A novel technology life cycle analysis method based on LSTM and CRF

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Abstract

Technology life cycle (TLC) analysis provides essential support for investment-related strategies and helps to technology trajectory tracing, forecasting, and assessment. The most typical method used to identify TLC is the S-curve fitting method. However, doubts about its accuracy and reliability have been raised owing to the single indicator problem and the missing link between TLC and indicators. K-nearest neighbors(KNN) and hidden Markov model(HMM)-based methods are two influential methods that have been developed. However, something could be improved with these methods. The emerging order of stages is not under control, and the impact of early technology development on the later stages has yet to be addressed. These issues led us to propose a new method to identify TLC using multiple indicators based on machine learning techniques. We extracted ten indicators from the incoPat patent database and utilized a long short-term memory(LSTM) network–conditional random field(CRF) to identify TLC stages with the probability of technology being in a particular stage at a point of the year and changing to other stages during the following year. Moreover, this study investigates the theoretical meaning and empirical performance of indicators. 3-Dimensional print technology was selected as a case study, and its TLC was analyzed and prospects discussed. Comparison of this method and other methods are made as well. The results of our method that fit with the actual progression of technology are relatively accurate. Our analysis showed that the proposed method could offer a smooth and stationary TLC pattern that is accurate and easily understood.

Keyword: Technology life cycle, Technology progression, Long short-term memory network, Conditional random field, Multiple patent indicators

1 Introduction

It is widely accepted that technology usually progresses based on a particular life cycle, and it generally goes through four stages: emerging, growth, maturity, and saturation in accordance with its competitive impact and integration of products and processes (Little, 1981). Technological change follows a particular pattern, with different technological impacts and economic value in various development stages during the evolutionary process of technology. Moreover, technological research is usually cumulative. The externalities or spillovers that early innovators confer on later innovators should be considered other than looking at innovations in isolation(Scotchmer, 1991). Some models and methods to analyze technology life cycles (TLCs) have already been proposed, which not only play an essential role in technology trajectory tracing, forecasting ,and assessment(Huang and Zhu et al., 2021; Zhang and Daim et al., 2021)but also provide essential support for investment-related strategies in both government and industry(Ayres and Martinàs, 1992; Popper and Buskirk, 1992; Akron and Gelbard, 2020). However, the combination of the regular pattern of life cycles and the cumulative nature of technological research poses problems for designing methods to identify TLCs. Therefore, developments of quantitative methods are still needed to identify TLCs(Gao and Porter et al., 2013; Lee and Kim et al., 2016; Lin and Liu et al., 2021).

The most typical method to identify TLC is the S-curve fitting method(Ac Hilladelis and Schwarzkopf et al., 1990; Merino, 1990; Achilladelis, 1993; Ernst, 1997; Andersen, 1999; Gao and Porter et al., 2013). However, doubts about its accuracy and reliability have been raised due to using a single indicator(Watts and Porter, 1997; Haupt and Kloyer et al., 2007; Gao and Porter et al., 2013). The result of this method is still ambiguous and relies on experts at critical points. Hypothetically, the number of patent applications is now 100. Can we say that the technology has transitioned to its next stage if the number of patent applications changes to 150? Or is it just a fluctuation in a particular stage? This method cannot directly indicate the current stage of the technology, and the link between TLC and indicators remains missing(Lee and Kim et al., 2016).

These issues are critical to the TLC problem and should be addressed. First, the TLC stages cannot be observed directly. Only proxy indicators can be used to infer how technology has been developed. The characteristics of indicators have been discussed in previous research, and it has been concluded that more effective indicators result in more descriptive information about the TLC that can be used to identify them (Haupt and Kloyer et al., 2007). In addition, some research provides a theoretical explanation of the relevant indicators(Gao and Porter et al., 2013; Lee and Kim et al., 2016). However, there has been little methodological study on the interaction between indicators and technology progression stages and the correlation between each indicator. Thus, indicators must be further investigated based on their theoretical meaning and empirical performance to estimate the TLC.

Secondly, considering the link between TLCs and indicators emerges as a priority for the problem of identifying TLCs. Compared with methods that use one or more related indicators to fit the equation to estimate the TLC (Merino, 1990; Gao and Porter et al., 2013), our method views the TLC as a hidden state and the values of related indicators as observational sequences, which is consistent with the relationship between TLC and related indicators and can reveal their links(Lee and Kim et al., 2016). Furthermore, the possibility of technology in each life cycle stage is represented by a possibility score, and the stage with the highest score is identified as the TLC. This solves the problem of ambiguous boundaries between stages.

The drawbacks of S-curve necessitate the development of new methods to estimate technology progression. Among those methods, k-nearest neighbors (KNN) and hidden Markov model (HMM) analyses are highly influential (Gao and Porter et al., 2013; Lee and Kim et al., 2016). However, they have two disadvantages: the emerging order of stage needs to be under control, and they ignore the impact of early technology development on its later stage.

On the one hand, technology develops gradually based on a specific discipline paradigm in the route of normal science(Kuhn, 1962). In this study, the emerging order of each technology progression stage is considered. In addition, the order in which the emerging, growth, maturity, and saturation stages appear also conforms to the definition of TLC.

Alternatively, new inventions tend to follow cumulative trajectories where new technical progression builds on a foundation provided by earlier innovators(Scotchmer, 1991). The development of technology in its early stage will affect its later stage. Thus, the stages of technology progression are not entirely independent. Our method has considered the impact of the early stage of technology on its later stage rather than simply taking each stage in isolation.

We considered these issues and proposed a new method to identify TLCs based on machine learning techniques using multiple indicators. We defined and adopted three new indicators, prior knowledge, patent novelty, and patent family, with seven indicators, including patent application, technology applicant, technology breadth, backward citation, forward citation, examination period, and protection coverage used in previous studies. Both the theoretical meaning and empirical performance of these selected indicators were discussed. We then utilized a long short-term memory network (LSTM)-conditional random field (CRT) to identify the TLC stages. This method models the TLC as hidden stages and indicators as observation stages, and it can provide precise results of the stage sequence with a transformation probability matrix. The LSTM was used to capture the influence of previous observational values and correspondence between the indicators and stages. The CRT ensured that the stage sequences followed the four-stage order. In addition, this model can accept correlated indicators. Thus, this method overcomes the defects of HMM. A case study of three-dimensional (3D) print technology proved that the results of our method are consistent with the actual condition of technology progression and are, thus, relatively accurate. In addition, the prospects of technology were discussed.

Since this method can be universal, an automated software system was created to help users not interested in code and algorithms extract indicators, identify TLC, and easily predict the prospect of technology.

This study is organized as follows: Section 2 shows the background of our research. Section 3 details the data collection, indicator extraction, and a TLC identification method. Section 4 is the results of a case study of 3D printing. In section 5, we discuss the results and provide the conclusion.

2 Background

2.1 Approaches to identify the TLC

Modeling technology progression through the TLC is not a problem that could lead to a fully determined answer owing to the uncertainty, complexity, and data availability of technology fields in the real world. It is a natural attempt to use a method dependent on expert knowledge, such as direct analysis and the Delphi method. However, applying this method costs time and energy, and requires specific human resources, making it unacceptable and unavailable to small and medium-sized enterprises (SMEs) with a possible lack of financial or personal resources.

Early studies show that the S- or SS-curve is typical to technology evolution, so there were studies that attempted to determine the TLC stages using a curve-fitting method with a single patent indicator (usually the number of patents)(Ac Hilladelis and Schwarzkopf et al., 1990; Achilladelis, 1993; Ernst, 1997; Andersen, 1999). This curve-fitting method is the most classical among all the approaches used to identify the TLC and has still been utilized in recent research(Huang and Zhu et al., 2021; Zhang and Daim et al., 2021). The pros and cons of this method are obvious. It is easily explained and used. However, it is a half-qualitative and half-quantitative method based on empirical studies, which indicates that it may be vague.

Subsequent research shifted its direction in two aspects. One is to identify and apply multiple indicators other than the single one, whereas the other focuses on applying more mathematical methods to solve the TLC identification problem.

For the first aspect, Haupt et al. (2007) identified six patent indices as appropriate life cycle indicators by examining their significant change in mean value in different stages. Gao et al. (2013) used 13 indicators to identify the TLC and analyzed their cross-correlation. Hikkerova et al. (2014) indicated that the delivery term and the cumulative number of citing patents are influential variables during the stages of the patent life cycle. Lee et al. (2016) concluded seven patent indicators from related research. The consensus among these studies is that a single indicator can only show part of the characteristics of TLC, which could lead to deviations in its identification. Huang and Li et al., (2022) analyze TLC from a new perspective: characteristics of patent citation networks, including the number of independent communities and the number of connected linkages. It contributes to the research of indicators. Nevertheless, more generally effective indicators failed to play their roles by looking only at the network indicators. To depict technology progression more precisely, more appropriately designed indicators can decrease the systematic biases between single measures and will help this process.

For the second aspect, Gao et al. (2013) proposed a method based on a k-nearest neighbors classifier (KNN). This was the first method to apply machine learning algorithms and effectively solved the problem of identifying the TLC. However, this method do not consider stages in algorithm theory. It simply fits data through the distance and is sensitive to noise in the dataset. Lee et al. (2016) presented a stochastic model based on the hidden Markov model (HMM). This method is ingenious to consider the TLC stages as the hidden stages and patent indicators as the observation stages. However, there is a limitation in that the stages generated by HMM are representations of technological changes, which do not involve the TLC stages following the time order. In addition, the HMM contains two inappropriate assumptions when addressing the problem of identifying the TLC. Lin and Liu et al.(2021) used entropy to describe the indicators change, thus determining TLC in a specific technical field. It is an extending method of the S-curve. However, the drawback it inheriting from the S-curve method is that it still can not handle more than one indicator and consider their effect together.

In this study, we first adopted three new indicators that were properly designed and were more effective at determining the TLC. We then drew from the highly innovative idea of Lee et al. (2016). We proposed a method based on the developmental model of HMM, in which the two unreasonable hypotheses are discarded. This research proposed a new framework that enables extensive multi-indicators and analyzes TLC considering the development and prior stage of technique simultaneously.

2.2 Long Short-Term Memory Network

Recurrent neural networks (RNN)(Elman, 1990) is a network structure that maintains a memory based on historical information, which enables the model to predict the current output conditioned on long-distance features. Figure 1 shows the RNN structure, which has an input layer *x*, hidden layer *h*, and output layer *y*.

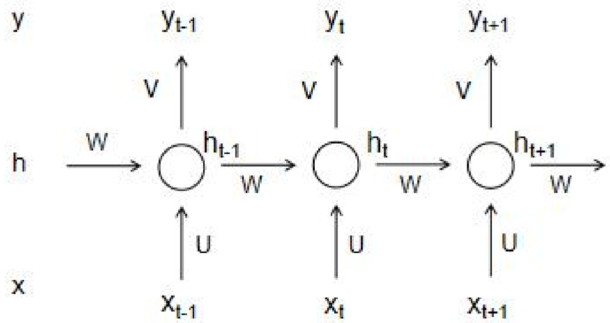


Figure 1 A simple RNN model.

The input layer represents the features at time *t*, with the same dimension as the feature size. The output layer represents a probability distribution over labels at time *t*, with the same dimension as the size of the labels. Compared with the standard full connection neural network, the innovation part of RNN is that it introduces the connection between the previous and current hidden states represented by the recurrent weight parameters. The recurrent weight is designed to store historical information. Thus, the value of h_t depends on not only x_t but also h_{t-1}. Thus, the values in the hidden and output layers are calculated as follows:

$$h_t = f(U \cdot x_t + W \cdot h_{t-1}) \quad (1)$$

$$y_t = g(V \cdot h_t) \quad (2)$$

Where U, W, and V are connection weights to be computed while training. The functions *f* and *g* represent sigmoidal and SoftMax activation functions, respectively.

In this study, we utilized a long short-term memory (LSTM) network(Hochreiter and Schmidhuber, 1997), a development of RNN that has effectively solved the inability to connect the long range information problem in RNN. The difference between them is that the hidden layer updates of the normal RNN are replaced by purpose-built memory cells, which help to exploit long-range dependencies in data. Figure 2 shows a single LSTM cell(Gers and Schmidhuber et al., 2000).

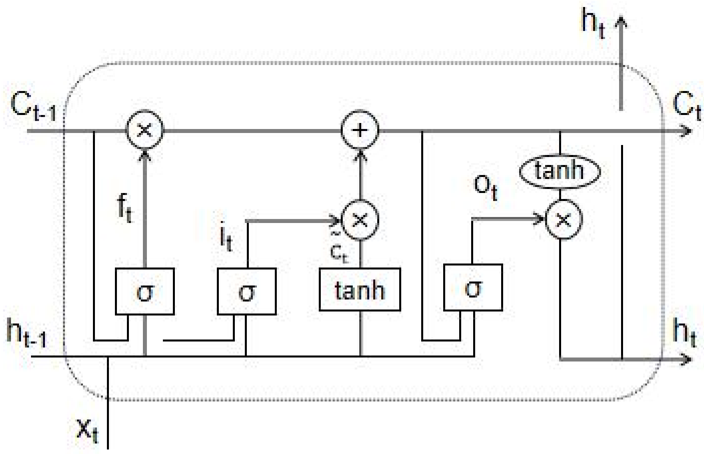


Figure 2 A long short-term memory cell

In an LSTM cell, a "gate" is designed to remove or add information to the cell state and contains a sigmoid layer and pointwise operation. The sigmoidal layer outputs a value between 0 and 1, which describes how much information can pass through. The lines transfer vectors, and the circles represent multiple or plus operations. σ and tanh are both functions. The combined lines represent the concatenation of vectors, and the separated lines represent copy vectors and send them to different locations. Based on Figure 2 and the description above, the LSTM cell can be implemented as follows:

$$f_t = \sigma(W_f \cdot [C_{t-1}, h_{t-1}, x_t] + b_f) \tag{3}$$

$$i_t = \sigma(W_i \cdot [C_{t-1}, h_{t-1}, x_t] + b_i) \tag{4}$$

$$o_t = \sigma(W_o \cdot [C_t, h_{t-1}, x_t] + b_o) \tag{5}$$

$$\widetilde{C}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_C) \tag{6}$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{7}$$

$$h_t = o_t * tanh(c_t) \tag{8}$$

where σ is the sigmoidal logistic function and *f*, *i*, *o* and *c* are the forget gate, input gate, output gate, and cell state, respectively. All are the same size as the hidden vector *h*. W represents the weight matrix.

2.3 Conditional Random Field

To introduce the conditional random field (CRF) model, we first introduced the Markov chain, a statistical model developed by Andrei A. Markov in 1907. It describes a sequence of possible states; the probability of each state is dependent on the previous state and its mathematical expression as follows:

$$\mathrm{p}(\mathrm{X}_{t+1}|\mathrm{X}_t, \ldots, \mathrm{X}_1) = \mathrm{p}(\mathrm{X}_{t+1}|\mathrm{X}_t) \tag{9}$$

where X is the Markov chain and X_t is the state at time t.

The HMM(Rabiner and Juang, 1986) goes steps further than the Markov chain. In the HMM, an underlying stochastic process is not directly observable but can be observed using a set of stochastic progressions. The primary difference between the conventional Markov chain and the HMM is that the state sequence of HMM cannot be directly observed. In contrast, the observational states can be generated by these hidden states. In TLC identification, different stages of technology development can be considered the hidden stage, while indicators are considered the observational stage. Thus the HMM method was used to analyze the TLC in a previous study(Lee and Kim et al., 2016). The HMM was implemented as follows:

$$A = [a_{ij}] = p(q_{t+1} = s_j | q_t = s_i);\ i, j = 1, \dots, N \tag{10}$$

$$B = b_j(m) = p(o_t = v_m | q_t = s_j);\ j = 1, \dots, N \tag{11}$$

$$\Pi = \pi_i = p(q_1 = s_i);\ i = 1, .., N \tag{12}$$

where S={s_1,s_2,...,s_N}; V={v_1,v_2,...,v_m}, and A, B and Π represent hidden states, observation values, and the state transition probability matrix, observation probability density matrix, and an initial state probability vector, respectively. q_t is the state, and o_t is the observation from time *t*.

The HMM is a directed graph model with two strict assumptions: homogeneous Markov property and observation independence, which indicates that a state only depends on the previous single state, and the observation only depends on the state at the current time. These two assumptions can simplify the calculation, and eliminate the dependence between variables. This results in the unpractical nature of the HMM to represent multiple interacting features or long-range dependencies of the observations. Further research based on HMM proposes a conditional random field model to solve this problem.

The CRF(Lafferty and Mccallum et al., 2001) is a machine learning technique based on an undirected probability graph. The linear-chain conditional random field is the most widely used CRF model. Thus, CRF is commonly used to refer to the linear-chain CRF. It is modeled as follows:

$$p(y|x) = \frac{1}{Z(x)} \exp\left(\sum_{i,k} \lambda_k t_k(y_{i-1}, y_i, x, i) + \sum_{i,l} u_l s_l(y_i, x, i) \right) \tag{13}$$

$$Z(x) = \sum_y \exp\mathrm{I} \sum_{i,k} \lambda_k t_k(y_{i-1}, I, x, i\mathrm{I} + \sum_{i,l} u_l I(y_i, x, i)) \tag{14}$$

$$t_k(y_{i-1}, y_i, x, i) = \begin{cases} 1, & s.t. \\ 0, & else \end{cases} \tag{15}$$

$$s_l(y_i, x, i) = \begin{cases} 1, & s.t. \\ 0, & else \end{cases} \tag{16}$$

where k and l are the numbers of maximal cliques, representing any non-redundant two neighboring y_i,y_{i+1}, and x_i,y_i, and t_k,s_l are feature functions. λ_k and u_l are the corresponding weights. Z(x) is a normalization factor. Figure 3 shows the structures of the three models described above.

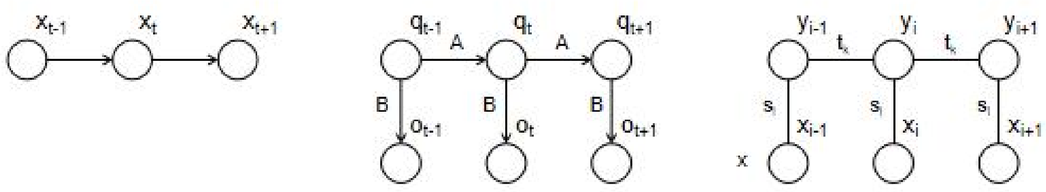


Figure 3 Structure of the Markov chain (left), HMM (center) and linear-chain CRF (right).

2.4 LSTM-CRF model

Huang et al. (2015) combine LSTM and CRF to form the LSTM-CRF model, which can efficiently use past input features via the LSTM layer and tag information via a CRF layer(Huang and Wei et al., 2015). Figure 4 shows the structure of the LSTM-CRF model.

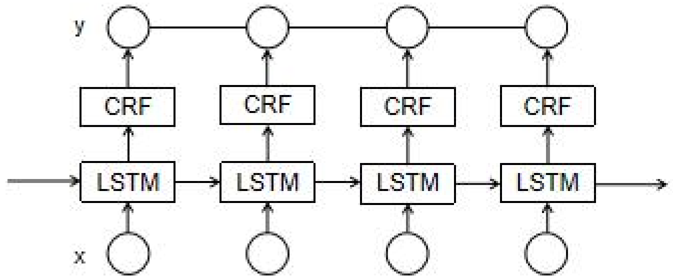


Figure 4 Structure of the LSTM-CRF model.

The score of a feature sequence x along with its tag sequence y is provided by the sum of CRF transition scores and LSTM output scores:

$$s(x, y, \tilde{\theta}) = \sum_{t=1}^{T} (A_{y_{t-1}, y_t} + f_{\theta_{y_t, t}}) \quad (17)$$

where $f_{\theta_{i,t}}$ is the element of the LSTM output scores matrix, and $f_\theta(x)$ with parameters θ for sequence x and for the i-th tag at t time. $A_{i,j}$ represent the CRF transition scores to model the transition from i-th state to j-th through a pair of consecutive time steps. $\tilde{\theta} = \theta \cup \{A_{i,j} \forall i, j\}$ is the new parameter for the whole network. The following steps are the same as those of the CRF model, and the negative log likelihood function is used as the loss function.

$$p(y|x) = \frac{\exp(s(x, y, \tilde{\theta}))}{Z(X)} \quad (18)$$

$$Z(x) = \sum_y \exp(s(x, y, \tilde{\theta})) \quad (19)$$

$$loss = -\log p(y|x) \quad (20)$$

Dynamic programming(Rabiner, 1989) is usually used to compute $A_{i,j}$ and optimal tag sequences(Lafferty and Mccallum et al., 2001). The Viterbi algorithm determines the inferences among optimal tag sequences, i.e., to obtain the most probable state sequence.

3 Data and Methods

3.1 Data collection

The cathode ray tube (CRT) and thin film transistor-liquid crystal display (TFT-LCD) are two typical examples of technologies used in TLC identification(Gao and Porter et al., 2013; Altuntas and Dereli et al., 2015; Chang and Fan, 2016; Lin and Liu et al., 2021). These two examples originate from Gao et al. (2013) (Gao and Porter et al., 2013), who devised several patent-based indicators and then chose CRT and TFT-LCD as training technologies. 3D printing technology is a case study of the research of Lin et al. (2021) (Lin and Liu et al., 2021), which uses computer-aided design to adhere successive layers of materials to form complex 3D objects and is currently one of the most advanced manufacturing technologies with a long period of development. Understanding the stages of progression and TLC of 3D printing technology is vital for governments and enterprises that evaluate potential investments. Thus, we consider it a testing technology and a case for analysis in our study.

We used the incoPat patent database because it contains more data over a larger time span than the Derwent database. Since 18 months are typically required to progress from the patent application to patent publication, we selected a patent whose application date was before the end of 2020. We also referred to the search terms of previous studies to obtain the patent data of the four technologies chosen.

The search term for CRT was (ALL=(cathode ray tube*) OR ALL=(CRT)) AND (CPC=(H01J) OR CPC=(H05G) OR IPC=(H01J) OR IPC=(H05G)). Simply using the term cathode ray tube* or the abbreviation CRT brought up many irrelevant records, so the CPC and IPC codes were added to control the search results. Code H01J represents electric discharge tubes or discharge lamps, and code H05G represents the X-ray technique. In this manner, we obtained 96,247 records for CRT technology.

The search term for TFT-LCD was (ALL = (thin film transistor* liquid crystal display*) OR (ALL=(TFT) AND ALL=(LCD))) AND (IPC=(G02F1/13) OR CPC=(G02F1/13)). Again, we controlled the search results with the IPC and CPC code G02F1/13, which stands for techniques based on liquid crystals, e.g., single liquid crystal display cells. In this way, we obtained 82,828 records for TFT-LCD technology.

The search term for 3D printing was TIAB=("3D print") OR TIAB=("3D printer") OR TIAB=("3D printing") OR TIAB=("additive layer manufacture") OR TIAB=("additive manufacture") OR TIAB=("rapid prototyping") OR TIAB=("rapid manufacture") OR TIAB=("direct digital manufacture") OR TIAB=("layer manufacture"). These terms have related meaning as 3D printing. As a result, we obtained 76360 records for 3D printing.

The number of patent applications over time in each field is shown in Figure 5.

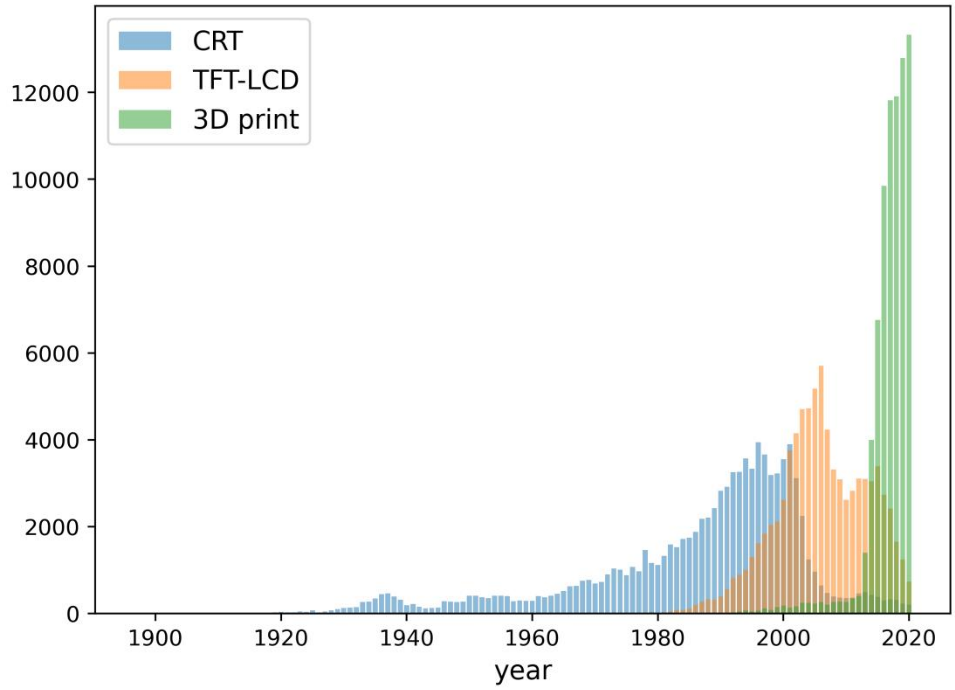


Figure 5 The number of patent applications over time

3.2 Extraction of the time-series patent indicators

A wide range of patent indicators have been utilized to analyze TLCs. To define and extract the time-series patent indicators, the indicator should first be theoretically meaningful to capture technology development, i.e., it can be used to assess the technological impact or economic value of patents. Secondly, the mean value of the indicator should differ significantly to more effectively characterize the different TLC stages, thus, reducing the deviation in TLC identification. In addition, data to extract those indicators should be available. We utilized these criteria to select indicators from previous studies and build some new indicators after referring to relevant research to help identify the TLC.

Patent application (PA_t): Patent application has been defined as the number of patents applied in a technology filed at time t, which has been the most frequently used indicator since the research on S-curves. The increase and decrease in the number of patent applications can be interpreted as a sign of research and development (R&D) investment(Ernst, 1997). Previous studies also show that it tends to increase in the emerging and growth stages, fluctuate in the maturity stage and rapidly decrease to the saturation stage(Andersen, 1999; Haupt and Kloyer et al., 2007; Gao and Porter et al., 2013). Since the patent number differs in each technology field, we normalized the patent applications per year with the total number of patent applications.

Technology applicant (TA_t): Technology applicant is defined as the average number of standardization applicants in a technology field at time t. Studies have found that there are only a small number of patent applicants in the emerging stage who are willing to bear the risk; as the technology develops, more applicants will engage and gradually withdraw when the technology is under recession(Campbell, 1983; Haupt and Kloyer et al., 2007).

Technology breadth (TB_t): Technology breadth is defined as the average number of different subclasses of IPC numbers in a technology field at time t. The IPC subclass can effectively represent the use of methods under different technical topics(Lerner, 1994). Research on technology diffusion has shown that patents are usually more concentrated on specific problems during the early stages of technology progression, which can be represented by the small number of IPC subclass, and the technology will gradually diffuse to other fields as the technology develops, represented by the increasing number of subclasses(Campbell, 1983; Haupt and Kloyer et al., 2007).

Backward citation (BC_t): Backward citation is defined as the average number of references of patents in a technology field at time t. Backward citation is essential for inventors to describe the background and demonstrate the advancement of their invention(Collins and Wyatt, 1988) and for examiners to provide evidence to limit the scope of patent claims(Li and Chambers et al., 2014). The results of previous research suggest that the number of references to a patent is positively related to its value(Harhoff and Scherer et al., 2003).

Forward citation (FC_t): Forward citation is defined as the average time patents have been cited in a technology field at time t. This indicator has been a typical indicator for measuring patent quality and patent value(Harhoff and Scherer et al., 2003; Lanjouw and Schankerman, 2004; Nemet, 2012). During the early stage of technology development, the appearance of significant essential patents will always lead to a substantial number of forward citations. Then the number of forward citations will decrease(Haupt and Kloyer et al., 2007).

Examination period (EP_t): The examination period is defined as the average months between publication and application dates in a technology field at time t. The period of examination is also affected by the stages of TLC. This could happen because the examiners may lack experience in examining an emerging technology and have a heavier task of citation owing to a broad claim at the early stage of technology development, leading to a long examination period(Haupt and Kloyer et al., 2007).

Protection coverage (PC_t): Protection coverage is defined as the average number of claims of patents in a technology field at time t. The claim defines the scope of protection provided by the patent or patent application in scientific terms, which is of vital importance in the patent application and litigation(Tong and Frame, 1994). Relevant studies have shown that this indicator is positively related to patent novelty, usefulness of a patent, and patent value(Tong and Frame, 1994; Lanjouw and Schankerman, 2004; Reitzig, 2004).

Prior knowledge (PK_t): Prior knowledge is defined as the average semantic similarity of patents and their citations in a technology field at time t, which represents the knowledge absorbed by patents. Usually, the number of backward citations is used to represent prior knowledge(Almeida and Paul, 1996; Jaffe and Trajtenberg et al., 2000; Chang, 2012). However, it is not precise to consider only the number of citations and assume each citation is equivalent while ignoring the diversity of patent citation motives and differences in their contribution(Zhu and Turney et al., 2015; Lin, 2018). Thus, we utilized the Sentence-BERT model to compute the semantic similarity between the citing and cited patent pairs to measure the prior knowledge precisely.

Patent novelty (PN_t): Patent novelty is defined as the average similarity of knowledge units in semantic networks in a technology field at time t. Novelty is an essential characteristic of technological innovation and economic success(Cozzens and Gatchair et al., 2010). Compared with conventional backward citation and patent classification analyses to measure the novelty of patents(Ahuja and Lampert, 2001; Strumsky and Lobo, 2015; Verhoeven and Bakker et al., 2016), text mining with deep learning methods is more strongly recommended(Zhou and Dong et al., 2021). In this study, the Sentence-BERT model was used to compute the similarity of knowledge units of each patent in semantic networks to measure the patent novelty.

Patent family (PF_t): A patent family is defined as the average number of countries in which the inventor(s) applied for a patent. For each of these countries in which a patent was applied for, application and maintenance fees have to be paid to the respective offices. Therefore, an application for a patent in a foreign country indicates that the patent is highly valuable and is likely to bring profits for establishments to cover the additional costs for patent protection(Peter and Neuhusler et al., 2013). The average size of a patent family has proven to be a convenient indicator of the quality and economic value of the patent(Lanjouw and Schankerman, 2004; Neuhäusler and Frietsch et al., 2011).

3.3 Methods to identify the stages of TLC

As with previous studies, we used the CRT and TFT-LCD indicator matrix and their stage labels as training data(Gao and Porter et al., 2013) and an indicator matrix of 3D printing as the testing data. The indicator-extracting program was coded by Python. To eliminate the units of measurement and rescale data to values between 0 and 1, so as to improve the convergence speed of the deep learning model, we used the L2-norm to standardize the time series values of the selected indicator. An example of the indicator matrix of CRT is shown in Table 1.

Table 1 Example of the indicator matrix of CRT

id	year	stage	pa	td	ts	bc	tv	dep	pc	pk	pf	pn
1	1897	0	6.94E-05	0.154449121	0.063572977	0	0.107527955	0.005830985	0.04684456	0	0.018649159	0
2	1898	0	6.94E-05	0.154449121	0.063572977	0	0	0.23615489	0.1171114	0	0.018649159	0
3	1901	0	6.94E-05	0.154449121	0.063572977	0	0	0.122450683	0.1171114	0	0.018649159	0

…	…	…	…	…	…	…	…	…	…	…	…	…
119	2019	3	0.016036724	0.068866924	0.089717708	0.147494378	0.004965216	0.039150899	0.125223012	0.146415253	0.047793515	0.079121795
120	2020	3	0.013606917	0.074860544	0.084655852	0.069492306	0.004206025	0.022000068	0.135992626	0.077390202	0.037298317	0.102031511

We continued to use the TLC stages of CRT and TFT-LCD in (Gao and Porter et al., 2013) research, which was acquired from 10 experts in CRT, TFT-LCD, or display fields using the Dephi method. The results were determined based on related studies(Lai, 2003). Those stage labels of training data are shown in Table 2.

Table 2 Technology life cycle stages of CRT and TFT-LCD

	Emerging	Growth	Maturity	Saturation
CRT	1897-1929	1930-1972	1973-2000	2001-
TFT-LCD	1974-1990	1991-2007	2008-2014	-

The LSTM-CRF program was coded using PyTorch. We used the Adam optimizer with a learning rate of 0.01, and the weight_decay as $1e^{-3}$, which helps to improve the accuracy while reducing the learning time. We set epoch = 500 to ensure that the loss was minimized.

4 Results and discussion

4.1 Evaluating the effectiveness of indicators

To more effectively characterize the different stages of TLCs, the mean value of the indicator should differ significantly. These criteria enabled the interaction between indicators and the technology progression stages of CRT and TFT-LCD data to be checked.

Since the sample size of each stage was small (< 30), and it was uncertain whether the sample was normally distributed, we used the rank sum test to test the significance of indicators in each stage. The results of the significance test are shown in the Appendix. The number of time points was different in each stage. Thus, the Mann-Whitney rank sum test was used in this study. The results show that only the value of patent novelty does not change significantly between each stage and cannot meet the requirements as an indicator of TLC. Thus, it was eliminated during the process of identifying the TLC. The significance of patent novelty between each stage is shown in Table 3.

Table 3 Significance of the patent novelty between each stage.

Stage	CRT	TFT-LCD
0-1	0.9908393458721586*	0.9698768478748033*
0-2	0.8045851781539962*	1.0*

0-3	0.6039570028422234*	0.0
1-2	0.02280844065519899	0.4090085908090605*
1-3	0.02084290675910274	0.0
2-3	0.9916574134322095*	0.0

*noted that P value > 0.05, means the change was not significant. Stage 0, 1, 2, 3 represent the emerging stage, growth stage, maturity stage and saturation stage respectively. This description will continue to be used in following tables and figures.

This result of the mean value of patent novelty over time was consistent with the results of related studies(Jeon and Ahn et al., 2022). These findings indicated that novelty is an indicator of technological impact for a single patent rather than an indicator for numerous patents over time.

Another criterion to consider when determining the patent indicator is that an indicator should not be entirely related to other indicators. Thus, a correlation between these indicators were checked in this study. Since the distribution of indicator values cannot be determined, the Spearman rank correlation coefficient was used to distinguish the correlation between indicators, as shown in the Appendix. The results show that no indicator completely correlated with the other indicators.

Considering the analytical results of significance and correlation, we chose nine indicators, including patent application, technology applicant, technology breadth, backward citation, forward citation, examination period, protection coverage, prior knowledge, and patent family, as the indicators to identify the TLC.

4.2 Technology life cycle of 3D printing

The TLC in the field of 3D printing was identified and is shown as the blue line in Figure 6 . The emerging stage was 1990-2002, and the growth stage was 2003-2018. In 2019, the technology entered the maturity stage.

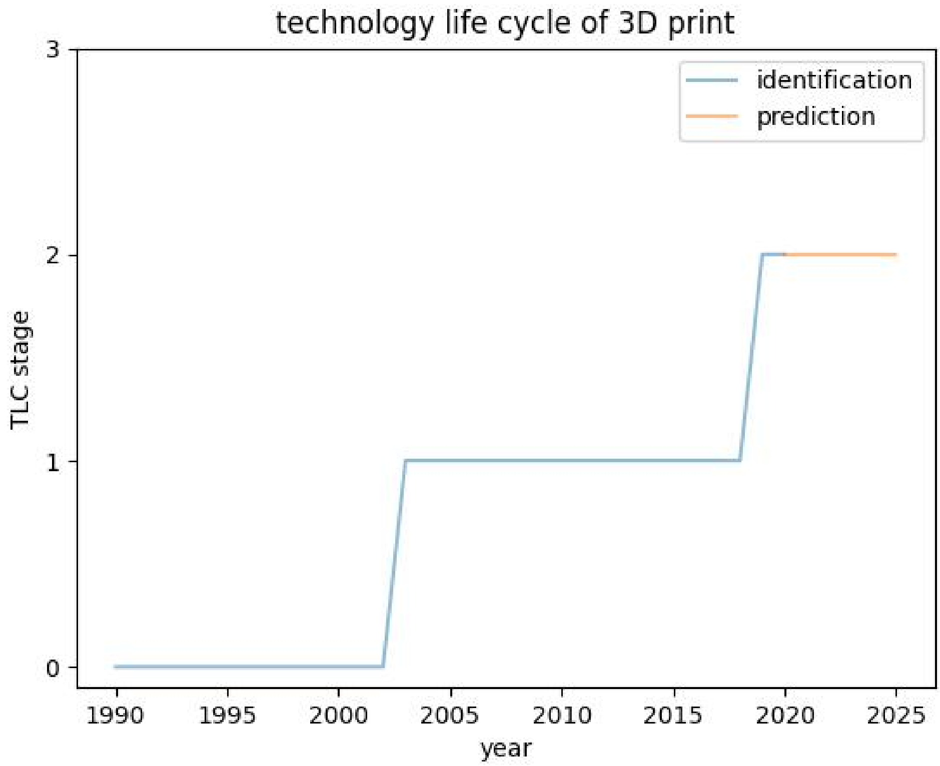


Figure 6 Technology life cycle of 3D printing technology

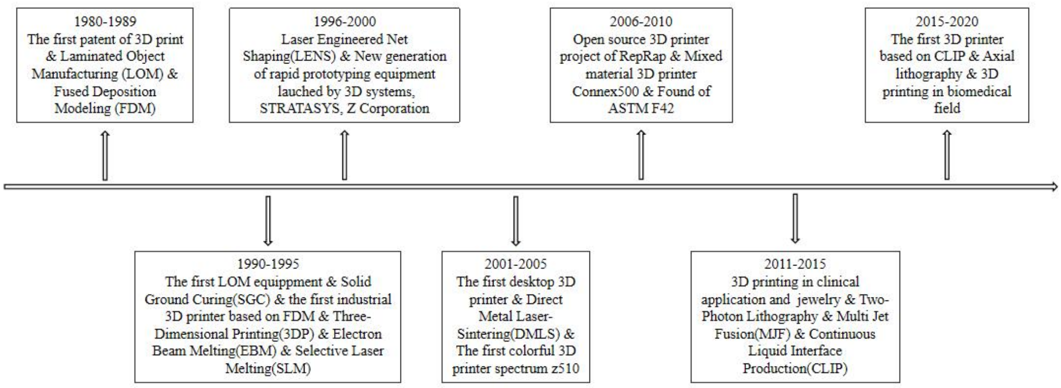


Figure 7 Evolution of 3D printing technology

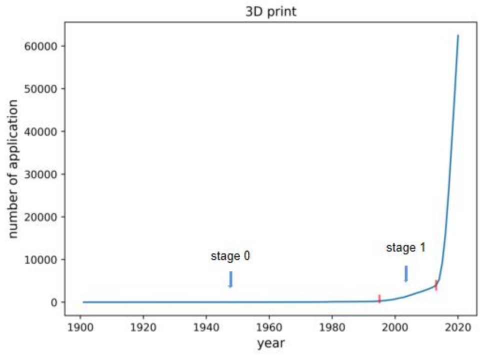
Previous research found that although the first patent for 3D printing and two of the essential early technology patents, laminated object manufacturing (LOM) and fused deposition modeling (FDM), appeared between 1980 and 1989, it was not until 1990 that 3D printing technology gradually came into commercialization with a substantial increase in patent applications (Miao and Du et al., 2020). During the emerging stage from 1990 to 2002, the development of 3D printing technology focused on basic technology and equipment. Examples include the first LOM equipment and solid ground curing (SGC), the first industrial 3D printer based on FDM, three-dimensional printing (3DP), electron beam melting (EBM), and selective laser melting (SLM) technology. Some more advanced technology materialized in this stage. Examples include laser-engineered net shaping (LENS), direct metal laser-sintering (DMLS), two-photon lithography, multi-jet fusion (MJF), and continuous liquid interface production (CLIP). In addition, the 3D printing technology from this period did not only address the improvement of methods but also equipment invention. Examples include the new generation of rapid prototyping equipment launched by 3D systems, STRATASYS, and Z Corporation, the first desktop 3D printer. During the growth stage from 2003 to 2018, the invention of equipment continued, including the first colorful 3D printer Spectrum z510, the mixed material 3D printer Connex500 and the first 3D printer based on CLIP. What is more, in this stage, consideration of the technology appeared, and regulations were established, along with the open-source 3D printer project of RepRap and the foundation of the American Society of Testing Materials (ASTM). The technology began to have applications in specific areas, such as clinics, jewelry, and the biomedical field, in addition to traditional manufacturing. The year 2019 was identified as the mature stage. Thus, one can predict that there will be more advanced 3D printer products and applications with various novel this year and future. In light of the evolution of 3D printing technology, the results of LSTM-CRF method are consistent with its actual development. As a strategic recommendation, the period between 2003 and 2018 would have been an ideal time for R&D investment.

Furthermore, this study used secondary exponentially weighted moving average methods to predict the value of indicators during the next five years and then identify the stage of TLC in the next five years according to the predicted value. The predicted results are also shown as the orange line in Figure 6. The 3D printing technology will continue to be at the maturity stage from 2021 to 2025.

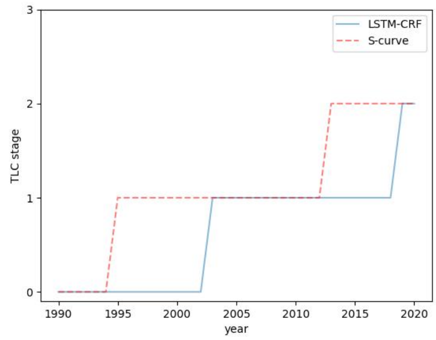
However, as the critical technologies of 3D printing are primarily in the hands of the United States, Japan, and European countries, other countries, particularly developing countries, are still well advised to guide and support 3D printing technology by increasing their research efforts and supporting key enterprises to participate in the progression of technology.

4.3 Comparison of the results from different methods

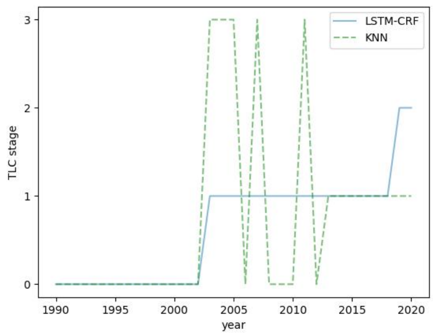
To show the advantage of our LSTM-CRF based method, we utilized three universally used methods, including the S-curve, KNN-based and HMM-based methods, and compared their results of the TLC in the field of 3D printing. The number of patent applications per year was selected since it is the most commonly used indicator in the S-curve based method. The KNN-based method was realized using Python based on the mathematical formula listed in Gao et al. (2013) (Gao and Porter et al., 2013). The HMM-based method was realized with the use of hmmlearn - a package in Python. What needs to be mentioned is that only five of the nine indicators, including patent application, technology applicants, technology breadth, duration of examination processes, and patent family, have been used in the HMM-based calculation process owing to the non-positive definite problem. Figure 8 shows the stage results for each method of 3D printing.



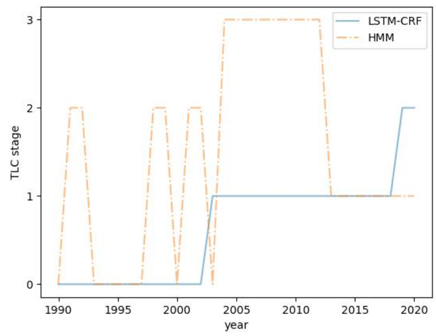
(a) S-curve of 3D printing technology



(b) TLC stage of 3D printing technology by the S-curve and LSTM-CRF based method.



(c) TLC stage of 3D printing technology by the KNN and LSTM-CRF based methods.



(d) TLC stage of 3D printing technology by the HMM and LSTM-CRF based methods.

Figure 8 Technology life cycle of 3D printing

The number of accumulated patent applications per year is nearly S-shaped, as shown in Figure 8(a). However, the boundaries between each TLC stage are usually decided manually. In this study, we chose 1995 as the boundary between the emerging and growth stages since the number of patent applications per year began increased in 1995. 2013 was chosen as the boundary between the growth and maturity stages because it is a transition point. The number of patent applications per year sharply increased after 2013. The red line shows the results for the S-curved stage based on the method in Figure. 8(b). The emerging stage was 1990-2012, and the growth stage was 2013-2017. The technology was in the maturity stage from 2018 to 2020. This result was very different from our LSTM-CRF based method, shown in the blue line. In reality, the basic 3D printing technology had already been completed and entered into the advanced technology development with equipment inventions occupying their position in the market since 2003 but not since 2012. We found that the result of the S-curve-based method was not precise enough to describe the situation of technology development realistically.

The green line shows the stage results for each test point of KNN in Figure 8(c).

The first thirteen points (1990-2002) matched with the emerging stage. The points (2006, 2008-2010, and 2012) matched the emerging stage again. The points (2003-2005, 2007, and 2011) matched the saturation stage. Finally, the points (2013-2020) matched to the growth stage. There is no point at the maturity stage. It is apparent that the stage result of KNN irregularly fluctuated over time, which is inconsistent with the reality of technology development. The reason for this is that the KNN is a method that computes the distance between each train point and test point, and the stage label of the nearest train point of a test point is then set as the result stage. This method does not consider the connotations of stages and the order of their occurrence.

The yellow line in Figure 8(d) shows the stage results for each point of HMM. The points (1990, 1993-1997, 2000, and 2003) are at the emerging stage. The points (1991-1992, 1998-1999, and 2001-2002) are at the maturity stage. The points (2004-2012) are at the saturation stage, and the points (2013-2020) are at the growth stage. The stage result of HMM shows a fluctuating pattern as well. Since the stage of HMM is defined to reveal the intrinsic change in technology, which differs from the usual definition of TLC, the result is theoretically acceptable. However, this unusual definition could cause confusion and limit the practical application of the TLC result using HMM. In addition, the HMM method requires each indicator to be completely independent, which restricts the use of indicators. Based on previous research, the number of effective indicators can directly affect the accuracy of identification. Thus, less use of indicators reduces the accuracy of the identification result of HMM method.

In conclusion, we found that the stage of LSTM-CRF results in a smooth and stationary pattern and fits with the reality of technology development in the 3D printing field as the analysis of TLC of 3D printing in the last section. Thus, we consider LSTM-CRF a more effective method for identifying the TLC than the S-curve-, KNN- and HMM-based methods.

5 Conclusion

This study proposed a new method to identify TLC based on machine learning techniques using multiple indicators. We defined and adopted nine indicators: patent application, technology applicant, technology breadth, backward citation, forward citation, examination period, protection coverage, prior knowledge, and patent family. We utilized the LSTM-CRF model to identify the TLC stages. The case study of 3D printing technology proved that the results of our method fit with the actual condition of the progression of technology and are relatively accurate. The prospect of technology was predicted and discussed.

The contribution of this research is as follows: First, two new indicators, including prior knowledge and patent novelty, were added to capture the TLC. In addition, the interaction between all indicators and technology progression stages and the correlation between each indicator were investigated. Second, this method has considered the link between the TLC and patent indicators during technology progression and, thus, provides an obvious result of the TLC stage at each time point. Third, this method considered the emerging order of each technology progression stage and the impact of the early stage of technology on its later stage. Thus, the results of this method show a smooth and stationary pattern are more accurately and conveniently understood. Furthermore, although this method was designed to identify the TLC, it can also be applied to the product or other cycle analyses with different indicators. Overall, this method is practical and can provide easily understandable and accurate results to quickly analyze technologies and support decision making at a minimal cost.

The limitation of this study lies in that the method proposed is a supervised method, which indicates that label data is acquired. The number of labeled data and the similarity between training and testing technology could also affect the TLC identification. The method can be used with any number of indicators (more than one) if the indicators available to users are limited. Nevertheless, in such a situation, the precision of the analysis result may be affected. To sum up, the data collection and data quality affect the model's performance. Therefore, to gain more precise results, we recommend carefully selecting the training and testing technique and using as many effective indicators as possible for analysis when conditions allow as long as the indicator is theoretically meaningful, significantly differential during various TLC stages and data available. It should also be noted that patents are not the only data that can be used to describe technology progression. Various data sources, including product, R&D investment, and market reports, can also be used as proxy indicators to provide more information about TLC.

For further study, we suggest more indicators, particularly some network indicators, to be combined in this framework to help improve the effectiveness of this model. Another thing is that since the case study has limited the 3D printing technology, further testing on diverse technologies is suggested to check and improve on this method.

Appendix

Significance test for CRT

	PA	TD	TS	BC	TV	DEP	PC	PK	PF	NO
0-1	8.44E-13	2.25E-11	2.55E-05	4.06E-13	3.22E-07	0.00028548	2.69E-07	2.36E-11	2.81E-07	0.9908393458721586*
0-2	9.56E-11	8.84E-11	4.86E-08	3.76E-12	0.016977548	0.05855146475329279*	0.000115382	3.76E-12	2.10E-10	0.8045851781539962*
0-3	3.85E-09	0.00031641	1.31E-06	3.75E-11	0.20335510325045414*	0.11030147717671471*	6.26E-09	3.75E-11	7.80E-08	0.6039570028422234*
1-2	1.60E-12	1.60E-12	0.004660513	0.33171990288417497*	3.88E-06	9.44E-06	0.7462773817120136*	0.7284853516568065*	5.14E-06	0.022808441
1-3	0.027790268	0.06601548406206072*	0.038026564	1.49E-08	0.004910473	3.33E-10	2.27E-10	3.35E-07	0.006738683	0.020842907
2-3	1.18E-05	5.74E-09	0.49672946301674914*	5.74E-09	0.45785645107132533*	2.22E-08	5.07E-09	5.74E-09	0.07046646391957853*	0.9916574134322095*

*noted that p value is > 0.05, the change was not significant.

Significance test for TFT-LCD

	PA	TD	TS	BC	TV	DEP	PC	PK	PF	NO
0-1	1.62E-06	0.025880382	1.95E-06	0.003224392	0.7625743346751044*	9.95E-06	0.000249292	7.34E-05	0.4500960463794056*	0.9698768478748033*
0-2	0.000246838	0.1209505245948936*	0.000246838	0.000246838	0.002436631	0.000246838	0.000246838	0.000246838	0.007392005	1.0*
0-3	0	0	0	0	0	0	0	0	0	0
1-2	0.525358404	0.11233872582	0.00631	0.00017	0.001858081	0.00017	0.02223	0.00047	0.005198449	0.4090085908

	466242*	982299*	4983	8867		8867	166	7465		090605*
1-3	0	0	0	0	0	0	0	0	0	0
2-3	0	0	0	0	0	0	0	0	0	0

*noted that p value is > 0.05, the change was not significant.

Correlation test for CRT

	PA	TD	TS	TV	DEP	PC	PK	PF
PA	0	1.16E-37	8.14E-09	0.36966411877299776	0.9532638258118833	1.05E-06	4.83E-09	1.33E-28
TD		0	0.000974267	0.7454001739588079	0.1013748310021 4108	0.026952172	0.000610062	8.54E-17
TS			0	0.000443933	0.7447983107252159	1.48E-18	1.62E-70	3.45E-08
TV				0	0.000188406	0.09849323528083621	0.00410691	0.044259009
DEP					0	0.1572885785770753	0.7201350524847525	0.5702004328850458
PC						0	6.41E-16	1.95E-11
PK							0	8.34E-07
PF								0

Correlation test for TFT-LCD

	PA	TD	TS	TV	DEP	PC	PK	PF
PA	0	0.7764856763297947	6.53E-09	0.002028188	2.46E-10	5.36E-12	3.91E-13	0.000574973
TD		0	0.06370653287497208	0.042484304	0.5220277826156827	0.07492814905736057	0.17666735283297502	0.01453162

TS	0	0.004123628	2.86E-12	2.88E-11	7.01E-15	2.58E-05
TV		0	0.001002066	0.001222774	0.001069423	0.000187177
DEP			0	3.95E-10	1.04E-10	0.000269272
PC				0	7.35E-14	1.14E-08
PK					0	3.59E-05
PF						0

Conflict of interest statement

Authors have no conflict of interest to declare.

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