2019). Such different notions and evaluations become particularly visible in complex and uncertain situations that are not "objectively knowable but, rather, are merely interpretable" (Mischel, 1977; Hambrick, 2007, p. 334). Thus, in the complex information-processing context of digital M&As, it might be particularly valuable for managers to possess digital knowledge—that is, the skills and experiences in domains related to digital technologies (Firk et al., 2022).

More specifically, digital knowledge could help managers consider the domain's broader context in interpreting information (Santos and Eisenhardt, 2009), scan critical dimensions of the decision-making problem (Ericsson, 2006), and create a deeper understanding of the dimensions of the problem rather than perceiving characteristics merely on the surface (Chi et al., 1988; Hinds et al., 2001). Therefore, top managers who can draw on digital knowledge are less likely to accept readily available information as "satisfactory; " instead, they will be able to engage in a more comprehensive information search and interpretation process that moves beyond widespread, overly optimistic claims and accounts for the deal's potential limitations and risks. Moreover, domain experts can serve as filter mechanism in collective discussions, filtering out potential misconceptions or invalid assumptions of non-domain experts (Hodgkinson and Sadler-Smith, 2018). The information that underlies the decision-making of TMTs with digital experts should, thus, be more independent from hyped expectations and instead better match the actual potential and value of a digital target.

In sum, TMTs with digital experts should be less prone to incorporate the exaggerated claims associated with a technology hype into their assessments and are likelier to form a less inflated impression of the digital target's value, resulting in a lower willingness to pay higher acquisition premiums:

**H2**. *Acquirer TMT digital knowledge negatively moderates the association between technology hype and acquisition premiums.*

***The role of firm digital M&A experience***. Another crucial factor in influencing the socio-cognitive processes in digital M&As may lie in the acquirer's cumulative M&A experience. Previous M&A research emphasized that M&A experience could help firms to codify their experience, identify best practices, and make routines and approaches accessible to managers in future M&A processes (Zollo and Singh, 2004; Trichterborn et al., 2016). However, the processes of learning from prior M&As are not straightforward; rather, they often depend on the specific type of deal and some degree of similarity to current M&As (Strobl et al., 2022; Barwinski et al., 2025). Thus, we focused specifically on a firm's accumulated experiences in M&As that involve digital target firms (i.e., digital M&As).

The accumulated experiences of firms with digital M&As can help establish information-processing routines that suit the evaluation of digital targets. For example, such routines may institutionalize cross-functional assessments that address technological uncertainties, establish checklists that ensure that potential risks are considered, and include the structured involvement of technology experts during due diligence (advice that not all M&A advisory firms may provide sufficiently). Moreover, experiences from previous digital M&As can heighten awareness of pitfalls and obstacles when integrating digital targets and their know-how. Previous experiences with unmet expectations in digital M&As should create awareness and caution regarding overly optimistic assessments. Because of these experiences and related routines, managerial decision-making is likelier to be informed beyond highly salient and easily available media narratives. Instead, established routines may ensure that the information base also incorporates more reflective and critical assessments of both the technology's potential and the synergistic value of the digital target. Hence, while assessing a target firm's value remains challenging for managers, exaggerated and overly optimistic claims are likely to become less dominant in their information processing.

In sum, managers of firms with more digital M&A experience are likely to become less susceptible to relying on hype-driven expectations via the availability heuristic in their decisions, ultimately making them less willing to pay inflated premiums:

**H3**. *Acquirer firm digital M&A experience negatively moderates the association between technology hype and acquisition premiums.*

## 3. Methods

### 3.1. Sample and data

We tested our predictions on a sample of digital M&As made by firms listed on the S&P 1500 index between 2004 and 2018. To analyze the acquisition premiums in deals involving digital technologies, all deals in our sample involved a pair of a publicly listed acquiring firm and a publicly listed target firm to obtain data on the premium paid for an acquisition (Laamanen, 2007). We further include only those deals that meet the following requirements: The deal has to be classified as completed, the acquiring firm needs to own at least 50 % of the target after the completion of the deal, the acquiring firm does not own any stock of the target firm before the deal,[1] and the deal is not classified as a buyback of shares.

Furthermore, all deals in our sample need to be classified as digital M&As. For the classification of digital M&A, we followed Hanelt et al. (2021b), who defined digital M&As as "acquisitions of (or mergers with) digital target firms that intensely leverage digital technologies as critical elements of their business models" (Hanelt et al., 2021b, p. 8). We extracted all M&A deals that complied with

[1] We included this restriction to ensure no prior information exchange due to the ownership of the acquiring firm of the target firm. An ownership stake in the target firm would grant the acquirer access to critical information regarding the technological resources of the target firm and significantly reduce the uncertainty involved.

our prior restrictions from the commonly used SDC Platinum database (Bates and Lemmon, 2003; Fu et al., 2013). Afterwards, we assigned two independent researchers to thoroughly analyze the description of the target firm provided in the SDC Platinum database to evaluate whether the firm leverages digital technologies as an important part of its business model (Hanelt et al., 2021b) and to specify the underlying technology.

In many cases, the description of the target was complemented with further information sources, such as the business description of the target firms' SEC 10-K reports. After the completion of the classification, we compared the overlapping ratings of the independent researchers for interrater reliability, which suggested strong agreement (0.90).[2] The remaining ambiguous cases were discussed to reach a consensus. All deals not classified as digital M&A were excluded, resulting in a final sample of 237 deals with 22 distinct digital technologies involved (see Appendix C). The sample size is comparable to other studies on acquisition premiums (Hambrick and Hayward, 1997; Reuer et al., 2012; Fralich and Papadopoulos, 2018).

We further collected data on relevant deal information from SDC Platinum, data on firms' financial information from Refinitv and Compustat, data on the employment history of TMT members from Wharton BoardEx, and data on the news coverage of digital technologies from Ravenpack News Analytics.

### 3.2. Variables

***Premium.*** We calculate our variable *Premium* as the ratio of the offer price and the share price of the target firm 42 trading days before the acquisition announcement minus one (Bates and Lemmon, 2003; Fu et al., 2013):

$$Premium_t = \frac{OfferPrice_t}{PriceBefore_{t-42}} - 1$$

The 42-day window between the deal announcement and the baseline measure of the target firm's market value was chosen to account for market anticipation and information leakage effects that may influence the share price of merging firms before the deal announcement (Nathan and O'Keefe, 1989; Schwert, 1996).[3] Our premium measure thus represents the percentage by which the acquirer exceeds the target's market price (Officer, 2003). Like previous literature (Officer, 2003), we also ensure that the distribution of the variable is bounded between zero and two by winsorizing it at the 0.05 level.[4]

***Technology hype.*** Technology hype refers to a situation in which intense interest in a technology is paired with inflated expectations of the technology's capabilities (Dedehayir and Steinert, 2016; Heupel et al., 2024). To capture these inflated expectations, we focused on the media coverage of digital technologies in major US news outlets. This focus is consistent with prior research indicating that technology hype typically emerges and becomes visible through widespread enthusiasm in the mass media (Fenn and Raskino, 2008; Dedehayir and Steinert, 2016). To link each deal with the media coverage of the digital technology involved in the deal, we scanned the headlines of news articles from the Ravenpack News Analytics database in major US news outlets and newswires.[5] We kept all articles with a positive sentiment score (optimistic articles), as assigned by Ravenpack, and counted the number of optimistic news articles in a given month for each technology cluster.

In the next step, we use the number of optimistic news articles in a given month *t* for a technology *i* ($PosMedia_{i,t}$) and divide it by the total news articles in the respective month ($TotalMedia_t$). This adjustment ensures that optimistic media attention is evaluated relative to general media attention and mitigates the concern that general trends in media attention confound our hype measure.[6] We multiply this ratio by the mean of the media coverage over the total sample period *T* ($MeanTotalMedia_T$) to receive values that are meaningfully greater than zero:

$$PosMedia_{i,t}^{TimeAdj} = \frac{PosMedia_{i,t}}{TotalMedia_t} \times MeanTotalMedia_T \qquad \text{I}$$

Next, we normalize optimistic media attention across each technology to mitigate the concern that our measure is biased by some technologies that generally receive greater attention. This adjustment enables us to identify technological lifecycle phases in which a technology receives greater attention relative to earlier or later phases of the same technology. As such, this is consistent with the conceptualization of a technology hype as a phase that can emerge within the lifecycle of each technology instead of being restricted to

[2] We followed the method by Holsti (1969) and recommended by Short et al. (2010) by calculating the interrater reliability with the formula $PA_0 = 2A/(n_A + n_B)$, where $PA_0$ is the observed agreement proportion, $A$ is the number of agreements between the three researchers, and $n_A$ and $n_B$ are the number of cases assessed by the researchers.

[3] We also reran our regression with a 63-day window in order to consider an even longer gap before the deal and receive similar results (see Online Appendix O1).

[4] Setting the bounds between zero and two is a common approach to reduce the measure's sensitivity to different calculation methods. Most premium estimates tend to fall within this range, whereas the values outside of this range are often driven by the specific calculation method (Officer, 2003). We also combine two different calculation methods to alternatively eliminate extreme values in our premium measure and obtain similar results (see Online Appendix O1).

[5] Similar to Ardia et al. (2023), we included news articles from the following major outlets: New York Times, Washington Post, Los Angeles Times, Wall Street Journal, Houston Chronicle, Chicago Tribune, Arizona Republic, USA Today, New York Daily News, and New York Post, as well as the newswires Associated Press Newswires and Reuters News.

[6] We observed a substantial increase over time in the total articles covered by the Ravenpack database. To account for this trend, we also included the overall media attention as a control variable. The results remain robust (see Online Appendix O4).

some popular technologies (Fenn and Raskino, 2008; Dedehayir and Steinert, 2016). To account for this temporary, technology-specific nature of a hype, we divide our score ($PosMedia_{i,t}^{TimeAdj}$) by the mean of each technology's optimistic media attention over the total sample period ($MeanPosMedia_{i,T}$). The resulting score yields an adjusted measure of optimistic media attention that is comparable over time and across technologies ($PosMedia_{i,t}^{Adj}$), with higher values indicating a greater and more optimistic media attention within the lifecycle of a technology:

$$PosMedia_{i,t}^{Adj} = \frac{PosMedia_{i,t}^{TimeAdj}}{MeanPosMedia_{i,T}} \quad \text{II}$$

To create our final measure of technology hype, we built on the notion that hype reflects a situation in which positive expectations surrounding a technology inflate exponentially, exceeding a linear development trajectory (Fenn and Raskino, 2008; Dedehayir and Steinert, 2016). To capture this nonlinear and exaggerated formation of hype, we used OLS regressions and predicted the optimistic media attention of each technology based on optimistic media attention from the preceding years. The underlying logic is that when the actually observed optimistic media attention surpasses the expected linearly predicted values, this indicates a disproportionate accumulation of optimistic expectations, consistent with the emergence of a hype. Mathematically, we implemented this logic by predicting optimistic media attention for a given technology in the 12 months before the official deal announcement (i.e., at the time of the negotiation and due diligence phase)[7] ($\widehat{PosMedia}_{i,t-1:t-12}^{Adj}$) by the adjusted optimistic media attention from the 24 months leading up to this phase ($PosMedia_{i,t-13:t-37}^{Adj}$)[8]:

$$\widehat{PosMedia}_{i,t-1:t-12}^{Adj} = \alpha_i + \beta_i {}^* \, PosMedia_{i,t-13:t-37}^{Adj} + \varepsilon_{i,t} \quad \text{III}$$

The residual from this prediction $\left(\varepsilon_{i,t} = PosMedia_{i,t-1:t-12}^{Adj} - \widehat{PosMedia}_{i,t-1:t-12}^{Adj}\right)$ reflects the extent to which the observed optimistic media attention deviates from an expected linear trend. We define *Technology hype* as the positive residual; that is, the portion of optimistic media attention exceeding the expected linear trajectory, thereby capturing the level of a nonlinear accumulation of expectations. If the residual is zero or negative (i.e., actual media attention aligns with or falls below the predicted linear development), our hype measure is set to zero,[9] indicating the absence of exaggerated expectations[10]:

$$Technology\ hype_{i,t} = \max\left(0, PosMedia_{i,t-1:t-12}^{Adj} - \widehat{PosMedia}_{i,t-1:t-12}^{Adj}\right) \quad \text{IV}$$

To facilitate interpretation of our measure, Fig. 2 illustrates the technology hype measure for two exemplary digital technologies: cybersecurity and software as a service (SaaS). The figure plots the actual optimistic media attention and the predicted optimistic media attention over time. Technology hype is represented by the grey-shaded area, which indicates the extent to which the observed optimistic media attention exceeded the predicted level. This figure further serves as an initial face validation. For cybersecurity, we observed a pronounced hype phase around 2017. This surge in optimism was likely associated with the introduction of several major offerings during that year, such as Microsoft's Defender Advanced Threat Protection System (Microsoft, 2017) and new machine learning-based threat detection tools in response to global ransomware attacks and the Equifax data breach (Bracy, 2017). For SaaS, the figure shows heightened expectations around 2010, potentially coinciding with the launch of Microsoft's Office 365, which marked an important milestone in the enterprise SaaS landscape. While this initial hype subsequently subsided, another phase emerged around 2014, likely associated with the rapid growth of new platforms, such as Slack, Workday, and ServiceNow, which promised a more sophisticated and integrated SaaS ecosystem.[11]

***Acquirer TMT digital knowledge.*** We measure the acquirer's TMT digital knowledge following the approach set forth by Firk et al. (2022). In the first step, we define which managers belong to the TMT of a firm. We included all managers who were either "executive directors" or "senior managers" and excluded all managers holding titles corresponding to "supervisory directors." In the second step, we identify managers within the defined TMT with work experience associated with digital technologies. Specifically, we searched the

[7] As digital M&A and the related premium itself may induce media attention related to the underlying digital technology, we focus on the media coverage in the months preceding the announcement of the deal. In this time, the deal preparation is kept confidential and, therefore, this focus helps us to mitigate concerns of a potential reverse causality between the deal and media attention. Moreover, focusing on this deal preparation phase aligns with our theoretical idea that hype influences managerial decision-making at the time when managers search for information to evaluate the target.

[8] In an alternative specification, we predict the optimistic media attention in the twelve months before the deal announcement by using the pessimistic media attention as an additional predictor. Our results remain robust (see Online Appendix O3).

[9] Our results remain unchanged if we create a continuous measure of technology hype that considers both the positive and negative residual (see Online Appendix O2).

[10] To account for the prevalence of pessimistic media attention in the phase before the deal announcement, we ran two robustness checks. First, we subtract the pessimistic media attention from our technology hype measure to create an alternative measure of technology hype. Second, we use pessimistic media attention as an additional control variable. Under all specifications, our results remain robust (see Online Appendix O3).

[11] While these examples provide face validity for our measure, we also compared the technology hype scores for each technology with associated Google searches of individuals located in the United States. We find that the hype measure exhibits positive and significant correlation coefficients for alle technology clusters (see Online Appendix O5).

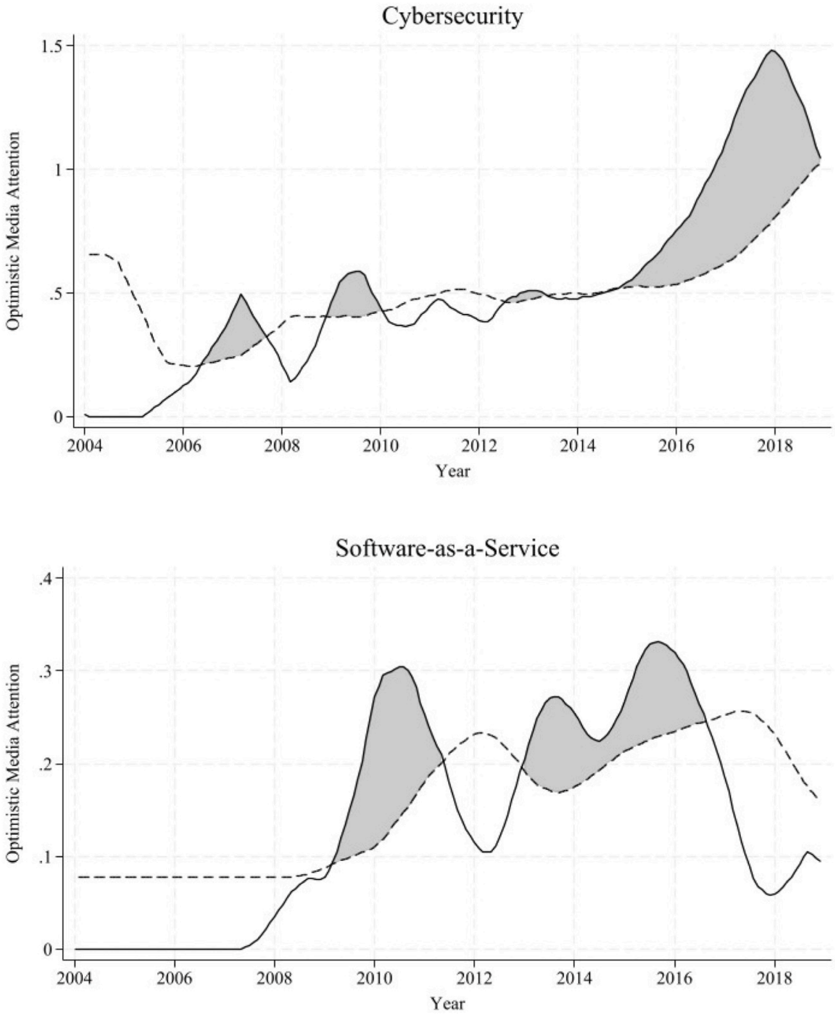


**Fig. 2.** Exemplary digital technologies and related technology hype *Notes:* This figure exemplifies our *Technology hype* measure over time. The solid black line represents the observed optimistic media attention of the respective technology. The dotted black line shows the predicted optimistic media attention of the respective technology based on its historical media attention. The grey-shaded area between the lines marks the positive residual between the observed and predicted optimistic media attention. Our *Technology hype* measure captures the level of these positive residuals, otherwise we set it to zero.

employment history of the managers for prior positions that included terms such as "CIO," "CTO," "CDO," "information," "comput*," "software," "e-commerce," "IT," "technolog*," and "digital" (van Peteghem et al., 2019; Firk et al., 2022). Lastly, we sum the TMT members with positional digital experience and calculate our variable *Acquirer TMT digital knowledge* as the percentage of TMT members with digital knowledge.

***Acquirer digital M&A experience.*** To capture the acquirer's experience with digital M&As, we focused on the number of digital M&As that the acquirer had completed in the past. Specifically, we measured the variable *Acquirer digital M&A experience* as the number of digital M&As that the acquiring firm conducted in the five years before the focal deal. A higher value indicates a greater number of digital M&As that the acquirer had done, and hence proxies for a greater digital M&A experience that the firm has accumulated.

***Controls.*** To mitigate concerns of omitted variables confounding our analyses, we included control variables that cover deal-specific characteristics as well as potentially influential factors at the level of the acquiring and target firms. First, covering deal-specific characteristics, we included the variable *Deal size* (Beckman and Haunschild, 2002), measured as the natural logarithm of the transaction value. We included the dummy variable *Friendly deal*, equaling one if the deal was friendly and zero if the deal was hostile. Given the influence of the method of payment on acquisition premiums (Huang and Walkling, 1987), we included the dummy variable *Cash payment*, equaling one if the deal was paid in cash and zero otherwise. Given the influence of competing bidders on acquisition premiums (Bradley et al., 1988), we included the dummy variable *Competing offer*, equaling one if another offer was announced in the 12 months before the announcement date of the focal deal and zero otherwise. We also included the dummy variable *Merger of equals* that may lower the acquisition premium, as these deals often do not involve a bidding process (Li and Haleblian, 2022).

We further included the variable *Patent overlap*, measured as the cosine similarity of the patent portfolios of the acquiring and target firms. We included this variable to control for the importance of R&D capabilities and the unique synergies that technology acquisitions entail (Chondrakis and Farchi, 2014; Sears and Hoetker, 2014; Chondrakis, 2016).

Second, covering the characteristics of a target firm, we included *Target firm profitability*, given its potential influence on the acquisition premium (Zhu, 2013), measured as the earnings before interests, taxes, amortization, and depreciation divided by the net sales of the firm. Furthermore, we included the variable *Target financial advisers* to control for the mitigating effect that financial advisers can have on the payment of acquisition premiums (Cho et al., 2016; Li and Haleblian, 2022). The variable is measured as the natural logarithm of the number of financial advisers the target firms consulted in the focal deal.

Third, we included control variables covering the characteristics of the acquiring firm. Like the controls on the target firm, we included *Acquirer firm profitability* and *Acquirer financial advisers* in our model, measured analogously to the corresponding variables on the target firm. We also include *Acquirer relative size* (Beckman and Haunschild, 2002), measured as the acquirer's net sales divided by the target firm's net sales, and the average premium an acquirer has paid in previous deals (*Acquirer average premium*), as both may influence the acquirer's decision-making concerning a premium. Lastly, we included the variable *Acquirer digital firm*, equaling one if the acquiring firm is classified as a digital firm[12] and zero otherwise. Appendix A summarizes all variables.

### 3.3. Empirical strategy

To test our hypotheses, we ran OLS regressions in line with prior studies in the context of acquisition premiums (e.g., Bertrand et al., 2016; Fralich and Papadopoulos, 2018; Li and Haleblian, 2022). We included fixed effects at the industry and year levels as well as robust standard errors clustered at the firm level. Like other studies on acquisition premiums (Bertrand et al., 2016; Fralich and Papadopoulos, 2018), the inclusion of firm fixed-effects was not suitable given the event sample of our study, with an average of 1.71 deals per firm over the course of our sample period and many firms with just one deal in our sample period.[13]

Our sample consisted of only firms that completed a digital M&A, which may differ significantly from firms that did not complete digital M&As. To mitigate the potential sample selection bias caused by this sample restriction, we included a correction factor in all of our main models, following Heckman (1979). To do so, we ran a first-stage probit model regressing a dummy variable for conducting a digital M&A (equaling one if a firm conducts a digital M&A and zero otherwise) on firm and industry characteristics. As proposed by Lennox et al. (2012), we included an additional exclusion criterion. Specifically, we chose the natural logarithm of the number of digital startups founded per industry-year as the exclusion criterion. A higher number of digital startups found exemplifies a greater potential of applying digital technologies in the respective industry as well as a greater volume of target firms, and hence makes it likelier that incumbent firms initiate a digital M&A (relevance condition). At the same time, it is not necessarily linked with acquisition premiums (exclusion condition), as premium decisions are rather focused on deal-specific characteristics. Based on this exclusion criterion, we ran a probit estimation (see Appendix B) and calculated the inverse Mills ratio (*Sample selection control*), which is subsequently included as an additional control variable in all models.

## 4. Results

### 4.1. Descriptive statistics

In Table 1, the summary statistics of all variables included in the regression are provided. The average acquisition premium in our sample of 50.5 % indicates that, on average, acquirers pay a premium of more than half of the target's share price 42 trading days before the deal announcement. This is comparable to prior studies analyzing acquisition premiums in technology acquisitions (e.g., Laamanen, 2007) and higher compared to studies investigating premiums of non-technology deals (Krishnan et al., 2007; Cho and Arthurs, 2018).

The correlations of all variables included in our main model are displayed in Table 2. The correlation between *Technology hype* and *Premium* is positive and significant. We found some fairly high correlations between other variables, for example, *Transaction value* and *Acquirer financial advisers* (0.57). To mitigate any risk of obtaining confounding results due to high correlations, we tested the corresponding variance inflation factors and obtained results below the critical threshold of five. This indicates that multicollinearity should be less of a concern for our results.[14]

[12] Firms are classified as digital if they belong to the industry codes of the microchip industry (SIC codes: 3622, 3661–3679, 3810, 3812), computer industry (SIC codes: 3570–3689, 3695, 7373), telecommunications industry (SIC codes: 4800–4822, 4880–4890, 4892–4899), or business services industry (SIC codes: 7370–7380, 7385–7390, 7392, 7399, 8700–8748).

[13] We also ran our regressions with robust standard errors instead of clustering the standard errors at the firm-level. Our results remain robust (see Online Appendix O7).

[14] To further mitigate multicollinearity concerns, we also re-run our analyses with reduced sets of control variables. Specifically, we stepwise exclude control variables at the levels of deal, acquiror, and target characteristics, exclude control variables that are highly correlated (>0.2) with any of our main independent variables, and re-run our analyses without any control variable. Our results remain robust (see Online Appendix O6).

**Table 1**
Descriptive statistics of regression variables.

| Variables | Obs. | Mean | Std. | p25 | p75 |
|---|---|---|---|---|---|
| (1) Acquisition premium[a] | 237 | 0.50 | 0.42 | 0.25 | 0.62 |
| (2) Technology hype[b] | 237 | 0.17 | 0.28 | 0.00 | 0.25 |
| (3) Acquirer TMT digital knowledge[c] | 237 | 0.17 | 0.11 | 0.08 | 0.24 |
| (4) Acquirer digital M&A experience[c] | 237 | 3.14 | 1.72 | 2.00 | 5.00 |
| (5) Acquirer relative size | 237 | 1.29 | 0.21 | 1.12 | 1.41 |
| (6) Acquirer prior performance[b] | 237 | 0.20 | 0.12 | 0.13 | 0.27 |
| (7) Acquirer financial advisers[d] | 237 | 0.66 | 0.43 | 0.69 | 0.69 |
| (8) Acquirer digital firm | 237 | 0.68 | 0.47 | 0.00 | 1.00 |
| (9) Acquirer average premium | 237 | 0.26 | 0.36 | 0.00 | 0.47 |
| (10) Target prior performance[b] | 237 | 0.06 | 0.32 | 0.01 | 0.19 |
| (11) Target financial advisers[d] | 237 | 0.79 | 0.27 | 0.69 | 0.69 |
| (12) Friendly deal | 237 | 0.99 | 0.09 | 1.00 | 1.00 |
| (13) Deal payment | 237 | 0.72 | 0.45 | 0.00 | 1.00 |
| (14) Transaction value[d] | 237 | 6.51 | 1.71 | 5.41 | 7.76 |
| (15) Competing offer | 237 | 0.07 | 0.26 | 0.00 | 0.00 |
| (16) Merger of equals | 237 | 0.01 | 0.11 | 0.00 | 0.00 |
| (17) Patent overlap[b] | 237 | 0.22 | 0.28 | 0.00 | 0.38 |
| (18) Sample selection control | 237 | 0.88 | 0.44 | 0.54 | 1.13 |

*Notes:* a) Winsorized at 0.05 level. b) Winsorized at 0.01 level. c) Standardized in our regression analyses. d) Log-transformed.

### 4.2. Regression results

To test our hypotheses, we employed a series of OLS regressions presented in Table 3. Model 1 shows the results for the control variables. The results indicate that *Premium* is positively associated with *Merger of equals*, while it is negatively associated with *Acquirer prior profitability* and *Patent overlap*. Moreover, the adjusted R-squared indicates that the model explains 11.4 % of the variance in paid premiums. This corresponds to 23 % in the (unadjusted) R-squared (unreported) and is comparable to prior studies on acquisition premiums (e.g., Fralich and Papadopoulos, 2018). The F-test yields a significance level less than 1 percent, which allows us to reject the null hypothesis of no joint effect of the control variables on acquisition premium. We include our *Technology hype* variable and the respective interaction variables in Models 2 to 5.

Model 2 tests our first hypothesis, which states that technology hype is positively associated with an acquisition premium. Including our *Technology hype* variable yields an increase of 1.1 percentage points (12.5 % minus 11.4 %) in the adjusted R-squared compared to Model 1. The F-change statistic of 3.53 ($p = 0.063$) further supports that the inclusion of the *Technology hype* variable leads to an improvement in model fit compared to Model 1. Moreover, Model 2 shows a statistically significant and positive relationship between *Technology hype* and *Premium* ($\beta = 0.193$; $p = 0.032$). Using marginal effects analysis, this result corresponds to an acquisition premium of 51 % if *Technology hype* is at the mean (0.17), and it equals 56 % if *Technology hype* is one standard deviation above the mean (0.17 + 0.28). In economic terms, this result implies an average increase in the acquisition premium by 10 % (calculated as 56 % minus 51 % divided by 51 %) if *Technology hype* increases by one standard deviation from the mean. Fig. 3 illustrates the marginal effects.

Model 3 tests our second hypothesis, proposing that the positive association between technology hype and acquisition premium is less pronounced for higher TMT digital knowledge of the acquirer. Model 3 shows a significant negative interaction term between *Technology hype* and *Acquirer TMT digital knowledge* on *Premium* ($ß = -0.233$; $p = 0.002$). The marginal effects analysis indicates that under a high technology hype (one standard deviation above the mean), firms with low TMT digital knowledge (one standard deviation below the mean) are associated with an acquisition premium of 67 %, and 46 % if firms have high TMT digital knowledge (one standard deviation above the mean). This result corresponds to a 45 % higher acquisition premium (calculated as 67 % minus 46 % divided by 46 %) for acquirers with low TMT digital knowledge compared to acquirers with high TMT digital knowledge under a high technology hype. Fig. 4 illustrates the marginal effects of this interaction.

Model 4 tests our second hypothesis, proposing that the positive association between technology hype and acquisition premium is less pronounced for acquirers with higher digital M&A experience. Model 4 shows a significant negative interaction term between *Technology hype* and *Acquirer digital M&A experience* on *Premium* ($ß = -0.249$; $p = 0.015$). The marginal effects analysis indicates that under a high technology hype (one standard deviation above the mean), firms with low digital M&A experience (one standard deviation below the mean) are associated with an acquisition premium of 65 %, while firms with high digital M&A experience (one standard deviation above the mean) are associated with a premium of 48 %. This result corresponds to a 35 % higher premium (calculated as 65 % minus 48 % divided by 48 %) for acquirers with low digital M&A experience compared to acquirers with high digital M&A experience under a technology hype. Fig. 5 illustrates the marginal effects of this interaction.

Model 5 provides the full model, which further supports the hypotheses. Overall, these results suggest that higher technology hype is associated with higher acquisition premiums, while firms with greater digital technology-related knowledge, both in the TMT and in terms of M&A experience, are less sensitive to a technology hype in their premium decisions.

**Table 2**
Correlation table of regression variables.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Acquisition premium[a] | 1.00 | | | | | | | | | | | | | | | | | |
| (2) Technology hype[b] | 0.03 | 1.00 | | | | | | | | | | | | | | | | |
| (3) Acquirer TMT digital knowledge[c] | −0.01 | 0.02 | 1.00 | | | | | | | | | | | | | | | |
| (4) Acquirer digital M&A experience[c] | −0.05 | −0.03 | 0.40 | 1.00 | | | | | | | | | | | | | | |
| (5) Acquirer relative size | 0.06 | −0.12 | 0.21 | 0.29 | 1.00 | | | | | | | | | | | | | |
| (6) Acquirer prior performance[b] | −0.16 | 0.03 | 0.18 | 0.16 | −0.08 | 1.00 | | | | | | | | | | | | |
| (7) Acquirer financial advisers[d] | 0.01 | −0.04 | 0.09 | 0.07 | −0.33 | 0.17 | 1.00 | | | | | | | | | | | |
| (8) Acquirer digital firm | −0.02 | −0.04 | 0.27 | 0.36 | −0.20 | 0.22 | 0.11 | 1.00 | | | | | | | | | | |
| (9) Acquirer average premium | −0.05 | 0.04 | 0.29 | 0.42 | 0.34 | 0.00 | −0.12 | 0.08 | 1.00 | | | | | | | | | |
| (10) Target prior performance[b] | −0.14 | 0.07 | −0.10 | 0.05 | −0.20 | 0.17 | 0.20 | −0.03 | −0.08 | 1.00 | | | | | | | | |
| (11) Target financial advisers[d] | −0.04 | −0.05 | −0.06 | 0.04 | −0.21 | 0.16 | 0.29 | 0.13 | 0.07 | 0.07 | 1.00 | | | | | | | |
| (12) Friendly deal | −0.02 | 0.00 | 0.01 | −0.05 | 0.04 | 0.03 | 0.02 | −0.06 | 0.04 | 0.01 | −0.04 | 1.00 | | | | | | |
| (13) Deal payment | 0.11 | −0.03 | 0.19 | 0.30 | 0.30 | −0.13 | −0.22 | −0.04 | 0.23 | −0.18 | −0.17 | −0.06 | 1.00 | | | | | |
| (14) Transaction value[d] | −0.15 | 0.11 | 0.14 | 0.27 | 0.27 | 0.36 | 0.52 | 0.25 | 0.03 | 0.37 | 0.39 | 0.08 | −0.31 | 1.00 | | | | |
| (15) Competing offer | 0.05 | 0.03 | 0.03 | 0.01 | 0.02 | 0.05 | 0.14 | 0.01 | 0.01 | 0.05 | 0.25 | −0.15 | −0.04 | 0.11 | 1.00 | | | |
| (16) Merger of equals | 0.16 | 0.04 | −0.06 | −0.16 | −0.12 | −0.12 | 0.04 | −0.17 | −0.08 | −0.05 | 0.01 | 0.01 | −0.18 | 0.11 | −0.03 | 1.00 | | |
| (17) Patent overlap[b] | −0.18 | 0.10 | 0.11 | 0.04 | 0.04 | 0.11 | 0.08 | 0.18 | 0.05 | −0.03 | −0.01 | 0.04 | −0.13 | 0.24 | −0.03 | 0.04 | 1.00 | |
| (18) Sample selection control | −0.03 | 0.04 | −0.35 | −0.56 | −0.54 | −0.36 | −0.09 | −0.59 | −0.25 | −0.03 | −0.13 | 0.00 | −0.15 | −0.38 | 0.00 | 0.13 | −0.21 | 1.00 |

*Notes:* Correlations with an absolute value greater than 0.16 are significant at $p < 0.01$; a) Winsorized at 0.05 level. b) Winsorized at 0.01 level. c) Standardized in our regression analyses. d) Log-transformed.

**Table 3**
OLS regressions estimating acquisition premiums.

| Model | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent variable | Premium | Premium | Premium | Premium | Premium |
| Technology hype | | 0.193** | 0.237*** | 0.190** | 0.226*** |
| | | (0.032) | (0.009) | (0.018) | (0.007) |
| Technology hype × Acquirer TMT digital knowledge | | | −0.237*** | | −0.185** |
| | | | (0.001) | | (0.013) |
| Technology hype × Acquirer digital M&A experience | | | | −0.253*** | −0.218** |
| | | | | (0.009) | (0.021) |
| Acquirer TMT digital knowledge | | | 0.000 | | −0.010 |
| | | | (0.996) | | (0.795) |
| Acquirer digital M&A experience | | | | 0.024 | 0.020 |
| | | | | (0.608) | (0.673) |
| Acquirer relative size | −0.192 | −0.163 | −0.130 | −0.146 | −0.110 |
| | (0.455) | (0.534) | (0.595) | (0.573) | (0.653) |
| Acquirer prior profitability | −0.408* | −0.446* | −0.409* | −0.516** | −0.462* |
| | (0.081) | (0.062) | (0.079) | (0.037) | (0.055) |
| Acquirer financial advisers | 0.084 | 0.100 | 0.102 | 0.117* | 0.120* |
| | (0.233) | (0.137) | (0.135) | (0.093) | (0.096) |
| Acquirer digital firm | 0.048 | 0.063 | 0.089 | 0.080 | 0.104 |
| | (0.613) | (0.507) | (0.337) | (0.388) | (0.260) |
| Acquirer average premium | −0.112 | −0.129* | −0.133* | −0.116 | −0.118 |
| | (0.142) | (0.089) | (0.059) | (0.132) | (0.108) |
| Target prior performance | −0.106 | −0.101 | −0.086 | −0.103 | −0.091 |
| | (0.332) | (0.348) | (0.429) | (0.341) | (0.397) |
| Target financial advisers | −0.003 | 0.013 | −0.015 | 0.022 | −0.006 |
| | (0.982) | (0.923) | (0.912) | (0.873) | (0.967) |
| Friendly deal | 0.111 | 0.129 | 0.145 | 0.113 | 0.128 |
| | (0.556) | (0.483) | (0.417) | (0.560) | (0.502) |
| Cash payment | 0.037 | 0.031 | 0.022 | 0.022 | 0.017 |
| | (0.626) | (0.687) | (0.771) | (0.773) | (0.823) |
| Transaction value | −0.046 | −0.051 | −0.051 | −0.051 | −0.050 |
| | (0.167) | (0.119) | (0.108) | (0.108) | (0.110) |
| Competing offer | 0.136 | 0.132 | 0.152 | 0.123 | 0.142 |
| | (0.227) | (0.224) | (0.160) | (0.264) | (0.200) |
| Merger of equals | 0.700* | 0.703* | 0.684* | 0.651* | 0.645* |
| | (0.083) | (0.067) | (0.082) | (0.067) | (0.079) |
| Patent overlap | −0.219* | −0.229** | −0.221** | −0.258** | −0.248** |
| | (0.051) | (0.041) | (0.047) | (0.023) | (0.029) |
| Sample selection control | −0.322 | −0.340 | −0.361 | −0.373* | −0.388* |
| | (0.139) | (0.120) | (0.102) | (0.094) | (0.082) |
| Constant | 1.361 | 1.389 | 1.413* | 1.459* | 1.439* |
| | (0.111) | (0.106) | (0.078) | (0.082) | (0.068) |
| Industry fixed-effects | YES | YES | YES | YES | YES |
| Year fixed-effects | YES | YES | YES | YES | YES |
| Observations | 237 | 237 | 237 | 237 | 237 |
| F test (p value) | 2.58 (0.000) | 2.85 (0.000) | 2.76 (0.000) | 2.50 (0.000) | 3.09 (0.000) |
| $R^2$ adjusted | 0.114 | 0.125 | 0.142 | 0.145 | 0.154 |
| F change (p value) | | 3.53 (0.063) | 4.03 (0.009) | 3.25 (0.024) | 4.41 (0.001) |

*Notes:* ***p < 0.01, **p < 0.05, *p < 0.1; p-values in parentheses; Standard errors clustered at the firm level; Two-tailed (one-tailed) tests for nondirectional effects of control variables (hypothesized directional effects of main independent variables).

### *4.3. Robustness tests*

We conducted several tests to validate the robustness of our results. First, we tested alternative specifications of our dependent variable *Premium*. To fully account for any market anticipation and information diffusion effects that may influence the share price of merging firms for up to two months before the deal announcement (Nathan and O'Keefe, 1989; Schwert, 1996), we used a 63-day window before the announcement date to calculate our premium variable. Also, we combined the share price information provided in SDC Platinum with records of the amount of each form of payment offered to the shareholders (cash, equity, debt, etc.) to calculate an alternative measure of premium that eliminates the extremes of both distributions (see also Officer, 2003). Second, we tested alternative specifications of our independent variable *Technology hype*. Specifically, we used a continuous measure of the residual (without setting negative values to zero) and calculated a dummy variable equaling one if optimistic media attention is greater than linearly predicted; otherwise, zero. We also considered alternative specifications that account for the pessimistic media attention by subtracting it from our hype measure, and by considering it as an additional predictor in the creation of our hype measure. All tests yielded quantitatively and qualitatively similar results (see Online Appendices O1–O4).

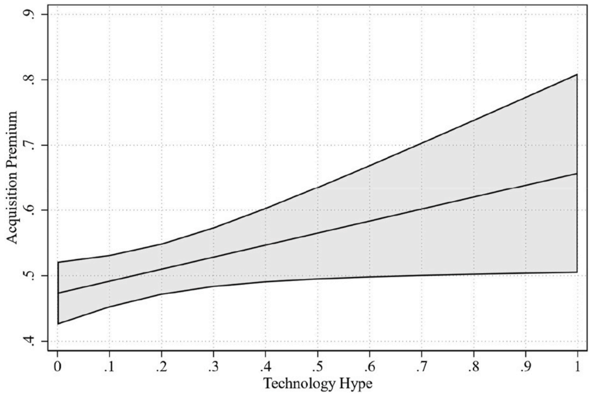


**Fig. 3.** Margins plot of the association between technology hype and premium *Notes:* This figure shows the linear prediction and 90 % confidence intervals for acquisition premiums across different values of technology hype.

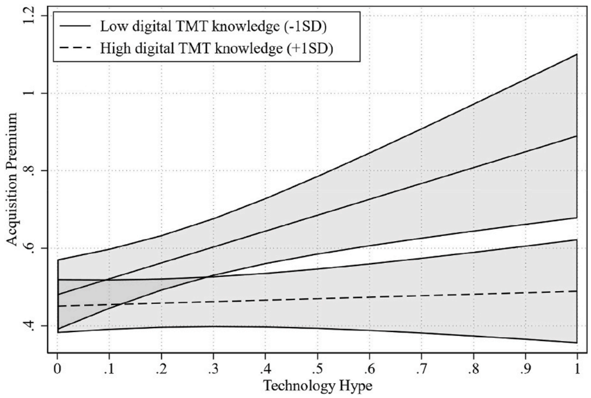


**Fig. 4.** Margins plot of the interaction effect with Acquirer TMT digital knowledge *Notes:* This figure shows the linear prediction and 90 % confidence intervals for acquisition premiums across different values of technology hype under high and low digital TMT knowledge.

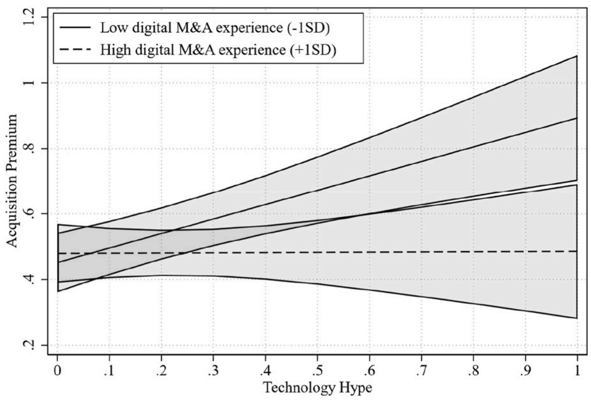


**Fig. 5.** Margins plot of the interaction effect with Acquirer digital M&A experience *Notes:* This figure shows the linear prediction and 90 % confidence intervals for acquisition premiums across different values of technology hype under high and low digital M&A experience.

### *4.4. Additional analysis*

To further investigate whether the influence of technology hype on acquisition premiums reflects a bias in which inflated expectations are priced into the target, we ran a series of additional analyses on the long-term value implications of these deals. Specifically, we compare the long-term value implications of digital M&As that have been completed in the phase of a technology hype with those that have been completed in the absence of a technology hype. If deals in the phase of a technology hype deliver superior value creation in the long run, this would suggest that our technology hype measure captures an abnormal opportunity for investing in the respective technology. Paying higher premiums would then constitute rational investments, anticipating superior long-term value creation. Conversely, if digital M&As during a technology hype phase do not deliver superior long-term value, it would support our suggestion that the influence of technology hype on acquisition premiums reflects a bias in the assessment of the value of digital targets.

We focus on two established indicators of long-term value creation: the change in the acquirer's Tobin's Q from the year before to the two years after the deal, and the BHARs over three years. We regress these indicators on our previous set of control variables and a dummy variable that compares the deals that have been completed in the phase of a technology hype (equaling one if *Technology hype* is greater than zero) and those that have been completed in the absence of a technology hype (equaling zero). Table 4 provides the results. The results show that, on average, the acquirer's Tobin's Q decreases for digital M&As that have been completed in a phase of a technology hype compared to those digital M&As that have been completed in the absence of a technology hype ($ß = -0.203$; $p = 0.091$). Moreover, we found significantly weaker BHARs for digital M&As that had been completed in a technology hype phase

**Table 4**
OLS regressions estimating the long-term value implications.

| Model | (1) | (2) |
|---|---|---|
| Dependent variable | Change in Tobin's Q (three years) | BHARs (three years) |
| Deal during hype | −0.203* | −0.163** |
| | (0.091) | (0.048) |
| Acquirer relative size | 0.593 | 0.142 |
| | (0.141) | (0.589) |
| Acquirer prior profitability | −0.830 | −0.032 |
| | (0.160) | (0.935) |
| Acquirer financial advisers | −0.534*** | −0.112 |
| | (0.001) | (0.301) |
| Acquirer digital firm | −0.193 | −0.329** |
| | (0.321) | (0.014) |
| Acquirer average premium | 0.222 | 0.141 |
| | (0.201) | (0.232) |
| Target prior performance | 0.123 | 0.070 |
| | (0.539) | (0.591) |
| Target financial advisers | 0.051 | 0.060 |
| | (0.834) | (0.726) |
| Friendly deal | −0.111 | −0.298 |
| | (0.854) | (0.425) |
| Cash payment | 0.126 | −0.008 |
| | (0.407) | (0.942) |
| Transaction value | 0.153*** | −0.022 |
| | (0.005) | (0.569) |
| Competing offer | 0.097 | −0.297* |
| | (0.665) | (0.070) |
| Merger of equals | −0.347 | 0.216 |
| | (0.522) | (0.712) |
| Patent overlap | 0.068 | 0.027 |
| | (0.758) | (0.861) |
| Sample selection control | −0.203* | −0.163** |
| | (0.091) | (0.048) |
| Constant | −2.751** | −0.163 |
| | (0.040) | (0.853) |
| Industry fixed-effects | YES | YES |
| Year fixed-effects | YES | YES |
| Observations | 237 | 190 |
| F-test (p value) | 2.21 (0.000) | 1.81 (0.008) |
| $R^2$ adjusted | 0.155 | 0.128 |
| F change (p value) | 2.89 (0.091) | 3.96 (0.048) |

*Notes:* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; p-values in parentheses (two-tailed); Standard errors clustered at the firm level. *Change in Tobin's Q (three years)* is the difference between the Tobin's Q in the year before the deal and the Tobin's Q two years after the deal. *BHARs (three years)* is calculated as $\left(\prod_{t}^{T}(1+R_{i,t})\right)-\left(\prod_{t}^{T}(1+R_{b,t})\right)$ over the days from −21 to 780 around the announcement of the deal with $R_{i,t}$ reflecting the return of the shares of Acquirer *i* on day *t* and $R_{b,t}$ reflecting the return of the S&P500 market index (*b*) on day *t*. Observations are lower compared to our initial sample because of missing daily share price data. The F change statistics provide an indication on the change in model fit compared to the (unreported) Model without the *Deal during hype* variable.

compared to those that had been completed in the absence of a technology hype (ß = −0.163; $p = 0.048$). In sum, these results suggest that the higher premiums paid for digital M&As in the phase of a technology hype do not seem to be justified from a long-term value-creation perspective.

## 5. Discussion and conclusion

An emerging stream of research suggests that managers use heuristics to process information more efficiently during M&A decisions (Malhotra et al., 2015; Gamache et al., 2019). This study adopts a socio-cognitive perspective and proposes that such reliance on heuristics can also bias premium decisions in digital M&As. Specifically, we propose that managers are susceptible to an availability heuristic that, during the phase of a technology hype, brings inflated expectations to mind, thereby biasing the assessments of digital targets by acquiring managers. We further suggest that the susceptibility to this heuristic is driven by the cognitive burden of processing complex and uncertain information surrounding digital technology. If managers possess greater knowledge of digital technologies or can rely on established routines from previous digital M&As, they should have a lower cognitive burden in processing information related to digital technologies, making them less prone to tap into the availability heuristic and rely on the overly optimistic expectations of a technology hype.

Our results show that, on average, digital M&As associated with technology hype are related to higher acquisition premiums. This supports our idea that managers incorporate exaggerated expectations of a technology that is readily available into their decision-making when evaluating a digital target. We further found that the positive relationship between technology hype and paid premiums is less pronounced when the TMT possesses higher digital knowledge and when the firm has greater experience with digital M&As. These findings suggest that domain-specific knowledge and experience reduce the cognitive burden of evaluating digital targets, enabling managers to look beyond easily accessible, exaggerated expectations and create less inflated judgments. Finally, our additional analysis shows that the acquisition of targets with a hyped technology is associated with lower long-term value creation. This result suggests that the higher premiums paid during the phase of technology hype do not translate into superior financial returns, thereby supporting the notion of a decision-making bias in the pricing of digital M&As.

### *5.1. Contributions to the literature*

This study offers three major contributions to the academic literature. First, this study contributes to the literature on heuristics and biases in managerial decision-making (Hodgkinson et al., 2023; Vuori et al., 2024). Research on heuristics is based on fragmented programs that differ, for instance, in terms of what level of analysis is focused on (e.g., individual versus organizational) and how they evaluate the success of heuristics (e.g., against rational choice versus real-world effectiveness) (Vuori et al., 2024). This study makes a step toward integrating these fragmented programs by connecting Simon's (1956) organizational-level satisficing principle with Tversky and Kahneman's (1974) individual-level availability heuristic to explain how rationally bounded search processes interact with universal heuristics in managerial judgment under complexity. This shifts the application of the availability heuristic from individual probability judgments to a broader role within organizational search and decision-making. In the setting of M&A premium decisions under technology hype, we further explain how heuristics can shift from functional simplifications that economize on cognitive effort to sources of biased judgment. We conceptualize the availability heuristic as a cognitive gateway through which managers accept socially constructed optimism, media enthusiasm, and stakeholder-promoted promises as satisfactory, thereby importing potential misconceptions from public discourse into firm-level decisions. As such, this study outlines when and why the use of heuristics can lead to biased decision-making in a real-world setting. While our setting is focused on digital M&As and technology hype, these implications may also be valid in other decision-making contexts characterized by high complexity and (optimistic) information overload.

Second, we contribute more specifically to M&A research on acquisition premiums. M&A research has largely portrayed universal heuristics as functional, allowing managers to solve complex problems, such as M&A premium settings, more efficiently, without collecting and processing all available information. For instance, previous studies have outlined the use of heuristics, such as managers anchoring their acquisition bids to recent peer transactions (Malhotra et al., 2015; Li and Haleblian, 2022) and interpreting media attention as a form of social feedback to inform their decisions (Hayward et al., 2004; Liu and McConnell, 2013; Gamache et al., 2019) as a means to make a decision and cope with uncertainty. Our study complements this literature by investigating how the impact of technology hype, defined as the cumulative (often unrealistic) expectations surrounding a technology, can alter the functional nature of universal heuristics for setting prices in digital M&As. We suggest that the complex and uncertain information environment of digital M&As, combined with the considerable cognitive effort required to assess the synergy potential, makes managers susceptible to relying on information that is highly salient and easily accessible, consistent with the availability heuristic. During phases of technology hype, reliance on readily available information may transform from a functional shortcut into a source of bias: Incorporating media-transmitted, inflated technological expectations into decision-making increases managers' willingness to pay higher acquisition premiums; however, these elevated premiums rarely translate into superior long-term value creation. As such, our study contributes to a better understanding of when and why heuristics can shift from being functional to inducing biases in M&A premium decisions.

Third, we contribute to the literature on digital transformation (Hanelt et al., 2021a; Verhoef et al., 2021). While previous studies have separately highlighted digital M&As as an important vehicle for this transformation (Hanelt et al., 2021b) and the TMT competencies to progress with this transformation (Firk et al., 2022; Christofi, 2024), we integrated these streams to create a better understanding of when and why digital knowledge and experience are particularly valuable for a firm's digital transformation. Specifically, this study highlights the relevance of technology expertise for managers and firms to navigate the complex process of digital M&As and make rational decisions, even in the phase of inflated, exaggerated claims regarding the development of a technology. This study emphasizes the relevance of digital knowledge and cumulated experience as critical means for avoiding economically dysfunctional decisions, such as paying excessive premiums in M&A. Thereby, our study underlines the need for digital competencies and experiences among upper echelons, not just for a better understanding of how to drive digital transformation from a socio-technical perspective and realize digital innovation (Firk et al., 2022), but also for ensuring a rational financial perspective in the process of digital transformation. This is an important distinction, as digital transformation is often linked to exaggerated expectations and widespread narratives (Wessel et al., 2025), requiring managers to navigate a complex landscape often shaped by exaggerations and distractions. As such, this study informs the debate on the characteristics needed to make progress with digital transformation, not just strategically but also economically (Hanelt et al., 2021a) and thereby has important practical implications for the composition of TMTs and decision-making in digital M&As.

### 5.2. *Managerial implications*

Our results offer important managerial implications. Most importantly, this study raises awareness of technology hype (Chowdhury and Marler, 2024) and potential dysfunctional consequences. Technology hype can inflate premiums paid in M&As. Therefore, managers should carefully approach a technology hype and continuously reflect on the heuristics they may use in their decision-making to avoid relying on the exaggerated claims prevalent during a phase of technology hype. Firms might consider requiring that managers undergo training—or at least receive training materials—that raise awareness of biases and heuristics, such as the availability heuristic, and that specific managers' characteristics can activate these biases. A critical means for avoiding such heuristic biases during decision-making lies in top managers' digital knowledge and a firm's accumulated experiences in evaluating digital acquisition targets. Therefore, creating digital knowledge and accumulating experience with digital technologies and business models are particularly important for firms. Board members, consulting firms, and headhunters should consider this relevance when planning to digitally transform a company and searching for appropriate candidates to drive this transformation.

### 5.3. *Limitations and future research*

This study has some limitations that also provide avenues for future research. First, our sample is limited to publicly listed firms. While this limitation is inevitable when studying acquisition premiums, including privately held firms could yield valuable insights, as these firms are often younger and closer to emerging technologies. Future studies could study our proposed mechanisms in this context, complementing existing research in the context of initial public offerings (Reuer et al., 2012) and venture capital funding of technology startups (Petkova et al., 2013). Second, our measurement of technology hype has some limitations. Specifically, we calculated our measure based on media news articles. While news articles play a crucial role in facilitating the emergence of a technology hype (Dedehayir and Steinert, 2016), other media types, such as social media or online forums, may also contribute to the emergence of a hype (Chowdhury and Marler, 2024). Therefore, future research could build on our measure and use complementary data sources to further enrich the measure of a technology hype. Finally, there may be alternative explanations for the association between technology hype and acquisition premiums. For example, managers might deliberately pay high premiums for digital M&As during a hype phase to secure a technological opportunity. However, our additional tests showed that the long-term value destruction of deals during a hype phase contradicts this rational view. Another possibility is that managers seek to build their reputations and exploit media attention during a hype to boost their prominence with a deal related to the hyped technology. Our long-term value analyses at least question whether the benefits of increased prominence outweigh the costs of value destruction for managers. Hence, while we cannot fully rule out all alternative explanations, we suggest that managers who are subject to the availability heuristic (unconsciously) import biased expectations into their valuations and end up overpaying while believing they have struck a good deal. Future research could further explore this complex socio-cognitive decision-making process, for instance, via qualitative interviews or survey methods.

We encourage future research to study heuristics and cognitive biases in the context of M&A and their influence on acquisition outcomes. Research at the intersection of managerial and psychological concepts can help us better understand how managers are influenced by the environments in which they operate and how this can shape strategic firm outcomes.

## CRediT authorship contribution statement

**Sebastian Firk:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Yannik Gehrke:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Julian Meier:** Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Michael Wolff:** Writing – review & editing, Writing – original draft, Resources, Conceptualization.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lrp.2025.102589.

## Appendix A. Descriptions and data sources of used variables

| Variable | Description | Data source |
|---|---|---|
| *Main analyses* | | |
| Premium | Ratio of the offer price and share price of the target firm 42 trading days prior to the acquisition announcement minus one. | SDC Platinum |
| Technology hype | Positive residual of a prediction model that predicts a technology's positive media coverage in the deal preparation phase (12 months prior to the acquisition) from the technology's historical media coverage in the two years leading up to the deal preparation phase. | Ravenpack News Analytics |
| Acquirer TMT digital knowledge | Percentage of top managers with experience in positions, firms, or industries related to digital technologies. | BoardEx |
| Acquirer digital M&A experience | Number of digital M&A conducted by acquiring firm in the five years prior to the focal deal. | SDC Platinum |
| Acquirer relative size | Ratio of the Acquirer's net sales and the target's net sales. | Refinitiv |
| Acquirer firm profitability | Ratio of EBITDA and net sales. | Refinitiv |
| Acquirer financial advisers | Natural logarithm of the number of financial advisers. | SDC Platinum |
| Acquirer digital firm | Dummy variable equaling one if firm belongs to industries classified as digital and zero otherwise. | Own data |
| Acquirer average premium | The average premium of the Acquirer paid in the previous M&A deals. | SDC Platinum |
| Target firm profitability | Ratio of EBITDA and net sales. | Refinitiv |
| Target financial advisers | Natural logarithm of the number of financial advisers. | SDC Platinum |
| Deal size | Natural logarithm of the transaction value. | SDC Platinum |
| Friendly deal | Dummy variable equaling one if deal was friendly and zero if deal was hostile. | SDC Platinum |
| Cash payment | Dummy variable equaling one if deal is paid in cash, zero otherwise. | SDC Platinum |
| Competing offer | Dummy variable equaling one if another acquisition offer has been made within 12 months prior to deal, zero otherwise. | SDC Platinum |
| Merger of equals | Dummy variable equaling one if both firms are of equal size, zero otherwise. | SDC Platinum |
| Patent overlap | Cosine similarity of patent portfolios of acquiring and target firm. | USPTO |
| Sample selection control | Inverse Mills ratio from first stage probit model (see Appendix B). | First stage probit model |
| *Additional analysis* | | |
| Change in Tobin's Q | The difference between the Tobin's Q in the year before the deal and the Tobin's Q two years after the deal. | Refinitiv |
| BHARs (three years) | Calculated as $\left(\prod_{t}^{T}(1+R_{i,t})\right)-\left(\prod_{t}^{T}(1+R_{b,t})\right)$ over the days from −21 to 780 around the announcement of the deal with $R_{i,t}$ reflecting the return of the shares of Acquirer *i* on day *t* and $R_{b,t}$ reflecting the return of the S&P500 market index (*b*) on day *t*. | CRSP |
| *First-stage probit model* | | |
| Industry Digital Startups | Natural logarithm of one plus the number of digital startups in the Fama French 17 industries. | Crunchbase |
| Free cash flow | Difference of operating cashflow and investment cashflow. | Refinitiv |
| Sales growth | Year-to-year change in net sales. | Refinitiv |
| R&D intensity | Ratio of R&D spending to net sales. | Refinitiv |
| Tobin's Q | Ratio of market capitalization and total assets. | Refinitiv |
| ROA | Ratio of EBIT and total assets. | Refinitiv |
| Leverage | Ratio of total debt and total assets. | Refinitiv |

## Appendix B. First stage probit model predicting digital M&A

| Dependent Variable | Digital M&A |
|---|---|
| Industry Digital Startups | 0.100*** |
| | (0.000) |
| Firm size | 0.258*** |
| | (0.000) |
| Free cash flow | 0.011 |
| | (0.458) |
| Sales growth | 0.182*** |
| | (0.000) |
| R&D intensity | 2.287*** |
| | (0.000) |

(*continued on next page*)

(*continued*)

| Dependent Variable | Digital M&A |
|---|---|
| Tobin's Q | 0.068*** |
| | (0.000) |
| ROA | 0.004*** |
| | (0.002) |
| Leverage | −0.713*** |
| | (0.000) |
| Constant | −6.008*** |
| | (0.000) |
| Industry effects | YES |
| Year effects | YES |
| Observations | 26,679 |
| Wald chi2 (p-value) | 3437.89 (0.000) |
| Pseudo $R^2$ | 0.195 |

*Notes:* This table shows the first stage model predicting a dummy variable equaling one if the firm conducts a digital M&A, otherwise zero. Industry Digital Startups is the exclusion criteria and defined as the natural logarithm of one plus the number of digital startups founded per Fama French 17 industry-year. The inverse Mills ratio is derived from the predicted probability and included as a correction factor (sample selection control) in the main analyses. All independent variables are lagged by one year. Robust standard errors are included. *p*-values in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

## Appendix C. Digital technology clusters and related search terms

| Technology cluster | Related search words |
|---|---|
| Automation | Automation systems, Autonomous vehicles, Driver assistance |
| Biometrics | Fingerprint sensor, Face recognition |
| Business Intelligence | Predictive analytics, Business analytics, Simulation |
| Cyber security | Internet security, Firewall |
| Digital health | Telemedicine monitoring, Medical software, Electronic patient record |
| Digital marketing | Online advertising, Mobile advertising, Online marketing service |
| Digital media | Multimedia services, Digital imaging, TV services |
| E-commerce | Online shop, E commerce, Ecommerce |
| FinTech | Mobile banking, Financial services, Electronic payment |
| IIOT | Industrial internet of things, Facility automation |
| Image analysis | Video analysis |
| Information technology services | Information technology analysis, information technology research, Information services |
| IT consultancy | IT consulting, Computer consultancy, Technical consulting |
| IT infrastructure | Data warehouse, Computer hardware, Network management |
| Mobile services | Wireless telecommunication, Mobile network, Mobile phone applications |
| Online forum | Online community |
| Process software | Robotic process automation software, RPA software, Process integration |
| SaaS | Software as a service |
| Software development | App development, Software development kit, SDK |
| Telecommunication | VoIP platform, Broadband, Network services |
| Telematics | Telematics box, GPS tracking, Fleet management |
| Web platform | Website management, Online multimedia services |

*Notes:* This table shows the technology clusters that were constructed for our analysis of digital M&As between 2004 and 2018. Both the technology cluster and the related search terms were used to search for news headlines covering the respective technology.

## Data availability

The authors do not have permission to share data.

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