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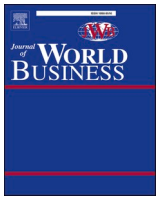

Cross-border acquisition completion by emerging market MNEs revisited: Inductive evidence from a machine learning analysis

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ABSTRACT

Existing empirical studies of cross-border acquisition completion by emerging market multinational enterprises remain highly contextual, yielding inconsistent evidence regarding the determinants of deal success or failure. We apply machine learning to expose underlying complexities. The learning results of LightGBM, from data on 24,693 cross-border acquisition deals involving 29 emerging countries, unveil a comprehensive picture of the relative importance and impact patterns of 59 predictors that were fragmentally, inconsistently, or not at all presented in the extant literature. Our findings offer fresh insights into the deal completion of cross-border acquisitions by emerging market multinational enterprises, suggesting novel future research priorities.

1. Introduction

International business (IB) phenomena are inherently complex, given their cross-border nature, involvement of diverse actors, and intricate organizational dynamics (Fainshmidt et al., 2021). Specifically, Eden and Nielsen (2020) identify three factors contributing to this complexity: the multiplicity of entities (i.e., the number and variety of actors, industries, countries, institutions, et cetera), the multiplexity of interactions (i.e., the number and variety of ties or relationships among these entities), and the dynamism over time (i.e., the changing nature of the international business system). This complexity presents challenges to IB research, which tends to feature idiosyncratic samples or contexts, less-than-ideal research designs, and insufficient evidence of causal relationships (Aguinis et al., 2017; Eden & Nielsen, 2020). The current study focuses on cross-border acquisitions (CBAs) conducted by emerging market multinational enterprises (EMNEs) as a typical example of an IB issue featuring such complexities.

CBAs have been extensively researched in the field of IB (e.g., Dikova et al., 2010; Fuad & Gaur, 2019; Zhang, 2022), as well as in Finance (e.g., Chira et al., 2017; Schwert, 2000) and Strategy (e.g., Muehlfeld et al., 2013; Hawn, 2021). In recent years, there has been a growing interest in CBAs conducted by EMNEs (see the review by Kumar & Sengupta, 2020). Setting out from specific theories (e.g., institutional, organizational learning, and corporate finance theories), empirical studies of EMNE CBA completion are often designed to fit with a specific context and theory, narrowing their choices to a limited set of underlying factors. Hence, these studies usually focus on a few key explanatory variables (predictors) out of a potentially much larger number, and cherry-pick a specific data sample out of large data sets, being subject to variable choice and sample selection biases [see George (2000) and Berk (1983), respectively].

Take a few studies to illustrate this state of the art. Li et al. (2019) used a sample of 1170 acquisitions announced by Chinese acquirers from 1990 to 2010. The deals without required transaction information (e.g., deal size, whether the acquirer employed any financial advisor, the attitude of the target, the percentage of ownership sought by the acquirer, and the payment method) were excluded from the analysis, implying that about two-thirds of the total number of deals during this period were excluded. J. Zhou et al. (2016) only focus on 747 CBAs conducted by four EMNEs from BRIC countries between 1995 and 2010. Popli et al. (2016) only consider 332 deals of Indian firms that sought to obtain percentages above 50 percent. In the words of Bettis et al. (2016, p. 2194), these studies produced statistical results that "only apply to the particular sample and nothing definitive can be said by sample statistics about the population."

Not surprisingly, empirical findings are (very) different across studies, depending upon the specific variable choice, sample selection, and model specification biases (Woodward, 2016). Indeed, this is clearly

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the case for studies on EMNEs' CBA completion, as summarized in Table 1 in the next section. We see three important problems that need to be tackled in CBA completion studies. First, the empirical results are far from unambiguous and conclusive. For example, some studies find that deal size is negatively related to acquisition completion (e.g., Li et al., 2019), but others report a positive effect (e.g., Fuad & Gaur, 2019; Zhu et al., 2014). Even within the same study, different model specifications and/or estimations can come with problematic inconsistencies. The analyses often produce inconsistent statistics, in terms of sign, size and/or significance, for the same variables in different models. Unfortunately, the differences are frequently ignored if published (e.g., because they are not part of the set of reported estimates), or are probably not published at all.

Second, empirical findings are oftentimes not in line with theoretical predictions. Because negative and null findings are much more difficult to publish, these are frequently not reported and discussed in published work, or even archived in the waste bin or washed away with questionable research practices [see, e.g., Meyer et al. (2017) on this well-established, widespread and very damaging issue of questionable research practices, including publication bias, in IB]. For example, studies usually predict that sought percentage is negatively related to acquisition deal completion because the more stake an acquiring firm seeks, the more complex the acquisition is, and the more likely it will be subject to regulatory scrutiny (Muehlfeld et al., 2007). However, here too, recent EMNE CBA completion studies show inconsistent sign effects without seriously discussing them (Li et al., 2019; C. Zhou et al., 2016).

Third, since any single study in the published literature usually focuses on a few variables selected on the basis of the theory or theories of choice, we lack a comprehensive and overall grasp of what are the important factors out of many. For example, based on institutional theory, Zhang et al. (2011) hypothesize and report evidence that the institutional quality of the host country positively influences the likelihood of acquisition deal completion, and based on the similarity-attraction argument, Li and Sai (2020) theorize and confirm that linguistic and religious distance between host and home countries both negatively influence the likelihood of acquisition deal completion. However, such scattered findings across these fragmented studies fail to provide the systematic comparative insight required to distinguish important from unimportant factors when bringing many factors together to comprehensively predict the CBA completion outcome.

To tackle these three problems, we move beyond the conventional explanatory approach, applying a specific machine learning (ML) technique known as gradient boosting decision tree (GBDT) to comprehensively analyze EMNEs' CBA completion. For most empirical studies on (EMNE) CBA completion, as is the case in IB generally, the aim is to test a limited number of theory-specific causal hypotheses – i.e., an assumed causal relationship between a small set of underlying factors (variables **X**) and an underlying outcome variable (measured by **Y**), mostly using observational data. Typically, this causal explanation is quantified in regression models of the form $\mathbf{Y}=f$(predictor variables, parameters, random noise) or simplified as $\mathbf{Y}=f(\mathbf{X})$, where f is a pre-specified function (Breiman, 2001b). In the case of selectively choosing theorized variables and specific samples, supposing that there are m theories to be applied to n countries to seek answers to the CBA completion questions, we will have a maximum of $m\times n$ empirical contingencies, reflecting the extreme case where the countries (or other sample contexts) are heterogeneous (independent) enough. In the ML approach, basically, we link the underlying factors **X** to an underlying outcome variable **Y**, too, and still do so in the form of a simplified function $\mathbf{Y}=f(\mathbf{X})$. However, in contrast, here f is not pre-specified, but is a flexible function that ML will 'learn' to predict **Y** well, with the number of variables in **X** not being limited *a priori*. The shape or the structure of the function f is learned by the ML learning algorithm from input (in-sample) data and validated by test (out-of-sample) data. This is largely a process of learning from the facts or observations (data). Ideally, this approach accounts for all the factors (**X**) involved in the $m\times n$ contingencies for the CBA completion problems in a nonrestrictive setting.

The predictive power of ML techniques is generally much higher than that of traditional statistics, precisely because they are designed to flexibly deal with complexity – i.e., to discover complex structures that were not specified in advance (Mullainathan & Spiess, 2017). With state-of-the-art ML techniques, we can examine a large set of underlying factors across many contexts to discover unknown patterns and relationships, and hence develop a better understanding of the comprehensive web of determinants of an outcome variable, including insight into the importance ranking of and high-order interaction among large sets of determinants. In so doing, ML algorithms can play an important role in inductive theorizing after analyzing large sample data (Shrestha et al., 2021). Specific to the current context of EMNE CBA completion, ML helps to explore possible answers to three crucial but unresolved questions: (1) Which factors are more important than others in predicting EMNEs' CBA completion when most possible factors are pooled in the analysis of a full sample of emerging countries?; (2) What are the complex and unknown effect patterns that can account for the heterogeneous results across previous studies?; and (3) Is there any important predictor being missed, insufficiently investigated or overrated in the extant literature?

The current study makes a two-fold contribution. First, we demonstrate how ML can advance research in the field of IB, particularly when dealing with complex phenomena. Our research showcases the capabilities of ML in addressing the complexity of CBA completion by accounting for a multitude of underlying factors and their interactions in an all-embracing and flexible way beyond what can be achieved in extant empirical studies applying non-ML techniques. Second, because of this, we provide inductive evidence suggesting novel insights regarding EMNE CBA. Drawing on inductive evidence that is very challenging to obtain through traditional statistical methods, our study explores alternative perspectives on explaining the outcomes of EMNE CBAs, in so doing identifying promising opportunities for future research. Below, we first review the literature in an effort to survey the determinants of the likelihood of EMNE CBA completion. Next, we briefly introduce ML and describe the overall method, presenting the step-by-step procedures, the underlying rationales, and the practical issues involved in each step within ML's research process pipeline. Subsequently, we present our empirical results. After that, we summarize and discuss the major findings, highlight the contributions of the paper, and discuss a promising future research agenda.

2. Cross-border acquisition completion

Acquisition deal completion happens "when the parties have agreed on the deal terms, have obtained the necessary consents, sign the definitive share purchase agreement, and execute the mutual responsibilities defined in the contract" (Welch et al., 2020, p. 857). Completion or incompletion of an announced acquisition is often noted as success or failure in the pre-acquisition phase. In practice, acquisition deal completion is important for acquirers because they bear upfront financial costs and termination fees, and cancelation may result in losses in terms of the firm's reputation, credibility, time, diversion of managerial attention, negative market reaction, and releasing valuable private information regarding strategy (Dikova et al., 2010; Hawn, 2021; He & Zhang, 2018; Li et al., 2017; Neuhauser et al., 2011). This is particularly true for acquirers from emerging countries, given their fast growth in number and value, and their relatively lower completion rate compared with acquirers from advanced countries (Zhang, 2022). Not surprisingly, this new trend has attracted increasing research efforts to identify the factors that explain EMNEs' CBA completion.

Jointly but often separately, empirical studies have found that a large number of multi-level factors may explain EMNEs' CBA completion. Specifically, deal-level characteristics such as deal size (Dong et al., 2019), industry relatedness (He & Zhang, 2018), advisor involvement (Zhang et al., 2011), cash payment (Kim & Davis, 2019), and tender

Table 1
Summary of empirical research on EMNEs' cross-border acquisition completion.

	Authors	Journal	Predictors of acquisition completion (probit/logit regression)*	Theory	CBA/ Domestic deals	Acquirers' home country	Sample period	Sample size
1	Zhang, Zhou & Ebbers (2011)	*International Business Review*	Advisor (+), SOE acquirer (-), private target (+), experience (+), target country institutional quality (+), natural resource industry (-); the effects of percentage sought, industry relatedness, SOE target, private acquirer, and export intensity are not significant	Institutional theory	CBA	China	1982–2009	1324 CBA deals
2	Zhang & Ebbers (2010)	*Journal of Current Chinese Affairs*	Advisor (+), SOE acquirer (-), subsidiary acquirer (+), experience (+), cultural similarity (-), trade intensity (+), sensitive industry (-); the effects of percentage sought, industry relatedness, private acquirer, high-tech target, target bureaucracy quality are not significant	Institutional theory	CBA	China	1982–2009	1324 CBA deals
3	Zhu, Jog & Otchere (2014)	*Emerging Markets Review*	Target firm size (+), target firm leverage (-); deal size (+); public acquirer (-); Idiosyncratic volatility (+), tender offer (-); the effects of target firms', age, target country institutional quality and development level are not significant	Financial economics	Both	ECs and advanced countries	1990–2007	874 deals.
4	Zhou, Xie, & Wang (2016)	*Journal of International Business Studies*	Cash payment (+), percentage sought (+), competing bidders (-), disclose (+), acquirer size (+), public target (-), success/failure experience (+/-), legal and regulatory difference (-); the effects of industry relatedness, friendly acquisition, country-risk difference, geographic distance are not significant	Organizational learning, and institutional theory	CBA	BRIC	1995–2010	2736 inbound acquisitions; 747 outbound acquisitions
5	Popli, Akbar, Kumar & Gaur (2016)	*Journal of World Business*	Cultural distance (+); the effects of percentage sought, industry relatedness, public target, public acquirer, experience, joint venture, business group, cultural cluster dispersion are not significant in all or part of models	Organizational learning, and cultural friction perspective	CBA	India	2001–2010	332 CBA deals
6	Zhou, Lan & Tang (2016)	*Management Decision*	Industry relatedness (+), institutional shareholder (+); target country common law (+), acquirer size (+); exchange rate (-); the effects of public target, percentage sought, target countries' GDP growth rate, openness, and geographic location are not significant	Agency theory, and institutional theory		China	1985–2012	273 CBA deals
7	Madhavan & Gupta (2017)	Book chapter	Cash payment (+), depth of experience (+), breath of experience (-), target country regulatory quality (+), public sector (-); the effects of industry relatedness, language, and HDI of target country are not significant	Institutional theory, organizational learning, and organization status	CBA	India	1999–2013	1864 CBA deals
8	Zhang et al (2017)	*Thunderbird International Business Review*	Advisor (+), industry relatedness (+), SOE acquirer (-), experience (+), acquirer economic freedom (EF) (+), parent EF (+), EF difference between target and parent (-), EF difference between target and acquirer (-), target GDP (+), natural resource (-), energy (-), real estate (+); the effects of SOE target and other industry variables are not significant	Institutional theory, and Dunning country-specific and ownership advantages	Both	10 ECs	1981–2012	5174 CBA deals
9	He & Zhang, (2018)	*Journal of Business Research*	Advisor (+), SOE acquirer (-), SOE target (-), foreign partnership (+), subsidiary acquirer (+), experience	institutional theory, and springboard perspective	CBA	10 ECs	1981–2012	17,109 CBA deals directly and

(*continued on next page*)

Table 1 (*continued*)

	Authors	Journal	Predictors of acquisition completion (probit/logit regression)*	Theory	CBA/ Domestic deals	Acquirers' home country	Sample period	Sample size
			(+), industry relatedness (+), acquirer institutional quality (+), institution difference (-), target GDP (+), natural resource (-)					indirectly by EMNEs
10	Dong et al. (2019)	*Baltic Journal of Management*	Cash payment (+); percentage sought (-), private acquirer (+), private target (+), local experience (+), economic difference (-), cultural distance (-), institutional difference (-); the effects of industry relatedness, SOE acquirer, advisor, acquisition experience, technology-intensive industry, knowledge-intensive industry are not significant	Development economics, and institutional theory	CBA	China	2000–2015	768 CBA deals in 88 economies
11	Li, Li & Wang (2019)	*Strategic Management Journal*	Deal size (-), percentage sought (+), SOE acquirer (-), opaqueness (-), experience (+), public target (-); the effects of cash payment, friendly acquisition, industry relatedness, advisor, past failure rate, sensitive industry, bilateral political relationship, target country institutional quality, GDP per capita, GDP and GDP growth are not significant	Signaling theory	CBA	China	1990–2010	1170 deals used; 1990 and 2010 SDC Platinum Database
12	Fuad & Gaur (2019)	*Journal of World Business*	Deal size (+), wave deals (-), entry time inverted U-shape), business group affiliation (+), experience (-),; the effects of percentage sought, cash payment, industry relatedness, acquirer size, acquirer age, acquirer previous performance, institutional difference, export intensity, developed host are not significant	Frictional lens perspective, and industrial organization	CBA	India	1995–2015	208 CBA deals
13	Sun, Zhao, He & Zhang (2019)	*China Journal of Accounting Research*	Advisor (+), SOE acquirer (-), experience (+), IFRS (-), high-tech industry (+); the effects of industry relatedness and regulated industry are not significant		CBA	China	2002–2016	2643 CBA deals
14	Wang, Schweizer & Michaelis, (2020)	*International Journal of Emerging Markets*	Cash payment (+), industry similarity (+), acquirer size (+), SOE acquirer (-), public target (-), subsidiary target (-), domestic experience (-), cultural difference; the effects of percentage sought, industry relatedness, foreign experience are not significant	Organizational learning	CBA	China	2002–2012	705 CBA deals
15	Hawn (2021)	*Strategic Management Journal*	Country experience (+), industry experience (-), negative media coverage of CSR (-), subsidiary target (+), economic difference (-), political difference (-), financial difference (-); the effects of cash payment, percentage sought, public acquirer, public target, SOE acquirer, demographic difference, knowledge difference, differences in tourism and internet use, cultural difference, administrative difference, geographic distance are not significant	CSR literature	CBA	Brazil, Russia, India, China, and South Africa	1990–2011	4087 CBA deals
16	Liu, Muradoglu & Peng, (2022)	Working paper	Advisor (+), cash payment (+), friendly acquisition (+), public target (+), acquirer CSR (+); the effects of percentage sought, relative deal size, tender offer, acquirer size, acquirer leverage, political connection, acquirer ROA, institutional difference, cultural difference are not significant in all or part of models	Corporate finance theory		China	2010–2018	317 CBA deals

(*continued on next page*)

Table 1 (*continued*)

	Authors	Journal	Predictors of acquisition completion (probit/logit regression)*	Theory	CBA/ Domestic deals	Acquirers' home country	Sample period	Sample size
17	Zhang (2022)	*International Business Review*	Advisor (+), SOE acquirer (-), SOE target (-), subsidiary acquirer (+), experience (+),acquirer institutional quality (reversed institutional LOE) (+), acquirer economic development (reversed economic LOE) (+), host institutional quality (+), developed host (+), host unemployment (+); the effect of industry relatedness is not significant.	Neo-institutional theory, and the concept of legitimacy		24 ECs	1995–2016	23,459 CBA deals directly and indirectly by EMNEs
18	Zhou et al. (2022)	*Asia Pacific Journal of Management*	Cash payment (+) success/failure experience (+/-),developed host (+); the effect of friendly acquisition, percentage sought, public target, acquirer size and performance, institutional difference, cultural distance, geographic distance, industry relatedness are not significant.	Organizational learning		ECs mainly from Asia	1980–2015	4510 CBA deals (only listed acquirers)

offer (Chira et al., 2017), firm-level features such as experience, ownership, foreign partnership, and subsidiary acquisition strategy (He & Zhang, 2018; Zhang et al., 2011; Zhang & Ebbers, 2010; C. Zhou et al., 2016), and host-home country attributes and differences such as institutional quality (Zhang et al., 2011), institutional distance (C. Zhou et al., 2016), cultural distance (Dong et al., 2019), and economic disparity (Lim & Lee, 2017) are identified as significant predictors of the completion rate of EMNEs' CBAs across the literature. Attempting to explain EMNE CBA completion from different perspectives, empirical studies start from institutional and organizational learning theories more often than from other theories, such as agency theory, signaling theory (Spence, 1973), and the springboard perspective (Luo & Tung, 2007). Method-wise, a majority of these studies are quantitative, mainly employing logistics (logit/probit) regression (see the review by Kumar & Sengupta, 2020). Table 1 presents a summary of these studies, detailing the predictors, theories, and samples (home country, period, and size). The summary exposes that studies tend to be theory- and context-specific, reporting much mixed evidence (e.g., regarding deal size, public target, public acquirer, percentage sought, and others).

Studies usually employ the causal explanation approach to test a limited number of theory-specific hypotheses using observational data (cf. Shmueli, 2010). Their goal, however, may not be satisfactorily attained when the causality is too complex to be predicted by available theories and/or because of the biases implied by traditional regression's need to impose simplicity. On the one hand, theories may be under-developed, biased, imperfect, or even wrong when used to explain fast-emerging empirical phenomena; on the other hand, rich and ever-expanding data, as witnessed in the modern business world and accelerated by the information revolution, often contain complex relationships and patterns that are hard to hypothesize theoretically *ex ante* and/or difficult to test empirically *ex post* with traditional statistics. Importantly, regression-based quantitative methods conventionally used for causal explanation are incapable of including a sufficiently large number of variables, their often subtle non-linearities, and their many (high-order) interactions. The pervasive variable choice and model specification biases that this implies, being associated with imposed simplicity, may be an unavoidable side effect of the causal explanation approach *per se*. Clearly, when there is a complex and non-linear system of underlying factors, researchers are confronted with these issues, and should be at pain to answer the question as to whether their choices of variables and specifications are sufficient to really explain their outcome variable. From the low explained variance reported in extant work, even on the basis of inflated within-sample fit metrics, we can be sure the answer to this critical question is no.

In short, the causal explanation approach faces fundamental and substantial challenges in dealing with complexity in terms of large number of underlying factors and their many non-linearities and (often high-dimensional) interactions (cf. Eden & Nielsen, 2020; Nielsen et al., 2023). There remains, as a result, a confusing and inconsistent picture of the effect, in terms of direction, sign, and importance, of the many factors potentially co-determining (EMNE) CBA deal completion, despite the large number of studies (see the review by Kumar and Sengupta, 2020). In this respect, two remarks are worth making, as reflected in Table 1. First, existing studies tend to oversimplify the relationship of predictors with CBA completion as negative/positive, rarely reporting non-linear effects. This over-simplicity is not in line with the reality of complex CBA phenomena, being a likely source of inconsistence across individual studies. Second, the effect of some predictors is significant in some studies but insignificant in others, seemingly being context or theory-dependent. For example, *Percentage sought* is significant in three studies, but insignificant in nine other studies.

This two-fold observation suggests that there are two essential issues with existing explanations. One is the lack of clarity regarding the complex nature of relationships between the predictors and the outcome – i.e., linear or not, and with what shape, in the case of the latter. Another issue involves the lack of comprehensive understanding of the relative importance of the many predictors, as prior evidence regarding predictor significance is frequently highly inconsistent across studies. We, therefore, need a new approach that can handle a vast array of potentially important predictive factors flexibly to uncover any underlying complex non-linearities. Here, the ML approach does offer such a promising toolkit that is capable of inductively identifying potential complex causality and hence aids in consolidating the multitude of ambiguous explanations into a more concise set of crucial explanations while specifying their nature. This allows us to revisit relevant theories, affirming or reshaping our current understanding while uncovering alternative explanations that might have been previously overlooked.

3. Machine learning and its research process pipeline

ML is different from traditional causal explanation statistics, due to (a) the key role of self-learning algorithms and (b) the focus on predictive modeling. ML tends not to follow the prototypical approach of causal explanation – hypothesize first and test next (Hair & Sarstedt, 2021). Rather, ML can identify complex and often hidden relationships and patterns in datasets that might not be captured by existing causal

explanation models and techniques (Shmueli, 2010). ML involves algorithmic modeling such that the problem is to find an algorithm $f(\mathbf{X})$ that is a good predictor of $\mathbf{Y}$ (Breiman, 2001b). It has iterative and (self-) learning characteristics that render reliable results that reflect the underlying complexity (Attaran & Deb, 2018), not *a priori* assuming any (simple) data generation process, as traditional regression does. Hence, ML does offer a very promising complementary toolkit for addressing the challenges associated with traditional regression's weaknesses that imply a failure to capture the complexity that is so prevalent in the social sciences, including IB. Indeed, there is increasing interest to apply ML techniques – in particular neural networks, which is a subset of ML – to IB empirical research.

Particular neural network analysis (e.g., self-organizing maps, multi-layered perceptron, MLP, and artificial neural networks) has been applied in IB, to date. Four examples may illustrate this. First, in cross-cultural studies, such analyses aim to gain insight into the underlying patterns or trace effects of national culture (Veiga et al., 2000), intra-country cultural heterogeneity, intercultural differences, and cultural isolation (Messner, 2022a, 2022b, 2022c), and dimensions of culture and perceptions of justice (Palocsay & White, 2004). Second, in FDI studies, they facilitate the identification of geographic clusters of countries (Deichmann et al., 2003) and international market selections (Brouthers et al., 2009). Third, in joint venture studies, neural network analyses are applied to explore the relationship between transaction cost factors and majority/minority ownership (Hu et al., 2004), as well as the underlying clusters in collaborative venture formation and their associated characteristics (Nair et al., 2007). And fourth, in HRM studies, they contribute to uncovering clustered patterns of HR practices among organizations (Stavrou et al., 2007).

The ML toolkit is composed of a large set of algorithms, of which neural networks are only one example. These algorithms come in many different forms and shapes, implying that a first step in any ML analysis involves the choice of the 'best' algorithm. We focus on supervised ML, with the algorithm aiming for the prediction of a pre-selected outcome variable (in our context, EMNE CBA completion). The key criterion for algorithm selection is model performance: Which algorithm outperforms the others in terms of predictive accuracy? Two key features of this approach are worth emphasizing. First, model performance is assessed out-of-sample. Algorithms are trained on a part of the data, known as the training dataset, with the other part set aside for assessment purposes, referred to as the validation or test dataset. This is very different from what is normally done in the causal explanation regression tradition in IB (and Business broadly), where model statistics are calculated within-sample, implying highly inflated model fit metrics.

Second, ML's model performance metrics relate to predictive accuracy. Key is how well the algorithm (in the validation data with unseen observations) performs in accurately predicting the value of the observations. Although not completely similar, the underlying logic of these metrics is much like what we are used to in the classic causal explanation approach. As explained below, on our data, the GBDT model outperforms all other tried algorithms on almost all considered metrics. So, in the following, we take GBDT as our workhorse. GBDT was advocated in the early 2000s, but recent development in software implementation (such as XGBoost in 2016 and LightGBM in 2017) gave this technique a second life. Table 2 presents a brief overview of the steps in the research process pipeline, including our concrete implementation decisions. For more general guidance, we refer to Choudhury et al. (2021).

Table 2
Overview of ML Procedure and concrete implementation decisions.

Steps	Decision	Illustration
Step 1: Select sample, predictor set and outcome variable	Specify the data sample and which variables are included as predictors (explanatory variables) and the outcome variable (dependent variable).	Sample: 24,693 deals of EMNE acquirers from 29 emerging countries. Predictors: 59 variables (based on a thorough review of extant literature). Outcome variable: The result of deal-making (completed or not).
Step 2: Algorithm selection	Select the algorithm out of a set of competing ones, based on their predictive performance, which is assessed through a K-fold cross-validation on training data.	LightGBM, an implementation of the gradient boosting decision tree model (GBDT) outperform seven competing algorithms, according to predictive performance quantified by a series of metrics (Accuracy, RoC-AUC, F1-score, Average precision, et cetera). Performance is evaluated via a four-fold cross-validation on the training data set, which is randomly split (accounting for 70% of observations) from our sample.
Step 3: Set regulation and other hyperparameters	Choose and fine-tune the hyperparameter to avoid over- and under-fitting. This involves running multiple trials that train and cross-validate the model as selected in Step 2.	Leaf number = 31; data sample size per leaf = 20; and tree number = 100.
Step 4: Evaluate final predictive performance and interpret models using variable importance	(1) Train the fine-tuned model on the training set and validate the final model on the test set. (2) Report the final validation result, the model predictive performance quantifying by multiple metrics, as a generalized model fit diagnosis. (3) Interpret the underlying complex ML model by revealing which variables are important.	LightGBM predictive performance metrics: (1) precision; (2) recall; (3) F1-score; (4) accuracy; and (5) ROC-AUC. SHAP as a simple interpretable approximation of the underlying complex LightGBM model, and SHAP values as a measure of variable importance.

3.1. Step 1: select the sample, predictor set and outcome variable

Sample. Emerging countries can be defined as low-income but rapid-growth countries using economic liberalization as their primary engine of growth (Hoskisson et al., 2000). There is no consensus list of emerging countries. We selected emerging countries by one of the following criteria: (1) a country in MSCI's (Morgan Stanley Capital International) emerging markets list (MSCI, 2021); or (2) a non-developed country that is not a tax haven with an outward foreign direct investment (FDI) stock of more than 5 billion USD in 2018. We noticed that a country with outward FDI stock lower than this was very inactive with CBAs. Using these criteria, 29 countries were selected: Argentina, Azerbaijan, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Kuwait, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, South Korea, Thailand, Turkey, Ukraine, United Arab Emirates, and Vietnam. We exclude Singapore and Greece because they are often listed among the developed countries, and Taiwan because important macro-level indicators are not available.

The CBA sample is restricted to announced deals in which acquirers are from one of these emerging countries. The CBA data were obtained from the Thomson Financial Mergers & Acquisitions database. This database has been widely used in EMNE CBA research (Zhang et al., 2011; C. Zhou et al., 2016). This database provides daily updated information regarding completion status, acquirer and target characteristics, and deal-specific attributes. The data was downloaded in May

2021. To increase the accuracy of the measurement of the predicted variable, we only used the deals announced during the 1980–2018 window. Following C. Zhou et al. (2016), we considered the CBAs to be uncompleted if they were still pending until May 2021, which is two and half years after the end of 2018. In addition, we excluded deals with the status 'rumor' and 'unknown'. In the end, 24,693 deals involving 29 emerging countries and 205 host economies were used in the analysis – a sufficiently large sample size to apply ML comprehensively.

Predictors. To select the potentially relevant predictors to be included in the ML model, and to do so comprehensively, we have conducted an extensive literature review to identify the factors that have been introduced in extant work to influence (EMNE) CBA completion. Bibliographic databases EBSCO, JSTOR, ProQuest, and Google Scholar were searched using the following keywords: cross-border, acquisition, acquire, takeover, abandon, abandonment, terminate, termination, complete, completion, emerging market, and multinationals. With a focus on EMNEs' CBAs, we could identify 18 quantitative studies relevant to the current context, of which 16 were published in international peer-reviewed journals, one was a book chapter, and one was a working paper. Based on this literature review and data availability, we include a large total of 59 predictors in the ML model, covering all three levels of analysis (deal, firm, and country), which is many more than typically added to a classic causal explanatory regression model specification. The definitions, measurements, and data sources of the predictors are presented in Table 3.

We used three criteria to select predictors. First, a sufficient condition is a plausible theoretical basis for the relationship between predictor and outcome based on relevant research, both being measured reliably and validly. Constrained by space, we refer to the original studies, as listed in Table 1, for the theoretical rationale, as well as the measures. Second, a predictor should contribute to predictive accuracy. To explore potential predictors, we also include variables that were not explored in the literature, but may influence CBA completion. Third, a predictor should not be a linear combination of other predictors, to not restrict ML's learning flexibility. For example, institutional distance between home and target country is often examined in the literature, but instead we include the institutional quality of both home and target economies separately in our model, because then we can identify the unique effect of the institutional profile of either macro side of the announced transaction. In addition, studies found that absolute institutional distance has limitations in explaining the effect of institutions on EMNEs' performance (Konara & Shirodkar, 2018). Harzing and Pudelko (2016) also reported that the explanatory power of distance is highly limited once home and host country contexts are accounted for. Similar reasoning applies to economic distance. However, we decided not to do so for cultural indicators, hence including cultural distance in the model. We also include the cultural profile of host economies, without including the cultural profile of home economies, to avoid the linear combination with cultural distance. The reason for this is that, in theory, and in contrast to institutional quality and economic development, culture cannot be defined as good or bad, or as high or low. Therefore, cultural differences may be more relevant than the cultural profile of the home country *per se* when explaining cross-border businesses. Our estimates indeed show that doing so gives higher prediction accuracy than the model that uses cultural profiles of both home and host economies separately.

Outcome variable. Our primary interest in our comprehensive study is in the outcome of the announced EMNE CBA attempt. We encode this outcome as a category variable **Y**, which is valued at 1 if the CBA deal attempt is completed and 0 otherwise. This binary variable is our predictive object or target outcome, in ML terminology, which is equivalent to the dependent variable in conventional regression analysis.

3.2. Step 2: algorithm selection

This step involves three stages: (1) split data into training and hold-out (test) sets; (2) train different algorithms (using cross-validation) on training data; and (3) determine the 'best' algorithm according to performance metrics obtained in a cross-validation process. In the first stage, the rationale to split data into two parts is to assure that the model learnt during training will perform well on new and unseen (test) data. Earlier work revealed that the increase in the relative size of the training dataset from 30% to 80% of all observations improved training performance and made the model more stable, but the increase in relative size from 80% to 90% has an opposite effect (Nguyen et al., 2021). Nguyen et al. (2021) show that the training/test ratio of 70/30 is most suitable for training and validating ML models. Therefore, we randomly took 70% of all observations as the training set and the rest as the test set. In the second stage, we performed a four-fold cross-validation on the training data with each of the eight algorithms. In the third stage, we compared these eight ML algorithms, taking the mean score of a series of model performance metrics for the validation data as our decision yardstick. We refer to Online Appendix I for technical details and Online Appendix II for a list of definitions. We find that LightGBM, a software implementation of the GBDT, without imputation outperforms all other tried algorithms on almost all metrics. So, we take GBDT without imputation as our ML workhorse.

Concerning the choice of GBDT, two remarks are worth making. The first involves the generalizability issue. For any given ML problem, the choice of the 'preferred' or 'best' learning algorithm is highly dependent on the dataset. In the ML tradition, the standard practice for finding a suitable algorithm for the given dataset is to compare different techniques' out-of-sample predictive accuracy in validation data. On our data, the decision tree-based algorithm performs best. This may be due to the tabular and imbalanced nature of our data (i.e., the proportion of completed cases is much larger than that of incompleted cases). This is in line with the literature. Grinsztajn et al. (2022) found that, on tabular data, tree-based models more easily yield good predictions, with much less computational cost, beating deep learning models that are active in creating tabular-specific learning architectures. This superiority is explained by specific features of tabular data: i.e., irregular patterns in the target function, uninformative features, and non-rotationally-invariant data. Regarding imbalanced data, many algorithms are known to perform poorly (Brown & Mues, 2012; Visa & Ralescu, 2005), with tree-based algorithms (specifically random forests and gradient boosting trees) significantly outperforming, in terms of higher accuracy, other classification techniques such as logistic regressions, neural networks, k-nearest neighbors, and support vector machines.

Another issue relates to practicability. Certainly, another algorithm might have won the model fit race. Take neural networks as an example. Neural networks have demonstrated excellent performance in classification tasks (cf. LeCun et al., 2015). In IB, as we reviewed earlier, neural networks have a few applications. However, neural network techniques require higher skill capacity for tuning and additional practical solutions for them to work well. Zhang et al. (1998) argue that the design of neural networks is more art than science. In addition, for neural networks to work well (i.e., to alleviate the degradation of performance) on imbalanced data, the training procedure would require customized solutions such as using specialized loss functions and improved gradient descent algorithms, or rebalancing the dataset by resampling known data (Huang et al., 2022; Zhang et al., 2018). This entails substantial technical hurdles. On top of this, to account for missing entries in the data, neural networks require an imputation preprocessing step before they can be trained. Given these operational complexities, neural networks are less competitive if they do not demonstrate significant prediction accuracy superiority over tree-based algorithms.

3.2.1. Gradient boosting decision tree

Next, we briefly introduce GBDT and its software implementation, LightGBM. For a better understanding of the technicalities, we refer to Online Appendix III. Gradient boosting (GB) is a powerful ML technique

Table 3
Variable definitions.

			Variables (short names)	Measurement	Sources
Deal level	1	D1	*Cash payment (ofCash)*	Percentage of cash payment in transaction	Thomson Reuters M&A Database
	2	D2	*Percentage sought (sought)*	Percentage of stake being acquired	
	3	D3	*Deal size (deal_size)*	Logarithm of the value of transaction (in million US $)	
	4	D4	*Friendly acquisition (friendly)*	Binary variable, 1 if attitude of the target firm's management or board of directors toward the transaction is friendly, 0 otherwise.	
	5	D5	*Industry relatedness (relatedness)*	Binary variable, 1 if the acquirer and target in a transaction are in the same industry, 0 otherwise.	
	6	D6	*Advisor (advisor)*	Binary variable, 1 if the acquirer hires an international advisor, 0 otherwise	
	7	D7	*Tender (tender)*	Binary variable, 1 if a tender offer is launched for the target, 0 otherwise.	
Firm level	8	F1	*Equity value (equity_value)*	Logarithm of the equity value of a target firm (in million US $)	
	9	F2	*Target performance (tarEBITDA)*	Earnings before interest, taxes, depreciation and amortization for the last 12 months ending on the date of the most current financial information prior to the transaction in last 12 months ($mil)	
	10	F3	*Target firm size (tarSize)*	Logarithm of the target firm's total assets (in million US $)	
	11	F4	*Acquirer firm size (acqSize)*	Logarithm of the acquiring firm's total assets (in million US $)	
	12	F5	*Advanced parent (acqAdvance)*	Binary variable, 1 if the acquiring firm has a parent company from an advanced country, 0 otherwise.	
	13	F6	*Global experience (experience_G)*	Logarithm of one plus the count of announced cross-border acquisitions that the acquiring firm conducted before the current acquisition.	
	14	F7	*Local experience (experience_L)*	Logarithm of one plus the count of announced acquisitions that the acquiring firm conducted in the host country before the current acquisition.	
	15	F8	*SOE acquirer (acqSOE)*	Binary variable, 1 if the acquirer is a state-owned company. We identified a firm as an SOE if the government owned a stake of more than 50%.	
	16	F9	*Private acquirer (acqPriv)*	Binary variable, 1 if the acquirer is a private company.	
	17	F10	*Public acquirer (acqPub)*	Binary variable, 1 if the acquirer is a public company.	
	18	F11	*Foreign subsidiary (acqForeignsub)*	Binary variable, 1 if the acquirer has a foreign parent.	
	19	F12	*SOE target (tarSOE)*	Binary variable, 1 if the target is a state-owned company. We identified a firm as an SOE if the government owned a stake of more than 50%.	
	20	F13	*Private target (tarPriv)*	Binary variable, 1 if the target is a private company.	
	21	F14	*Public target (tarPub)*	Binary variable, 1 if the target is a public company.	
Country level institution	22	C1	*Acquire institution (acqWGI)*	Institutional quality of the acquiring firm's home country, measured by the average value of six indicators, voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption, in the year that the deal was announced.	World Bank's Worldwide Governance Indicators (WGI)
	23	C2	*Target institution (tarWGI)*	Institutional quality of the target firm's country, measured by the average value of six indicators, voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption, in the year that the deal was announced.	
	24	C3	*Target restrict (restrict)*	Restrictions on cross-border acquisitions in host countries. It takes the value 1 when a host country has restrictions (e.g. regulations for fair competition, and/or foreign investment review agency) on cross-border acquisitions, and 0 otherwise.	MOFCOM, and Pelsy and Bris (2018)
Country level economy	25	C3	*Acquirer HDI (acqHDI)*	Human development index of the acquiring firm's home country in the year that the deal was announced.	United Nations' Human Development Index (HDI)
	26	C4	*Target HDI (tarHDI)*	Human development index of the target firm's country in the year that the deal was announced.	
	27	C5	*Acquirer GDP growth (acqGDPg)*	GDP growth rate of the acquiring firm's home country in the year that the deal was announced.	World Bank's World Development Indicators
	28	C6	*Target GDP growth (tarGDPg)*	GDP growth rate of the target firm's country in the year that the deal was announced.	
	29	C7	*Acquirer GDP (acqGDP)*	Logarithm of GDP of the acquiring firm's home country in the year that the deal was announced.	
	30	C8	*Target GDP (tarGDP)*	Logarithm of GDP of the target firm's country in the year that the deal was announced.	
	31	C9	*Acquirer unemployment (acqUnemployment)*	Unemployment rate of the target firm's country in the year that the deal was announced.	
	32	C10	*Target unemployment (tarUnemployment)*	Unemployment rate of the acquiring firm's country in the year that the deal was announced.	
Country level culture (target)	33	C11	*Uncertainty avoidance (tar_uncertainty_p)*	The extent to which a society, organization, or group relies on social norms, rules, and procedures to alleviate unpredictability of future events; the higher the score, the lower the uncertainty avoidance.	GLOBE project
	34	C12	*Assertiveness (tar_assertiveness_p)*	The degree to which individuals are assertive, confrontational, and aggressive in their relationship with others; the higher the score, the less assertive they are.	
	35	C13	*Gender differentiation (tar_gender_p)*	The degree to which a collective minimizes gender inequality; the higher the score, the lower the gender equality.	
	36	C14	*Performance orientation (tar_performance_p)*	The degree to which a collective encourages and rewards group members for performance improvement and excellence; the higher the score, the lower the performance orientation.	
	37	C15	*Humane Orientation (tar_humane_p)*	The degree to which a collective encourages and rewards individuals for being fair, altruistic, generous, caring, and kind to others; the higher score, the lower the humane orientation	

(*continued on next page*)

Table 3 (*continued*)

			Variables (short names)	Measurement	Sources
	38	C16	*In-Group collectivism (tar_collectivismgroup_p)*	The degree to which individuals express pride, loyalty, and cohesiveness in their organizations or families; the higher score, the lower the in-group collectivism.	
	39	C17	*Institutional collectivism (tar_collectivism_p)*	The degree to which organizational and societal institutional practices encourage and reward collective distribution of resources and collective action; the higher the score, the lower the collectivism.	
	40	C18	*Power distance (tar_power_p)*	The extent to which the community accepts and endorses authority, power differences, and status privileges; the higher the score, the lower the power distance.	
	41	C19	*Future orientation (tar_future_p)*	The extent to which individuals engage in future-oriented behaviors such as planning, investing in the future, and delaying gratification; the higher the score, the lower the power distance.	
Cultural distance	42	C20	*Culture distance in practice (CD_p)*	The cultural distance (practice) between the host and home country. It was calculated by the following formula (Kogut & Singh, 1988): $CD\_p = \sum_{i=1}^{9}\{(I_{pit} - I_{pia})^2 / V_{pi}\}/9$ CD = cultural distance, I = a dimension index score, V= variance of an index, p = culture in practice, i = cultural dimension, t = target country, a = acquirer.	
	43	C21	*Culture distance in value (CD_v)*	The cultural distance (value) between the host and home country. It was calculated by the following formula (Kogut & Singh, 1988): $CD\_v = \sum_{i=1}^{9}\{(I_{vit} - I_{via})^2 / V_{vi}\}/9$ The notations in the formula are the same as above, except v indicates culture in value.	
Language and religious	44	C22	*Religious diversity (relig_diversity)*	Religious diversity in the target firm's country; the higher score, the higher the diversity.	The research web page for Douglas Dow, http://dow.net.au
	45	C23	*Language diversity (languagediversity)*	Language diversity in the target firm's country; the high the score, the higher the diversity.	
	46	C24	*Religious distance (relig_dist)*	Religious distance between the home and host country; the high score, the higher the distance.	
	47	C25	*Language distance (langdist)*	Language distance between the home and host country; the high the score, the higher the distance.	
Industry	48	I1	*Retail*	Binary variable, 1 if the target firm is in retail industry, 0 otherwise.	Thomson Reuters M&A Database
	49	I2	*Finance*	Binary variable, 1 if the target firm is in financial sector, 0 otherwise.	
	50	I3	*Telecom*	Binary variable, 1 if the target firm is in telecom industry, 0 otherwise.	
	51	I4	*Energy*	Binary variable, 1 if the target firm is in energy industry, 0 otherwise.	
	52	I5	*CPS*	Binary variable, 1 if the target firm is in consumer product and service industry, 0 otherwise.	
	53	I6	*Health*	Binary variable, 1 if the target firm is in health sector, 0 otherwise.	
	54	I7	*Media*	Binary variable, 1 if the target firm is in media and entertainment sector, 0 otherwise.	
	55	I8	*Staples*	Binary variable, 1 if the target firm is in consumer staples sector, 0 otherwise.	
	56	I9	*Realest*	Binary variable, 1 if the target firm is in real estate sector, 0 otherwise.	
	57	I10	*High-tech*	Binary variable, 1 if the target firm is in high-tech industry, 0 otherwise.	
	58	I11	*Resource*	Binary variable, 1 if the target firm is in resource industry, 0 otherwise.	
	59		*Year (y)*	The year that the acquisition is announced.	

for regression and classification problems that brings state-of-the-art predictive performance to a variety of practical tasks, such as web search, recommendation systems, weather forecasting, and many others (Dorogush et al., 2017). The term boosting refers to the computational learning approach that combines "the performance of many 'weak' classifiers to produce a powerful 'committee'" (Friedman et al., 2000, p. 337). The main idea of boosting is to add new models to the 'committee', 'ensemble' or 'network' sequentially. GB iteratively combines (often many) weak predictors (weak 'learners') into a single strong learner via a greedy procedure that corresponds to gradient descent in function space, standing on strong theoretical foundations. Gradient boosting typically uses decision trees (especially classification and regression trees, known as CART) as its base learners.

Gradient boosting decision tree (GBDT) is a special case, proposed by Friedman (2001), that seeks to improve the quality of each base learner. Importantly, GBDT has the advantage of containing multicollinearity, as claimed by Piramuthu (2008, p. 1225): "the presence of multi-collinearity is not of concern for decision trees". Similarly, Chan et al. (2022, p. 14) note that " machine learning algorithms are better than the simple OLS estimators with multicollinearity." Techniques in, e.g., the GBDT and random forest (Breiman, 2001a) class involve decision trees and recursive partitioning (Tomaschek et al., 2018) in combination with regularization and penalizing to counter overfitting (Chan et al., 2022), which facilitates mitigating the problem of multicollinearity. GBDT is a kind of supervised ML, which is robust and easy to use. As explained in Online Appendix III, the essence of GBDT is the estimation of a 'nonparametric' function, which does not require any *a priori* assumption regarding the form of underlying functions (e.g., linear, quadric or anything else) and model specifications (e.g., the nature, number, and dimensionality of interactions). GBDT, like any other ML technique, can result in (much) higher predictive – or explanatory – performance compared to traditional regression, particularly so in the case of large datasets and insufficient prior knowledge regarding the 'right' predictors or, in ML terminology, features and the associated data generation process (Russell & Norvig, 1995).

The literature provides user-friendly tools to run GBDT, including LightGBM (Ke et al., 2017), XGBoost (Chen & Guestrin, 2016), pGBRT (Tyree et al., 2011), scikit-learn (Pedregosa et al., 2011), and gbm in R (Ridgeway, 2007). While LightGBM and XGBoost outperform the other three implementations, LightGBM, developed by a Microsoft team, significantly outperforms XGBoost in terms of computation speed and memory consumption (Ke et al., 2017). In addition, using a loss function that is quite different from that of a normal decision tree, LightGBM (along with XGBoost) is capable of handling missing values. It puts data points containing missing values to whichever side of the split that reduces the loss the most. As we will argue and show below that missing values actually represent meaningful information, we should not ignore or simply impute them subjectively, but threat them as potentially informative. Based on these advantages, we choose LightGBM for our estimation, using the LightGBM Python module.

3.3. Step 3: set regulation and other hyperparameters

The third step involves algorithm tuning. We purposely introduce the math in Online Appendix III to make the underlying ML logic explicit. And as said, we list definitions of key ML jargon in Online Appendix II. Regarding regularization, a decision tree is subject to the danger of overfitting training data. To avoid overfitting, implementations of GBDT often involve adding a regularization term to the loss function. The introduction of such a regularization technique is a tradeoff between fitting the data and reducing the complexity of the model, and enables to select simpler but more predictive functions. Concerning the leaf split, GBDT needs to scan all the data instances (i.e., observations), for every feature, to estimate the information gain of all possible split points. Hence, it is most time-consuming to find the best split points for leaves in learning to grow the optimal decision trees, especially when handling Big Data, which usually contain high-dimensional features and many instances. Besides a number of conventional algorithms, such as pre-sorted and histogram-based algorithms, there are state-of-the-art techniques to tackle this challenge – e.g., gradient-based one-sampling (GOSS) and exclusive feature bundling (EFB) (Ke et al., 2017).

The term hyperparameter refers to the parameter regulating the design of the model (like learning rate and regularization) (Aggarwal, 2018). According to the documentation of LightGBM's Python package (Open source, assessed from https://lightgbm.readthedocs.io/en/v3.3.2/), the following list includes important parameters for tuning the LightGBM model: number of leaves (to set the maximum number of leaves in each weak learner and control the complexity of the tree model) or maximum depth for the tree model (to avoid growing deep tree), minimal number of data in one leaf (dealing with overfitting), and number of boosted trees to fit. After a grid-search experiment in which we trained and evaluated the model (using four-fold cross-validation) with many combinations of those hyperparameters, we short-listed the best-performing models through jointly evaluating multiple metrics (the same as those presented in Online Appendix I). We choose one candidate from the shortlist, the model with a combination of leaf number at 31, data sample per leaf at 20, and tree number at 100, which happened to be the default hyperparameter values of the software package, to proceed to the next step.

3.4. Step 4: evaluate final predictive performance and interpret models using variable importance

Model performance evaluation. After fine-tuning the hyperparameters, we have built the best-performing model possible for our data. Subsequently, we need to train this model on the training dataset and must evaluate the final predictive performance by applying the model to the test dataset. Note that this test sample was not used to train or validate in the previous steps, but represents the clean out-of-sample data that were set apart to evaluate model performance. This is a standard implementation step in ML's research process pipeline, following a firewall principle (Mullainathan and Spiess, 2017): None of the data (including those used in cross-validation and tuning processes) involved in fitting the prediction function is allowed to be used to evaluate the prediction function that is fitted in the training process. Model performance is evaluated using various metrics, such as those mentioned in Online Appendix I, which will be explained in the next section.

Model interpretation. Using complex models, the ML algorithms aim to generate the most accurate predictions for large datasets, outperforming simple models (e.g., linear combinations of predictors). The outcomes of these complex models, however, are often hard to interpret (Lundberg & Lee, 2017). Indeed, the output of the GBDT model is considered to be a black box by many (Alvanpour et al., 2020), containing many decision trees that are difficult to understand without further support. Hence, simpler metrics are needed as an interpretable approximation of the underlying complex models. SHAP (SHapley Additive exPlanations) is a prominent example of a metric serving this purpose, offering a unified approach for interpreting predictions (Lundberg et al., 2018; Lundberg et al., 2020). SHAP improves interpretability without deteriorating predictive accuracy.

The goal of SHAP is to explain the prediction of an instance by computing the (marginal) contribution of each feature to the prediction. Treating feature values of an instance as "players" in a cooperative "coalition game" (the prediction task with the prediction being the "payout"), the SHAP explanation method computes the optimal Shapley values by averaging the marginal contributions of feature values across all possible coalitions. SHAP has three important properties: (1) local accuracy, meaning that the explanation model $g(x')$ at least matches the output of the original model $f(x)$ for the simplified input x' (which corresponds to the original input x); (2) missingness, implying that missing features have no impact on the prediction; and (3) consistency, in the sense that if a model changes so that the marginal contribution of a feature increases or stays the same regardless of other features, that feature's attribution should not decrease (Lundberg & Lee, 2017).

Among a very broad range of explainable ML methods that have been developed in the AI community, known as Explainable Artificial Intelligence (XAI), SHAP is a widely used approach in the ML research community. According to a recent review article (Loh et al., 2022), of all the 10 XAI methods used in the 99 studies published in the top-Q1 healthcare journals up to March 2022, SHAP (used in 45 studies) is the most widely used XAI technique for explaining feature importance, followed by Gradient-weighted Class Activation Mapping (GradCAM) (used in 25 studies for visual explanation), and Local Interpretable Model-agnostic Explanations (LIME) (used in 3 studies). Recently, in Business research, we see a few examples of SHAP applications emerging (e.g., Fuad & Gaur, 2019; Valizade et al., 2022; Wang et al., 2022).

Note that, to further clarify how ML differs from traditional regression, we should be aware of the non-parametric nature of ML techniques. In this paper's example of GBDT, this implies that the SHAP value should not be interpreted as if this metric is similar to a ß coefficient produced by a traditional regression. Other ML techniques are associated with other interpretation-enhancing metrics (such as, e.g., Contribution, Feature Importance, and Most Frequent Interactions in random forests; see van Witteloostuijn and Kolkman, 2019), but all should be interpreted with care, taking account of the non-parametric nature of the underlying pattern-identifying algorithms. However, such measures are very useful by offering proxies for features' contribution and importance, the direction of influence, as well as prominent higher-dimensional 'interaction' candidates. Hence, contrary to what the 'black box urban myth' seems to suggest, ML does come with meaningful metrics that support explanatory interpretation, implying that the alleged black box colors are much more greyish than is oftentimes assumed.

4. Results

4.1. Model accuracy

The dataset used for the LightGBM prediction, with 59 predictors and 24,693 deals over the 1980–2019 period, is randomly split into a training set (17,778 deals) to learn the model to perform optimally, and a test set (6915 deals) for assessing the out-of-sample performance of the model, avoiding the misleading inflation of in-sample model fit statistics. Table 4 reports the LightGBM's model accuracy for the test datasets with different metrics. Table 5 provides LightGBM's prediction result on the test or validation set, of which 5133 deals are predicted correctly to

Table 4
Model accuracy of test dataset.

Category	Precision	Recall	f1-score	Support
0	0.60	0.28	0.38	1512
1	0.82	0.95	0.88	5403
Accuracy	0.80			6915

Table 5
Confusion matrix (test data).

	Actual = 1	Actual = 0
Predicted = 1	5133	1089
Predicted = 0	270	423

be in the completed class (True Positive) and 423 deals are predicted correctly to be a failure (True Negative).

We report five metrics. First, 'precision' is the ratio of the number of cases correctly predicted as completed (uncompleted) to the total number of cases coded as completed (or uncompleted) in the dataset. For example, the precision value of 0.60 in Table 4 corresponding to category 0 (i.e., uncompleted) in the test data tells that there are 423 cases correctly predicted as uncompleted out of a total of 693 (270+423) uncompleted cases (see Table 5). Second, 'recall' is the ratio of the number of cases correctly predicted as completed (or uncompleted) to the total number of cases actually being completed (or uncompleted). For example, the recall value of 0.95 corresponding to category 1 (i.e., completed) in the test data implies that 5133 cases are correctly predicted as completed out of 5403 cases that are actually completed. Third, the 'f1-score' is a harmonic mean of precision and recall. For example, the f1-score 0.88 corresponding to category 1 (i.e., completed) is the result of 2/(1/0.82+1/0.95). Fourth, 'accuracy' is the ratio of the number of cases correctly predicted as completed and uncompleted to the total number of cases. For example, the precision figure of 0.80 means that 5556 (=5133+423) cases are correctly predicted as completed and uncompleted out of all 6915 cases in the test data. Fifth, 'support' is the number of actually observed cases. The LightGMB's prediction has an overall accuracy of 0.80 for the test data.

Fig. 1 reports the area under the curve (AUC) of the receiving operating curve (ROC) of the test dataset, referred to as ROC-AUC. ROC is a probability curve that plots the true positive rate (TPR, also the recall corresponding to category 1 – i.e., the proportion of the positive class that is correctly classified) against the false positive rate (FPR, the proportion of the negative class that is incorrectly classified at various threshold values). AUC is a single number summarizing ROC, measuring the overall model performance despite any chosen threshold that is a prior probability set to distinguish different classes from one another. AUC can be interpreted as the probability that a randomly chosen positive instance is more likely to be ranked (classified) as positive by the classifier than a randomly selected negative case (Hajian-Tilaki, 2013). AUC ranges between 0 and 1, with 1 suggesting a perfect model. When AUC > 0.5, the (binary) classifier is considered to have a higher chance to distinguish the positive from the negative class. The LightGBM classifier yields an AUC of 0.80 for the test dataset, as shown in Fig. 1, whilst outperforming a set of alternative models, in terms of AUC, as revealed by the cross-validation results on the training dataset (see Online Appendix I for further detail).

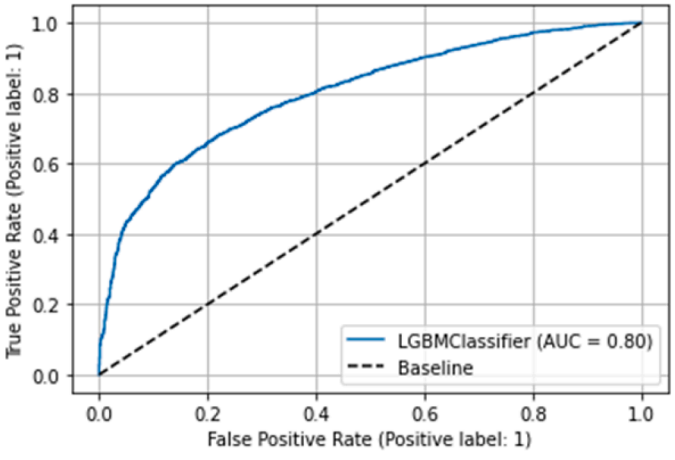

Fig. 1. Area under the curve (AUC) of the receiving operating curve (ROC)
The upper blue curve represents the model's ROC, which is a probability curve that plots the TPR against the FPR. The dashed straight line represents a random (i.e., equally likely to classify a case as completed or incompleted) model's ROC. The area under the ROC reflects the model's overall performance. LightGBM's AUC equals 0.80. This means that a randomly chosen completed case is more likely (with a 0.8 probability) to be classified as completed by the LightGBM than a randomly selected incompleted case.

4.2. *Interpretation of the output of the lightGBM model*

A larger SHAP value in the positive direction represents a larger contribution of the corresponding predictor (feature) in a positive direction, implying that a CBA with a higher value of this predictor (feature) is more likely to be completed; a larger SHAP value in the negative direction reflects a larger contribution of the corresponding predictor (or feature) in the negative direction, meaning that a CBA with a higher value of this feature is less likely to be completed. Fig. 2 presents the mean absolute SHAP values for features over the test dataset. With this figure, we provide a general picture of the importance of features in predicting EMNE CBA deal completion. *Public acquirer* enjoys the highest SHAP value of 0.67, and the other 14 predictors from *Public target* to *Acquirer HDI* rank from 2nd to 15th in the diagram. Note that the sum of the SHAP values of the rest 44 predictors is only 0.74. Although this does not seem to be impressive, this does not mean that they are negligible.

Further, to gain detailed information on the importance of each predictor, we display the SHAP value distribution and effects of all predictors for the test dataset in Fig. 3. Corresponding to Fig. 2, from the top to the bottom along the vertical axis, the predictors are sorted in descending order according to their contribution or importance to the model's prediction. The horizontal axis indicates the SHAP value. Each dot on the diagram represents an instance (observation), where the position is determined by the SHAP value of the corresponding feature. Overlapping dots form a larger or smaller shadow. A large positive SHAP value (right) indicates a high contribution of the variable in a positive direction; in contrast, a large negative SHAP value (left) indicates a high contribution of the variable in a negative direction. The color represents the value of a predictor, with red being a higher value, blue being a lower value, and grey being a missing value. If the red falls in the positive and the blue in the negative direction, we interpret this as a positive relationship between the variable and acquisition completion (e.g., *tarPriv*). If the red falls in the negative and the blue in the positive direction, we take this as a negative relationship between the variable and acquisition deal completion (e.g., *acqPub*).

Note that we removed redundant predictors that reduced the model's predictive accuracy along the way. This is a common practice in feature selection in ML, which is a critical process to minimize classification error by following the MRMR (max-relevance and min-redundancy) principle (Peng et al., 2005). This process is similar in spirit to backward or forward stepwise regression, which is not very popular in IB (and Business broadly) due to its mechanistic and a-theoretical nature. Seen through a causal explanation lens, this is understandable. However, in the context of importance identification, this mechanistic approach has value added by producing relevant information in its own right. That is, being removed from the model implies that the associated predictor is unimportant, which is a very relevant insight from the perspective of stock-taking knowledge solidification, also indicating that this variable should probably not be a building block in an inductively developed theory. In terms of stimulating effective and efficient theoretical progress, knowing what not to focus on is important, too, next to the identification of what does deserve further attention.

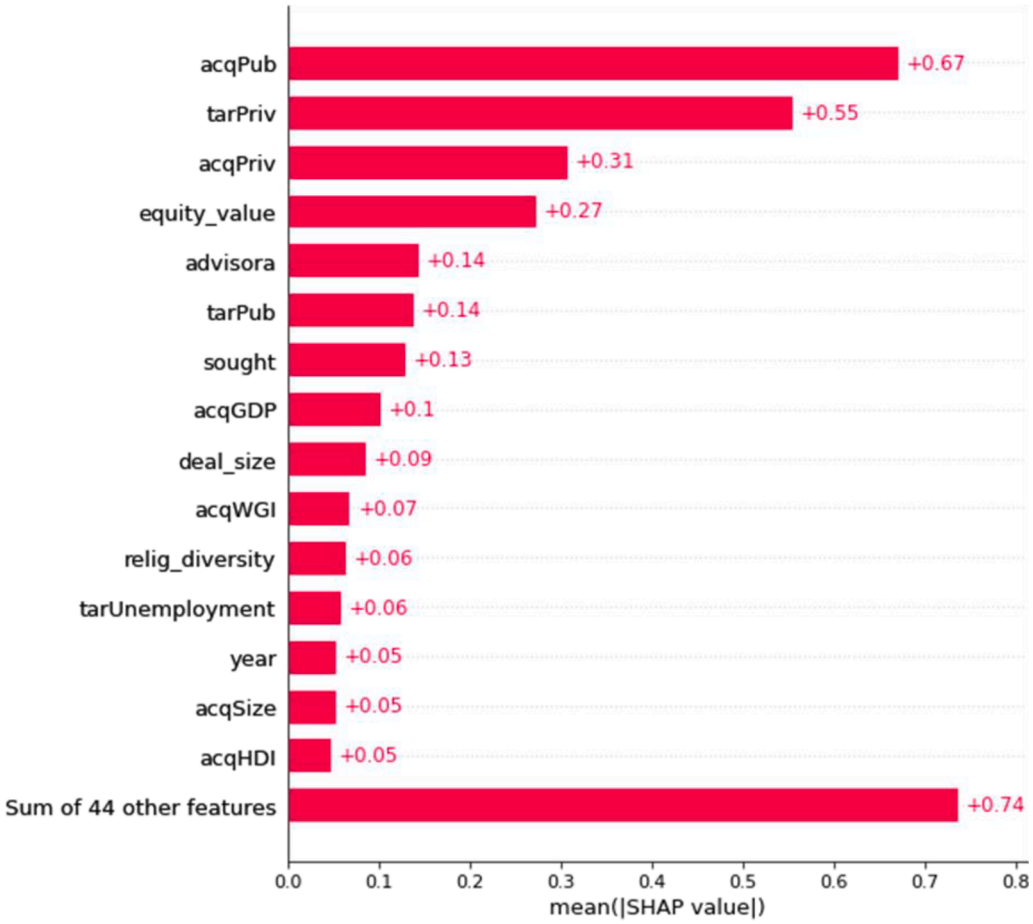

Fig. 2. Mean SHAP values of predictors in the test set
The numbers beside the red bars are the mean SHAP values of each of the predictors. For long variable names, we refer to Table 3.

4.3. Important predictors

Below, we reflect on feature importance (as shown in Fig. 2), and compare the LightGBM predicted results (as illustrated in Fig. 3) with the findings from prior studies on EMNE CBA completion. To facilitate this comparison, we categorize predictors into four groups based on their relative importance/unimportance as revealed by LightGBM and the confirmed/unconfirmed evidence as reported in earlier empirical studies. This is presented in Table 6, which includes the mean absolute SHAP value, the associated rank for each variable in terms of this SHAP value, their relationships with CBA completion as predicted by LightGBM, and any evidence in prior work.

Group 1 includes 12 variables that LightGBM identifies as relatively important and for which prior EMNE CBA studies have provided evidence about their impact, representing influential predictors for deal completion revealed in both this study and existing research. Here, the LightGBM outcomes for some predictors (e.g., *Private target, Private acquirer, Public target, Advisor*, etc.) regarding their relationships with CBA completion are in line with earlier studies' evidence. However, we have noted instances that present inconsistencies compared to prior evidence. Take *Percentage sought*, for example. Evidence documented in prior work points to a rather simple relationship with CBA completion: either positive (C. Zhou et al., 2016; Li et al., 2019) or negative (Dong et al., 2019). But its SHAP pattern suggests a U-shaped relationship, as shown in Fig. 4, which means that a medium range of sought percentages may be more failure-prone than very low or high percentages.

A possible explanation could be that such a medium-range acquisition may encounter extra obstacles from stakeholders when an acquirer tends to seek a certain percentage of shares to control or overstep other shareholders. Another argument could be that the relationship is conditional on a not-yet-identified contingency that is related to the range of sought percentages. These possibilities are under-researched in extant work. Instead, earlier studies tend to assume that deals with a high percentage sought are inherently more complex and are subject to closer regulatory scrutiny, hence being less likely to be completed (Muehlfeld et al., 2007). The U-shape suggests that more research is needed to investigate the underlying mechanism that explains the non-linear relationship.

Another example involves *Acquire institution*, for which prior studies reported a positive effect (He & Zhang, 2018; Zhang, 2022). In contrast, its SHAP pattern indicates ambiguity, perhaps due to missing values. Here, the LightGMB outcome for missing values is very informative. Since the institutional data needed to construct the *Acquire institution* measure, derived from worldwide governance indicators (WGI), are only available after 1996, the values from 1981 to 1995 are inevitably missing. As explained above, the ML model also takes the missing values on board in learning the 'optimal' prediction: The acquisitions with missing values are more likely to be completed. This may suggest that institutional voids of emerging countries were not a failure factor for EMNEs in their earlier stage of internationalization. In addition, we see a few exceptions at the left-hand side of the distribution, where higher values (red) of *Acquirer institution* are associated with negative SHAP values. These findings call for more research, too.

Group 2 includes eight variables that prior empirical studies have not identified as influential, but turn out to be relatively important predictors in our LightGBM analysis. Among these variables, the finding related to *Equity value* is particularly intriguing. Despite this variable's informative accounting information, its influence has remained,

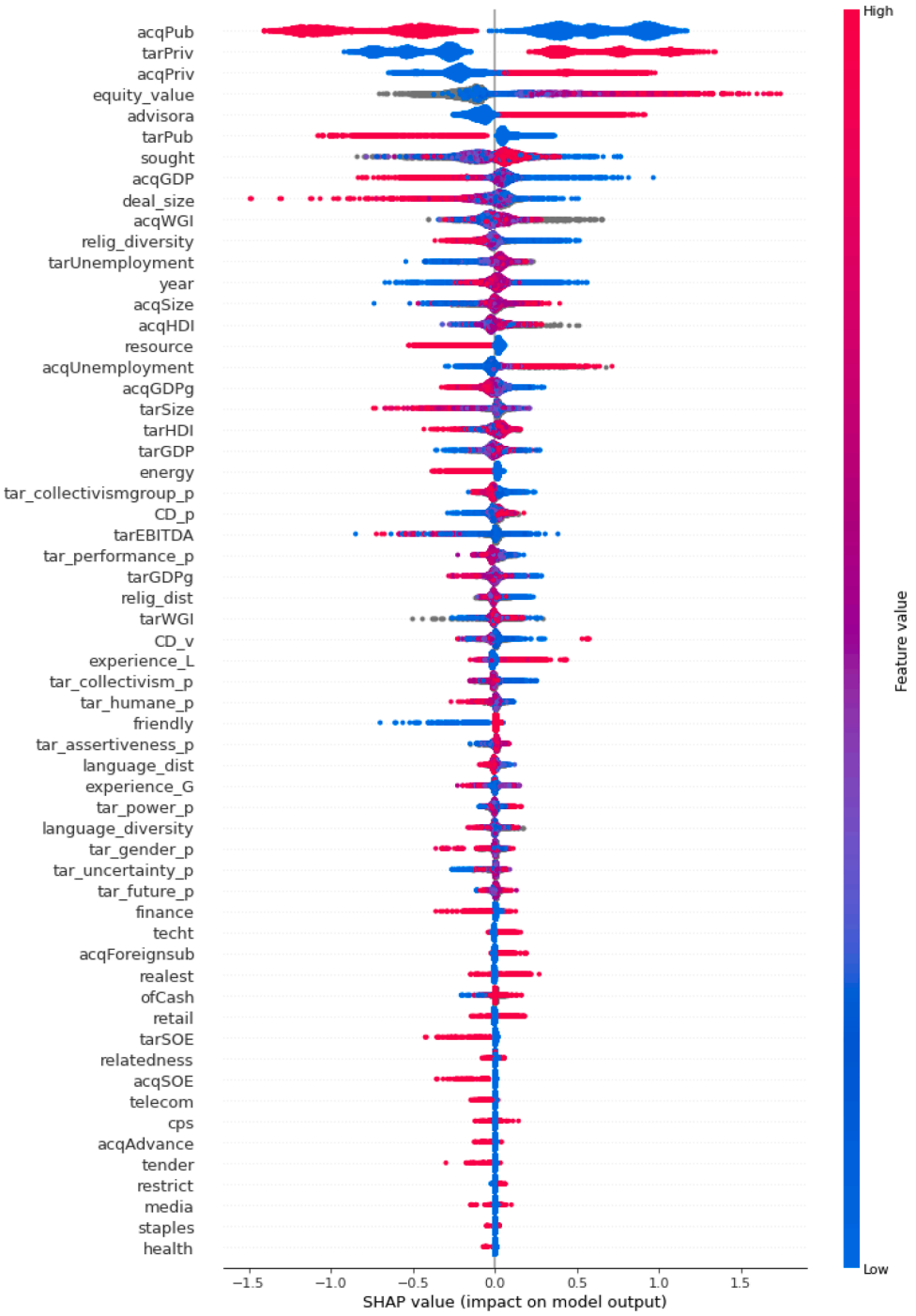

Fig. 3. SHAP values of the predictors

This is a scatter plot of SHAP values for the predictors. The predictors' labels are presented at the left-hand side. SHAP values are presented on the horizontal axis. The color of each point represents the values of each predictor of individual CBAs, as indicated by the color bar at the right-hand side, with red being a higher value, blue being a lower value, and grey being a missing value. If the red falls at the positive (right) and the blue at the negative (left) side, we have identified a positive relationship between the variable and acquisition completion (e.g., *tarPriv*). If the red falls at the negative and the blue at the positive side, this means we have detected a negative relationship between the variable and acquisition deal completion (e.g., *acqPub*). For long variable names, we refer to Table 3.

surprisingly, unexplored in prior research. It ranks fourth in terms of mean absolute SHAP value, indicating a positive relationship with acquisition completion, as depicted in the SHAP diagrams. As *Equity value* captures the book value of a target firm, information asymmetry could provide an explanation for this result. After all, in the M&A market, target valuation is critically important. To assess target valuation, the target firm's accounting information, such as book value, is key to form an estimate of the target's present value, with book value demonstrating the value of the firm's resources, independent of how a firm uses these resources (Rabier, 2018).

Indeed, acquirers typically use targets' historical accounting information to decide on their bids (McNichols & Stubben, 2015). Hence, equity value is a very relevant factor, offering an estimate of both current and potential future value. On the other side of the potential marriage, if target firms have valuable resources and create financial value, their managers are more willing to signal value-creating features (Uyar

Table 6
Comparison of LightGBM-predicted results with findings from prior EMNE CBA research.

Group 1: Predictors that LightGBM identifies as relatively important and for which prior EMNE CBA studies have provided evidence about their impact

Predictor	SHAP value	SHAP rank	ML predicted direction	Prior empirical evidence
Public acquirer	0.671	1	(-)	(+) (Liu et al., 2022) (-) (Zhu et al., 2014)
Private target	0.555	2	(+)	(+) (Zhang et al., 2011; Dong et al., 2019)
Private acquirer	0.307	3	(+)	(+) (Dong et al., 2019)
Advisor	0.143	5	(+)	(+) (Zhang & Ebbers, 2010; Zhang et al., 2011; Zhang et al., 2017; He & Zhang, 2018; Sun et al., 2019; Liu et al., 2022;Zhang, 2022)
Public target	0.138	6	(-)	(+) (Liu et al., 2022) (-) (C. Zhou et al., 2016; Li et al., 2019;Wang et al., 2020)
Percentage sought	0.129	7	A	(+) (C. Zhou et al. 2016; Li et al. 2019) (-) (Dong et al., 2019)
Deal size	0.085	9	(-)	(+) Zhu et al., 2014; Fuad & Gaur, 2019) (-) (Li et al., 2019)
Acquire institution	0.067	10	A	(+) (He & Zhang, 2018; Zhang, 2022)
Target unemployment	0.057	12	(+)	(+) (Zhang, 2022)
Acquirer firm size	0.051	14	(+)	(+) (C. Zhou et al., 2016; Wang et al., 2020; J. Zhou et al., 2022)
Resource	0.045	16	(-)	(-) (Zhang et al., 2011; Zhang et al., 2017; He & Zhang, 2018)
Target firm size	0.042	19	(-)	(-) (Zhu et al., 2014)

Group 2: Predictors that LightGBM identifies as relatively important, but for which prior EMNE CBA studies have not provided evidence about their impact

Predictor	SHAP value	SHAP rank	ML predicted direction	Prior empirical evidence
Equity value	0.272	4	(+)	None
Acquirer GDP	0.101	8	(-)	None
Religious diversity	0.064	11	(-)	None
Year	0.052	13	A	None
Acquirer HDI	0.047	15	A	None
Acquirer unemployment	0.044	17	(+)	None
Acquirer GDP growth	0.043	18	(-)	None
Target HDI	0.041	20	A	NS (1 study)

Group 3: Predictors that LightGBM identifies as relatively unimportant, but for which prior EMNE CBA studies have provided evidence about their impact

Predictor	SHAP value	SHAP rank	ML predicted direction	Prior empirical evidence
Target GDP	0.034	21	A	(-) (Zhang et al., 2017; He & Zhang, 2018)
Energy	0.03	22	(-)	(-) (Zhang et al., 2017)
Target institution	0.024	29	A	(+) (Zhang et al., 2011; Zhang, 2022)
Culture distance in value	0.023	30	A	(+) (Popli et al., 2016) (-) (Dong et al., 2019)
Local experience	0.023	31	A	(+) (Dong et al., 2019; Hawn 2021) (-) (Wang et al., 2020)
Friendly acquisition	0.017	34	(+)	(+) (Liu et al., 2022)
Global experience	0.014	37	A	(+) (Zhang & Ebbers, 2010; Zhang et al., 2011; Zhang et al., 2017; He & Zhang., 2018; Li et al., 2019) (-) (Fuad & Gaur, 2019)
High-tech	0.008	44	A	(+) (Sun et al., 2019)
Foreign subsidiary	0.007	45	(+)	(+) (He & Zhang, 2018; Zhang, 2022)
Real estate	0.007	46	A	(+) (Zhang et al., 2017)
Cash payment	0.007	47	(+)	(+) (C. Zhou et al., 2016; Madhavan & Gupta, 2017; Dong et al., 2019; Wang et al., 2020; Liu et al., 2022; Zhou et al., 2022)
SOE target	0.005	49	(-)	(-) (He & Zhang, 2018; Zhang, 2022)
Industry relatedness	0.004	50	A	(+) (J. Zhou et al., 2016; Zhang et al., 2017; He & Zhang, 2018)
SOE acquirer	0.004	51	(-)	(-) (Zhang & Ebbers, 2010; Zhang et al., 2011; Zhang et al., 2017; He & Zhang, 2018; Li et al., 2019; Sun et al., 2019; Wang et al., 2020; Zhang, 2022)
Tender	0.002	55	A	(+) (Zhu et al., 2014)

Group 4: Predictors that LightGBM identifies as relatively unimportant and for which prior EMNE CBA studies have not provided evidence about their impact

Predictor	SHAP value	SHAP rank	ML predicted direction	Prior empirical evidence
In-Group collectivism	0.03	23	(-)	None
Culture distance in practice	0.028	24	(+)	None
Target performance	0.027	25	A	None
Performance orientation	0.027	26	(-)	None
Target GDP growth	0.024	27	A	NS (2 studies)
Religious distance	0.024	28	(-)	None
In-Group collectivism	0.02	32	(-)	None
Humane Orientation	0.02	33	(-)	None
Assertiveness	0.015	35	(+)	None
Language distance	0.014	36	(-)	None
Power distance	0.013	38	A	None
Language diversity	0.013	39	A	None
Gender differentiation	0.011	40	A	None
Uncertainty avoidance	0.01	41	A	None
Future orientation	0.01	42	A	None
Finance	0.01	43	A	None
Retail	0.006	48	A	None
Telecom	0.003	52	(-)	None
CPS	0.002	53	A	None
Advanced parent	0.002	54	A	None
Target restrict	0.001	56	A	None
Media	0.001	57	A	None
Staples	0.001	58	A	None
Health	0.001	59	(-)	None

Note: A = sign ambiguity; NS = non-significant; for the sake of brevity, we only explicitly refer to studies reporting significant estimates.

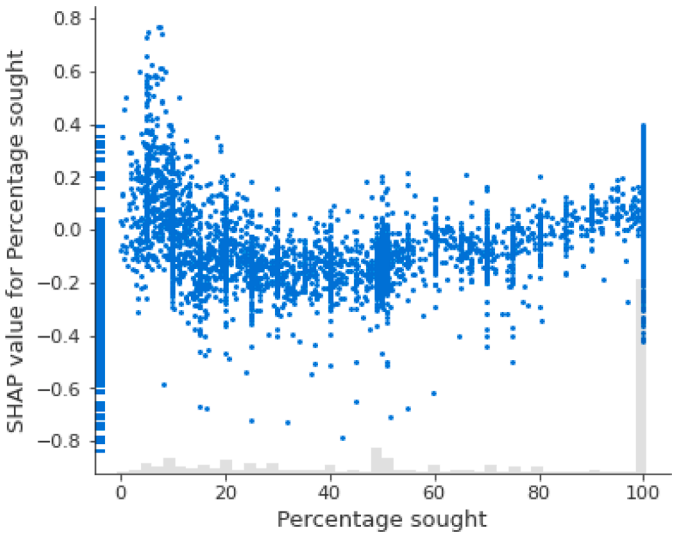

Fig. 4. Scatter plot of SHAP value of *Percentage sought*
Each CBA deal is plotted as a blue dot in the frame, which specifies a deal uniquely by a vertical coordinate (a SHAP value) and a horizontal coordinate (a *Percentage sought* value).

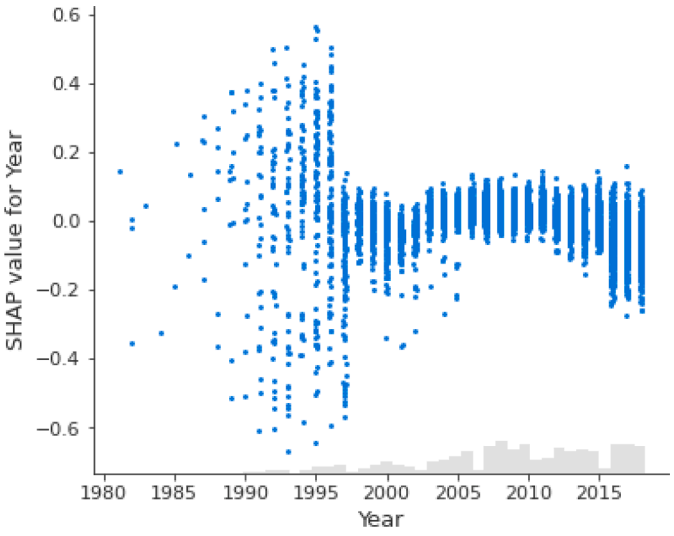

Fig. 5. Scatter plot of SHAP value of *Year*
Each CBA deal is plotted as a blue dot in the frame, which specifies a deal uniquely by a vertical coordinate (a SHAP value) and a horizontal coordinate (a *Year* value).

& Kiliç, 2012) or "fair" equity valuation (DeAngelo, 1990) to stakeholders by disclosing information. In line with this, empirical studies found a positive relationship between information disclosure and a firm's equity value (Aksu & Kosedag, 2006; Uyar & Kiliç, 2012). Information disclosure decreases information asymmetry, leading to an increased likelihood of deal completion (Li & Sai, 2020). Additionally, we notice that missing values of *Equity value* are clustered at the left-hand side, and are apparently associated with low SHAP values in Fig. 3: When *Equity value* information is missing, acquisition deals are less likely to be completed. Thus, a higher equity value may facilitate the marriage valuation process, which is plagued with information asymmetry, by signaling value-creating features that otherwise would be hidden behind the smoke of asymmetric and non-disclosed information.

However, higher book value does reflect a mix of elements, including firm size (as a component of firm assets on the balance sheet), shareholders' claims (particularly important during financial stress or bankruptcy liquidation), and financing decisions, as well as historically accumulated earnings plus future expected earnings. Our explanation above mainly relates to the earning aspect implied by earnings-based cashflow discount valuation models. Those other factors may or may not translate into attractiveness or may or may not mean anything for the value of firm resources, having or not having an impact, all generating a different effect on deal completion. Hence, further work is needed to unravel the relative importance of rival explanations. In all, here we have a clear example of an ML analysis identifying a new predictor that deserves detailed attention in future research – for instance, by focusing on the underlying mechanisms through in-depth qualitative studies.

The finding regarding *Year* is yet another interesting example. Its SHAP diagram shows that lower values (earlier years) are associated with both high and low SHAP values. In the later years (1998 and onward), the SHAP values are concentrated in the middle (around zero). This pattern is further detailed in Fig. 5 with a scatter plot. *Year* can be linked to boom and bust in the economic cycle, and volatility and uncertainty in the financial and M&A market. In the current context, *Year* may reflect different stages of a merger wave or none wave, concurring with the argument that timing is a critical factor influencing acquisition completion (Fuad & Gaur, 2019). Fuad and Gaur (2019) argue that around the merger wave peak, implying intense acquisition activity, uncertainty increases and creates frictional dissonance between both the target and the acquirer. Hence, they found that, compared to non-peak deals, deals conducted within merger wave booms are less likely to be completed. Moreover, Kumar and Sengupta (2020) claim that volatility, uncertainty, complexity, and ambiguity all lead to conflict during negotiations, which causes the abandonment of deals. In line with these arguments, our finding suggests that before and after the burst of the dot.com bubble (around 2000), the effect patterns of *Year* are totally different. But more research is needed to investigate how precisely timing affects acquisition completion (for a recent attempt, see Doan et al., 2021).

Groups 3 and 4 are home to variables identified as unimportant in our comprehensive ML analysis. On the one hand, Group 3 includes 15 variables that prior empirical studies have identified as influential and relevant, but which emerge as unimportant (or less important) in our LightGBM analysis. For example, *Industry relatedness, SOE acquire, Cash payment, Local experience* and *Global experience* were frequently emphasized in prior studies as critical, but our model suggests that these variables are less important. Further down the line, we will discuss the implications of our findings for these variables. On the other hand, Group 4 involves 24 variables that LightGBM identifies as relatively unimportant and for which prior empirical work has not provided evidence about their impact. Hence, although these variables are put forward as potentially relevant in the extant literature, their empirical impact seems to be negligible.

On the basis of the comparison of evidence from our ML analysis and prior empirical studies, we shortlist variables that are particularly important and interesting, hence signaling promising future research avenues. This list consists of the top 15 variables ranked by SHAP value (see Fig. 2 and Table 6), topping the lists of Groups 1 and 2. The SHAP metrics establish the importance of these variables. Notably, both our ML model and prior empirical analyses support the critical influence of the majority of these variables, albeit not always with similar effects. While we have discussed a few above already, a more extensive exploration of these variables, along with a few additional Group-3 variables (e.g., *Global experience, Local experience, Acquirer SOE*, and *Industry relatedness*) extensively studied in prior empirical works, will follow further down the line.

4.4. The importance versus complexity framework

The SHAP diagrams of a large number of predictors exhibit complex patterns. We construct an importance versus complexity (simplicity)

framework to further elucidate the influence of each of the 59 predictors. This framework focuses on two dimensions: importance and direction. Based on this pair of dimensions, four quadrants representing four types of predictors are distinguished and visualized in Fig. 6. The vertical dimension in Fig. 6 captures the importance of each predictor, as measured by the rank of SHAP value, which ranges from 1 (the least important) to 59 (the most important). The horizontal dimension reflects the complexity or simplicity of the relationship, indicating whether there is a simple relationship between a predictor and CBA completion (i.e., linear relationship) or a complicated relationship (e.g., non-linear relationship, or a relation conditional on certain contextual contingencies).

Our ML algorithms provide a SHAP value for each variable for each observation (announced acquisition deal). We calculate the correlation coefficient between the SHAP values of a variable and the values of this variable within the test sample. The simplicity of the relationship is measured by the absolute value of a correlation coefficient that we refer to as the simplicity metric. We create this measure based on the following rationale. A SHAP value indicates the importance of the effect of a variable, but this effect could be negative, positive or both. We need a metric to reveal whether the effect is directional (negative or positive) or ambiguous (both) – that is, to identify whether or not the effect of a variable is monotonically increasing or decreasing. A high positive (negative) correlation coefficient between the SHAP value of a variable and the value of this variable indicates a clear positive (negative) relationship. Therefore, the simplicity metric ranks from 0 (very complicated and unclear relationship) to 1 (very simple and clear relationship).

Quadrant 1 (North-East) represents predictors that are important with a straightforward impact (either positive or negative). In total, there are 20 predictors in this quadrant. Among them, 11 are among the top-15 (in red color) discussed above. The rest include one firm-level factor, *Target firm size* (+), two country-level economic factors, *Acquirer unemployment* (+), and *Acquirer GDP growth* (-), four cultural factors, *In-Group collectivism* (-, likelihood of completion is high in collectivist societies), *Performance orientation* (-, likelihood of completion is high in the performance-orientated societies), *Religious distance* (-), and *Cultural distance in practice* (-), and two industry-level factors, *Resource* (-) and *Energy* (-). The impact of these predictors on acquisition completion is in line with theoretical predictions and available evidence (see Table 1 for details). All of these 20 predictors are candidates for inclusion in a comprehensive model of EMNE CBA deal completion. This quadrant provides important practical implications for EMNEs, as we will briefly discuss below.

Quadrant 2 (North-West) includes predictors that are important, but with an unclear, and hence probably complex, impact. We have 10 predictors in this quadrant, which are perhaps the most intriguing features. On the one hand, these predictors have an important contribution to the prediction of EMNE CBA completion. However, on the other hand, we have insufficient knowledge about how precisely they influence the outcome. The possible reasons could be that the influence is non-linear, is conditional on certain contextual contingencies, or is interacting with other factors. Besides *Percentage sought, Acquirer institution, Acquirer HDI* and *Year* that we discussed above, this quadrant houses four country-level factors, *Target HDI, Target GDP, Target GDP growth, Target institution* and *Cultural distance in value*, and one firm-level factor, *Target performance*. These predictors call for future research to further unravel the underlying complexity in search of explanations of switches in the sign of their impact. Qualitative studies may be required, in addition to quantitative studies, to deepen our understanding and explain the complex interdependencies.

Quadrant 3 (South-West) is home to predictors that are less important, and with ambiguous impact. This ambiguity can be found in the extant EMNE CBA completion literature, too. For example, *Industry relatedness* is normally anticipated to be a positive predictor, which means that completing a deal is easier when the acquirer and target are in the same industry. In line with this theoretical prediction, a few prior studies have found a positive and significant relationship (He & Zhang, 2018; Zhang et al., 2017). However, other prior work reported that the relationship is not significant (e.g., Fuad & Gaur, 2019; Popli & Kumar, 2016). The ambiguity also accounts for other predictors in this quadrant, such as *Experience* and *Cash payment* (see Table 1 for an overview of earlier findings). In all, our ML analysis suggests that this set of predictors may not be high on the list of candidates for future research, being unimportant and without a clear direction.

Quadrant 4 (South-East) includes predictors that are less important, but with their impact being straightforward. Some predictors in this quadrant have been discussed in the extant literature, such as *SOE acquirer* (-) and *SOE target* (-) (Li et al., 2019; Zhang et al., 2011), *Friendly acquisition* (+) (Liu et al., 2022), *Language diversity* (-) (Li & Sai, 2020), and *Foreign subsidiary* (+) (He & Zhang, 2018). Additionally, we notice

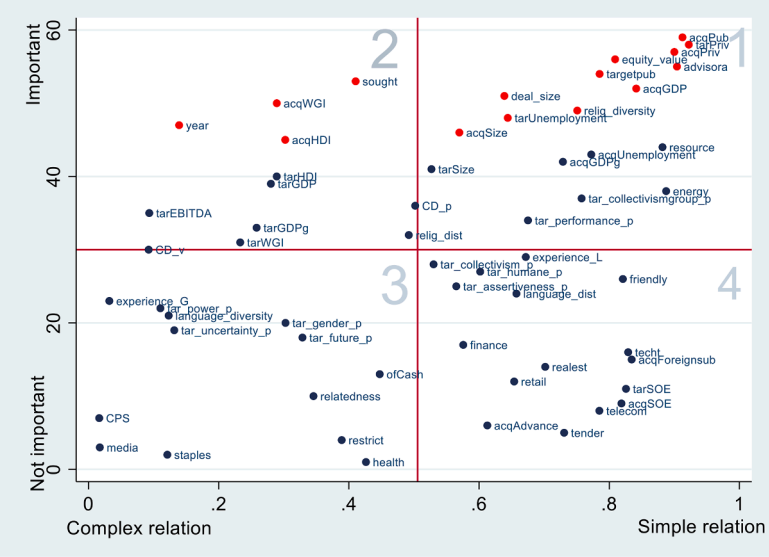

Fig. 6. Importance and complexity of the effect of predictors on CBA completion
The vertical dimension captures the importance of the predictors, which ranges from 1 (the least important) to 59 (the most important). The horizontal dimension indicates the simplicity of the relationship, which ranges from 0 (the least simple relationship, with no linear pattern at all) to 1 (the simplest relationship with a clear linear pattern). The red dots are the top-15 predictors. For long variable names, we refer to Table 3.

that the impact of a number of cultural aspects in the target country is relatively important in the prediction, such as *Institutional collectivism* (-), *Humane orientation* (-), and *Assertiveness* (+). To explore the causal rationale behind these predictors, we need more research. However, given their lower importance, the ML analysis indicates that this set of variables need not be placed high on the research agenda's priority list.

It is worth noting that although the predictors in Quadrants 3 and 4 are less important than those in Quadrants 1 and 2, they may well be theoretically and practically relevant in specific circumstances. Two predictors regarding *Experience* are a case in point. Organizational learning theory suggests that experience can create a positive learning effect on firm performance because experience helps a firm to create knowledge and build problem-solving ability. In line with theory, studies have revealed a positive impact of acquisition experience on EMNE CBA completion (He & Zhang, 2018; Zhang et al., 2017; C. Zhou et al., 2016), as well as in the case of MNE CBA completion in specific industries (Dikova et al., 2010; Muehlfeld et al., 2012). However, other studies found experiences to have a negatively significant effect on acquisition deal completion in multi-country samples (Lim & Lee, 2016, 2017) and in Indian cases (Fuad & Gaur, 2019; Madhavan & Gupta, 2017), and yet others report the effect not to be significant in Chinese cases (Dong et al., 2019; Wang et al., 2020). Indeed, Muehlfeld et al. (2012) conclude that the positive effect of experience is conditional on the context.

Related to this, our prediction model indeed reveals potentially more complex patterns. Fig. 6 shows that *Global experience* has a complicated relationship with acquisition completion (Quadrant 3). Its SHAP diagram (Fig. 3) indicates that higher values of the variable (more experience) are associated with both high and low SHAP values, suggesting a non-linear relation. In contrast, the relationship between *Local experience* and acquisition completion is more straightforward (Quadrant 4). Its SHAP diagram in Fig. 3 reveals that higher values of the variable (more local experience) are mostly associated with higher SHAP values, suggesting a positive relationship. This complicated impact of different types of experience on acquisition completion calls for more research that may reveal that features identified as less important in the current ML analysis are important after all in the specific context of a complex web of interdependencies.

4.5. Robustness analysis

One issue deserves additional attention. Our data are multi-level in nature, with deal, firm, and country-level features. Models dealing with such nested data may be subject to ecological fallacy if not specified correctly (Robinson, 1950) – i.e., the error of interpreting variations in groups as variations among individuals. To avoid the ecological fallacy bias, multi-level analysis would be appropriate. To explore this issue, therefore, we decided to run a classic multi-level regression with our data to see whether or not the results from such an analysis are aligned with the ML pattern of findings reported above. To not stretch the length of the current manuscript beyond reasonable limits, we refer to Online Supplementary Material for all the details. Here, we only discuss the main conclusions from this systematic comparison.

The standardized beta coefficients, reflecting the predictors' effects on the deal completion outcome (expressed as log-odds), estimated from the multi-level models controlling for random (group) effects, are systematically compared with the effects reported in our paper as derived from the interpretation of SHAP values. The findings are two-fold. First, the comparison between the relative effect sizes (standardized beta coefficients) and SHAP-indicated relative importance of predictors reveals that the correlations between the two measures are highly positive (above 0.85). This suggests that the results estimated by ML models in our paper, in terms of SHAP values, are largely compatible with those estimated by the multi-level logistic models in terms of effect size. Second, the SHAP-indicated negative directions in the ML models are highly aligned with the negative beta coefficient signs in the multi-level models, the SHAP-indicated positive directions are largely in line with the positive beta coefficient signs, and the SHAP-indicated ambiguous directions correspond to rather mixed beta coefficient signs.

Up-front, we want to emphasize four key differences between both analyses – differences that reflect critical strengths of ML that cannot be accommodated by classic multi-level regression. The first is that the number of observations in classic regression drops from 24,693 to 15,893 because, in contrast with ML, many observations must be deleted due to missing values. Second, and related, six variables had to be dropped from the analyses altogether since these are associated with too much missingness. Third, as traditional multi-level modeling requires the *a priori* specification of a data generation process, we could not accommodate unknown complexities (such as subtle nonlinearities) as we can with ML, as explained and illustrated above. ML algorithms, including LightGBM, find the function to "learn" the underlying complex relationships (including their ecological intricacies), more flexibly approaching the (real) data generation process. In contrast, multi-level regression addresses this issue by "manually" specifying models that either control for or allow for fixed and/or random effects, being restrictive and susceptible to possible misspecifications. Fourth, LightGBM demonstrates a better overall model fit than the multi-level model in terms of ROC-AUC. The AUC of our LightGBM classifier for the test dataset is 0.803 (as mentioned earlier), whereas the AUC of our multi-level regression ranges from 0.723 to 0.736 across various random intercept and fixed slope models. This suggests another advantage of LightGBM over traditional regression in correctly distinguishing between completed and not completed CBA deals.

5. Discussion

5.1. Main findings

5.1.1. An overview

To contribute to a comprehensive understanding of the many potential determinants of the success or failure of EMNEs' CBA attempts, and their relative importance, we conducted an empirical investigation into a large set of underlying factors that are identified as (potentially) relevant across the literature. After a careful comparison of different ML algorithms, we opted for LightGBM, which is a modern ML technique generating high predictive accuracy by creating powerful ensembles of predictors through an iterative learning algorithm, avoiding overfitting by regularization and out-of-sample validation. Using a large data sample covering 24,693 EMNE CBAs and 59 predictors over the 1980–2019 period, our LightGBM analysis produced a ranking of variables predicting EMNE CBA completion or failure in descending order of importance. In this way, we performed a helicopter-view study that takes stock of what is more and what is less important to understand EMNE CBA completion. The major findings are summarized below.

As one of the first efforts to comprehensively explore the importance of predictors of acquisition completion, this study provides an overall picture of the relative contribution of a large number of multi-level factors. Our algorithm clearly ranks 59 factors according to their SHAP values, indicating their contribution to the prediction of the likelihood of an EMNE CBA being completed or not. The top 15 variables, also representing influential factors in both our ML analysis and prior empirical work, include *Public acquirer, Private target, Private acquirer, Equity value, Advisor, Public targets, Percentage sought, Acquirer GDP, Deal size, Acquire institution, Religious diversity, Target unemployment, Year, Acquirer firm size* and *Acquirer HDI*. The majority of these variables pertain to firm-level factors involving ownership and size features of acquirers and targets, as well as deal-level factors.

To further explore the complicated patterns displayed in terms of SHAP values, we comparatively assess the effect of the 59 factors synthetically by constructing two matrices. The first matrix relates the ML outcomes to empirical evidence (or lack thereof) in the literature. In so doing, we identify gaps or inconsistencies in extant knowledge that

deserve further attention in future work. In the second matrix, we place all predictors along two criteria, importance and complexity/simplicity (or ambiguity, put differently), classifying all factors into four quadrants. In general, this two-dimensional analytical framework discloses two aspects of the effect of a factor: their importance in predicting CBA deal completion, and the way the effect completion is realized (i.e., through a simple, directional or complex, ambiguous channel). This, too, clarifies where future work is needed to further deepen our understanding of the revealed complexities. Below, we briefly reflect on a few of these key future research opportunities.

5.1.2. Novel insights from machine learning

Our analytic importance-complexity framework triggers three further observations, which are all rather systematically patterned. First, eight out of the top-10 predictors are deal or firm-level variables, and they all fall in Quadrant 1. Second, most industry-level predictors are located in Quadrants 4 and 3, with the two exceptions of *Energy* and *Resource* falling into Quadrant 1. Third, a few important country-level predictors – i.e., *Acquirer institution* (*acqWGI*), *Target institution* (tarWGI), *Acquirer HDI* (*acqHDI*), *Target HDI* (*tarHDI*), *Target GDP (tarGDP), Target GDP growth (tarGDPg), Religious distance* (*relig_dist*), and *Culture distance in practice* (*CD_p*) – are all in Quadrant 2. In sum, these findings suggest that micro (deal and firm-level) factors have a substantially more important and/or more straightforward impact on EMNE CBA completion, with macro-level factors (aggregated at the industry, culture or institutional level) revealing a rather complex impact that can be non-directional, being less prominent and/or subtly conditional. This type of evidence has not been identified in traditional regression analyses.

Second, this study finds a few factors that are important in the prediction, ranking in the top 15, but regarding which we have very limited, if any, knowledge as to their roles, due to a lack of earlier work on these predictors. An example is *Equity value.* It ranks 4th in importance. And the ML result demonstrates that an EMNE CBA targeting a firm with a higher valuation prospect is more likely to be completed. This result has not yet been documented in extant research. Given the multi-dimensional nature of this variable, as hinted at above, capturing different firm-level aspects, further work is needed to unravel the relative importance of the underlying mechanisms. Another interesting example is *Year*, which ranks 13th. Again, as we discussed above in detail, extant empirical studies have documented limited evidence about how and why time plays a role in (EMNE) acquisition completion, notwithstanding the theoretical importance of timing, reflecting different stages of a merger wave or non-wave (Fuad & Gaur, 2019), economic cycles (boom or bust), and/or volatile or complacent states of the financial market. So, we need more work to deepen our understanding of the role of time and timing.

Third, interestingly, findings with missing values are informative, too, which tend to be ignored in traditional regression studies. For example, missing values of *Acquirer institution* and *Acquirer HDI* are linked positively with completion, whereas missing values of *Target institution* are associated with negative effects. In our dataset, the missing values of acquiring countries' institutions and HDI are concentrated in the period before 1995 and 1990, respectively, and the missing values of target countries' institutions are mainly in the period before 1995. This set of findings suggests that, in these periods, when emerging countries were in their earlier stages of internationalization, institutions (and human development) of acquirer countries were not, but institutions of target countries were a failure factor for EMNEs' M&A completion likelihood. This example shows that missing values may possess valuable information that should be included in estimations. Hence, our standard practice to rely solely on their deletion or imputation is unwise. Indeed, in extant empirical EMNE CBA completion studies, missing values are often not taken on board, but simply dropped from estimation.

5.2. Theoretical implications

5.2.1. Comprehensive perspective

Extant empirical studies are highly fragmented regarding specific theories, contextual themes and sample sizes, and hence have advanced our understanding of the completion of EMNE CBAs from different perspectives for different settings. However, precisely because of this very heterogeneity, we cannot be sure about the robustness of any reported empirical regularity. For example, institution-focused studies document that institutional quality, foreign relations, and institutional distance matter (e.g., Dong et al., 2019; He & Zhang, 2018; Zhang et al. 2011, Zhang 2022), whereas studies taking an organizational learning lens conclude that cultural experience, industry similarity, and prior success experience are relevant (e.g., Popli et al. 2016, Wang et al. 2020, Zhou et al. 2022). The list can be extended with many other examples. When putting all these findings together, we currently lack a comprehensive understanding of the factors that underlie EMNE CBA completion. It is here where ML can have great value added, capturing complexity head-on.

Our ML findings reveal that ownership- and size-related predictors, including *Public acquirer, Private target, Private acquirer, Public target, Equity value, Deal size, Acquirer size* and *Target size,* top the rank list and have clear impact patterns. The overall effect patterns indicate that deals involving public targets and public acquirers, large targets, and/or large deals are *less* likely to be completed, and those involving private targets, private acquirers and/or large acquirers are *more* likely to be completed. The rationale behind these too-public-to-succeed and too-large-to-succeed phenomena are arguably multifaceted. Public targets or acquirers and large deals or targets face more constraints than private and small firms, such as more scrutiny from regulators and other stakeholders (Chira et al., 2017; Dong et al., 2019), as well as more media attention (Liu & McConnell, 2013). Contrary to the case of larger targets and deals, a larger acquirer may have more money and power than a smaller acquirer to push a deal to continue toward the final completion stage. A large acquirer may also influence a public agency's decision-making or key political actors, lobby for favorable rules in shaping the market, and obtain political resources that could not be obtained through market exchange (Hillman et al., 2004; Lord, 2000; Yim et al., 2017). However, these factors have not received sufficient theoretical consideration, not having often been considered as "main effects" or having been overshadowed by other significant "main effects" in support of specific theories in extant work, to date. This points to a need for further theory development. In this regard, comprehensive theorizing is warranted, complementary to only focusing on a single or a few theories. Theoretical strands such as, for example, the process-based perspectives (e.g., Welch et al., 2020), which account for the processes of CBA decision-making, and stakeholder theory (e.g., Dong et al., 2019), which addresses value creation or destruction of CBAs from the perspective of different stakeholders, are worthy of consideration. Incorporating these theories into the study of (EMNE) CBAs can advance our understanding of the effects of a wide variety of factors at the micro level, which are more direct, instant and dynamic, and hence can be regarded as endogenous driving forces of CBAs (Kumar & Sengupta, 2020; Luo & Bu, 2018).

5.2.2. Contingency perspective

Our study finds that many industry and country-level factors are associated with complex effect patterns, suggesting a need for fine-grained macro theory regarding EMNE CBA completion. Given the less developed level of emerging economies, the motives of EMNE CBAs are labeled as (other's) ownership advantage-seeking rather than (own) ownership advantage-exploiting. Hence, distance in technology, institutional context, human development and national culture between the home and the host countries, which can be interpreted as country-specific disadvantages or advantages, is often considered to be a driving force of such CBAs. However, the complex effect patterns of

these macro factors possibly point to two counter-effects associated with the same factor or interacting effects with micro-level predictors, implying that we must carefully explore the underlying complexities when theorizing on these factors. For example, poor institutional quality of the target country can have either positive or negative effects on EMNE CBA completion, with the negative relation being associated with higher transaction cost and the positive association being linked to the lubricant transactional effect, as produced by corruption (Ghosh et al., 2022).

Specific to EMNE CBAs, Zhang (2022) found, on the one hand, that the institutional quality of the home country could be positively related to CBA completion, but also, on the other hand, that this positive relationship evaporated when host countries were going through or were stuck with economic adversity, such as manifested in high unemployment, where firms were facing difficulties to survive. Furthermore, institutional factors such as policy support influence EMNE CBA completion via firm-level predictors related to risk-taking behavior (Luo & Bu, 2018), which also increases complexity. Apart from such counter and/or interaction effects, the multi-dimensional nature of many aggregate factors such as cultures and institutions does add further complexity, being associated with a fine-grained multi-faceted effect, with multiple non-linearities and higher-order interactions, requiring refined theorizing.

Our study also reveals the negligible effects of a series of other factors, such as *Acquirer SOE* and *Industry relatedness*, which have been documented as important in prior studies. These factors' effects may have been over-emphasized, over-rated and/or over-estimated, theoretically and/or empirically, in the state of the art. Their importance might be context-specific. Indeed, studies in the context of China's CBAs (e.g., Zhang et al., 2011; Li et al., 2019) consistently found a negative effect of *Acquirer SOE*, suggesting that Chinese government-controlled SOEs are likely to provoke political and public concerns in the target countries. In the current study, the different and much larger sample of the 29 emerging countries yields a different result. Another example is *Industry relatedness*, which is often simply theorized as having a positive effect on CBA completion. However, such a simple variable aggregates away very different types of relatedness in a simple measure, such as horizontal, vertical and unrelated M&As, which all may well affect CBA completion differently (Muehlfeld et al., 2012). For instance, reduced asymmetric information, higher expected return and lower perceived risk (Lim & Lee, 2016) all point to different contingencies. Hence, for those factors, we need to deepen theoretical thinking, while integrating contingent and multiple perspectives.

5.2.3. The puzzle

The literature on EMNEs commonly recognizes their engagement in cross-border acquisitions to achieve diverse strategic goals, such as to acquire strategic assets including strategic resources (e.g., energy and other natural resources), technology, intellectual property, talents, and distribution networks, with the aim of enhancing competitiveness (Kumar et al., 2020; Luo & Tung, 2007; Mathews, 2006; Ramamurti, 2012). Observing a rapid increase in CBA activities by EMNEs over the past three decades, IB researchers and practitioners may be curious about the extent to which EMNEs' strategic assets-seeking motives are rewarded, in terms of success in deal completion. Our findings shed light on this matter. For example, our findings indicate that *Energy* and *Resource* exhibit clearer negative and larger effects, while other sectors such as *Technology, Retail* and *CPS*, and country-level factors such as *Target HDI* show mixed effects. This implies that CBAs aimed at securing non-renewable resources are less likely to give positive outcomes, while the results of CBAs targeting other strategic assets, such as technology (which is assumed to be predominantly found in the *Technology* industry), talent (which is presumed to be abundant in host countries with high HDI – i.e. *Target HDI*) and distribution networks (which are expected to be prevalent in the *Retail* and *CPS* industries) are uncertain, potentially depending on international and external conditions. Similarly, the mixed effects of *Target GDP* suggest that outcomes of market-seeking motives are also uncertain. Overall, these findings suggest that EMNEs' well-motivated CBA strategic moves are not adequately rewarded in terms of deal completion. This raises a puzzle: what has perpetuated the phenomenal growth of EMNE CBAs over the past decades, despite the inconsistent rewards for these highly motivated strategic moves?

In essence, this puzzle is related to another oft-debated question: How can "the new species of EMNE" (Mathews 2002) compete in the CBA market that was dominated by developed-country MNEs (DMNEs)? This implies a follow-up question: What competitive advantages of EMNEs may explain this? In this regard, views within IB diverge. The literature mostly agrees that there is a significant difference between the sets of competitive advantages possessed by EMNEs and DMNEs (Amighini et al., 2015). DMNEs enjoy the firm-specific (O) advantages developed in advanced home countries and explore the host country-specific (L) advantages by internalization (I), as explained by the OLI framework (Dunning, 1981, 1988). But EMNEs are considered to be lacking such ownership advantages. Alternatively, EMNE CBAs are explained by, e.g., the linkage–leverage–learning (LLL) model (Mathews, 2006) and the springboard perspective (Luo & Tung, 2007). With EMNEs' well-motivated CBA strategic moves, they aggressively seek strategic assets so as to overcome their latecomer disadvantages.

The latter perspectives emphasize, implicitly, the innate ownership disadvantages of EMNEs. In contrast, there is an emerging view that EMNEs may well possess ownership advantages, too, such as entrepreneurial ability, prowess in quicker adopting new innovative business models, networking skills and advantages (e.g., deriving from their ethnic and cultural ties), and notably, at least for a handful of EMNEs, nimble product design adaption capabilities (e.g., the Chinese firm Haier) and cutting-edge technology (e.g., Indian Suzlon, the world's largest wind turbine developer, and Serum Institute, the world's fourth largest vaccine producer) [see Gaur & Kumar (2010) and Hernandez & Guillén (2018) for a thorough review]. In addition, EMNEs enjoy a few home country-specific advantages, such as low cost of production factors (e.g., an abundance of labor), large home market and great market power, and preferential loans, favorable tax regimes and linkages to domestic institutions (i.e., central and local governments, financial institutions, trade associations, and research centers) [see, e.g., Amighini et al. (2015) for detailed review].

Our ML analyses produced results that might shed light on this ongoing debate. Overall, on the one hand, our findings regarding the higher success rate for private or larger acquirers point to the materialization of certain firm-specific and/or home country-specific advantages for these types of firms in the international CBA marketplace. On the other hand, by revealing features of the EMNEs failing in CBA deal completion, such as public and SOE acquirers, we may explain why they might not enjoy these advantages. Examples are the impact of a negative country image or 'liability of emergingness' (Madhok & Keyhani, 2012; Zhang, 2022), which may have outweighed firm-specific and country-specific advantages. Clearly, the evidence induced by our comprehensive ML analysis only provides first insights into the potentially important pieces of the puzzle. Extensive follow-up research is needed that brings together multiple theoretical considerations.

5.2.4. The underpinning of core theories

Connecting our ML evidence to underlying theories, we see that our comprehensive set of variables relates to the core theories that underpin CBA research. Of these theories, institutional theory stands out in the extant literature as the most prominent one in explaining CBA completion. For example, institutional constraints (such as foreign investment and anti-trust laws, and industrial and stock exchange regulations) are reflected by predictors such as *Public acquire, Private target, Private target, Percentage sought*, and *Deal size*, and institutional quality is related to *Acquire institution*. Other prominent theories include signaling theory, agency theory, and the social trust perspective. In line with signaling

theory, asymmetric information is captured by *Advisor* [e.g., deriving a tax advantage and avoiding fraudulent white-collared crimes (Reddy et al., 2016)] and *Religious diversity* [i.e., leading to complexity and increasing the *ex ante* cost for investors to collect information (Baldwin & Huber, 2010)]. Agency theory is included in the form of *Private targets* and *Private acquirers* (both coming with fewer agency problems). The social trust perspective is mirrored in *Public acquirer* and *Deal size*, as both are subject to public perception and societal trust, affected by the press (Kim, 2019), and managers' reputational risk, which increases with media attention (Liu & McConnell, 2013).

Importantly, our set of variables comes with a multidisciplinary perspective. Other theories covered by our set of variables are corporation valuation theory from Accounting [*Equity value* – i.e., information feeding into target valuation (e.g., McNichols & Stubben, 2015], real options theory from Finance (*Percentage sought* – i.e., cost of commitment under exogenous uncertainty (e.g., Ahammad, 2017)], evolutionary theory from Sociology [*Year* – i.e., timing over the evolution of the merger cycle (e.g., Fuad & Gaur, 2019)], labor market theory from Economics [*Target unemployment* – i.e., the pragmatic policy motivation to attract employment-generating EMNE investment (e.g., Jude & Silaghi, 2016)], and competitiveness theory from Strategy [*Acquirer HDI* – i.e., motivation to increase competitiveness by accessing advanced technologies and human resources (e.g., Zhang, 2022)].

Note that there are multiple theoretical accounts for a few of the 59 predictors. *Industry relatedness* and *SOE acquirer* are the notable cases. *Industry relatedness* could affect CBA completion differently due to differences in scrutiny by regulators in association with horizontal, vertical and unrelated M&As (as suggested by institutional theory; see, e.g., Muehlfeld et al., 2012), reduced asymmetric information (as suggested by signaling theory; see, e.g., Reddy et al., 2016), and higher expected return and lower perceived risk (as suggested by the corporate diversification perspective in financial economics; see e.g., Lim & Lee, 2016). The impact of *SOE acquirer* could be explained by suspicious and stringent scrutiny (as suggested by institutional theory and social trust perspective; see, e.g., Zhang & He, 2014; Chira et al., 2017; Dong et al., 2019), and financing and tax advantages as well as strategic asset-seeking behavior (as suggested by the springboard perspective; see, e.g., Luo & Tung, 2007; Lui & Bu, 2018). Here, both the subtle and ambiguous effect revealed by our ML is in line with the complex theoretical reasoning pointing to a potential complex and interacting set of mechanisms behind these relationships.

5.3. Methodological implications

This study demonstrates how ML can help ease the inconsistencies pervasive in a specific example of extant IB work, providing the first step to gaining a comprehensive understanding of the effect of a multitude of potentially important variables on EMNE CBA completion, looking at complexity right in the face. By identifying intricate effect patterns of underlying predictors, ML techniques have the potential to expose the shape of complex non-linear causalities, in line with the value added of neural network techniques (e.g., self-organizing maps and deep learning models) in earlier IB work (Messner, 2022a, 2022b, 2022c; Palocsay & White, 2004). ML techniques cannot only be applied to establish the robustness of known evidence, but also to inform theory inductively by identifying the relative importance of predictors, as well as the complex nature of the associated relationships. Consequently, ML is capable of consolidating numerous ambiguous explanations into a more concise set of crucial explanations while specifying their nature, moving beyond traditional approaches to findings integration, e.g., meta-analysis.

Generally, ML techniques are complementary to the traditional statistics toolkit, being highly appropriate to explore complex patterns in high-dimensional data. By not *a priori* assuming any specific data-generating process, ML algorithms can flexibly handle complexity. Indeed, many ambiguous or null effects reported in IB might well mask complex conditional (high-order) interaction and/or non-linear relationships, which are very hard to detect with traditional probabilistic statistics. In recent pleas to take complexity very seriously in IB (see, e.g., Eden & Nielsen, 2020; Nielsen et al., 2023), ML is briefly referred to as a set of techniques that will help IB to progress further in this context, with ML algorithms being superior to traditional probabilistic regression in terms of capturing and identifying complexities. In the current study, we illustrate in detail what such ML work could look like, providing insight into how this can be achieved by applying ML's research process pipeline, including general practices such as algorithm selection and out-of-sample validation.

So, basically, we would suggest including ML as a standard option in our methodological toolkit for the quantitative study of complexity. In traditional probabilistic statistics, we have to – mostly implicitly – assume that we already know the 'true' data generation process before we start to analyze our data, as we must specify the to-be-estimated model fully in advance. And not only that, we subsequently also have to introduce a series of auxiliary assumptions regarding the data generation process to develop an estimation machinery. Hence, we are forced to intervene before and during the process of applying traditional probabilistic statistics. ML is fundamentally different by essentially offering the machines the freedom to explore the data without any pre-set assumptions regarding the data generation process, precisely to have these machines identify a congruent (and hence not assumed) data generation process iteratively and sequentially by systematically learning from the data, however complex the learned model might turn out to be. In the context of many IB issues, inherently featuring much complexity, adding ML to our toolkit will therefore increase the field's predictive accuracy and explanatory power.

5.4. Limitations and future research

As with any other, our study is not without limitations, which suggest promising future research opportunities. First, with the ML technique, we can identify complex structures that are not specified in advance. The benefit of this kind of approach comes at costs, though. For one, the increased model complexity in combination with the greater black box nature of the ML algorithms may reduce the interpretability of the output generated by these techniques (cf. Aas et al., 2019; Rudin, 2019), due to the lack of parametric betas, standard errors, and the possible estimation bias resulting from ML's regularization techniques (Mullainathan & Spiess, 2017). As an additional example, we have not been able to identify an approach within the ML toolkit that directly addresses the potential issue of ecological fallacy. These limitations suggest two promising future research avenues. The first is to combine ML with traditional statistics, by adding a second-stage traditional statistical analysis, with the second-stage specification inspired by the first-stage ML outcomes, to produce the usual parametric estimates (including techniques targeted at analyzing nested data and identifying causalities). The second is to benefit from the ongoing investment in the IAX community by applying more and more advanced algorithms and insightful ML metrics and visualizations. A few examples of multi-level decision tree algorithms are the generalized linear mixed-effects model tree (GLMM tree) (Fokkema et al., 2018), the mixed-effects random forest (MERF) (Hajjem et al., 2014), and the derived mixed-effect machine learning (MEml) (Ngufor et al., 2019).

Second, although we have incorporated a large number of multi-level explanatory variables in a broad multi-country sample, we might well have missed other potentially relevant variables, due to data unavailability. For instance, demographic and personality attributes of the top managers involved in deal decision-making are hard to come by in such large datasets. This may constrain the comprehensibility and generalizability of our stock-taking findings, due to what essentially is an omitted variables issue. Future research could aim to expand the scope of the study by incorporating a wider range of variables to gain an even more comprehensive understanding of the predictors of EMNEs CBA completion, enhancing the generalizability of the findings.

Certainly, omitted variables issues are endemic in CBA research (and IB and the social sciences, more broadly). But with ML highly capable of handling a large number of variables, we can benefit from collecting and compiling larger and larger datasets.

Third, our study only focuses on EMNEs, leaving MNEs originating from advanced countries outside the scope of our analyses. Clearly, this limits the opportunities to empirically and systematically compare the differences between these two prominent groups of acquirers. Future research can expand the scope of meta-analytic or stock-taking CBA completion studies by including both groups to explore the potential differences in the effects of the explanatory variables across MNEs from advanced economies and EMNEs. Doing so will advance our understanding of the uniqueness of EMNEs, and will help to answer a long-debated question: Do we need new theories for EMNEs? And if so, what should be the key building blocks of such tailored theories?

CRediT authorship contribution statement

Jianhong Zhang: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Arjen van Witteloostuijn:** Writing – original draft, Writing – review & editing. **Chaohong Zhou:** Methodology, Writing – original draft, Writing – review & editing. **Shengyang Zhou:** Data curation, Formal analysis, Methodology, Software, Validation, Visualization.

Declaration of competing interest

None

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Supplementary materials

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