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Towards expert–machine collaborations for technology valuation: An interpretable machine learning approach

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ABSTRACT

Although technology valuation has benefited considerably from recent advances in machine learning technology, the results of prior studies in this field are of limited use in practice because they rely solely on black box models whose internal mechanisms are hidden. We develop an analytical framework for successful expert–machine collaborations for technology valuation using interpretable machine learning that makes a model's behaviors and predictions understandable to humans. First, a technological characteristics–economic value matrix is constructed using patent and technology transaction databases. Second, machine learning models are developed to examine the nonlinear and complex relationships between the technological characteristics and economic value of technologies. Third, the performance of the machine learning models is assessed using quantitative metrics. Finally, the SHapley Additive exPlanation method is applied to the best-performing model to explain which technological characteristics influence the economic value of technologies. By these means, we investigate the importance of the features of technological characteristics (and their interactions) in technology valuation and offer theoretical and practical implications of the analysis results. A case study of the technologies registered in the Office of Technology Licensing at Stanford University confirms that our framework is a useful complementary tool for technology valuation.

1. Introduction

Technology valuation is a challenging task because the economic value of technologies is affected by many uncertain factors and the ground truth of analysis results can be ascertained only after commercialization of the technology (Fischer and Leidinger, 2014). The first official valuation of technology was performed by the New Deal's National Resource Commission to examine the potential of 13 major inventions and predict the economic and technological impacts of these technologies (Coates et al., 2001). Since then, technology valuation methods have evolved through various stages with shifts in perspectives, focuses, and approaches in the public and private sectors. Historically, early research focused on developing expert-centric (Chiu and Chen, 2007) and model-based approaches (Park and Park, 2004), whereas recent literature presents a trend towards developing data-driven approaches (Chung and Sohn, 2020; Kim et al., 2021; Ko et al., 2019; Lee et al., 2018). In particular, technology valuation has substantially benefited from recent advances in machine learning technology, i.e., models and methods used to examine and discover meaningful patterns, relations, and insights within an immense volume of data across heterogeneous sources (Chen et al., 2012).

Organizations should aim to use a variety of approaches within their resource limitations to deal with the high level of uncertainty and complexity associated with technology valuation, although the dominant approach in practice is based on expert appraisals (Kim et al., 2021). Experts and machine learning technology have different skills that can create synergies and overcome each other's limitations. Specifically, experts can integrate knowledge from heterogeneous sources, whereas the strength of machine learning technology lies in its ability to compute large-scale data at the lowest level of granularity (Jarrahi, 2018). However, while various machine learning models (mostly supervised machine learning algorithms) have reduced the time and cost

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associated with technology valuation, the results of prior studies are of limited practical use. This is because these studies relied solely on black box models that do not reveal their internal mechanisms and thus do not assist expert decision-making and communication among various stakeholders effectively (Gunning and Aha, 2019; Gunning et al., 2021; Molnar, 2020). The daunting challenge of combining the generally high level and comprehensive thinking of experts with the efficient pattern analysis of machine learning technology is possible and worth the effort (Lee, 2021).

The key to successful collaborations between experts and machine learning technology for technology valuation is interpretability, which makes the models' behaviors and predictions understandable to humans and further transfers learning into a knowledge base. Interpretability is closely related to the human desire to find meaning and manage social interaction (Miller, 2019). When it is integrated into machine learning models, interpretability engenders user trust, provides insights into how a model may be improved, and supports understanding of the process being modeled (Du et al., 2019). For instance, if the results of machine learning models differ from those of experts, the inconsistency is reconciled by verifying, interpreting, and understanding how machine learning models arrived at their conclusions. If machine learning models can explain their mechanisms, it is easier for experts to assess the validity and reliability of the analysis results and manage communications among multiple stakeholders (e.g., communications among inventors, licensing managers, and potential licensees).

In this study, we develop an analytical framework for successful expert–machine collaborations for technology valuation using interpretable machine learning that makes the model's behaviors and predictions understandable to humans. Our review of previous methods identifies three main issues central to this challenge, as follows. First, in terms of the inputs and outputs of machine learning models, distinct technological characteristics of technologies should be incorporated into the analysis model because technological factors are the most basic consideration in technology valuation processes, especially for early-stage technologies (e.g., technologies at the proof-of-concept or prototype stage) (Kim et al., 2021; Ko et al., 2019; Lee et al., 2016, 2018; Reitzig, 2004). In this respect, patent databases are considered a valuable data source because (1) patents contain detailed technology information across a wide spectrum of fields in a highly structured format and (2) an extensive number of patents has accumulated over a long time (Lee, 2021). Furthermore, any approach that is proposed should measure the monetary worth of technologies to give practical assistance (Kogan et al., 2017; Park and Park, 2004), although previous studies employ indirect post-grant outcomes such as patent forward citations and patent renewals (Higham et al., 2021). Second, with respect to the model development, the relationships between technological characteristics and the economic value of technologies are characterized by complexity and nonlinearity (Kim et al., 2021). These relationships cannot be generalized easily. Furthermore, they differ across technology fields and even individual technologies, which makes the use of explicit mathematical models difficult in practice (Lee et al., 2018). Hence, any approach that is proposed should adopt context-specific data-driven approaches and use nonlinear models (e.g., multilayer perceptron and ensemble models) instead of traditional linear models (e.g., linear regression and logistic regression). Finally, regarding the analysis results, technology valuation is recognized as an iterative and interactive process in practice where human intelligence is indispensable and communications among multiple stakeholders are essential (Baek et al., 2007). Hence, any approach that is proposed should provide a practical tool for explaining predictions to experts with diverse knowledge and backgrounds and for improving the effectiveness of communications.

With these considerations in mind, our analytical framework is designed to be executed in four discrete steps. First, a technological characteristics–economic value matrix is constructed using patent and technology transaction databases. Second, five supervised machine learning algorithms—i.e., multilayer perceptron (MLP), support vector machine (SVM), factorization machine (FM), random forest (RF), and extreme gradient boosting (XGBoost)—are employed to model the nonlinear and complex relationships between technological characteristics and the economic value of technologies. Third, the performance and reliability of the machine learning models are examined using quantitative metrics. Finally, the SHapley Additive exPlanation (SHAP) method is applied to the best-performing model to explain which technological characteristics influence the economic value of technologies.

We apply our analytical framework to 1698 technologies registered with the Office of Technology Licensing (OTL) at Stanford University. Based on this, we investigate the importance of the features of technological characteristics (as well as their interactions) on the economic value of technologies while offering the theoretical and practical implications of the analysis results. In particular, we observe that the implications of the features (mainly ex-ante patent quality indicators) vary according to the context of technology valuation, necessitating more research on the appropriate combination of the context of technology valuation and the features of technology characteristics used. Furthermore, machine learning models can create synergies with expert appraisal, reducing the number of technologies that need to be assessed by experts. To achieve this, practitioners should consider using nonlinear machine learning models for technology valuation because our analysis results confirm, with statistically significant outcomes, that nonlinear models noticeably outperform linear models. It is expected that the proposed analytical framework is a useful complementary tool for technology valuation and serves as a starting point to gain a deeper understanding of the relationships between technological characteristics and the economic value of technologies.

The remainder of this paper is organized as follows: Section 2 presents the research background. Section 3 explains the data and analytical framework, which is then illustrated through a case study of the technologies registered in the OTL at Stanford University in Section 4. Section 5 discusses the quality of model interpretation and presents the theoretical and practical implications of the analysis results. Finally, Section 6 concludes with the limitations of the current study and suggests future research directions.

2. Theoretical background

2.1. Data-driven approaches to technology valuation

The dominant data-driven approach to technology valuation uses patents, which are considered a crucial precursor to innovation (Trajtenberg, 1990). A variety of patent-based technology valuation methods have been developed using various techniques. Historically, early studies focused on developing curve-fitting techniques (Shin et al., 2013) and stochastic models (Jang et al., 2017; Lee et al., 2012), whereas recent literature presents a trend towards developing supervised machine learning models to examine the nonlinear and complex relationships between technological characteristics and technology value (Chung and Sohn, 2020; Kim et al., 2021; Ko et al., 2019; Lee et al., 2016, 2018; Woo et al., 2019).

Prior studies have presented various supervised machine learning models for technology valuation, which can be classified into three broad categories based on the type of data and methods employed. The first group relies on the bibliometric information of patents (as a proxy for the technological characteristics of patents) and indirect measures of technology value (e.g., patent forward citations and patent renewals) for patent valuation. For instance, Lee et al. (2018) developed an MLP model to predict the number of forward citations of patents using multiple ex-ante patent indicators that can be extracted immediately after the relevant patents are issued. Choi et al. (2020) similarly presented an MLP model to predict the likelihood that a patent will survive until its maximum expiration date using 24 internal and external patent indicators and historical maintenance fee event data. These approaches can be used after the relevant patents are issued. Focusing more on the timing of the approaches, the second group uses the textual information of patents and indirect measures of technology value to assess the value of technological ideas in the early stages of technology development. For instance, Woo et al. (2019) proposed a *k*-nearest neighbors method to screen early-stage ideas by associating the technical contents of ideas embodied in patents with their forward citation counts. Hong et al. (2022) presented a word2vec and convolutional neural network approach to associate the technical descriptions of ideas implied in patents with the number of patent forward citations as a proxy for the technological value of ideas. Specifically, word2vec is used to examine the semantic relationships among words and construct matrices representing the technical content of ideas implied in patents. A convolutional neural network is used to model the nonlinear relationships between the matrices and the number of patent forward citations. These approaches can screen early-stage ideas using only the technical descriptions of the ideas, enabling more prompt analysis for technology valuation. Finally, focusing on the directly observed economic value of technologies, Ko et al. (2019) proposed a deep learning model to assess patent transferability using 36 internal and environmental patent indicators. Kim et al. (2021) developed an RF model to assess the economic value of technologies (i.e., a set of patents) using patent, publication, and technology transaction databases.

The results of previous studies have proven quite useful within various contexts of technology valuation. In particular, previous machine learning models have been found effective in identifying the least valuable technologies in the early stages of technology development, rather than identifying breakthrough technologies. However, the results of prior studies have been of limited use in practice because they have relied solely on black box models whose internal mechanisms remain hidden. For problems and tasks associated with a high level of uncertainty and complexity (e.g., technology valuation), experts prefer models and systems that provide decisions with explanations over those that provide only decisions (Gunning and Aha, 2019). Explanations are also more helpful when machine learning models are incorrect and particularly valuable in edge cases (i.e., identifying breakthrough technologies) (Gunning et al., 2021). That is, if machine learning models for technology valuation can explain their mechanisms, it is easier for experts to understand the rationale behind the models' decision, assess the validity and reliability of the analysis results, incorporate the analysis results into expert appraisals, and manage communications among multiple stakeholders to provide final valuation outcomes. Furthermore, the performance of machine learning models can be improved based on the experts' feedback (Molnar, 2020). This provides our underlying motivation and is fully addressed in this study.

2.2. Interpretable machine learning

Interpretable machine learning is based on the mechanisms of how humans explain decisions and behave with each other. Although a considerable body of literature has emerged in the last couple of years, interpretable machine learning has a much longer tradition, which can be divided into two categories: intrinsic interpretability and post-hoc interpretability models. Intrinsic interpretability is achieved by constructing machine learning models that incorporate interpretability directly into their structures by making certain distributional assumptions or restricting the model complexity. This category includes regression models and decision trees. For instance, the results of linear regression are interpreted by examining the model structure and the weights in terms of the effects that the features have on the prediction. The results of decision trees are interpreted by examining the trained model structure and tracing how the model makes predictions. While these methods are simple to use, they cannot capture the complicated patterns or nonlinear relationships between features and targets. To address the lack of interpretability of nonlinear and complex machine learning models, post-hoc interpretability models have model-agnostic interpretation methods to assess the contribution of features to an individual prediction and determine why the model makes a particular decision given certain features. By examining the predicted outputs for pairs of features, these model-agnostic interpretation methods can be applied to any kind of machine learning models. They can also interpret the behaviors and predictions of models without sacrificing their predictive power.

Among various interpretable machine learning methods such as local interpretable model-agnostic explanations (LIME) (Ribeiro et al., 2016) and Anchors (Ribeiro et al., 2018), SHAP is the most scientific model-agnostic method because it is based upon the solid theoretical background of Shapley values (Shapley, 1953) and reduces the time required to compute these values. SHAP calculates the marginal contribution of features by computing the predicted value with and without the feature value and calculating the difference (Lundberg and Lee, 2017; Lundberg et al., 2018). Here, the importance value of a feature can be separated into interaction and main effects, enabling the calculation of local interaction effects (Lundberg et al., 2020). Furthermore, individual local interpretations in SHAP are combined to provide global interpretations, resulting in better consistency between local and global interpretations (Lundberg et al., 2020).

3. Data and methodology

The overall process of the proposed analytical framework is shown in Fig. 1. The framework is designed to be executed in four discrete steps: constructing a technological characteristics–economic value matrix; assessing the economic value of technologies; identifying the best performing model; and finally, understanding the model's behaviors and predictions.

3.1. Constructing a technological characteristics–economic value matrix

This study uses an integrated technology database that is developed by linking patent and technology transaction databases to measure technological characteristics and the economic value of technologies. Specifically, we use the technology transaction database of the OTL at Stanford University. Since its inception in 1970, the OTL at Stanford University has been pivotal in the field of university technology transfer. Cumulatively, it has >11,000 technology disclosures, has completed >3500 license agreements, and has generated over $1.8 billion in revenue for the university and Stanford inventors. From the technology transaction database, we consider 1643 technologies issued with U.S. patents up to July 2014 because (1) universities only apply for patents if the commercial viability of a technology is known (Thursby et al., 2001) and (2) sufficient time must elapse before it can be determined whether a technology is economically valuable or not (Kim et al., 2021). Note that the ground truth of the economic value of a technology can be ascertained only after commercialization of the technology. We then match the technologies in the technology transaction database to the patent information in the United States Patent and Trademark Office (USPTO) database, using the patent numbers. Here, the number of patents can be higher than the number of technologies because some technologies are issued with multiple patents. For technologies that are associated with multiple patents, we match the technology with all the patents that belong to the technology. Finally, the technology transaction database is integrated with the patent information after the relevant 2288 patents for the technologies in the technology transaction database are collected and parsed based on their structures to distinguish each patent document based on its content (e.g., classes and claims).

A technological characteristics–economic value matrix is constructed from the integrated technology database. In terms of the technological characteristics, prior studies have presented many indicators that may be indicative of the value of relevant technologies. However, some of these indicators are unsuited to the valuation of early-stage technologies. For example, patent generality, which has been widely

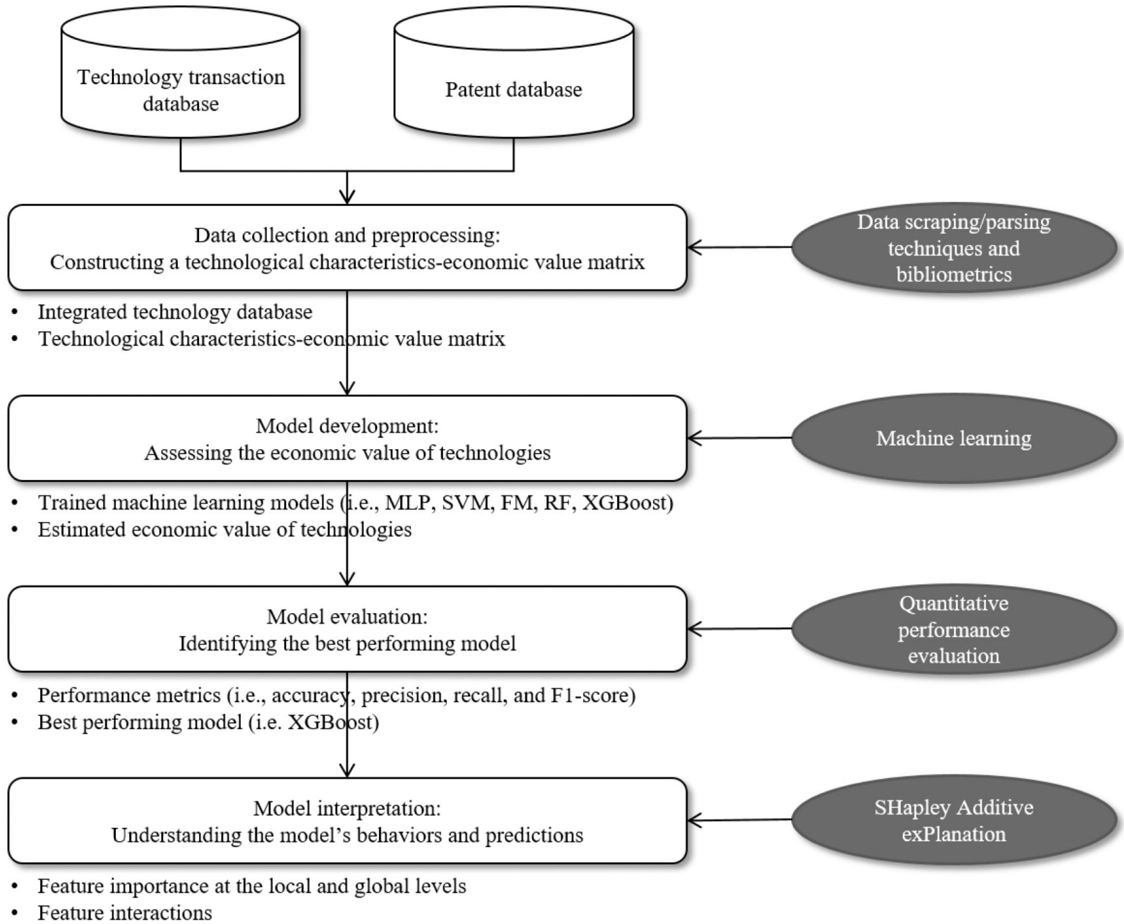

Fig. 1. Overall process of the proposed analytical framework.

used as a proxy for the scope of technological impact on subsequent inventions, cannot be used for the valuation of early-stage technologies because this indicator is based on patent forward citation information, and a substantial period of time must elapse for the relevant patents to be cited (or alternatively, to fail to be cited) (Reitzig, 2004). Based on the results of the literature review, we use 21 ex-ante features of technological characteristics that are available near patent grants and before licensing contracts, as summarized in Table 1. The features are divided into six categories according to their characteristics and implications: (1) technological novelty and originality, (2) technological scope, (3) technological superiority, (4) market coverage, (5) development efforts and capabilities, and (6) sponsorship and marketing. The features that belong to the same category measure similar concepts (e.g., prior knowledge and scientific knowledge) or measure the same concept at different levels (e.g., main class count and subclass count). A full description of how the features are associated with the value of relevant technologies is provided in Appendix A.

As a measure of the directly observed economic value of technologies, this study considers the royalty payments for a technology generated from licensing contracts (Kim et al., 2021; Min et al., 2021; Thursby et al., 2001). Specifically, following Kim et al. (2021), Hong et al. (2022), Lee et al. (2018), and Woo et al. (2019), we group the value of technologies into three categories using ordinal scales, as presented in Table 2. However, it should be noted that the proposed analytical framework is not limited to this level and can examine other types of direct measures (e.g., whether a technology is licensed or not (Kim et al., 2019) and patent auction prices (Fischer and Leidinger, 2014)) and more segmented value classes. Indirect measures based on patent forward citations (Hong et al., 2022; Jang et al., 2017; Lee et al., 2012, 2018; Shin et al., 2013; Woo et al., 2019) and patent renewals (Choi et al., 2020) can also be employed.

The resulting technological characteristics–economic value matrix is a 1644 × 24 matrix, which is used to train the machine learning models. The matrix is not reported here in its entirety given the space constraints, but a portion of the matrix is presented in Section 4. In the table, the first column represents the identifier of technologies followed by 21 features of technological characteristics, while the last two columns represent the categorized value of technologies.

3.2. Assessing the economic value of technologies

Given the uncertainty and complexity associated with technology valuation, we employ five machine learning models, i.e., MLP (Friedman et al., 2001), SVM (Cortes and Vapnik, 1995), FM (Rendle, 2010), RF (Ho, 1995), and XGBoost (Chen and Guestrin, 2016), to assess the economic value of technologies. MLP, SVM, and RF have presented a high performance in examining the relationships between quantitative indicators and the value of technologies (Choi et al., 2020; Kim et al., 2021; Ko et al., 2019; Lee et al., 2018). FM and XGBoost have achieved excellent predictive performance in many fields, although they have not yet been applied to technology valuation. Considering the diverse objectives of technology valuation, these models are used to assess the economic value of technologies in two ways (described in Fig. 2). The first classifies a technology into two classes (L and NL) based on the probability of the technology being licensed or not, while the second classifies a technology into two categories (L1 and L2) based on the expected economic value of the technology.

In this section, we explain XGBoost, which is identified as the best performing model in Section 4 (see Appendix B for the other models). XGBoost is an efficient algorithm for constructing the gradient-boosted

Table 1
Summary of the features of technological characteristics employed in this study.

Category	Data source	Feature	Operational definition	References
Technological novelty and originality	Patent database	Technology age (TA)	The amount of time between a technology being registered in the OTL and being licensed (or the current time)	Fischer and Leidinger (2014)
		Prior knowledge (PK)	Number of backward citations of the patents for a technology	Harhoff et al. (2003)
		Scientific knowledge (SK)	Number of non-patent literature references of the patents for a technology	Callaert et al. (2006)
		Technology cycle time (TCT)	Median age of cited patents	Bierly and Chakrabarti (1996)
		Main class-level originality (MCO)	Herfindahl index on classes of cited patents	Bessen (2008); Jaffe and Trajtenberg (2002)
		Subclass-level originality (SCO)	Herfindahl index on mainline subclasses of cited patents	
		Examination time (ET)	Time difference between the first patent publication and the patent application	Higham et al. (2021)
Technological scope	Patent database	Patent count (PC)	Number of patents for a technology	Hirschey and Richardson (2004)
		Main class count (MCC)	Number of main classes of the patents for a technology	Lerner (1994)
		Subclass count (SCC)	Number of mainline subclasses of the patents for a technology	
	Technology transaction database	Bio science relevance (Bio)	1 if a technology is related to bio science, otherwise 0	–
Technological superiority	Patent database	Independent claims (IC)	Number of independent claims of patents for a technology	Lanjouw and Schankerman (2001)
		Dependent claims (DC)	Number of dependent claims of patents for a technology	
	Technology transaction database	Federal government fund (FGF)	1 if technology development is funded by federal governments, otherwise 0	Corredoira et al. (2018)
		Edison awards winner (EAW)	1 if a technology wins the Edison awards, otherwise 0	–
Market coverage	Patent database	Patent family (PF)	Number of patents registered in multiple countries with the coverage of the same invention	Guellec and de la Potterie (2000)
	Technology transaction database	Application area (AA)	Number of potential application areas of a technology	–
Development efforts and capabilities	Patent database	Human resources (HR)	Number of inventors of the patents for a technology	Ma and Lee (2008)
		Collaboration (Col)	1 if patents for a technology have more than one assignee, otherwise 0	Ma and Lee (2008)
Sponsorship and marketing	Technology transaction database	Sponsors (Spon)	Number of sponsors for technology development	Wright et al. (2014)
		Recipients (Recip)	Number of marketing recipients	–

Table 2
Three categories of technologies depending on their economic value.

Category	Subcategory	Economic value	Number of technologies
Licensed (L)	Highly valuable (L1)	Above $500,000	68 (4.14 %)
	Valuable (L2)	0–$500,000	768 (46.74 %)
Not licensed (NL)		0	807 (49.12 %)
Sum			1643 (100 %)

decision tree, which is an ensemble learning method using a sequence of decision trees (Friedman, 2001). The gradient-boosted decision tree first builds a base decision tree estimating the value of the target variable and then adds a series of decision trees estimating residuals produced by previous trees with the aim of improving the overall estimation performance. Given a dataset with n samples and m features $D = \{(x_i, y_i), i = 1, \ldots, n\}$, where $x_i = (x_{i1}, x_{i2}, \ldots, x_{im})$ denotes an m-dimensional feature vector with the corresponding output y_i, the model predicts the output by using K additive functions, as given in Eq. (1).

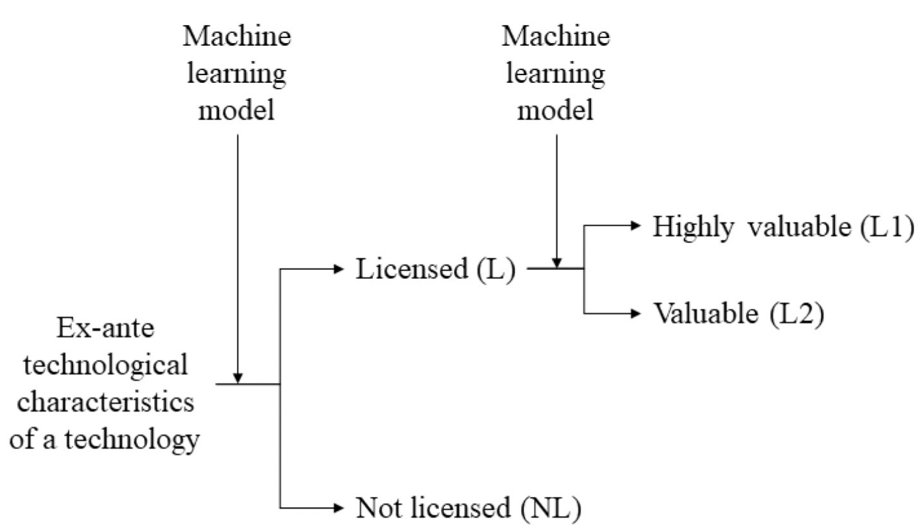

Fig. 2. High-level description of the data and machine learning models for two primary analyses.

$$\widehat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F, \tag{1}$$

where $F = \{f(x) = w_{q(x)}\}(q : \mathbb{R}^m \rightarrow T, w \in \mathbb{R}^T)$ is the space of trees, q represents the structure of each tree mapping a data sample to the corresponding leaf index, and T is the number of leaves in the tree. Each f_k represents an independent tree structure q and leaf weights w. More specifically, the prediction $\widehat{y}$ is made by adding the previous prediction at time $t-1$ and the estimated residual at time t in an iterative manner, as given in Eq. (2).

$$\widehat{y}^{(t)} = \widehat{y}^{(t-1)} + f_t(x_i), \tag{2}$$

where i is the index of data samples and t is the index of iterations. The model is then trained by minimizing the objective function combining a differentiable convex loss function and regularization term that helps to smooth the final weights to avoid overfitting, as given in Eq. (3).

$$J^{(t)}(\phi) = \sum_{i=1}^{n} l\left(\widehat{y}_i^{(t-1)} + f_t(x_i), y_i\right) + \Omega(f_t) \tag{3}$$

Here, l is a loss function and Ω is the regularization term for penalizing the complexity of the model. The regularization term is defined by using the number of leaves and the leaf weights, as given in Eq. (4).

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda||w_j||^2 \tag{4}$$

Here, γ is the complexity of each leaf, λ is a parameter to scale the penalty, and w_j is the vector of leaf weights of the jth leaf. Unlike general gradient boosting, XGBoost uses the second-order approximation to optimize the objective function efficiently, as given in Eq. (5).

$$J^{(t)} \simeq \sum_{i=1}^{n}\left[l\left(y_i, \widehat{y}^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \Omega(f_t) \tag{5}$$

Here, $g_i = \partial_{\widehat{y}^{(t-1)}} l\left(y_i, \widehat{y}^{(t-1)}\right)$ and $h_i = \partial^2_{\widehat{y}^{(t-1)}} l\left(y_i, \widehat{y}^{(t-1)}\right)$ are the first- and second-order gradient statistics on the loss function, respectively. By removing the constant terms, Eq. (5) can be simplified into Eq. (6).

$$\widetilde{J^{(t)}} = \sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \Omega(f_t) \tag{6}$$

By defining $I_j = \{i| q(x_i) = j\}$ as the set of data samples of leaf j and expanding Ω, the approximation of the objective function can be rewritten as Eq. (7).

$$\widetilde{J^{(t)}} = \sum_{j=1}^{T}\left[\left(\sum_{i \in I_j} g_i\right)w_j + \frac{1}{2}\left(\sum_{i \in I_j} h_i + \lambda\right)w_j^2\right] + \gamma T \tag{7}$$

For a fixed tree structure $q(x)$, the optimal weight $w_j{}^*$ of leaf j is computed as given in Eq. (8).

$$w_j^* = -\frac{G_j}{H_j + \lambda} \tag{8}$$

Here, $G_j = \sum_{i \in I_j} g_i$ and $H_j = \sum_{i \in I_j} h_i$. Finally, the optimal objective function for a tree structure can be obtained as Eq. (9).

$$\widetilde{J^{(t)}} = -\frac{1}{2}\sum_{j=1}^{T}\frac{G_j^2}{H_j + \lambda} + \gamma T \tag{9}$$

This can also be used as a scoring function to measure the quality of a tree structure q. A greedy algorithm is used to find the best split because it is impossible to enumerate all the possible tree structures. The final XGBoost model is obtained by iteratively generating a tree that adds branches to maximize the information gain, as formulated in Eq. (10).

$$Information\ Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}\right] - \gamma \tag{10}$$

3.3. Identifying the best-performing model

The performance of the five machine learning models for technology valuation is assessed using quantitative performance evaluation metrics based on 5-fold cross-validation techniques, after their confusion matrices are generated. k-Fold cross-validation techniques partition data into k equally sized folds and perform k iterations of training and validation (Friedman et al., 2001). In each iteration, $k-1$ folds are used for training a model while the remaining fold is used for validation. Upon completion, k samples of the performance evaluation metrics are combined to derive the average per-fold estimates.

Although accuracy is a basic metric (Eq. (11)), it can yield misleading results in this study because the number of highly valuable technologies is quite low. We employ precision, recall, and the F_1 score for a fair comparison, as given in Eqs. (12)–(14). Precision is the ratio of correctly predicted positive samples to total predicted positive samples. Recall is the ratio of correctly predicted positive samples to all positive samples. The F_1 score represents the overall effectiveness of a classifier (considering false positives and false negatives) and is defined as the weighted average of the precision and recall.

$$Overall\ accuracy = \frac{\sum_{i=1}^{l}\frac{tp_i + tn_i}{fp_i + fn_i + tp_i + tn_i}}{l} \tag{11}$$

$$Precision_i = \frac{tp_i}{tp_i + fp_i} \tag{12}$$

$$Recall_i = \frac{tp_i}{tp_i + fn_i} \tag{13}$$

$$F_1\ score = 2\cdot\frac{precision_i \cdot recall_i}{precision_i + recall_i} \tag{14}$$

Here, a true positive (tp_i), true negative (tn_i), false positive (fp_i), and false negative (fn_i) for class i represent the number of positive samples correctly classified, the number of negative samples correctly classified, the number of negative samples wrongly classified as positive, and the number of positive samples wrongly classified as negative, respectively. l denotes the number of classes.

3.4. Understanding the model's behaviors and predictions

This study uses SHAP to unlock the technology valuation results of the best-performing machine learning model. SHAP is a unified framework for interpreting the predictions of machine learning models based on the Shapley value of the conditional expectation of a model. Building upon cooperative game theory, SHAP assigns each feature an importance value for a particular prediction with two novel components: (1) the identification of a new class of additive feature importance measures and (2) a unique solution in this class with a set of desirable properties (i.e., local accuracy, missingness, and consistency) (Lundberg and Lee, 2017).

SHAP measures the variable importance based on additive feature attribution methods, as given in Eq. (15).

$$g(z') = \varnothing_0 + \sum_{i=1}^{M}\varnothing_i z'_i, \tag{15}$$

where $z' \in \{0,1\}^M$ is a coalition vector that indicates whether the ith predictor is present (=1) or absent (=0), M is the number of predictors, $\varnothing_i \in \mathbb{R}$ is the importance value of the ith predictor, and $\varnothing_0$ is the baseline outcome without any predictor. Specifically, SHAP identifies the importance of each predictor as the change in the expected model prediction when conditioning on that predictor and explains how to change from the base value E[f(z)] to the current output f(x). When the model is nonlinear or the predictors are not independent, the order in which predictors are added to the expectation matters, and SHAP averages the $\varnothing_i$ values across all possible orderings. Hence, when defining $f_x(S) = E[f(x)|x_s]$ for a subset of predictors (S), the SHAP value (ϕ_i) is expressed as in Eq. (16).

$$\phi_i = \sum_{S\subseteq\{x_1,\dots,x_m\}\setminus\{x_i\}} \frac{|S|!(M-|S|-1)!}{M!}\left(f_x(S\cup\{x_i\})-f_x(S)\right), \tag{16}$$

where $f_x(S \cup \{x_{ji}\})$ and $f_x(x_S)$ are the model outcomes with and without the ith predictor, respectively. Based on this, SHAP measures the pairwise interaction effect ($\phi_{i,\,j}$) for each prediction as expressed in Eq. (17).

$$\phi_{i,j} = \sum_{S\subseteq\{x_1,\dots,x_m\}\setminus\{x_i,x_j\}} \frac{|S|!(M-|S|-2)!}{2(M-1)!}\nabla ij(S) \tag{17}$$

Here, for i ≠ j, $\nabla ij(S) = f_x(S \cup \{x_i, x_j\}) - f_x(S \cup \{x_i\}) - f_x(S \cup \{x_j\}) + f_x(S)$.

4. Empirical analysis and results

4.1. Interpretable machine learning model for technology valuation

We developed the five machine learning models for technology valuation using the Scikit-learn, fastFM, and XGBoost packages provided by Python. Here, the hyperparameters should be carefully determined to achieve the best predictive performance of each machine learning model. To find the optimal hyperparameter values, we investigated the predictive performance of each machine learning model for every combination of hyperparameter values from the specified subset of hyperparameter space via a grid search algorithm. For this, we defined the type and range of the hyperparameters that need to be optimized for each machine learning model. For example, MLP was developed by adjusting the number and size of the hidden layers, activation function, and learning rate as its hyperparameters. For each combination of hyperparameters, we conducted a grid search based on 5-fold cross-validation techniques using the F_1 score as a performance evaluation metric to assess the overall effectiveness of the machine learning models. The optimal hyperparameter values for each machine learning model were determined to be the following: three hidden layers of 16, 32, and 64 neurons, a batch size of 32, an Adam optimizer with a 0.005 learning rate, and ReLU as the activation function for the MLP; the polynomial kernel and 1.0 as the regularization parameter for the SVM; 50 iterations for the FM; 750 trees and Gini impurity as the split criterion for the RF; and 100 trees, three levels as the maximum depth of the trees, and a 0.001 learning rate for the XGBoost.

Table 3 presents a portion of the results of technology valuation using the machine learning models. In the table, the economic value of technologies consists of two parts: one is based on the probability of a technology being licensed (i.e., L vs. NL) while the other is based on the (expected) royalty payments for a technology generated from licensing contracts (i.e., L1 vs L2). Here, "-" indicates that the corresponding technology has not been licensed. Although the machine learning models achieved reliable performance, there are some misclassified examples to be noted. For example, there is a clear tendency that the longer a technology stays in the OTL (i.e., high TA values), the lower the probability of the technology being licensed. Thus, technology 99–220 that was eventually licensed a very long time after the technology was registered in the OTL is misclassified by the models because of its high TA value.

The performance and reliability of the machine learning models with the optimal hyperparameter values were assessed based on the performance evaluation metrics using 5-fold cross-validation techniques, as summarized in Table 4. Although most machine learning models exhibit comparable performance in L vs. NL classification, ensemble models are found to be more effective in L1 vs. L2 classification. Given the precision, recall, and F_1 score, XGBoost, which classifies many L1 technologies correctly, was selected as the best-performing model. In particular, XGBoost presents almost perfect predictive performance for the L vs. NL classification. Although the performance for the L1 vs. L2 classification is lower than the L vs. NL classification, its "low precision yet high recall" indicates that XGBoost has the potential to reduce the time and effort associated with expert appraisals.

Calculation of the exact SHAP value is challenging because this task considers every possible subset of features and thus involves exponential computation complexity. For this reason, we used Tree SHAP, which computes the SHAP value based on the structure of tree-based models. Tree SHAP recursively tracks which subset of features flows down into which leaves of the tree to reduce the computational complexity from exponential to polynomial solutions (Lundberg et al., 2018, 2020). Using Tree SHAP, we obtained the SHAP values for every feature for

Table 4
Summary of performance evaluation of machine learning models.

Model	Level of analysis	Accuracy	Precision	Recall	Specificity	F1 score
MLP	L vs. NL	0.93	0.97	0.90	0.97	0.93
	L1 vs. L2	0.90	0.22	0.10	0.97	0.14
SVM	L vs. NL	0.56	0.54	1.00	0.10	0.70
	L1 vs. L2	0.92	0.00	0.00	1.00	0.00
FM	L vs. NL	0.90	0.88	0.93	0.87	0.91
	L1 vs. L2	0.84	0.21	0.34	0.89	0.26
RF	L vs. NL	0.95	0.97	0.93	0.97	0.95
	L1 vs. L2	0.92	0.33	0.03	0.99	0.05
XGBoost	L vs. NL	0.94	0.97	0.91	0.97	0.94
	L1 vs. L2	0.73	0.20	0.75	0.73	0.31

Table 3
A sample of the results of technology valuation using the machine learning models.

Technology ID	Technological characteristics					(Actual) Economic value		(Predicted) Economic value									
	TA	PK	…	Spon	Recip			MLP		SVM		FM		RF		XGBoost	
00-003	20	2	…	2	368	L	L2	L	L2	L	L2	L	L2	L	L2	L	L2
00-009	191	21	…	1	1367	NL	–	NL	–	NL	–	NL	–	NL	–	NL	–
00-010	206	5	…	1	7	NL	–	NL	–	NL	–	NL	–	NL	–	NL	–
00-045	−1	44.5	…	2	131	L	L1	L	L2	L	L1	L	L2	L	L2	L	L1
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
02-164	6	12	…	1	6	L	L1	L	L2	L	L1	L	L2	L	L2	L	L2
02-166	−3	6	…	1	0	L	L2	L	L2	L	L2	L	L2	L	L2	L	L2
02-170	206	4	…	1	2	NL	–	NL	–	NL	–	NL	–	NL	–	NL	–
02-181	50	2		1	78	L	L1	L	L2	L	L1	L	L2	L	L2	L	L1
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
99-220	154	18	…	1	151	L	L2	NL	L2	L	L2	NL	L2	NL	L2	NL	L2
99-231	−3	7.33	…	5	3	L	L2	L	L2	L	L2	L	L1	L	L2	L	L1
99-236	202	2	…	1	158	NL	–	NL	–	NL	–	L	L2	NL	–	NL	–

every technology, which allows us to understand the model's behaviors and predictions at the local level.

To visualize the model's behaviors and predictions using SHAP values, we employ force plots that illustrate how the input features contribute to the predicted output value. Specifically, the force plot for a technology shows the base value, predicted output value, the value of each feature, and the contribution of each feature to the predicted output value. The plot is symmetric because the SHAP values of a feature have the same magnitude but different signs for the two categories (i.e., N vs. NL and L1 vs. L2). In the plot, the features that push the prediction higher are represented using a red bar, while those that push the prediction lower are represented using a blue bar.

Fig. 3 presents three major examples of the summary plots. Technology 00-009, which has not yet been licensed, is classified as NL, and TA, AA, and Recip dominantly increase the probability of the technology not being licensed from 0.50 to 0.80, as shown in Fig. 3(a) and (b). Similarly, technology 02-181, which was licensed and earned more than $500,000, is classified as L and L1. TA and BT are the major factors affecting the probability of the technology being licensed, while PC, TCT, and PF are the major factors affecting the probability of the technology being highly valuable, as described in Fig. 3(c)–(f). Finally, technology 02-166, which was licensed and earned less than $500,000,

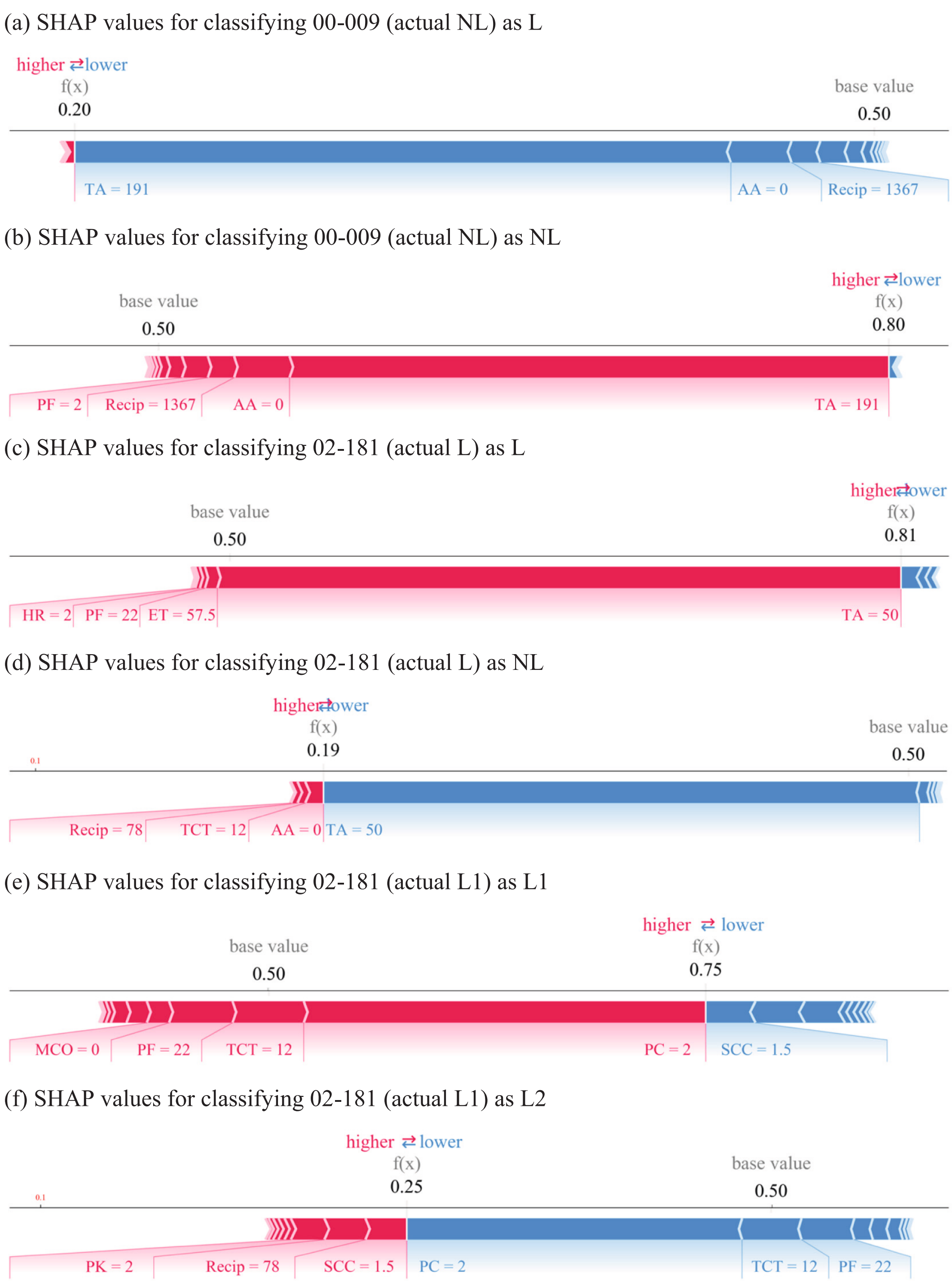

Fig. 3. Examples of the SHAP values for technology valuation.

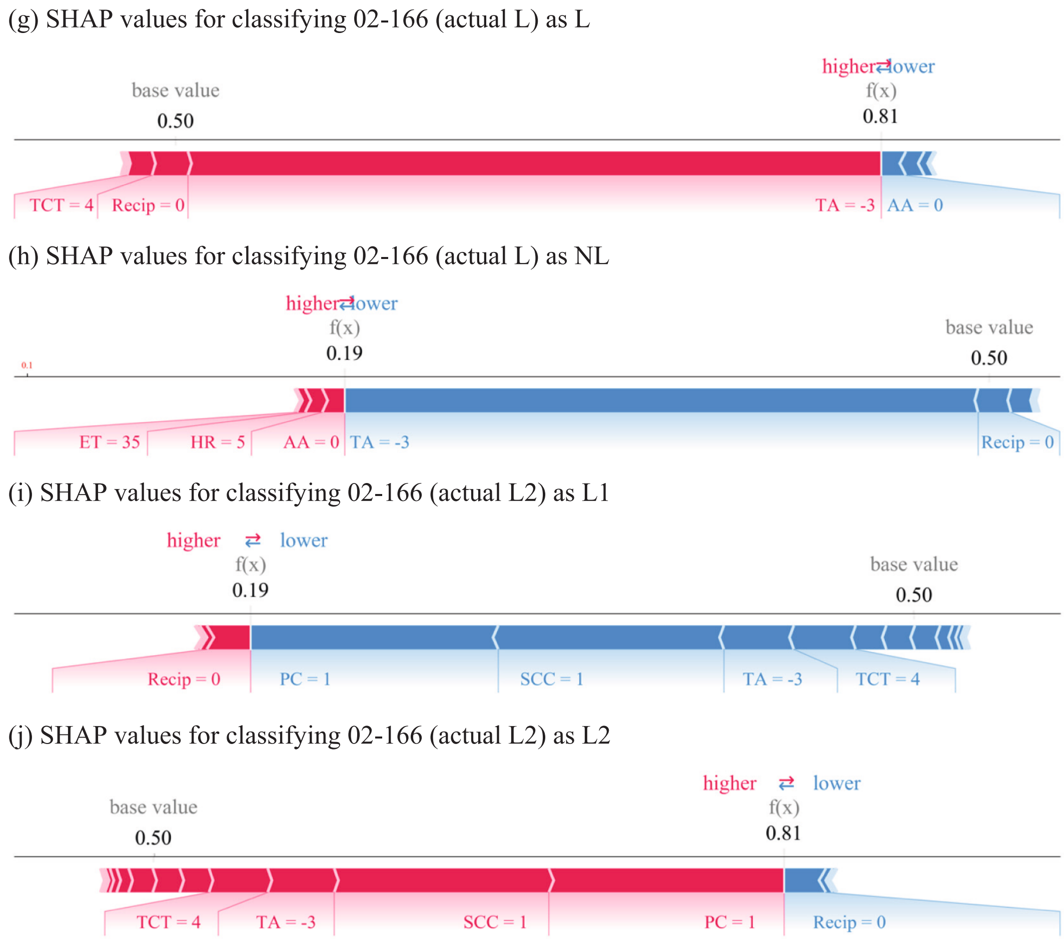

Fig. 3. (*continued*).

is classified as L and L2. Here, PC, SCC, and TA are the main factors determining the probability of the technology being valuable, as shown in Fig. 3(g)–(j). From these examples, we observe that the implications of the features may vary based on the context of technology valuation, although TA is the most influential factor for the L vs. NL classification. The importance of the features of technological characteristics and feature interactions will be investigated in detail in the following sections.

4.2. Feature importance on the economic value of technologies

We employ three types of plots (i.e., dependence plots, summary plots, and bar plots) to understand the model's behaviors and predictions and explore the implications of the features of technological characteristics on the economic value of technologies. Summary plots and bar plots allow us to understand the global trend of a feature's SHAP values. Specifically, summary plots present the distribution of the SHAP values for each feature across all technologies, whereas bar plots display the average of the absolute SHAP values for each feature, which corresponds to the overall importance of a feature on predictions.

Fig. 4 presents the summary plots and bar plots for the L vs. NL classification and the L1 vs. L2 classification. The features, such as TA, AA, Recip, TCT, and ET, are identified as the main features affecting the probability of a technology being licensed. Here, the feature values of AA and ET have a positive relationship with their SHAP values, whereas the feature values of TA, Recip and TCT have a negative relationship with their SHAP values, as shown in Fig. 4(a) and (b). Furthermore, although its contribution to predictions is relatively small, there is a negative relationship between the feature values of HR and its SHAP values. Regarding the L1 vs. L2 classification, features such as PC, SCC, TA, Recip, and TCT are identified as the main features affecting the probability of a technology being highly valuable. The values of these features, except Recip, have a positive relationship with their SHAP values, as shown in Fig. 4(c) and (d).

Dependence plots visualize the relationships between the values of a feature and the SHAP values of the feature, which are not reported in their entirety owing to space constraints. Fig. 5 presents the dependence plots for TA and PC affecting the probability of a technology being licensed and being highly valuable. We observe a clear inflection point: the probability of a technology being licensed drops steeply (i.e., classified as NL) if a technology had not been licensed over approximately 60 months, as shown in Fig. 5(a). The number of patents associated with a technology has a positive relationship with the probability of the technology being highly valuable (classified as L1), as shown in Fig. 5 (b).

Furthermore, we measure the differences of the SHAP values between the two levels of analysis to explore the implications of the features depending on varied technology valuation contexts, as reported in Table 5. In the table, a positive difference value indicates that the corresponding feature is more pertinent to the L vs. NL classification, while a negative difference value means that the corresponding feature is more pertinent to the L1 vs. L2 classification. For instance, TA and AA are found to be more important for the L vs. NL classification, while PC and SCC are more important for the L1 vs. L2 classification.

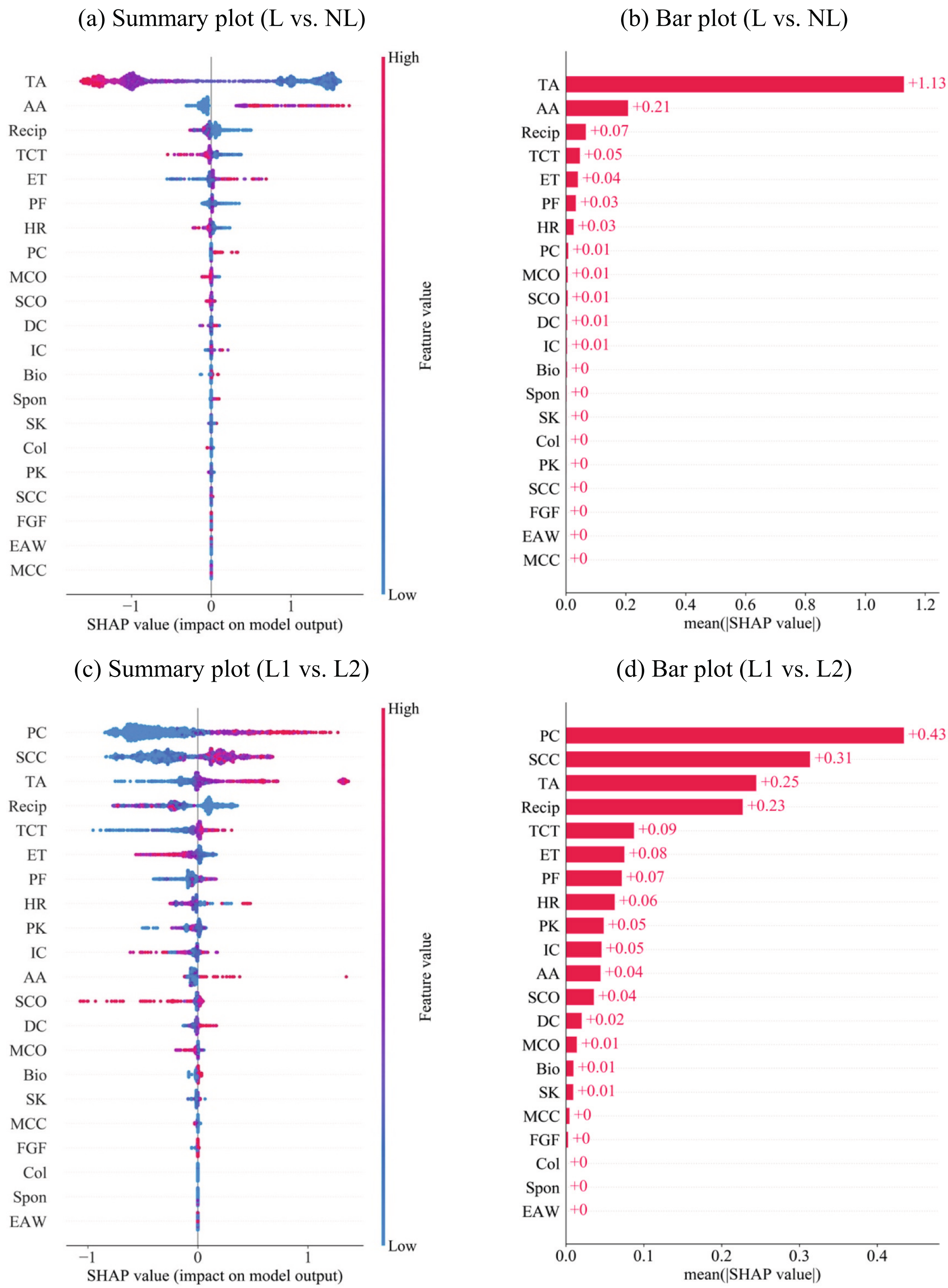

Fig. 4. Feature importance at the global level.

4.3. Feature interaction on the economic value of technologies

We examine the SHAP interaction values representing the pairwise interaction effects of a selected pair of the features of technological characteristics on the predictions. As expressed in Eq. (17), the SHAP interaction value is the additional combined contribution after accounting for the contribution of individual features, which provides the pure interaction effect on the predictions. The SHAP interaction values for each feature are visualized using the dependence plot and summary plot. The dependence plot shows the relationship between the SHAP interaction values and the feature values of the pair of indicators, as illustrated in Fig. 6(a) and (b). Here, the x-axis and the color of each dot represent the feature values of the primary and secondary features, while the y-axis indicates their SHAP interaction values. For example, for the L vs. NL classification, the interaction between TA and ET is significant when the feature values of TA are approximately 60 months.

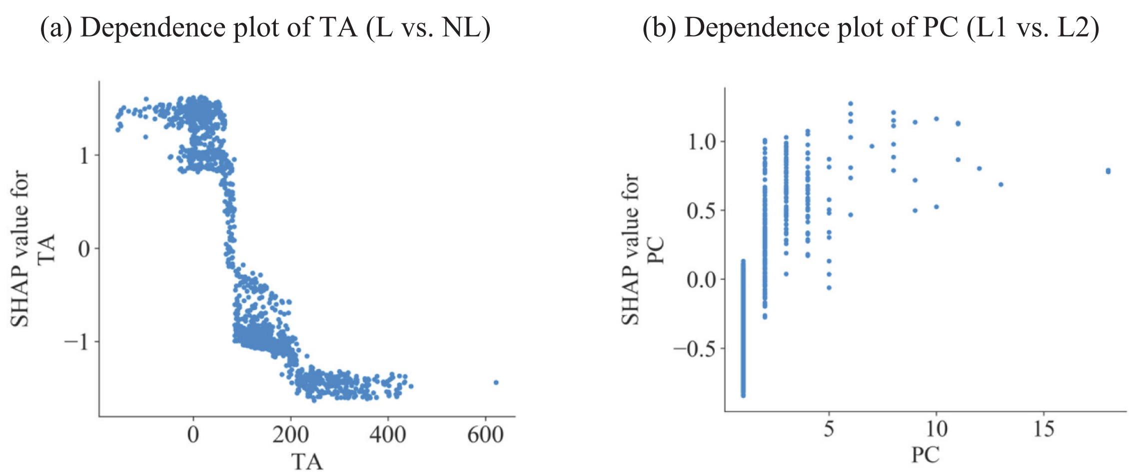

Fig. 5. Examples of feature dependence.

Table 5
Difference of SHAP values between the L vs. NL and L1 vs. L2 classifications.

Technological characteristics	Classifying L	Classifying L1	Difference
TA	0.9636	0.0634	0.9002
AA	0.2073	0.0326	0.1747
ET	0.0190	0.0141	0.0049
DC	0.0024	−0.0007	0.0031
SK	0.0010	−0.0010	0.0020
FGF	0.0000	−0.0019	0.0019
MCO	0.0019	0.0001	0.0018
MCC	0.0000	−0.0016	0.0016
Spon	0.0013	0.0000	0.0013
IC	0.0021	0.0008	0.0013
Col	0.0012	0.0000	0.0012
HR	0.0079	0.0068	0.0011
EAW	0.0000	0.0000	0.0000
Bio	0.0005	0.0010	−0.0005
PK	0.0009	0.0021	−0.0012
TCT	0.0134	0.0172	−0.0038
PF	0.0156	0.0245	−0.0089
SCO	0.0016	0.0149	−0.0133
Recip	0.0381	0.0748	−0.0367
SCC	0.0000	0.1965	−0.1965
PC	0.0076	0.5391	−0.5315

In particular, for the technologies with a TA of 60 months, a higher ET tends to shift predictions towards L while a lower ET tends to shift predictions towards NL. This implies that, for technologies that are nearly five years old, the examination time of the relevant patents is the key determinant in identifying if the technologies are licensed or not. For the L1 vs. L2 classification, PC and PF present a relatively clear trend in their interaction values as compared to other pairs of features. For technologies with multiple patents, the SHAP interaction values between PC and PF are found to increase as the number of patent families increases, as shown in Fig. 6(b). This indicates that a technology with multiple patents is more likely to be classified as highly valuable if its relevant patents are registered in multiple countries.

The summary plot presents the SHAP interaction values for every pair of the features across all technologies, where the individual effects are on the diagonal, the interaction effects are off the diagonal, and the color of each dot represents the feature value of the primary feature (i.e., the feature located in rows). Fig. 6(c) and (d) show the summary plots for the pairs of features that exhibit high SHAP interaction values. We observe that feature interaction effects are more critical to the L1 vs L2 classifications than the L vs. NL classification, although the interaction effects between TA and others are found to be significant for the L vs. NL classification.

In addition, the difference of SHAP interaction values between the L vs. NL and L1 vs. L2 classifications is measured to examine the implications of interaction effects for different technology valuation contexts, as reported in Table 6. The difference value is calculated by subtracting the SHAP interaction values for classifying a technology as L1 from those for classifying a technology as L. A positive difference value (e.g., TA and ET) indicates that the interaction effect between the corresponding features is more critical to the L vs. NL classification than to the L1 vs. L2 classification. These pairs of features, such as TCT and PC, PC and SCC, PK and PC, and PC and IC, are completely independent for the L vs. NL classification yet highly interactive for the L1 vs. L2 classification.

5. Discussion

5.1. Quality of model interpretation

The novelty of our framework stems from the use of interpretable machine learning that makes the model's behaviors and predictions understandable to humans. In particular, feature importance at the local and global levels and their interactions can be used to understand how machine learning models arrive at their conclusions. Following Honegger (2018), we examined the consistency and reliability of the model interpretation using three axiomatic explanation consistency metrics, as follows:

- Identity–The model should provide an identical explanation for the same object. In other words, if the distance between two objects is zero, the distance between their corresponding explanations should also be zero, as presented in Eq. (18).

$$d(x_a, x_b) = 0 \Rightarrow d(\varepsilon_a, \varepsilon_b) = 0, \forall a, b \tag{18}$$

Here, d is a distance function (e.g., Euclidean distance), x_i is a feature vector of the ith data sample, and ε_i is an explanation vector of the ith data sample with the SHAP value for each feature.

- Separability–The model should provide distinct explanations for distinct objects. That is, if the distance between two objects is not zero, the distance between their corresponding explanations should be higher than zero, as expressed in Eq. (19).

$$\mathrm{d}(x_a, x_b) \neq 0 \Rightarrow d(\varepsilon_a, \varepsilon_b) \rangle 0, \forall a, b \tag{19}$$

- Stability–If two objects have the same class prediction λ_i, their corresponding explanations should belong to the same explanation cluster $\overline{c_i}$, as presented in Eq. (20).

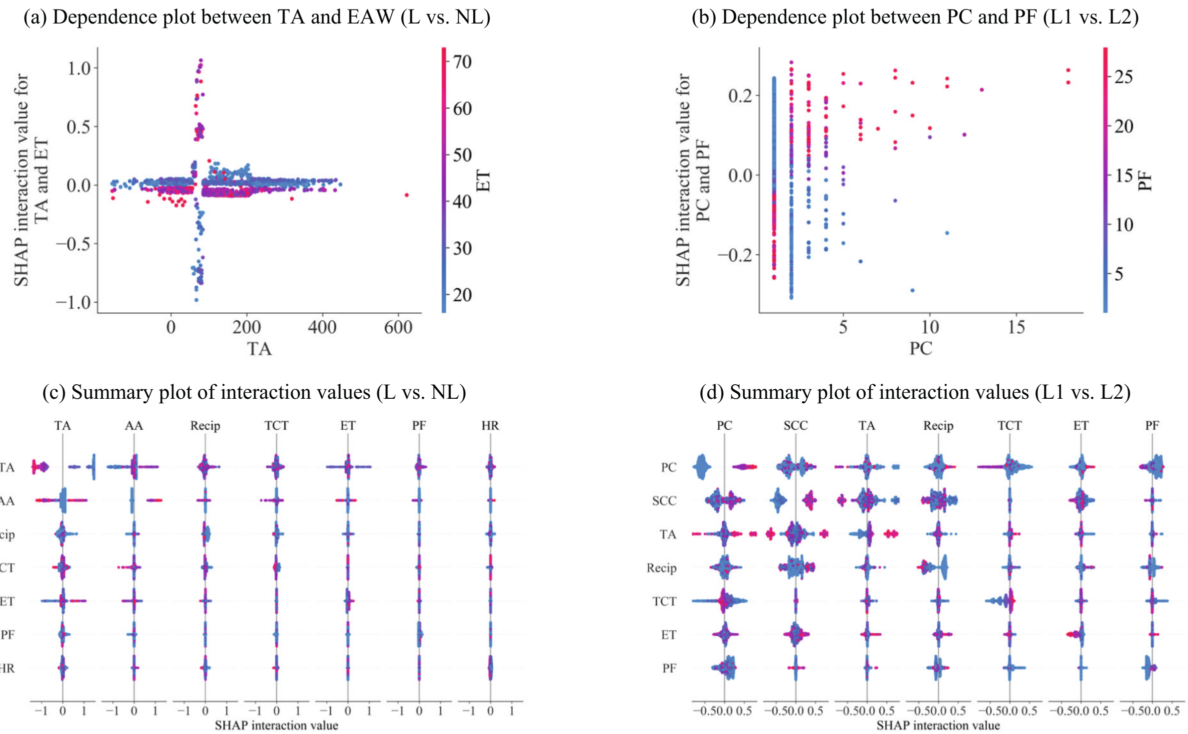

Fig. 6. Examples of feature interaction.

Table 6
Difference of SHAP interaction values between the L vs. NL and L1 vs. L2 classifications.

Features	L vs. NL	L1 vs. L2	Difference
TA and ET	0.0127	0.0054	0.0073
TCT and Recip	0.0049	0.0022	0.0027
TCT and Bio	0.0011	0.0000	0.0011
TCT and HR	0.0009	0.0000	0.0009
MCO and PF	0.0012	0.0004	0.0008
SCO and Recip	0.0008	0.0001	0.0007
TA and DC	0.0005	−0.0001	0.0006
PC and Bio	0.0000	−0.0006	0.0006
SCC and PF	0.0000	−0.0005	0.0005
…	…	…	…
PC and Recip	−0.0012	0.0263	−0.0275
ET and PC	0.0001	0.0328	−0.0327
PK and PC	0.0000	0.0327	−0.0327
TA and PC	−0.0025	0.0311	−0.0336
PC and SCC	0.0000	0.0351	−0.0351
PC and PF	0.0001	0.0430	−0.0429
TCT and PC	0.0000	0.0468	−0.0468
TA and AA	−0.0815	0.0051	−0.0866

$$p(x_a) = \lambda_i = p(x_b) \Rightarrow c(\varepsilon_a) = \overline{c_i} = c(\varepsilon_b), \forall a, b, \lambda_i \subset \Lambda, \overline{c_i} \subset \overline{C} \quad (20)$$

Here, p is a prediction function, X is the set of all data samples, Λ is the set of all predictions over X, and $\overline{C}$ is the set of all explanation clusters with $|\overline{C}| = |\Lambda|$.

Building on these notions, identity was calculated as the ratio of the pairs of data samples with identical SHAP value vectors to the pairs of data samples with identical feature vectors. Similarly, separability was computed as the proportion of the pairs of data samples having different SHAP value vectors to the pairs of data samples having different feature vectors. Stability is measured via k-means clustering analysis (Lloyd, 1982) and Jaccard similarity (Jaccard, 1912). Here, the optimal number of clusters was set to six based on the inertial measure. This measure represents how well the dataset was clustered. It is calculated, for a certain k, as the sum of the squared distance between each data sample and the centroid of the cluster to which the data sample is assigned, as formulated in Eq. (21).

$$Inertia_K = \sum_{j=1}^{K} \sum_{i=1}^{n} ||x_i - c_j||^2, \quad (21)$$

where n is the number of data samples, x_i is the ith data sample, and c_j is the centroid of the cluster to which x_i is assigned. Here, we labelled the clusters with the dominant predicted output of data samples in the clusters. For instance, if the majority of data samples assigned to a cluster was L1, the cluster is labelled as L1. Finally, the stability was calculated by the Jaccard similarity between the predicted labels and the clustered labels of the data samples, as expressed in Eq. (22).

$$Jaccard\ similarity(A, B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \quad (22)$$

Here, A and B are two non-empty sets. Table 7 presents the axiomatic explanation consistency metrics for each level of analysis. The proposed analytical framework provides consistent interpretation results for all pairs of data samples in terms of the identity and separability metrics. The stability metric for the framework is 0.95 for the L vs. NL classification and 0.52 for the L1 vs. L2 classification. This implies that there exists heterogeneity in the relationships between the economic value of technologies (i.e., L1 and L2) with technological characteristics. The results of machine learning models vary considerably because of slight differences in the feature vectors of data samples, although the

Table 7
Axiomatic explanation consistency metrics for the model interpretations.

Level of analysis	Axiomatic explanation consistency metric	Value
L vs. NL	Identity	1.0
	Separability	1.0
	Stability	0.95
L1 vs. L2	Identity	1.0
	Separability	1.0
	Stability	0.52

framework presents high recall values for the L1 vs. L2 classification.

5.2. Implications for theory and practice

This study provides an extensive understanding of the nonlinear relationships between technological characteristics and the economic value of technologies using interpretable machine learning. We can draw several conclusions from the analysis results that may help others use patent indicators in the field of technology and innovation management.

First, although prior studies have presented various types of patent indicators, only a few have examined the linkages between ex-ante patent indicators and the relevant technology's directly observed economic value. The most similar approaches to our analysis are provided by Fischer and Leidinger (2014) and Higham et al. (2021). Fischer and Leidinger (2014) examined the relationships between patent value indicators (i.e., the number of patent forward citations, the number of family members, and the number of distinct classes) and the directly observed auction price of patents using regression models. Higham et al. (2021) investigated the relationships between ex-ante patent indicators and post-grant outcomes at the level of art units using dominance analysis methods. However, neither of these works consider the nonlinear relationships between ex-ante patent indicators and the directly observed economic value of the relevant technologies in academic licensing contexts. The results of our empirical analysis extend the previous literature by assessing the importance of ex-ante technological characteristics on the economic value of technologies as well as their interactions. Although some findings are consistent with the results of prior studies, we observe that the implications of the features of technological characteristics (as well as their interactions) may vary depending on the context of technology valuation (i.e., L vs. NL classification and L1 vs. L2 classification). These findings necessitate more research on the appropriate combination of the context of technology valuation and the patent indicators employed.

Second, a key component of technology licensing is technology marketing, which involves valuing the commercial potential of technologies, disseminating information to inventors and potential buyers, and brokering technologies to the commercial market. Focusing on developing the supplementary tools that can be used in the valuation task, we performed an additional analysis to compare the performance of traditional linear models and nonlinear models. Table 8 presents the feature importance and the performance evaluation metrics of logistic regression using the same dataset employed in this study. XGBoost substantially outperformed logistic regression, especially for the L1 vs. L2 classification, suggesting that the former can capture nonlinearities and complexities that are not captured by the latter. Although the objective of this study is not to identify a definitive set of features of technology characteristics or a specific type of machine learning models for technology valuation, we believe that practitioners should consider using nonlinear machine learning models for technology valuation along with expert appraisals.

Finally, data-driven approaches and conventional expert appraisal approaches cannot be exclusively used; rather, they complement each other. It is important to compare the performance of machine learning models and that of the expert appraisal approach that is used in practice. The licensing managers at the OTL at Stanford University assess the technologies registered using three ordinal scales (i.e., A, B, and C). Table 9 reports the relationships between the results of expert appraisals and the three categories based on the royalty payments generated from licensing contracts. The performance evaluation metrics demonstrate that the analytical framework outperforms the expert appraisal approach in terms of accuracy and reliability for the N vs. NL classification, while the expert appraisals provide more accurate predictions in terms of the precision metric for the L1 vs. L2 classification. Based on the analysis results, we are confident that the proposed approach is a useful complementary tool for technology valuation, creating synergies with expert appraisals. Specifically, the proposed analytical framework is expected to be useful in identifying transferable technologies registered in the OTL based on the probability of the technologies being licensed. It can also be employed for screening technologies that are expected to be highly valuable, reducing the number of technologies that need to be assessed by experts.

Table 8
Results of performance evaluation of the logistic regression.

Model	Level of analysis	Accuracy	Precision	Recall	Specificity	F1 score
LR	L vs. NL	0.93	0.94	0.91	0.94	0.93
	L1 vs. L2	0.91	0.38	0.15	0.98	0.21

Table 9
Relationships between the results of expert appraisals and royalty payments.

(a) Confusion matrix for manual appraisal

		Categories based on the royalty payments		
Results of expert appraisals		L1	L2	NL
	A	29	64	14
	B	21	280	173
	C	18	424	620

(b) Performance evaluation metrics for manual appraisal

Category	Accuracy	Precision	Recall	Specificity	F1-score
L1 (A)	0.57	0.43	0.27	0.97	0.33
L2 (B)		0.36	0.59	0.58	0.45
NL (C)		0.77	0.58	0.68	0.66

6. Conclusion

This study proposes an analytical framework for successful expert–machine collaborations for technology valuation using interpretable machine learning. A central tenet of the framework is that achieving high predictability and interpretability is key to successful collaborations between experts and machine learning approaches to technology valuation. To achieve this, an interpretable machine learning model based on the SHAP method is developed to examine the importance of the features of technological characteristics (as well as their interactions) on the economic value of technologies. The validity and utility of our framework are assessed through a case study of the technologies registered at the Office of Technology Licensing at Stanford University.

The contributions of this study are two-fold. First, from an academic perspective, this study exchanges black box models that do not reveal internal mechanisms for interpretable machine learning approaches for technology valuation. No machine learning model for technology valuation can provide completely correct valuation outcomes due to the high level of uncertainty associated with the technology commercialization processes. For this reason, the effectiveness of previous black box models has been limited by the models' inability to explain their mechanisms and decisions to experts. The proposed analytical framework is therefore expected to serve as a starting point for developing more general and practically applicable models. Moreover, to the best of our knowledge, this is the first attempt at employing interpretable machine learning models in the field of technology and innovation management. The proposed approach could be useful for purposes other than technology valuation where the task to be performed is associated with a high level of uncertainty and complexity, the validation of a certain machine learning model is not easy, and human trust and acceptance are required. Second, from a practical standpoint, a software system was developed to automate our framework, benefiting even those unfamiliar with patent and technology transaction databases and interpretable machine learning models. The system enables the quick analysis of wide-ranging technologies and supports decision making quickly and inexpensively. In particular, our system is expected to effectively determine whether a technology will be licensed. This will reduce the time and cost involved in the technology valuation process that was previously conducted by domain experts and enable them to focus more on the technologies that are likely highly valuable.

Despite its contributions, this study is not without limitations. First, the analysis results may not be generalized easily because the analytical framework is only applicable to technologies having patents, although whether a technology is protected by patents is critical to its valuation. Furthermore, our empirical analysis has a narrow focus on technology valuation in academic licensing contexts. Second, this study focuses mainly on the relationships between technological characteristics and the economic value of technologies with a limited number of ex-ante patent indicators. Rare event data such as patent litigation should be examined to diversify the scope and implications of the analysis results. There are also many other factors, such as market and regulation factors, that may be indicative of the economic value of technologies. The proposed analytical framework could be further elaborated by including other types of features. Finally, our empirical analysis was limited to the technologies registered in the OTL at Stanford University. The analytical framework does not consider the heterogeneity of patenting behaviors across technology domains explicitly. Further testing on a wider range of technologies in varied technology valuation contexts would help establish the external validity of our method and identify the types of technologies in which our framework can best operate. Nevertheless, we believe that the predictability and interpretability our framework offers contribute substantially to current research and future practice.

CRediT authorship contribution statement

Juram Kim: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition. **Gyumin Lee:** Software, Validation, Formal analysis, Data curation, Visualization, Writing – original draft. **Seungbin Lee:** Investigation. **Changyong Lee:** Conceptualization, Methodology, Investigation, Supervision, Writing – original draft, Writing – review & editing.

Data availability

The data that has been used is confidential.

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Appendix A. Features of technological characteristics

A.1. Technological novelty and originality

This category comprises seven features. The first feature is technology age; the older a technology, the higher the chance that the technology has become obsolete (Fischer and Leidinger, 2014). This feature is defined as the difference between the time when a technology is registered in the OTL and the time it is licensed. For a technology that is not licensed, the current time is used instead of the time when the technology is licensed. The remaining six features are related to the backward citations of patents. Given the fact that patent applicants (or examiners) cite all related prior arts by the US patent law, the second and third feature measure the number of patent references and the number of NPL references respectively. Previous empirical studies demonstrated that the number of backward citations (Harhoff et al., 2003) and the number of NPL references including scientific articles and other types of publications relate to patent novelty and further patent values (Callaert et al., 2006). The fourth feature is technology cycle time. This feature identifies the recentness of prior knowledge or the pace of a technology's progress (Bierly and Chakrabarti, 1996) and is calculated as the mean value of differences, in years, between earlier patents cited by a target patent and the patent citing earlier patents. The fifth and sixth features measure the originality of patents (Bessen, 2008; Jaffe and Trajtenberg, 2002). These indicators use the diversity of prior arts for a patent and capture the extent to which the patented invention draws from multiple sets of technologies. Specifically, patent originality is measured on two levels. The class-level originality is calculated by using classes of cited patents, whereas the mainline subclass-level originality is calculated by using mainline subclasses of cited patents, as shown below:

$$1-\sum_{j\in S_B} B_j^2 \tag{23}$$

Here, B_j is the ratio of the number of cited patents that belong to class (or mainline subclass) j to the total number of cited patents. S_B is the set of classes of cited patents. Finally, the seventh feature measures the examination time, which is defined as the length of time between the initial application date and the eventual grant date for a patent. The examination time is found to vary according to the patent quality. In the case of claims with low technology quality, it may take longer to negotiate and examine, resulting in a large time difference (Higham et al., 2021).

A.2. Technological scope

This category comprises four features. The first feature measures the number of patents for a technology because a patent generally describes a single coherent invention. The number of patents is one of the most useful features to measure patent quality such as the pace of creative activity, investor growth, and economic worth (Hirschey and Richardson, 2004). The second and third features are concerned with the technological scope, which is defined as the number of classes of a patent (Lerner, 1994). These features represent the areas where the patented technology can be applied and the number of classes to which a patent is assigned has a positive relationship with its value (Fischer and Leidinger, 2014). Here, two levels of extraction, class-level scope and mainline subclass-level scope, enable a fine-grained characterization. Finally, the fourth feature focuses more on biotechnology and measures whether a technology is related to bio science.

A.3. Technological superiority

This category comprises four features. The first and second features are related to protection coverage, which represents the technology superiority depending on a patent's claims (Lanjouw and Schankerman, 2001). The number of patent claims is found to have a positive correlation with the patent value (Ernst, 2003) and has therefore been utilized as a convenient substitute for a patent's potential value for patent-holders intending to renew their patents. Here, we use the number of independent and dependent claims. The independent claims explain the essential characteristics of a patent, while dependent claims include additional features. The remaining features are related to technological superiority assessed by external evaluators. The third feature measures whether a technology is funded by federal governments. This feature can be adopted as an indicator in the sense that technologies funded by federal governments are associated with higher and broader influence and productivity (Corredoira et al., 2018). The fourth feature measures whether a technology has won the Edison awards.

A.4. Market coverage

This category comprises two features. The first feature measures the number of patents registered internationally for the same invention, i.e., the patent family. We leverage the patent family as a proxy for the economic value of patents, given that patent law is regional in nature, which means that only important patents are applied to many national or regional patent offices. Prior empirical studies presented positive relationships between the size of a patent family and the economic value of the patent (Guellec and de la Potterie, 2000). The second feature measures the number of potential application areas that inventors and licensing managers identify.

A.5. Development efforts and capabilities

This category comprises two features to measure development efforts and capabilities. The first feature measures the number of inventors, as multiple inventor patents tend to have higher significance than those by a single inventor (Ma and Lee, 2008) and larger teams of inventors involve more skills and expertise, thus leading to higher-quality patents (van Zeebroeck, 2007). The second feature is related to collaboration on the assignee side of patents. There appears to be a significant positive relationship between the number of co-assignees and the value of a patent (Ma and Lee, 2008; Meyer, 2006). If a patent has more than one assignee, the indicator is 1, otherwise it is 0.

A.6. Sponsorship and marketing

The probability of a technology being licensed is likely to be affected by the degree to which the technology is exposed to the outside world. In this respect, this category includes two features. The first feature measures the number of sponsors for technology development because corporate-sponsored inventions are licensed and cited more often than others (Wright et al., 2014). The second feature represents the number of marketing recipients.

Appendix B. Machine learning models

B.1. Multilayer perceptron

MLP is a supervised machine learning model that makes predictions through feed-forward computations to capture complex nonlinear relationships between inputs and outputs (Friedman et al., 2001). This method consists of multiple layers of computational units. Each node in a layer has directed connections to the nodes of the subsequent layer. In each layer, the latent feature vector for a data sample is calculated by applying weights and biases and using a nonlinear activation function, as given in Eq. (24):

$$o_l = \phi\left(\sum_i w_i x_i + b\right), \tag{24}$$

where i is the index of the data sample, l is the index of the layer, w_i denotes the weights, b represents the bias, and ϕ is the activation function. This method is trained using a back-propagation technique, which adjusts the weights and biases in the direction of minimizing the errors between the predicted output and actual values, as defined in Eq. (25), where y_i and $f(w_i, x_i)$ indicate the actual value and the output of the network, respectively.

$$J = \sum_i \frac{1}{2}(y_i - f(w_i, x_i))^2 \tag{25}$$

The error calculated from the nodes in the output layer is propagated backward to the nodes that point to them and the weights and biases are adjusted using the gradient of the error, as expressed in Eqs. (26) and (27), where α is the learning rate ranging between 0 and 1.

$$w_i^{new} = w_i^{old} + \alpha(\nabla J) \tag{26}$$

$$b = b^{old} + \alpha(\nabla J) \tag{27}$$

B.2. Support vector machine

SVM is a supervised machine learning model that constructs a hyperplane or set of hyperplanes separating the data points in a high-dimensional space. Given a training dataset (x_1, y_1), …, (x_n, y_n), where x_i is a multi-dimensional input vector, y_i is either 1 or −1 representing the class label, and n is the number of data points, the hyperplane is expressed as Eq. (28):

$$\boldsymbol{w}^T \boldsymbol{x} - b = 0 \tag{28}$$

Here, w is the normal vector to the hyperplane and b is an intercept. SVM is trained by finding the hyperplane that maximizes the margin between the two classes. This corresponds to solving a constrained optimization problem with a differentiable objective function, as follows:

$$\begin{aligned} & minimize \frac{1}{2}\|w\|^2, \\ & subject\ to\ y_i\left(\boldsymbol{w}^T\boldsymbol{x}+b\right) \geq 1, where\ i=1,2,\ldots,n \end{aligned} \tag{29}$$

B.3. Factorization machine

FM is a supervised machine learning model that combines the advantages of SVM and matrix factorization algorithms. Consequently, this method can work with any real-valued feature vector and estimate parameters under sparsity by considering implicit interactions between features through factorization. Given a training dataset (x_1, y_1), …, (x_n, y_n), where x_i is a multi-dimensional real vector and y_i is the class label, a two-way FM (degree $d = 2$) that captures all single and pairwise interactions between features is defined, as given in Eq. (30).

$$\widehat{y}(\boldsymbol{x}) = w_0 + \sum\nolimits_{i=1}^{n} w_i x_i + \sum\nolimits_{i=1}^{n}\sum\nolimits_{j=i+1}^{n} \langle \boldsymbol{v}_i, \boldsymbol{v}_j \rangle x_i x_j, \tag{30}$$

where the model parameters that need to be estimated are $w_0 \in \mathbb{R}$, $\boldsymbol{w} \in \mathbb{R}^n$, and $\boldsymbol{V} \in \mathbb{R}^{n\times k}$, and $\langle \cdot, \cdot \rangle$ represents the dot product of two vectors. The model parameters can be estimated by gradient descent methods.

B.4. Random forest

RF is an ensemble machine learning model based on a multitude of decision trees $\{T_1(X), T_2(X), \ldots, T_{n_{trees}}(X)\}$, where $X = \{x_1, x_2, \ldots, x_p\}$ is a p-dimensional input vector (Ho, 1995). Compared to standard decision trees, this method is found to reduce generalization error significantly by introducing random perturbations in the learning process. RF is trained to produce predictions through three steps. First, n_{tree} bootstrap samples are drawn from the training dataset by random sampling with replacement. Second, a decision tree for each of the bootstrap samples is constructed and fully grown; here, the best split from randomly selected input variables is chosen. Finally, classification is performed by aggregating the predictions of the n_{tree} decision trees $(\widehat{y_1}, \widehat{y_2}, \ldots, \widehat{y_{n_{tree}}})$.

References

Baek, D.H., Sul, W., Hong, K.P., Kim, H., 2007. A technology valuation model to support technology transfer negotiations. R&D Manag. 37 (2), 123–138.
Bessen, J., 2008. The value of US patents by owner and patent characteristics. Res. Policy 37 (5), 932–945.
Bierly, P., Chakrabarti, A., 1996. Generic knowledge strategies in the US pharmaceutical industry. Strateg. Manag. J. 17 (S2), 123–135.
Callaert, J., Van Looy, B., Verbeek, A., Debackere, K., Thijs, B., 2006. Traces of prior art: an analysis of non-patent references found in patent documents. Scientometrics 69 (1), 3–20.
Chen, T., Guestrin, C., 2016. XGBoost: a scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 785–794.
Chen, H., Chiang, R.H., Storey, V.C., 2012. Business intelligence and analytics: from big data to big impact. MIS Q. 36 (4), 1165–1188.
Chiu, Y.J., Chen, Y.W., 2007. Using AHP in patent valuation. Math. Comput. Model. 46 (7–8), 1054–1062.
Choi, J., Jeong, B., Yoon, J., Coh, B.Y., Lee, J.M., 2020. A novel approach to evaluating the business potential of intellectual properties: a machine learning-based predictive analysis of patent lifetime. Comput. Ind. Eng. 145, 106544.
Chung, P., Sohn, S.Y., 2020. Early detection of valuable patents using a deep learning model: case of semiconductor industry. Technol. Forecast. Soc. Chang. 158, 120146.
Coates, V., Farooque, M., Klavans, R., Lapid, K., Linstone, H.A., Pistorius, C., Porter, A.L., 2001. On the future of technological forecasting. Technol. Forecast. Soc. Chang. 67 (1), 1–17.
Corredoira, R.A., Goldfarb, B.D., Shi, Y., 2018. Federal funding and the rate and direction of inventive activity. Res. Policy 47 (9), 1777–1800.
Cortes, C., Vapnik, V., 1995. Support vector machine. Mach. Learn. 20 (3), 273–297.
Du, M., Liu, N., Hu, X., 2019. Techniques for interpretable machine learning. Commun. ACM 63 (1), 68–77.
Ernst, H., 2003. Patent information for strategic technology management. World Patent Inf. 25 (3), 233–242.
Fischer, T., Leidinger, J., 2014. Testing patent value indicators on directly observed patent value—an empirical analysis of ocean Tomo patent auctions. Res. Policy 43 (3), 519–529.
Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. Ann. Stat. 1189–1232.
Friedman, J., Hastie, T., Tibshirani, R., 2001. The Elements of Statistical Learning. Springer Series in Statistics, New York.
Guellec, D., de la Potterie, B.V.P., 2000. Applications, grants and the value of patent. Econ. Lett. 69 (1), 109–114.
Gunning, D., Aha, D., 2019. DARPA's explainable artificial intelligence (XAI) program. AI Mag. 40 (2), 44–58.
Gunning, D., Vorm, E., Wang, J.Y., Turek, M., 2021. DARPA's explainable AI (XAI) program: a retrospective. Appl. AI Lett. 2 (4), e61.
Harhoff, D., Scherer, F.M., Vopel, K., 2003. Citations, family size, opposition and the value of patent rights. Res. Policy 32 (8), 1343–1363.
Higham, K., De Rassenfosse, G., Jaffe, A.B., 2021. Patent quality: towards a systematic framework for analysis and measurement. Res. Policy 50 (4), 104215.
Hirschey, M., Richardson, V.J., 2004. Are scientific indicators of patent quality useful to investors? J. Empir. Financ. 11 (1), 91–107.
Ho, T.K., 1995. Random decision forests. In: Proceedings of the 3rd International Conference on Document Analysis and Recognition, pp. 278–282.
Honegger, M., 2018. Shedding Light on Black Box Machine Learning Algorithms: Development of an Axiomatic Framework to Assess the Quality of Methods That Explain Individual Predictions. arXiv preprint.
Hong, S., Kim, J., Woo, H.G., Kim, Y.C., Lee, C., 2022. Screening ideas in the early stages of technology development: a word2vec and convolutional neural network approach. Technovation 112, 102407.
Jaccard, P., 1912. The distribution of the flora in the alpine zone. New Phytol. 11 (2), 37–50.
Jaffe, A.B., Trajtenberg, M., 2002. Patents, Citations, and Innovations: A Window on the Knowledge Economy. MIT Press.
Jang, H.J., Woo, H.G., Lee, C., 2017. Hawkes process-based technology impact analysis. J. Informetr. 11 (2), 511–529.
Jarrahi, M.H., 2018. Artificial intelligence and the future of work: human-AI symbiosis in organizational decision making. Bus. Horiz. 61 (4), 577–586.
Kim, Y.C., Rhee, M., Kotha, R., 2019. Many hands: the effect of the prior inventor-intermediaries relationship on academic licensing. Res. Policy 48 (3), 813–829.
Kim, Y.C., Ahn, J.M., Kwon, O., Lee, C., 2021. Valuation of university-originated technologies: a predictive analytics approach. IEEE Trans. Eng. Manag. 68 (6), 1813–1825.
Ko, N., Jeong, B., Seo, W., Yoon, J., 2019. A transferability evaluation model for intellectual property. Comput. Ind. Eng. 131, 344–355.
Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. Q. J. Econ. 132 (2), 665–712.
Lanjouw, J.O., Schankerman, M., 2001. Characteristics of patent litigation: a window on competition. RAND J. Econ. 129–151.
Lee, C., 2021. A review of data analytics in technological forecasting. Technol. Forecast. Soc. Chang. 166, 120646.
Lee, C., Cho, Y., Seol, H., Park, Y., 2012. A stochastic patent citation analysis approach to assessing future technological impacts. Technol. Forecast. Soc. Chang. 79 (1), 16–29.
Lee, C., Kim, J., Kwon, O., Woo, H.G., 2016. Stochastic technology life cycle analysis using multiple patent indicators. Technol. Forecast. Soc. Chang. 106, 53–64.
Lee, C., Kwon, O., Kim, M., Kwon, D., 2018. Early identification of emerging technologies: a machine learning approach using multiple patent indicators. Technol. Forecast. Soc. Chang. 127, 291–303.
Lerner, J., 1994. The importance of patent scope: an empirical analysis. RAND J. Econ. 319–333.
Lloyd, S., 1982. Least squares quantization in PCM. IEEE Trans. Inf. Theory 28 (2), 129–137.

Lundberg, S.M., Lee, S.I., 2017. A unified approach to interpreting model predictions. In: Proceedings of the 31st International Conference on Neural Information Processing Systems, pp. 4768–4777.
Lundberg, S.M., Erion, G.G., Lee, S.I., 2018. Consistent Individualized Feature Attribution for Tree Ensembles. arXiv preprint arXiv:1802.03888.
Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., Lee, S.I., 2020. From local explanations to global understanding with explainable AI for trees. Nat. Mach. Intell. 2 (1), 56–67.
Ma, Z., Lee, Y., 2008. Patent application and technological collaboration in inventive activities: 1980–2005. Technovation 28 (6), 379–390.
Meyer, M., 2006. Are patenting scientists the better scholars?: an exploratory comparison of inventor-authors with their non-inventing peers in nano-science and technology. Res. Policy 35 (10), 1646–1662.
Miller, T., 2019. Explanation in artificial intelligence: insights from the social sciences. Artif. Intell. 267, 1–38.
Min, K.B., Lee, C., Kim, Y.C., 2021. The impact of the timing of patent allowance on technology licensing performance: evidence from university invention commercialization. R&D Manag. https://doi.org/10.1111/radm.12509.
Molnar, C., 2020. Interpretable Machine Learning. Lulu.com.
Park, Y., Park, G., 2004. A new method for technology valuation in monetary value: procedure and application. Technovation 24 (5), 387–394.
Reitzig, M., 2004. Improving patent valuations for management purposes—validating new indicators by analyzing application rationales. Res. Policy 33 (6–7), 939–957.
Rendle, S., 2010. Factorization machines. In: 2010 IEEE International Conference on Data Mining, pp. 995–1000.
Ribeiro, M.T., Singh, S., Guestrin, C., 2016. "Why should I trust you?" Explaining the predictions of any classifier. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1135–1144.
Ribeiro, M.T., Singh, S., Guestrin, C., 2018. Anchors: high-precision model-agnostic explanations. Proc. AAAI Conf. Artif. Intell. 32 (1).
Shapley, L.S., 1953. Additive and Non-additive Set Functions. Princeton University.
Shin, J., Coh, B.Y., Lee, C., 2013. Robust future-oriented technology portfolios: black-litterman approach. R&D Manag. 43 (5), 409–419.
Thursby, J.G., Jensen, R., Thursby, M.C., 2001. Objectives, characteristics and outcomes of university licensing: a survey of major US universities. J. Technol. Transfer. 26 (1), 59–72.
Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. RAND J. Econ. 172–187.
van Zeebroeck, N., 2007. Patents only live twice: a patent survival analysis in Europe. ULB–Universite Libre de Bruxelles.
Woo, H.G., Yeom, J., Lee, C., 2019. Screening early stage ideas in technology development processes: a text mining and k-nearest neighbours approach using patent information. Tech. Anal. Strat. Manag. 31 (5), 532–545.
Wright, B.D., Drivas, K., Lei, Z., Merrill, S.A., 2014. Technology transfer: industry-funded academic inventions boost innovation. Nat. News 507 (7492), 297.

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