

Empirical Study on the HCI Characteristics of Business Model Innovation Based on AI-Powered CAD

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Abstract. As organizations seek to adapt to rapidly changing markets, understanding how HCI elements impact the design and implementation of innovative business models becomes essential. This research analyses user interactions with AI-driven CAD tools and identifies key HCI features—such as usability, accessibility, and feedback mechanisms—that facilitate creative problem-solving and strategic thinking. According to the commercial operation process, this paper chooses the time series data mining method to process the data. It uses the residual entropy to test the autocorrelation or whitening degree of the residual series. Moreover, this paper measures the reasonable degree of time series pattern representation and combines big data technology to study the characteristics of business innovation. In addition, this paper combines data mining technology to perform data analysis and verify the attributes of business model innovation. Finally, this paper analyses the case through case studies and statistically verifies the data using big data clustering technology. Through empirical analysis, big data technology can play a good role in analyzing the characteristics of business model innovations.

Keywords: Human-Computer Interaction; Business model; AI-Powered CAD; innovation characteristics; empirical research DOI: https://doi.org/10.14733/cadaps.2025.S6.54-71

1 INTRODUCTION

In contemporary economic society, the business model has become one of the most frequently used professional terms, and we often directly use the term "business model theory." However, as long as we carefully review the relevant literature, we will find that the business model has yet to form a complete theoretical system. There are many reasons for this situation. First, because the business model is an organizational form between the enterprise and the market, understanding its essence requires a breakthrough and a leap in understanding. Second, the business model involves a wide range of content, so forming a system and a recognized theoretical framework is challenging. Nevertheless, with the development of information technology and management technology, business models have become a key factor affecting the success or failure of enterprises.

As we all know, the five core contents recognised by management are planning, organisation, personnel, leadership, and control, each of which is the principle and goal of the following content, and the latter content is precisely what ensures the realisation of the previous content. Specific methods and measures. It is worth noting that the relationship between planning and business model is the closest among the five management functions. The premise of the plan is to determine the enterprise, and the goal of the enterprise involves two aspects: goal decision-making and goal realisation. The establishment of strategic goals depends on the business philosophy of the enterprise and the objective conditions of the enterprise. In contrast, realising the strategic goals depends on the enterprise's business model.

This paper combines big data technology to study the characteristics of business model innovation. It combines data mining technology to conduct data analysis, verify business model innovation characteristics, and improve business models' innovative effects. One must be creative to be competitive in today's fast-paced corporate world. Business model innovation (BMI) is at the forefront, which focuses on reorganising value creation and capture within businesses. Big Data Technology and Human-Computer Interaction (HCI) are the two primary drivers of BMI in ecommerce. Big data enables data-driven decisions, while HCI enhances user experiences through intuitive interfaces, especially in e-commerce platforms. However, empirical research into BMI utilising these tools is limited. This study addresses this gap by investigating the impact of big data technology and HCI on BMI within the e-commerce domain. The findings will help e-commerce organisations understand theoretical concepts and develop practical strategies for navigating the digital realm.

2 RELATED WORK

At present, academia has made a lot of research results on the concept and connotation of business models. Literature [1] defines a business model as a logical statement that a company can obtain and maintain its benefits. Literature [2] pointed out that the connotation of the business model is a business method for enterprises to make profits to survive and sustain development. Literature [3] believes that the business model is the focus of innovation for enterprises and the decisive source for enterprises to create value for themselves, partners, and customers. Literature [4] defines a business model as the expression of the relationship and roles between customers, partners, and suppliers of an enterprise. Literature [5] defines an enterprise's business model from a strategic perspective. It believes the business model refers to establishing unique competitive advantages by integrating related elements such as positioning, strategic direction, economic logic, and operating structure. Literature [6] believes that the business model starts with the choice of customer value and the realisation of corporate value as the end, which solves the problem of how companies make sustainable profits. Business model design must first find unmet market needs or new market opportunities through analysis, discover the value of products/services, determine core and related profit points, and determine the value proposition of products/services. Based on core capabilities, integrate resources around the value network of stakeholders, create value through value allocation and management, and finally build business strategies and profit models through products/services, forming a series of business processes that provide customers with value. Literature [7] believes that a business model is a system composed of value proposition, support, and maintenance. Literature [8] defines the business model from the value chain perspective as the basic logic of enterprise value creation through internal activities. Literature [9] defines the business model as the enterprise market value realisation model. Also, from a strategic perspective, the literature [10] believes that a business model refers to a company integrating itself with customers, shareholders, suppliers, and other stakeholders by determining internal and external resources to form a structural system and profitable strategic intentions. Literature [11] believes that a business model is a system

for an enterprise to meet consumer needs. This system organises and manages various enterprise resources to form products and services that consumers cannot rely on but must purchase. Therefore, it can be copied but not to features copied by others.

The most successful time for high-tech companies in the information technology business is often when their products become the platform of the industry. In the era of information technology, business models' most basic value creation comes from the convenience, low cost, novelty, user stickiness, lock-in, and innovation of the Internet itself. The Internet has become a large platform, and people complete various interactions or exchanges to meet their multiple needs. While considering the seller's innovative decision-making and price competition, with the most optimised connection fee, the price competition between the buyer and the seller is reduced [12]. Now, only platform innovation can truly enable enterprises to become market leaders. Passing by two companies competing, one uses value chain business models to innovate strategies, and the other uses platform-based business models to establish new strategies. [13]. Literature [14] believes that mobile Internet and cloud use Internet platforms as general media. New technologies like computing, big data, and the Internet of Things have become critical areas for industrial upgrading, transformation, and innovative economic growth. The platform construction, operation, and regulation theory can provide in-depth interpretation and new-oriented cognition for the "Internet +" plan.

Literature [15] elaborated on the perspective of companies providing value results. How to balance the distribution of benefits between the final output and input has become the focus of research; Literature [16] The goal of the business model is related to the corporate strategy. This systematic approach can be called a business model when distinguishing customers' needs, mastering their value propositions, and using their resources and capabilities to carry out a particular strategy and obtain profits. From the income perspective, literature [17] regards it as a business method to obtain continuous income. It requires companies to clarify their position in the middle of the value chain and use their competitive advantages; literature [17] starts from the industrial structure and impacts the economics of the model. Awareness is raised to a whole new level. Creating value through excellent business methods and network relationships formed by cooperation with alliance partners is a business model.

Literature [19] pointed out that the goals of establishing a business model are consistent with the enterprise's objectives. They both aim to obtain a differentiated leading position in the game from competitors. Obtaining this position requires the organisation to make strategic preparations and efforts. Literature [20] emphasises that business models keep dynamic changes in the business environment and believes that the so-called appropriate business model is a series of process methods in which business organisations pass value propositions to customers through products or services and then obtain revenue and calculate benefits. In this process, we need to pay attention to the circulation of funds and the transmission of information. When the company can continue to apply this process in practice, it will find and summarise suitable differentiated management methods.

3 MINING OF CHARACTERISTICS OF BUSINESS MODEL INNOVATION BASED ON TIME SERIES

Time series data has high dimensionality, complexity, dynamics, and high noise and is easy to reach on a large scale. Therefore, data mining directly on the time series not only costs a high price in terms of memory storage and calculation time but also may affect the accuracy and reliability of the algorithm. Before mining the time series, we need to represent the time series data pattern. Time series pattern representation is a feature representation method that abstracts and generalises time series and re-describes time series at a higher level. For a time series X $X_1,...X_n$ of length n and a

$$
X = \begin{cases} F_1 \ t, W_1 + e_1 \ t, 1 \le t < \alpha_1 \\ \cdots \\ F_i \ t, W_1 + e_i \ t, \alpha_{i-1} \le t < \alpha_i \\ \cdots \\ F_k \ t, W_k + e_t \ t, \alpha_{k-1} \le t < n \end{cases} \tag{1}
$$

The candidate mode set M has many forms, divided into frequency domain mode, linear mode, and polynomial mode here. Therefore, the corresponding time series mode representation is divided into frequency domain mode representation, piecewise linear mode representation, and piecewise polynomial mode representation.

Discrete Fourier Transform (DFT) is a very common domain-independent transform. Discrete Fourier Transform is the earliest representation method in time series similarity feature extraction. The basic algorithm of DFT is described as follows:

For a time series X, for any subsequence $X^i = \left\langle X_1^i, X_2^i, \cdots, X_m^i \right\rangle$ with length mi , The discrete Fourier transform corresponds to mi points is defined as a sequence composed of mi complex numbers g, and the transformation formula is:

$$
X_f^i = \frac{1}{m_i} \sum_{l=1}^{m_i} X_l^i \exp\left(-\frac{2\pi f l}{m_i} j\right), f = 1, 2, ..., m_i
$$
 (2)

The corresponding inverse transformation is:

$$
X_{l}^{i} = \frac{1}{\sqrt{m_{i}}} \sum_{f=1}^{m_{i}} X_{f}^{i} \exp\left(\frac{2\pi f l}{m_{i}} j\right), l = 1, 2, ..., m_{i}
$$
 (3)

In the formula, j is the complex imaginary unit and $j = \sqrt{-1}$.

The DWT is mainly similar to DFT's processing method. We assume that in the square-integrable function space L^2 R , for the time series X, any subsequence $X'=\big\langle X_1^i,X_2^i,\cdots,X_{mi}^i\big\rangle, X\in L^2$ R of length $m^{}_i$ can be described by the wavelet function $\psi^{}_{j,t} = 2^{j/2} \psi \,\, 2^j t - k$. Among them, $\psi \in L^2$ R , and the , description is in series:

$$
X = \sum_{j,k} a_{j,k}^{j/2} \psi \ 2^{j} t - k = \sum_{j,k} a_{j,k} \psi_{j,k} \ t \tag{4}
$$

It is called the discrete wavelet transform of the sub-sequence *X*' and is composed of a sequence of two-dimensional coefficients $a_{j,k}$.

For the time series $X = X_1, \ldots, X_n$ of length n, the line segment point oblique linear equation is adopted, and the corresponding K segment model description:

$$
X_{1} + \frac{X_{\alpha_{1}} - X_{1}}{\alpha_{1} - 1} \cdot t - \alpha_{1,1} \leq t < \alpha_{1}
$$
\n
$$
X' = \begin{cases}\nX_{m-1} + \frac{X_{\alpha_{1}} - X_{m-1}}{\alpha_{1} - \alpha_{i-1}} \cdot t - \alpha_{i-1,1}, \alpha_{i-1} \leq t < \alpha_{i} \\
X_{m-1} + \frac{X_{\alpha_{1}} - X_{\alpha_{m-1}}}{\alpha_{1} - \alpha_{i-1}} \cdot t - \alpha_{i-1,1}, \alpha_{i-1} \leq t < n\n\end{cases}
$$
\n(5)

\ndivided into K non-overlapping ordered connected line segment sets. is generally expressed in the form of PLR, where the PLR form is $X' = X_{b}, X_{ab}, t_{1}, \ldots, X_{a-1}, X_{a,t_{i}}, \ldots, X_{a-a}, X_{a}, t_{k}$

\n(6)

\nto piecewise nonlinearity, due to the simplicity of the polynomial approximates each sub-sequence and its corresponding k-segment $Y' = \begin{cases}\nf_{1} t, w_{1} & 1 \leq t < \alpha_{1} \\
\vdots & \vdots \\
f_{k} t, w_{k} & \alpha_{i-1} \leq t < \alpha_{i}\n\end{cases}$

\n(7)

\n(8)

\n14. $t, w_{k} = W_{i_{0}} + W_{i_{1}t} + W_{i_{2}t}^{2} + \ldots + W_{i_{n}t}^{2}$

\n(9)

\n15. The complex $t, t, W_{i} = W_{i_{0}} + W_{i_{1}t} + W_{i_{2}t}^{2} + \ldots + W_{i_{n}t}^{2}$

\n(10)

\n16. The collection of their polynomial characteristics represents these ordered polynomials. The The collection of their polynomial characteristics represents these ordered polynomials. The The collection of their polynomial characteristics represents these $X' = W_{i}, t_{1}, \ldots, W_{i}, t_{i}, \ldots, W_{i}, t_{k}$

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The original time series X is divided into K non-overlapping ordered connected line segment sets. The ordered line segment set is generally expressed in the form of PLR, where the PLR form is described as:

$$
X' = X_b, X_{ab}, t_1, \dots, X_{a-1}, X_{a,t}t_i, \dots, X_{at-b}, X_n, t_k
$$
 (6)

From piecewise linearization to piecewise nonlinearity, due to the simplicity of the polynomial function, a P-order polynomial approximates each sub-sequence and its corresponding k-segment model description:

$$
\mathbf{X}' = \begin{cases} \n\mathbf{f}_1 \quad t, \mathbf{w}_1 & 1 \leq t < \alpha_1 \\ \n\vdots & \vdots \\ \n\mathbf{f}_t \quad t, \mathbf{w}_t & \alpha_{t-1} \leq t < \alpha_i \\ \n\vdots & \vdots \\ \n\mathbf{f}_k \quad t, \mathbf{w}_k & \alpha_{t-1} \leq t < n \n\end{cases} \tag{7}
$$

In the formula, w_i is the polynomial coefficient vector, $\alpha = \alpha_1, ..., \alpha_{k-1}$ is the time series polynomial segmentation point set of sequence X, f_i t , W_i is the P-order polynomial, and its general form is:

$$
f_t \ t, W_t = W i_0 + W i_1 t + W i_2 t^2 + \dots + W i_n t^p \tag{8}
$$

It is written in the form of a vector product:

$$
f_i \ t, W_i = \begin{bmatrix} 1 & t & t^2 & L & t^p \end{bmatrix} \times \begin{bmatrix} W_{i_0} & W_{i_1} & W_{i_2} & L & W_i \end{bmatrix}^T
$$
 (9)

The collection of their polynomial characteristics represents these ordered polynomials. The abbreviation is: f_i $t_iW_t = T_t$. The collection of their polynomial characteristics represents these ordered polynomials as:

$$
X' = W_1, t_1, \dots, W_i, t_i, \dots, W_k, t_k
$$
\n(10)

Among them, it represents the length of the i-th segment, and *Wt* represents the coefficient vector of its corresponding polynomial, which means the characteristics of this segment. For a time series $X\langle X_1,\!...,X_n\rangle$ of length n, the newly formed time series is called the fitted sequence after multiple segmented polynomials are valued at the corresponding sequence points. Relative to the files less than cap X sub 1, dot dot dot and cap X sub n are more significant than in what is called the original time series. A particular subsequence is denoted as $X\langle Xai-1,...,X_{ai}\rangle$, which represents the i-th subsequence in the polynomial segmentation process of the time series. It comprises all the sequence points between the segment points α_{i-1} and α_i of the time more si significant, abbreviated as $X^i\left(X^i_1,X^i_2,\cdots,X^i_\cdot\right)$. Among them, $mi=\alpha_1-\alpha_{i-1+1}$ represents the length of the subsequence, and the sequence formed by polynomial interpolation is denoted as $\overline{X}^i < \overline{X}^i_1, \overline{X}^{i^i_2}$ $X^{'i} < X_1^{'i}$, $X_2^{i_m^{i_m^{i_m}}}$, which is called the fitted subsequence. The subsequence and the fitted subsequence have the same length, *mi* .

The fitting deviation of the i-th segment is the difference between the fitted subsequence and the subsequence at each sequence point, and the fitting deviation Ei is expressed as:

$$
\begin{aligned}\n\mathbf{Ei} &= X^i \left\langle X_1^i, X_2^i, \cdots, X_{mi}^i \right\rangle \\
&\quad - X^i \left\langle X_1^i, X_2^i, \cdots, X_{mi}^i \right\rangle \\
&= \left\langle E_1^i, \ldots, E_i^i, \ldots, E_{mi}^i \right\rangle\n\end{aligned}\n\tag{11}
$$

The time series fitting error is the sum of the squares of the deviations, and its function is:

 $\mathbf{r} = \mathbf{r}$

$$
Li = \stackrel{\circ}{\mathcal{C}}_{j=1}^{mi} E i_j^2 = E i, E i \tag{12}
$$

Among them, $\langle \cdot, \cdot \rangle$ represents the inner product of the vector. After the polynomial order P is given, the polynomial subsequence is described in matrix-vector and vector form, expressed as:

$$
\begin{bmatrix} X^{i}_{1} \\ X^{i}_{2} \\ \vdots \\ X^{i}_{mi} \end{bmatrix} = \begin{bmatrix} 1^{0} & 1^{1} & \cdots & 1^{p} & Wi_{0} \\ 2^{0} & 2^{1} & \cdots & 2^{p} & Wi_{1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ m_{i}^{0} & m_{i}^{1} & \cdots & m_{i}^{p} & Wi_{j} \end{bmatrix} + \begin{bmatrix} Ei_{1} \\ Ei_{2} \\ \vdots \\ Ei_{mi} \end{bmatrix}
$$
 (13)

The above formula is abbreviated as $X^i = T \times W i + E i$, and its corresponding fitted subsequence is described as:

$$
\begin{bmatrix} X^{n_1} \\ X^{n_2} \\ \vdots \\ X^{n_n} \end{bmatrix} = \begin{bmatrix} 1^0 & 1^1 & \cdots & 1^p \\ 2^0 & 2^1 & \cdots & 2^p \\ \vdots & \vdots & \ddots & \vdots \\ m_i^0 & m_i^1 & \cdots & m_i^p \end{bmatrix} \begin{bmatrix} W_{i_0} \\ W_{i_1} \\ \vdots \\ W_{i_p} \end{bmatrix}
$$
 (14)

The above formula is abbreviated as $X^i = T \times Wi$, which is described in the form of matrices and vectors,

$$
Li\ Wi = Ei, Ei
$$

\n
$$
= Ei^{T} \cdot Ei
$$

\n
$$
= x^{\wedge} - X^{i}, x' - x^{i}
$$

\n
$$
= TWi - x^{i}, TWi - x^{i}
$$

\n
$$
= TWi - x^{1} rWi - x^{i}
$$
\n(15)

 Δ

To minimize the sum Li of squares of the fitting deviation, $\frac{\partial Li}{\partial \bm{x}\bm{x}} = 0$ $\frac{2\pi}{Wi} = 0$ needs to be established, that is:

$$
\frac{\partial L}{\partial W_i} = TW - X^i \frac{r \partial TW - X^i}{\partial W_i} + TW - X^1 \frac{r \partial TW - X^i}{\partial W_i} = 0 \tag{16}
$$

By simplifying formula (16), ∂ $TWi - X^{i\ T}T = 0$ is obtained. Because matrix T is $m_i \times p + 1$ Van der Monte matrix, and as long as it is guaranteed that $m_i \geq p+1$, $\bm{T}^T\bm{T}^{-1}$ must exist, there is:

$$
Wi = \left(T^T T^{-1} T^T X^i\right) \tag{17}
$$

For the polynomial parameter determined by the above formula, the sub-sequence and its regression sub-sequence corresponding start and end points do not necessarily overlap, so the mode representation of the entire time series is discontinuous. The following gives a piecewise polynomial continuous mode representation—CPPR.

Therefore, in the time series polynomial segmented mode representation, the polynomial parameter estimation of any subsequence is more generally described as:

$$
\begin{cases}\n\min.Li \; Wi = Ei^T \cdot Ei \\
St\begin{bmatrix}\n1^0 & 1^1 & \dots & 1^p \\
k^0 & k^1 & \dots & k^p \\
m_i^0 & m_i^1 & \dots & m_i^p\n\end{bmatrix} Wi = \begin{bmatrix}\nT_1 \\
T_k \\
T_m\n\end{bmatrix} Wi = \begin{bmatrix}\nX_1^i \\
X_m^i \\
X_m^i\n\end{bmatrix} \\
or \\
\begin{cases}\n\min.Li(Wi) = Ei^T \cdot Ei \\
St.T_c \times Wi = X_c\n\end{cases}
$$
\n(18)

At this time, we construct a Lagrangian function F Wi,λ , where $\lambda=|\lambda_1-\lambda_k-\lambda_m|$ is a row vector whose elements are real numbers and are not always equal to zero. The function expression is:

$$
F W i, \lambda = Li W i + \lambda T_c \times Wi - X_c \tag{19}
$$

If F Wi, λ is the smallest, its necessary condition is:

$$
\frac{\partial F W_{i,\lambda}}{\partial W_{i}} = 0
$$
\n
$$
\frac{\partial F W_{i,\lambda}}{\partial \lambda} = 0
$$
\n(20)

Then, there are:

$$
\begin{cases}\n2 T Wi - X^{i \t T} + \lambda T_c = 0 \\
T_c Wi - X_c = 0\n\end{cases}
$$
\n(21)

According to the above formula, the solution of *Wi* is obtained:

$$
Wi = TTT-1 TTXi - 0.5TcTXT
$$
 (22)

We eliminate wi in formula (21) and set $T^T T^{-1} = A$ to satisfy $A = A^T$. The following equation determines the coefficient λT of the above equation:

$$
T_c A T_c^T \lambda^T = 2 T_c A T^T X^i - X_c \tag{23}
$$

The coefficient matrix of λ^T is:

$$
T_c A T_c^T = \begin{bmatrix} T_1 A T_1^T & T_1 A T_k^T & T_1 A T_m^T \\ T_k A T_1^T & T_k A T_k^T & T_k A T_m^T \\ T_{mi} A T_1^T & T_{mi} A T_k^T & T_{mi} A T_{mi}^T \end{bmatrix} = B
$$
 (24)

Both the row vector and the column vector are linearly independent. There is $|\mathbf{B}| \neq 0$, so there is a unique solution for λ' , is, wi in formula (22) exists and is unique.

Compared with the unconditional polynomial parameter estimation $W_i = T^T T^{-1} T^T X'$, The calculation amount increases to a certain extent after adding the condition. The increased amount of calculation is reflected in the calculation of the coefficient matrix B, so this paper only makes the essential condition of segmental continuity. The estimated value of the polynomial parameter is obtained at this time:

$$
Wi = T^{T}T^{-1} T^{T}X^{i} - 0.5\lambda_{1}T_{1}^{T} - 0.5\lambda_{mi}T_{mi}^{T}
$$
 (25)

Among them, λ_1, λ_{mi} is determined by the solution of the equation represented by formula (23). For all segments, the time series can be expressed as:

$$
X = w_1, m_1, w_2, m_2, \dots, w_1, m_i, \dots, w_k, m_k
$$
 (26)

Among them, Wi, mi represents the i-th segment x^i of the time series, Wi represents its corresponding polynomial coefficient vector, and *mi* represents its length.

The continuity comparison between PPR and CPPR at segment points is shown in Figure 1.

Figure 1: Comparison of continuity between PPR and CPPR.

In the figure, the horizontal axis represents the time series time, and the vertical axis represents the sequence value at each time point. The curve TS represents a time sequence of length 33, and TS is divided into two sub-sequences S_1 and S_2 , at the 15th sequence point. When the polynomial order is $p = 4$, It can be seen that the overall shape of the PPR and CPPR fitting curves is similar, but there is a difference between the two endpoints. In PPR, the endpoint A of S_1 is not continuous with the start point B of S_2 , resulting in different values of PPR at the same sequence point.

Regardless of PPR or CPPR, the polynomial's parameter vector W is related to the matrix T, the length of the subsequence m, and the value $xⁱ$ of the subsequence at each point. From another perspective, we can use a high-order polynomial to represent the entire time series and a series of relatively low-order piecewise polynomials to represent the reasons for the whole time series.

In traditional time series analysis, after establishing a time series model, it is always necessary to check the built model to see whether it can represent the original time series. The same applies to the time series pattern representation, and a more scientific and reasonable judgment is given to the reasonable degree of the pattern representation.

We assume that a time sequence X of length n is inversely transformed to form a new sequence Y after a specific pattern, and its residual sequence is:

$$
E = E_1, E_2, \dots, E_n
$$

= $X_1, X_2, \dots, X_n - Y_1, Y_2, \dots, Y_n$
= $X_1 - Y_1, X_2 - Y_2, \dots, X_n - Y_n$ (27)

In time series analysis, the method based on mathematical statistics is mainly used to test the reasonable degree of the model. According to Shannon's information theory, if the probability of any value X_1 of the random variable, X is p_i $p_i > 0$ when the condition of $\sum_{i=1}^N p_i = 1$ $p_{i} = 1$ is satisfied, the information entropy of the random variable E is defined as:

$$
H X = -\sum_{i=1}^{N} p X_i \log p X_i
$$
 (28)

For a residual sequence E of length n, its joint probability density is P $E_1, E_2, ..., E_n$, then its joint entropy is:

the *H*
$$
E_1, E_2, ..., E_n = -\sum P E_1, E_2, ..., E_n \log P E_1, E_2, ..., E_n
$$
 (29)

According to the nature of information entropy, it is known that the joint entropy of multidimensional random variables is less than or equal to the sum of the entropy of each component, namely:

$$
H \ E_1, E_2, \dots, E_n \le H \ E_1 + H \ E_2 + \dots + H \ E_n \tag{30}
$$

In the inequality, the sum of the entropy of the components represented on the right side of the above formula and the joint entropy of the components are the difference, that is

$$
T En = \begin{bmatrix} H E_1 + H E_2 + \dots + H E_n \end{bmatrix} - H E_1, E_2, \dots, E_n
$$

=
$$
\sum_{i=1}^n H E_i - H E_1, E_2, \dots, E_n
$$
 (31)

In the formula, *T E*ⁿ is called the correlation quotient, which can be used to measure the degree of correlation between the components of the residual sequence. The difference T E^n reflects the amount of remaining information implicit and can also be called the entropy of the residual sequence, or residual entropy for short.

We assume that the distribution of each component of the residual sequence E is $\,$ 0, $\sigma_{\rm t}^2\,$, and E approximately obeys an n-dimensional random vector A_E that obeys a normal distribution, with a mean value of zero, and an autocorrelation matrix is *R* , and its probability distribution is:

$$
P A_E = [(2\pi)^n |R|] \frac{1}{2} \exp\left[-\frac{1}{2} A_E^T R^{-1} A_E\right]
$$
 (32)

Then, the joint entropy of the residual sequence is:

$$
H E_1, E_2, ..., E_n
$$

= $H A_E$
= $-E[\log P A_E]$
= $\frac{1}{2} E[n \log 2\pi + \log |R| + A_R^T R^{-1} A_E]$
= $\frac{1}{2} \left[n \log 2\pi + \log |R| + n \right] = \frac{1}{2} \left[n \log 2\pi + 1 + \log |R| \right]$ (33)

Because the entropy of each component is:

$$
H E_i = -E \left\{ \log \left(2\pi \sigma_E^2 \right)^{\frac{1}{2}} \exp \left(-\frac{\sigma_t^2}{2\sigma_E^2} \right) \right\}
$$

=
$$
\frac{1}{2} \left[\log 2\pi + 1 + \log \sigma_E^2 \right]
$$
 (34)

Then, there is

$$
\sum_{i=1}^{n} H \ E_{t} = nH \ E_{i} \tag{35}
$$

Finally, the residual entropy is:

$$
T En = \sum_{i=1}^{n} H E_i - H E_1, E_2, ..., E_n
$$

= $\frac{1}{2} [n \log 2\pi + 1 + n \log \sigma_E^2] - \frac{1}{2} [n \log 2\pi + 1 + \log |\mathbf{R}|]$ (36)
= $\frac{1}{2} n \log \sigma_E^2 - \frac{1}{2} \log |\mathbf{R}|$

In the calculation of $T \, E^n$, the calculation of the autocorrelation matrix R can be replaced by the estimated value of the variance matrix $\hat{\bf R}$. For a time series of finite length, its autocorrelation function is often assessed as follows:

$$
\hat{r} \ k \ = \frac{1}{n} \sum_{t=1}^{n-|k|} E \ t \ E \ t+k \tag{37}
$$

Among them, $k = 0, 1, 2, ..., n - 1$, then

$$
R = R_{ij} = \hat{R}_{\mid -\lambda} = [\hat{r} \; k \;]_{n \times n} = \left[\hat{r} \; k \; \right]_{n \times n} \tag{38}
$$

If the residual sequence E is white noise, the values of the sequence points on E are not correlated, and $\hat{\bm{R}}$ will be a diagonal matrix with σ_z^2 as the main diagonal element. At this time, T E^n = 0 .If

the values of each sequence point on E are correlated, T E^n $>$ 0 is true because of $|\mathbf{R}| > \sigma_{_F}^2$ n $\mathbf{R} |> \sigma_E^2$.The value T E^n Reflects the degree of correlation or whitening of the sequence. As the degree of

correlation of the residual sequence E increases or the degree of whitening decreases, the residual entropy also increases. Therefore, residual entropy (correlation entropy) can be used to test the autocorrelation or whitening degree of the residual sequence and measure the reasonable degree of the time series pattern representation.

4 EMPIRICAL STUDIES ON THE CHARACTERISTICS OF BUSINESS MODEL INNOVATION BASED ON BIG DATA TECHNOLOGY

With the development of the enterprise, more challenges require the team to conduct a more complete team management mechanism and better coordinate the balance between the elements. The behavioral changes brought about by the growth of internal economic strength respond to changes in the internal and external environment of the e-commerce enterprise more harmoniously and promote the long-term development of entrepreneurial e-commerce enterprises more effectively. The success of disruptive innovation in e-commerce depends on creating new and essential products or services that initially target customers in the low-end e-commerce market. The premise is that existing products cannot meet customer needs or customers cannot solve immediate problems with existing products. Based on fully controlling resources and capabilities, entrepreneurs need to transfer economic capital from low to high productivity through business model innovation. The theoretical model of disruptive innovation is shown in Figure 2.

Figure 2: Theoretical model of disruptive innovation.

This paper further analyzes two types of disruptive innovation: low-end and new markets. Moreover, this paper adds a third axis to the original destructive diagram to give a more vivid description. Figure 3 shows the disruptive innovation under the new value network.

In the business model, the interface of the structural dimension connects the part of the relationship between the enterprise and each component. It is the logical expression of the correlation between the three levels. By decomposing the structural dimensions of the business model, it is found that there are multiple structural dimensions in the interface. After abstraction, a general model of the structural dimensions of the business model is formed, as shown in Figure 4. For entrepreneurial enterprises, if they want to obtain a larger market share and a more generous return on market value, the path selection and innovation of the corresponding business model at each stage of entrepreneurship is the fundamental way to achieve it. According to the development process of the business model in different stages of entrepreneurship from conception-constructionapplication-consolidation, we can accordingly divide the business model development stages that run through entrepreneurial enterprises into development, efficiency, expansion, and polarization, as shown in Figure 5.

Figure 5: Business model development stage.

As a unique mechanism, the function of the business model is to create value for customers while also obtaining value for the enterprise. According to this function definition, combined with the analysis of the structural dimensions of the business model, three function templates can be extracted from it: namely, the value proposition corresponds to the positioning template, the value creation corresponds to the realization template, and the value potential corresponds to the income template. Since the functions of the above three templates are inseparable from the resource combination of the enterprise, the fourth template, the resource template, is added here. These four templates can form an intersection similar to a container, and the value conversion is completed in the space formed by this intersection. The container space composition of the business model is shown in Figure 6.

Figure 6: The composition of the container space of the business model.

Through the above theory of entrepreneurial process, this paper analyzes the innovation path of entrepreneurial enterprises' business model. It can deconstruct the innovation path of the business model, that is, from gradual expansion-partial variation-structural variation. During this process, we paid great attention to the innovation driven by three significant factors: value proposition, key resource capabilities, and profit model. Regarding innovation, the various stages of the business model have different focuses. Therefore, companies should analyze and grasp different innovation methods under the leadership of customer value, value chain, and value network, as shown in Figure 7:

Figure 7: Schematic diagram of business model innovation of entrepreneurial enterprises.

Based on the above, conduct empirical research on the characteristics of business model innovation. This paper takes the innovation factory as an example. The innovation factory has taken on more economic and technological development responsibilities by supporting entrepreneurial enterprises and projects. In the vision of the future business model of Innovative Workshop, a new venture capital model with "financial and talent" coexisting will eventually be constructed.

Under the business model of Innovative Workshop, funds and projects form a particular connection. Ideas will be put on the market after being cultivated and operated in the innovation workshop. After the enterprise passes the market operation test, the venture capital invested in the initial stage of its establishment can realize value-added, and some of it will continue to flow into the innovation workshop and be reinvested in new projects. The circular effect of this project and its funds are the core of the innovative factory business model. This paper draws on the nine elements analysis of Osterwalder's business model to get an overview of the innovative factory business model. The nine elements of the business model of Innovation Workshop are shown in Figure 8.

Figure 8: The nine elements of the business model of the innovation workshop.

Figure 9: Statistical diagram of data mining clustering for customer value innovation.

Figure 10: Statistical diagram of data mining clustering for value chain innovation.

Figure 11: Statistical diagram of data mining clustering for customer value innovation.

This paper researches and analyzes customer value, value chain, and value network innovation. It performs statistics through the model of this paper and obtains the results shown in Figure 9-11.

The business model of Innovation Workshop has undergone three stages of adjustments and changes through the redefinition of the value proposition and the attempt of large-scale industrial operations to implement innovative actions. After adjusting the value proposition, Innovation Workshop has also begun implementing customized services and improving product output methods and service performance. It creates value through mass customization to meet the specific needs of individual customers or customer segments. On the other hand, because in the process of value creation, innovation workshops, and customers participate in the interaction, to a certain extent, they also make use of the advantages of economies of scale as much as possible. In addition, the innovation workshop began to lead the establishment of alliance partnerships, trying to introduce more external relationships to strengthen the leading role of the value network. Moreover, it enables start-ups that have "graduated" from the innovation workshop to obtain more investment

opportunities and shape their investment potential. In this process, the innovation workshop also realizes its investment value.

5 CONCLUSIONS

The need for precise theoretical positioning is another prominent area for improvement in the current business model research field. Although many kinds of literature use business models to make propositions, they only borrow the concept of business models. These documents do not have any new meanings in terms of concept definition, content selection, theoretical system, and research methods. Instead, they borrow some content from other branches of management indiscriminately. Therefore, such research can only cater to the needs of certain popular concepts in society and cannot provide accurate information and correct guidance to people who care about business model issues. This paper combines big data technology to study the characteristics of business innovation and data mining technology to conduct data analysis to verify the characteristics of business model innovation and improve its effect. These findings provide valuable insights for e-commerce practitioners, directing them to develop user-centered platforms that satisfy consumers' changing needs in an increasingly data-driven economy.

Furthermore, this study lays the groundwork for future research to understand better the delicate interaction between human-computer interaction (HCI), big data technology, and ecommerce business model innovation. By prioritizing HCI, e-commerce practitioners can create intuitive interfaces that enhance user experiences, fostering engagement and loyalty. Additionally, integrating HCI principles into e-commerce platforms can optimize the utilization of big data, resulting in more personalized and effective customer interactions. This holistic approach to ecommerce development emphasizes the critical role of HCI in shaping the future of online business.

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REFERENCES

- [1] Basole, R. C.; Srinivasan, A.; Park, H.; Patel, S.: ecoxight: Discovery, Exploration, and Analysis of Business Ecosystems Using Interactive Visualization, ACM Transactions on Management Information Systems (TMIS), 9(2), 2018, 1-26. <https://doi.org/10.1145/3185047>
- [2] Daradkeh, M.: Critical Success Factors of Enterprise Data Analytics and Visualization Ecosystem: An Interview Study, International Journal of Information Technology Project Management (IJITPM), 10(3), 2019, 34-55[.https://doi.org/10.4018/IJITPM.2019070103](https://doi.org/10.4018/IJITPM.2019070103)
- [3] Drake, B. M.; Walz, A.: Evolving Business Intelligence and Data Analytics in Higher Education, New Directions for Institutional Research, 2018(178), 2018, 39-52. <https://doi.org/10.1002/ir.20266>
- [4] Gubler, H.; Clare, N.; Galafassi, L.; Geissler, U.; Girod, M.; Herr, G.: Helios: History and Anatomy of a Successful In-House Enterprise High-Throughput Screening and Profiling Data Analysis System, SLAS DISCOVERY: Advancing the Science of Drug Discovery, 23(5), 2018, 474-488. <https://doi.org/10.1177/2472555217752140>
- [5] Hilario, M.; Esenarro, D.; Vega, H.; Rodriguez, C.: Integration of the Enterprise Information to Facilitate Decision Making, Journal of Contemporary Issues in Business and Government, 27(1), 2021, 1042-1054.
- [6] Huber, T. C.; Krishnaraj, A.; Monaghan, D.; Gaskin, C. M.: Developing an Interactive Data Visualization Tool to Assess the Impact of Decision Support on Clinical Operations, Journal of Digital Imaging, 31(5), 2018, 640-645. <https://doi.org/10.1007/s10278-018-0065-z>
- [7] Jayakrishnan, M.; Mohamad, A. K.; Abdullah, A.: Journey of an Enterprise Architecture

Development Approach in Malaysian Transportation Industry, Int. J. Eng. Adv. Technol, 8(4), 2019, 765-774.

- [8] Kasemsap, K.: Knowledge Discovery and Data Visualization: Theories and Perspectives, International Journal of Organizational and Collective Intelligence (IJOCI), 7(3), 2017, 56-69. <https://doi.org/10.4018/IJOCI.2017070105>
- [9] Milani, A. M. P.; Paulovich, F. V.; Manssour, I. H.: Visualization in the Preprocessing Phase: Getting Insights from Enterprise Professionals, Information Visualization, 19(4), 2020, 273- 287. <https://doi.org/10.1177/1473871619896101>
- [10] Palanivel, K.: Modern Network Analytics Architecture Stack to Enterprise Networks, International Journal for Research in Applied Science & Engineering Technology (IJRASET), 7(4), 2019, 263-280. <https://doi.org/10.22214/ijraset.2019.4480>
- [11] Pashentsev, D. A.; Abramova, A. I.; Eriashvili, N. D.; Grimalskaya, S. A.; Gafurova, A. Y.; Kharisova, G. M.; Avilova, V. V.: Digital Software of Industrial Enterprise Environmental Monitoring, Ekoloji, 28(107), 2019, 243-251.
- [12] Po, L.; Bikakis, N.; Desimoni, F.; Papastefanatos, G.: Linked Data Visualization: Techniques, Tools, and Big Data. Synthesis Lectures on Semantic Web: Theory and Technology, 10(1), 2020, 1-157. <https://doi.org/10.1007/978-3-031-79490-2>
- [13] Rhodes, D. H.; Ross, A. M.: A Vision for Human Model Interaction in Interactive Model -Centric Systems Engineering, INSIGHT, 20(3), 2017, 39-46. <https://doi.org/10.1002/inst.12162>
- [14] Valdiserri, R. O.; Sullivan, P. S.: Data Visualization Promotes Sound Public Health Practice: the AIDSvu Example, AIDS Education and Prevention, 30(1), 2018, 26-34. <https://doi.org/10.1521/aeap.2018.30.1.26>
- [15] Walny, J.; Frisson, C.; West, M.; Kosminsky, D.; Knudsen, S.; Carpendale, S.; Willett, W.: Data Changes Everything: Challenges and Opportunities in Data Visualization Design Handoff, IEEE Transactions on Visualization and Computer Graphics, 26(1), 2019, 12-22. <https://doi.org/10.1109/TVCG.2019.2934538>
- [16] Wang, X.; Dong, Y.; Chen, M.; Su, F.; Ling, L.: Research on Real-time Temperature Control Method for Multi-Visualization of Hot Runner System Based on Internet of Things, Journal of Applied Science and Engineering, 22(4), 2019, 683-690.
- [17] Windsor, J. W.; Underwood, F. E.; Brenner, E.; Colombel, J. F.; Kappelman, M. D.; Ungaro, R.; Kaplan, G. G.: Data Visualization in the Era of COVID-19: An Interactive Map of the SECURE-IBD Registry, Official journal of the American College of Gastroenterology| ACG, 115(11), 2020, 1923-1924. <https://doi.org/10.14309/ajg.0000000000000953>
- [18] Wu, D. T.; Vennemeyer, S.; Brown, K.; Revalee, J.; Murdock, P.; Salomone, S.; Hanke, S. P.: Usability Testing of an Interactive Dashboard for Surgical Quality Improvement in a Large Congenital Heart Center, Applied Clinical Informatics, 10(05), 2019, 859-869. <https://doi.org/10.1055/s-0039-1698466>
- [19] Xu, T.; Song, G.; Yang, Y.; Ge, P. X.; Tang, L. X.: Visualization and Simulation of Steel Metallurgy Processes, International Journal of Minerals, Metallurgy and Materials, 28(8), 2021, 1387-1396. <https://doi.org/10.1007/s12613-021-2283-5>
- [20] Zhao, K.; Sun, R.; Deng, C.; Li, L.; Wu, Q.; Li, S.: Visual Analysis System for Market Sales Data of Agricultural Products, IFAC-PapersOnLine, 51(17), 2018, 741-746. <https://doi.org/10.1016/j.ifacol.2018.08.107>