Research Article

CCCAP-Pre: Predicting Price of Artwork Based on GM(1, N, x^{(1)}) Model and Cultural Services

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Predicting price of contemporary ceramic artworks is an important and difficult problem, particularly when every object is unique and potential bidder’s tastes may exhibit substantial variation. In recent years, China’s ceramic art market has shown a considerable developing trend, but at the same time, there are also problems that severely restrict its development, such as the chaotic price system. As cultural products, contemporary ceramic artworks have the value of cultural services. Unfortunately, the existing price evaluation models all ignore cultural services. By introducing the “cultural services” and “gray model GM(1, N, x^{(1)})”, a new predictor, called CCCAP-Pre, has been developed to predict prices of contemporary ceramic artworks. As demonstrated, the minimum error, the maximum error, and the average relative error of CCCAP-Pre were 0.02%, 6.19%, and 1.40% on ceramic sculpture artworks and 0.06%, 9.11%, and 3.63% on ceramic painting artworks, respectively. It will provide a reference for the benign development of ceramic art market.

1. Introduction

With the China’s transition toward a market economy since 1979, art transactions have gradually intervened in people’s daily life. However, there are still several problems in the art market. For instance, the boundary between the primary market and the secondary market is blurred, and the authoritative evaluation and appraisal institutions were scarce. The 2020 White Paper on China’s Art Wealth which was jointly produced by CICC Wealth Management, Central Academy of Fine Arts and AMRC Art Market Research Center, pointed out that the lack of clear quality standards of the domestic appraisal and valuation system was the main barrier for artworks included in the category of wealth management, and that the low asset liquidity of artworks was the main reason for people to worry about the large-scale purchase of artworks.

Valuation and pricing are major challenges for economists, collectors, art investors, and art dealers especially for contemporary artworks, since one cannot estimate the price of contemporary artwork by the working time, efforts, or materials used during the process of production. The contemporary artwork’s uniqueness, aesthetic quality, and the reputation of artist are major determinants of price [1].

The reasonable estimation of artwork price has attracted more and more attention because artwork price research is of the top priority in the construction of the art market system. In recent years, great progresses have been made in research of its internal determinants and external influencing factors, evaluation system, and prediction price model [2]. It is well recognized that the price of artwork is determined by its value, and its value depends on its many characteristics. The internal determinants of artwork mainly consist of the following factors: the style, size, subject matter, texture, level of production quality, reputation, artist’s age, the living status of the artist, the physical characteristics, artist’s history of museum exhibitions, artist’s awards, and so on [3, 4]. One of the most important internal factors determining the price of artwork is the reputation of artist. On the whole, the artist's reputation is proportional to the price: the greater the artist’s reputation, the higher the price of his artworks [5]. Agnello and Pierce found that works executed
in oil command higher prices than those done in other media including watercolor, charcoal, crayon, and pencils [6]. Solimano explored the effect of colors on the price of artworks and found the blacks, whites, and grays had a higher price. The external influencing factors of price include macroeconomic cycles [7], the changing preferences of buyers [8], the month and year when the artwork was sold, auction houses, the nationality of the artist, etc. Macroeconomic cycles and financial crises may influence the price of artworks. For example, the art market declined sharply when the banking crisis outbroke in 2009 [9] and art market was going upward when the economy was booming. Valsan investigated the relationship between the price of art and the nationality of the artist, and found that the price of Canadian painting is well below that of American painting in general [10]. Powell et al. explored the ideal length of the biography and description of artwork and pointed out that the number of words has an impact on the price of artwork by online sale [11]. According to a strand of the literature [6, 12], artworks of the same artist sold in Sotheby and Christie often attached higher prices than those sold in other auction houses. The reason is that leading auction houses have greater reputation and market power. Powell et al. explored the development of action rules for improving artwork price to another higher price level [13]. Prieto-Rodriguez and Vecco identified different art market segments by modeling art prices using the finite mixture models and found that each segment has its own price structure [14].

Actually, the automated prediction of the price of artworks has been an important topic in the field of economics and art theory. During the recent decades, various models have been proposed for predicting price. These models played a role in stimulating the development of predicting artwork price although they each had their own limitations. There are two models commonly used to predict the price of artworks: repeat sales regression (RSR) and hedonic regression (HR) models [15, 16]. RSR uses prices of same artworks traded at least twice [17]. The important drawback of RSR is sample selection bias because the number of artworks sold at least twice was far less than the number of total transactions [18]. The price of artwork in HR model is determined by a number of artwork’s characteristics, market variables, and time dummies [19]. The HR models enjoy the advantages of taking into account all sold lots and solving the problem of artwork heterogeneity though the relation between price and all its features. However, this model has two major drawbacks [20]. It is difficult to account for all the features that determine the price of an artwork, which may result in a feature selection bias. The second drawback is the functional form of the equation contains many less important variables. In the ordinary way, HR model performs better for artwork price prediction than RSR model when the sample size is small. For large samples, the results of the two models are similar. To overcome the limits of these models, Quigley estimated a hybrid model using RSR in combination with HR model and generated a more efficient estimation [21].

With the rapid development of machine learning, researchers had proposed many price prediction models based on machine learning. Liu proposed a two-way long short-term memory network to predict artwork price based on historical price information [22]. Aubry et al. developed a price prediction algorithm based on neural networks and found this model performed dramatically better than standard HR model on data set which contains paintings price at 372 different auctions over the period between 2008 and 2015.

Cultural services of artwork are associated with inspiration, creativity, emotions, etc. These contextual factors can affect consumer behavior. Plante et al. divided artworks into four categories: decorative art, emerging art, trending art, and blue-chip art according to their degree of cultural recognition [23], and found that the artworks belonging to the blue-chip art have higher price than those belonging to the other categories. As it is difficult to evaluate the cultural services value of artwork, the existing price forecasting models often ignore this impact.

Ceramic art is one of the important branches of the art market at present. In the ceramic art market, ancient ceramics are collected eagerly because of its historical value, while the artistic and economic values of modern and contemporary ceramic art are often underestimated. According to the Global Art Report 2020, China’s position in the world art market is becoming more and more important, and ceramic art accounts for nearly 30% of the total auction turnover in the Chinese art market. The research of Chinese ceramic art price evaluation system is relatively delayed compared with other assets. Ahmed and Kilic constructed the Chinese ceramic artwork price prediction model by using analytic hierarchy process and the price evaluation index of ceramic art [24]. Gray system theory is widely used in the study of the problem of few samples, and the problem of Chinese ceramic artwork price prediction just coincides with the characteristics of gray dynamic model. Wang used a gray dynamic model named GM(1, N) to price Chinese modern and contemporary artworks and improved the prediction quality [25]. The prediction accuracy of the above model is not very high.

However, due to the complex components of price and the low quality of price data, pricing of Chinese ceramic artwork faces two difficulties: the lack of evaluation system and the error of research results. The breakthrough direction in the research of art price is to make a technical breakthrough through objective and subjective indicators, quantitative model and expert experience, and the combination of automatic collection and manual collection. In this paper, a new predictor named CCCAP-Pre was developed by using gray model GM(1, N, $x^{(1)}$) and cultural services quantifiable valuation method to price the Chinese contemporary ceramic artwork. It has the following advantages: (1) cultural services refer to the nonmaterial benefits people obtain from the artwork, for example, spiritual and religious values, cultural diversity, knowledge systems, educational values, inspiration, aesthetic values, social relations, and cultural heritage values [26]. Cultural service is one kind of ecosystem services which have been defined by Millennium Ecosystem Assessment process of the United Nations [27]. We used quantitative model of cultural services to measure perceived aesthetic quality of purchaser within artworks.
context, which is a perfection of the existing price prediction model of artworks. (2) It has been proved that price prediction based on gray models is valid; however, there is a need to further improve the accuracy of the existing models. The present study was initiated in an attempt to develop a new and more powerful predictor by generalized GM(1, N, x(13)).

2. Materials and Methods

The Materials and Methods section should contain sufficient details so that all procedures can be repeated. It may be divided into headed subsections if several methods are described.

2.1. Benchmark Data Set. In today’s primary art market, many artists sell their works on auctions such as Sotheby, Christie, and Artron. In China’s art market, auctions are widely used as important devices to value contemporary ceramic art because other validating organizations are seen as untrustworthy [28]. The data comprise 263 sales transactions of Chinese contemporary ceramic artworks. Information on sales is obtained from the world’s authoritative art auction network: Artron Art Network (https://www.artron.net) which spans the period from 2017 to 2021, and the transaction records with detailed introduction were selected, including 73 ceramic sculpture artwork data and 190 ceramic painting artwork data.

2.2. The Most Relevant Characteristic of Artwork. Each artwork has its own unique characteristics. Buyers make a comprehensive evaluation through their own understanding and experience of each characteristic of the artwork, and finally offer their desired price for the artwork. What are the characteristics of artworks that buyers care about? What are the characteristics of artworks that we need to count? This is the basis of art price prediction.

In view of the subjectivity of the generation and acquisition of the “qualities” of cultural service people felt and the difficulty of identifying the relationship between the price and the characteristics of artwork, they are difficult to predict price according to the observed direct or indirect market behavior. We integrate structured questionnaire [29] and group discussion [30] to explore the key characteristics affecting the price of artwork, as elaborated in [31]. In order to ensure the reliability of the results, we choose people who have ceramic art knowledge and are familiar with ceramic art auction as interviewees, including ceramic artists, auctioneer, purchaser, and intermediary business. Finally, the variables affecting the price of Chinese contemporary ceramic artworks are divided into four categories: physical characteristics of artwork, ceramist characteristics, added values, and cultural service values. The variables of the ceramic art value evaluation system can be seen in Table 1, with a total of 19 variables.

The first set of variables represents the physical characteristics of the artwork. In this study, contemporary ceramic artworks are divided into two categories (i.e., ceramic painting and ceramic sculpture) because of the differences in mode of expression, creative technology, and evaluation criteria. Six characteristics of artwork such as dimensions, materials, craftsmanship, modeling, themes, and artistic language are selected as evaluation indicators. The dimensions of the ceramic painting are represented by its surface area and that of ceramic sculpture is its volume. The materials of ceramic paintings are mainly pottery and porcelain. With the development of technology, contemporary ceramic sculptures have more choices in materials, such as porcelain, pottery, and multiple materials.

The second set of variables represents the ceramist characteristics which are mainly reflected in the personal style, the social status, and ceramist’s age at the time of sale. Personal style reflects ceramists’ skill and aesthetic ideas, which is not only the personal label of ceramists, but also the embodiment of differentiation. Ceramic artworks with distinctive styles can often be distinguished from similar artworks. The social status of ceramists represents their social influence and reputation. It is well known that one of the most important variables determining the price of ceramic artwork is the reputation of ceramist. In similar artworks, the artworks of famous ceramist tend to be more expensive. The prices of artworks are likely to increase once a ceramist has died because of the rarity of the artworks.

The third set of variables represents added values which have incorporated the sale characteristics of the artworks including media exposure rate, market circulation, auction agency, and art index. The popularity of contemporary ceramic artworks depends to large extent on the media exposure rate and length of time the artworks are reported by authoritative media. The exposure and spread have a great influence on the price of artworks. The market trend should also be considered when evaluating the price of ceramic artworks. The art index reflects the overall trend of art prices over a period of time. One of the most important art indexes in China is the Artron index. We can use the Artron index to discount these historical prices of artworks. Generally speaking, the art index is closely related to the economic environment.

Market circulation is a key link in the art industry chain, and the value of ceramic artworks is generally realized through market circulation. Most artworks have a long market cycle with a low transaction turnover rate. The phenomenon of repeated transactions of artworks in a short period has a high probability of speculation, and it easily leads to bubbles, which is not beneficial to the healthy development of the art market.

The final set of explanatory variables is related to the cultural services value of artwork. In this paper, we have defined cultural services in terms of the “nonmaterial benefits people obtain from contemporary ceramic artworks,” and specifically listed “esthetic values, inspired values, entertainment values, symbolic values, educational values, religious values.” We represent aesthetic services based on “appreciation of ceramic artworks” and link aesthetic values in ceramic art areas with ceramic artworks that can meet the aesthetic needs of consumers and provide a beautiful and pleasant aesthetic experience for the viewer. The inspiration values are expressed as that appreciators can
obtain cultural information in the process of viewing and collide with their own learning experience to get inspiration and broaden their artistic horizons. Different from the serious aesthetic expression of traditional ceramic art, contemporary ceramic art is a mixture of nonutilitarian beauty and utilitarian pleasure, which is the characteristic of entertainment pleasure. The entertainment values of contemporary ceramic art are more represented by sensory feelings and emotional rendering. Economist Veblen believes that the degree of consumer demand for artworks will increase rather than decrease because of their higher prices in the case of "conspicuous consumption." Collectors’ pursuit of the works of famous artists also partly demonstrates their status and aesthetic taste. As ceramic artworks are the inheritance of culture, the viewer can learn about the traditional culture such as poetry, history, allusions, and myths stories from its decoration, which is the educational values of ceramic artworks. Ceramics are closely related to religion. On the one hand, ceramic art which expresses religious culture has become an important part of religious art, which provides a special form for understanding religious culture. On the other hand, the aesthetics of religious art also affects ceramic culture to some extent and plays an important role in promoting ceramic art. This is why ceramic artworks have religious values.

2.3. Data Transformation. How to objectively quantify the 19 qualitative variables to reflect the relationship between evaluation variables and prices is the first problem to be solved. For this reason, the data were transformed as follows. First of all, in the evaluation variables of artworks, the two variables of artwork dimensions and artist age are too scattered and need to be classified. Artwork dimensions are classified according to the height of 0–20 cm, 20–40 cm, 40–60 cm, 60–80 cm, and above 80 cm; the ages of the artist are classified based on 0–30 years old, 30–60 years old, 60–90 years old, and above 90 years old. Based on the previous survey and interviews, the artist’s social status and personal style are classified using a 9-point ordinal scale.

Secondly, 19 qualitative variables of contemporary ceramic artwork are quantified. The auction prices of all ceramic artworks with the same attributes of the qualitative variables are summarized, and the average value is taken as each attribute value of each variable. For example, the attribute value of the theme of flowers and birds is the average price value of all the samples of flowers and birds.

Finally, for the problem that some evaluation variable values are missing in some samples, the missing values are assigned by taking the average value of the variables in all samples. The values of 19 qualitative variables of samples are given in supplemental files S1 and S2.

2.4. Construction of the GM(1, N, x(1)) Prediction Model. Conventional machine methods such as deep learning require large samples in multivariate system modeling. However, the gray theory is particularly used for solving complicated problems with small data (sample size less than 300) that widely exist in the real world, and it is often used to process uncertain information and reduce random effects of acquired data. According to the gray theory, if the
information of a system investigated is partially known, it is called a "gray system"; if completely unknown, a "black system"; and if fully known, a "white system" [32]. In recent years, the gray theory has been recognized by many scholars, and its application fields have also been extended from the initial control science to many fields such as industry, agriculture, energy, economy, and management. How to use the input values of several variables to predict the associated output values has always been the focus of gray theory research. In order to solve this problem, many different types of multivariable gray models were established, such as GM(1, N). Gray model, referred to as GM, established a gray differential prediction model to make a fuzzy long-term description of the development law of thing through a small amount of incomplete information. The great critical feature of the GM is making use of accumulative generation operation to reduce the variation of the original data series by transforming the data series linearly [33]. However, the excessive error of simulation and prediction of multivariable gray models in practical application reflects the practicability of these models that needs to be improved. In this study, a novel model called generalized GM (1, N, x(i)) is introduced to predict the price of contemporary ceramic artworks.

GM (1, N, x(i)) is constructed based on GM(1, N) power model. The GM(1, N) power model can be expressed by the following equation [34]:

\[ x_i^{(0)}(k) + a z_i^{(1)}(k) = \sum_{i=2}^{N} (z_i^{(1)}(k))^\beta, \]  

where \( X_i^{(0)} = (x_i^{(0)}(1), x_i^{(0)}(2), \ldots, x_i^{(0)}(n)) \) is the system characteristic data sequence, and the related factor sequences are

\[ X_2 = (x_2^{(0)}(1), x_2^{(0)}(2), \ldots, x_2^{(0)}(n)), \]

\[ X_3 = (x_3^{(0)}(1), x_3^{(0)}(2), \ldots, x_3^{(0)}(n)), \]

\[ \vdots \]

\[ X_N = (x_N^{(0)}(1), x_N^{(0)}(2), \ldots, x_N^{(0)}(n)). \]

The coefficients \( a \) and \( b_i \) are called the system development and driving coefficients, respectively. The \( y_i \) is the power exponent of the \( i \)th related variable, and it can reflect the nonlinear effect of the \( i \)th related variable on the system characteristic variable. \( z_i^{(1)}(k) \) is the adjacent mean generating sequence of \( X_i^{(1)} \), and \( X_i^{(1)} \) is viewed as the first-order accumulative generation operation series for \( x_i^{(0)} \).

The whitening time response function of the above GM(1, N) power model is an approximate solution, it is likely that \( X_i^{(1)} \) varies greatly in practical application, \( \sum_{i=2}^{N} b_i (x_i^{(1)}(k))^\beta \) cannot be regarded as a gray constant, and there will be a big error when used in the actual prediction. In order to solve this problem, GM (1, N, x(i)) is given below.

In GM (1, N, x(i)), the background values of \( X_i^{(0)}(k) \) are represented by

\[ z_i^{(1)}(k) = x_i^{(1)}(k - 1) + 0.5x_i^{(0)}(k), \]

With putting equation (5) into GM(1, N) power model equation (1), and some mathematical calculations, we have

\[ x_1^{(0)}(k) = a\left[x_1^{(1)}(k - 1) + 0.5x_1^{(0)}(k)\right] \]

\[ \sum_{i=2}^{N} b_i (x_i^{(1)}(k))^\beta, \]  

\[ (1 + 0.5a)x_1^{(0)}(k) = \sum_{i=2}^{N} b_i (x_i^{(1)}(k))^\beta - ax_1^{(1)}(k - 1), \]

\[ x_1^{(0)}(k) = \sum_{i=2}^{N} b_i \left(\frac{1}{1 + 0.5a}x_i^{(1)}(k - 1)\right) \]

Equation (8) is the mathematical expression of GM (1, N, x(i)) power model, and the \( y_i \) reflects the nonlinear effect of \( X_i^{(1)} \) on the system characteristic sequence \( X_i^{(0)} \). In the process of GM (1, N, x(i)) modeling, the specific values of these power exponents \( y_i \) must be determined in advance before the structural parameter series \( a \) and \( b_i \) can be estimated, and then solve the time response function of the model.

From variables and weights of contemporary ceramic artwork price prediction system in Table 1, it can be seen that the GM (1, N, x(i)) multivariate gray prediction model should be constructed containing a total of 19 evaluation variables and 1 predicted price. Let us assume that \( \{x_i^{(0)}(k)\} \) is data sequence of the evaluation variables, it is original series of real numbers with an irregular distribution, \( \{y^{(0)}(k)\} \) is the data sequence of the prices of samples, \( i = 1, 2, \ldots, 19, k = 1, \ldots, m \), and \( m \) is the number of samples in benchmark data set. Then, \( x_i^{(1)}(k) \) and \( y^{(1)}(k) \) are viewed as the first-order accumulative generation operation series for \( x_i^{(0)}(k) \) and \( y^{(0)}(k) \), respectively; i.e., the components in \( x_i^{(1)}(k) \) and \( y^{(1)}(k) \) are given by

\[ y^{(1)}(k) = \sum_{i=1}^{k} y^{(0)}(j), k = 1, 2, \ldots, m, \]

\[ x_i^{(1)}(k) = \sum_{j=1}^{k} x_i^{(0)}(j), k = 1, 2, \ldots, m. \]

The GM (1, N, x(i)) model in this study can be expressed by the following equation:

\[ y^{(0)}(k) = \sum_{i=1}^{19} \beta_i (x_i^{(1)}(k))^\beta - ay^{(1)}(k - 1), \]

where \( \beta_i = bi/1 + 0.5a, a = a/1 + 0.5a \). The \( y_i \) is the power exponent of the \( i \)th related variable, and it can reflect the nonlinear effect of the \( i \)th evaluation variable on the price of ceramic artwork.

The power exponent \( y_i \) can be solved by the following nonlinear programming model:
\[
\min \left( \text{avg}(\epsilon(k)) = \frac{1}{n-1} \sum_{i=1}^{N} \frac{\bar{y}^{(0)}(k)}{y^{(0)}(k)} \right) = \frac{1}{n-1} \sum_{i=1}^{N} \frac{x_{i}^{(1)}(k)}{y^{(0)}(k)}, \quad i = 1, 2, \ldots, 19,
\]
\[
y^{(0)}(k) = \sum_{i=1}^{19} \frac{b_{i}}{1 + 0.5a} \left( x_{i}^{(1)}(k) \right)^{n} - \frac{a}{1 + 0.5a} y^{(1)}(k-1), \quad k = 1, 2, \ldots, m,
\]
\[
\bar{a} = (a, b_{1}, b_{2}, \ldots, b_{19})^{T}
\]

where \( \bar{a} = (a, b_{1}, b_{2}, \ldots, b_{19})^{T} = (B^{T}B)^{-1}B^{T}Y \), and matrix \( B \) and vector \( Y \) are given by

\[
B = \begin{bmatrix}
-z^{(1)}(2) & x_{1}^{(1)}(2) & \cdots & x_{N}^{(1)}(2) \\
-z^{(1)}(3) & x_{1}^{(1)}(3) & \cdots & x_{N}^{(1)}(3) \\
\vdots & \vdots & \ddots & \vdots \\
-z^{(1)}(19) & x_{1}^{(1)}(19) & \cdots & x_{N}^{(1)}(19)
\end{bmatrix},
\]
\[
Y = \begin{bmatrix}
y^{(0)}(2) \\
y^{(0)}(3) \\
\vdots \\
y^{(0)}(19)
\end{bmatrix},
\]
\[
z^{(1)}(k) = x_{1}^{(1)}(k-1) + 0.5x_{1}^{(0)}(k), \quad k = 2, 3, \ldots, 19.
\]

The above optimization problem can be solved by optimizing software LINGO. Once the optimal value of \( y_{i}^{*} \) is confirmed, the structural parameters \( \bar{a} \) of the model are determined. We can get the prediction result by above parameters and equation (8).

It is instructive, however, to point out that the average relative error \( \bar{\epsilon} \) and the absolute error \( \epsilon(k) \) are often used in literature of examining the performance quality of predicting price of artworks. The calculation formulas are as follows:

\[
\epsilon(k) = \bar{y}^{(0)}(k) - y^{(0)}(k),
\]
\[
\bar{\epsilon} = \frac{1}{m} \sum_{k=1}^{m} \frac{|\epsilon(k)|}{y^{(0)}(k)}.
\]

where \( \bar{y}^{(0)}(k) \) is the predicted price of ceramic artwork.

### 3. Results and Discussion

The benchmark data set includes 73 ceramic sculpture artwork data and 190 ceramic painting artwork data. Finally, two GM(1, N, \( x^{(1)} \)) price prediction models for ceramic sculpture artwork and ceramic painting artwork are obtained, respectively. For the prediction, the values of parameters \( a, b_{0}, \) and \( y_{i} \) in equations (2) and (3) were determined by minimizing average relative error \( \bar{\epsilon} \) of (6) using the numerical simulation test on the data set thru optimization software LINGO. The optimal parameter values thus determined for \( a, b_{i} \), and \( y_{i} \) in equations (2) and (3) are summarized in Table 2.

\( t \) is shown that the prediction prices of the GM (1, N, \( x^{(1)} \)) power model on the ceramic sculpture at this study are consistent with that of the theory and the minimum error is 0.02%, the maximum error is 6.19%, and the average relative error is 1.40%. The minimum error, the maximum error, and the average relative error achieved by the GM (1, N, \( x^{(1)} \)) power model for predicting price of the ceramic painting are 0.06%, 9.11%, and 3.63% respectively. The results show that two models have the capacity to deal with such a complicated and stringent system.

Compared with the single variable gray model, the multivariable gray model is more prone to the drift of data matrix in the process of parameter identification. It is best to preprocess the original data before establishing the GM (1, N, \( x^{(1)} \)) power model. The data transformation methods such as initialization or equalization can be used. In this study, the original data are quantitatively transformed including ceramic sculptures and ceramic paintings, respectively. Figures 1 and 3 show the predicted price values obtained by GM (1, N, \( x^{(1)} \)) power model with the process of data transformation, while Figures 2 and 4 show results including the process of data transformation. The ordinate of figures is the price, the blue is the real price, and the yellow is the predicted price. It can be seen from Figure 1 that the minimum error, the maximum error, and the average relative error of the GM (1, N, \( x^{(1)} \)) power model on ceramic sculptures without data transformation are 1.03%, 860.72%, and 225.18%, respectively, whereas the minimum error, the maximum error, and the average relative error of the GM (1, N, \( x^{(1)} \)) power model on ceramic paintings without data transformation are 1.43%, 901.91%, and 253.67%, respectively. From the results, it can be seen that there is a big gap between the predicted price and the real value. Figures 2 and 4 indicate that the GM (1, N, \( x^{(1)} \)) power model with data transformation can produce models with better fitting quality and predictive quality in comparison with GM (1, N, \( x^{(1)} \)) power model without data transformation, the prediction value error is smaller after the data transformation, and the results are more accurate.

The traditional GM(1, N) model is a special form of the GM(1, N) power model [34]. The existing GM(1, N) gray models and their extended multivariable models have linear characteristics in structure. This simplification of the real system brings convenience to the construction and solution of the model. However, as the structures of most real systems are nonlinear, using the GM(1, N) model to describe the system behavior of nonlinear structure will often lead to unacceptable modeling errors. In order to solve this problem, the power index was generally introduced to reflect the nonlinear effect of related variables on
system behavior, and the GM(1, N) power model was constructed.

We also compared our GM(1, N, x(1)) power model with the GM(1, N) power model, and the data transformation method was all used in two models. Figures 5 and 6 show the predicted results of the GM (1, N) power model on ceramic paintings and sculptures, respectively. The minimum error, the maximum error, and the average relative error of the GM (1, N) power model on ceramic paintings are 0.54%, 94.64%, and 19.83%, respectively. On ceramic sculptures, the minimum error is 0.46%, the maximum error 91.14%, and the average relative error 17.79%. The results show that there is still a certain gap between the predicted result and the real value. The main reason for the error of the GM (1, N) power model is that the solutions of the model still are approximate, but the solutions of GM(1, N, x(1)) power model are accurate. Therefore, the accuracy of GM(1, N, x(1)) power model is higher than that of the GM (1, N) power model.

To further validate the robustness and reliability of the prediction framework, we constructed another data set which comprised 387 sales transactions of Chinese contemporary ceramic artworks. Information on sales was also

Table 2: The optimal parameter values of two GM(1, N, x(1)) price prediction models.

| Model                        | The optimal parameter values of GM(1, N, x(1)) price prediction model |
|------------------------------|-----------------------------------------------------------------------|
| Ceramic sculpture artwork    | a = -2.9925, b_1 = 5.3613, y_1 = 0.6388, b_2 = 23.5656, y_2 = 0.3090, b_3 = 2.0137 |
|                              | y_4 = 0.1240, b_4 = 6.6514, y_4 = 1.0892, b_5 = 3.4024, y_5 = -0.1239, b_6 = 4.0001 |
|                              | y_6 = 0.9636, b_6 = 20.7602, y_6 = 1.1095, b_7 = 2.0181, y_7 = 0.1891, b_8 = 1.2799 |
|                              | y_9 = -1.4880, b_9 = 5.8109, y_9 = 0.2489, b_10 = 10.9471, y_10 = -1.3809, b_11 = 21.9981 |
|                              | y_11 = 1.3632, b_11 = 2.6448, y_11 = 2.1389, b_12 = 4.6381, y_12 = -0.1881, b_13 = 10.4581 |
|                              | y_13 = 1.9476, b_13 = 17.0286, y_13 = 1.2168, b_14 = 20.5602 |
| Ceramic painting artwork      | a = -0.2730, b_1 = 20.5439, y_1 = -0.2697, b_2 = 9.3959, y_2 = 1.7723, b_3 = 16.8501 |
|                              | y_4 = 0.6414, b_4 = 13.0020, y_4 = 1.8596, b_5 = 16.6395, y_5 = -0.1034, b_6 = 18.3659 |
|                              | y_6 = 0.3540, b_6 = 7.1028, y_6 = -0.8060, b_7 = 18.0570, y_7 = 1.5097, b_8 = 0.5258 |
|                              | y_9 = -1.1670, b_9 = 20.8207, y_9 = 1.0153, b_10 = 9.4670, y_10 = 0.8355, b_11 = 11.8334 |
|                              | y_12 = 1.5395, b_12 = 15.4672, y_12 = 1.9055, b_13 = 23.9189, y_13 = -0.6739, b_14 = 12.1785 |
|                              | y_15 = -0.1268, b_15 = 7.7067, y_15 = 1.6970, b_16 = 19.8455, y_16 = -0.6512, b_17 = 9.7430 |

Figure 1: Comparative results of real price and predicted price. The prices were predicted using GM (1, N, x(1)) power model based on the benchmark data set of ceramic sculptures without data transformation.
obtained from the world’s authoritative art auction network: Artron Art Network which spanned the period from 2012 to 2021, and the transaction records included 146 ceramic sculpture artwork data and 241 ceramic painting artwork data. The values of 19 qualitative variables of samples are given in supplemental files S3 and S4. The prediction results in Figures 7 and 8 showed that the performance generated by the same prediction framework was stable and reliable after a stringent criterion was imposed to construct the benchmark data set where the transaction records spanned ten years. Figure 7 shows that the minimum error of ceramic sculpture artwork is 0.07%.

Figure 2: Comparative results of real price and predicted price. The prices were predicted using GM (1, N, x(1)) power model based on the benchmark data set of ceramic sculptures with data transformation.

Figure 3: Comparative results of real price and predicted price. The prices were predicted using GM (1, N, x(1)) power model based on the benchmark data set of ceramic paintings without data transformation.
the maximum error is 14.77%, and the average error is 3.23%. Figure 8 shows that the minimum error of ceramic painting artwork is 1.03%, the maximum error is 17.26%, and the average error is 4.64%.

The previous RSR uses prices of same artworks traded at least twice. The important drawback of RSR is sample selection bias because the number of artworks sold at least twice was far less than the number of total transactions. The
drawback of HR models is the functional form of the equation contains many less important variables. The prediction models based on the deep learning require large trained data set. However, the gray models have been proved to be effective, especially used for solving complicated problems with small data. This paper considers nonlinear processing of the form of the relevant variables on the right side of the GM(1, N) model and introduces the power exponent to reflect the nonlinear effect of the relevant variables on the system behavior variables. In CCCAP-Pre, we added a new set of variables representing cultural services value of artwork, and these all affect the price of Chinese
contemporary ceramic artworks. The above two improvements improve the prediction accuracy of our model.

4. Conclusions

In this paper, we proposed a theoretical framework for the price evaluation of contemporary ceramic artworks. By introducing the "cultural services" and "GM(1, N, x(1)) power model," a new predictor, called CCCAP-Pre, has been developed that can be used to predict prices of Chinese contemporary ceramic artworks. The variables affecting the price of Chinese contemporary ceramic artworks are divided into four categories: physical characteristics of artwork, artist characteristics, added value, and cultural service value.

Experiments show that the GM (1, N, x(1)) power model can better describe the nonlinear relations between the price and their influencing factors, thereby effectively improving the accuracy of the multivariable gray system modeling. It is anticipated that this predictor will become a very useful tool for predicting the price of ceramic artworks, and the novel approach and technique can also be used to predict the price of other artworks.

Data Availability

The data used in this study are obtained from the world’s authoritative art auction network, Artron Art Network (https://www.artron.net), which spans the period 2017 to 2021, and the transaction records with detailed introduction were selected, including 73 ceramic sculpture artwork data and 190 ceramic painting artwork data. The authors also constructed another data set which comprised 387 sales transactions of Chinese contemporary ceramic artworks. Information on sales spanned the period from 2012 to 2021, and the transaction records included 146 ceramic sculpture artwork data and 241 ceramic painting artwork data.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

The values of 19 qualitative variables of 190 ceramic painting samples which span the period from 2017 to 2021 are given in supplemental file S1, the values of 19 qualitative variables of 73 ceramic sculpture samples which span the period from 2017 to 2021 are given in supplemental file S2, the values of 19 qualitative variables of 146 ceramic sculpture samples which span the period from 2012 to 2021 are given in supplemental file S3, and the values of 19 qualitative variables of 241 ceramic painting samples which span the period from 2012 to 2021 are given in supplemental file S4. (Supplementary Materials)

References

[1] J Beckert and J. Rössel, “The price of art,” European Societies, vol. 15, no. 2, pp. 178–195, 2013.
[2] X. D. Liu, “The dilemma and breakthrough direction of domestic art price research,” Journal of Beijing Union University (Humanities and Sciences), vol. 19, pp. 59–66, 2021.
[3] A. C. Worthington and H. Higgs, “A note on financial risk, return and asset pricing in Australian modern and
contemporary art,” *Journal of Cultural Economics*, vol. 30, no. 1, pp. 73–84, 2006.

[4] J. Fedderke and K. Li, “Art in Africa: hedonic price analysis of the South African fine art auction market, 2009-2014,” *Economic Modelling*, vol. 84, pp. 88–101, 2020.

[5] A. C. Worthington and H. Higgs, “Art as an investment: risk, return and portfolio diversification in major painting markets,” *Accounting and Finance*, vol. 44, no. 2, pp. 257–271, 2004.

[6] R. J. Agnello and R. K. Pierce, “Financial returns, price determinants, and genre effects in American art investment,” *Journal of Cultural Economics*, vol. 20, no. 4, pp. 359–383, 1996.

[7] A. Solimano, “The Art Market at Times of Economic Turbulence and High Inequality,” in *International Center for Globalization and DevelopmentSantiago, Chile* http://www.ciglob.org/wp-content/uploads/2020/05/2018–2019.pdf; 2019.

[8] E. Grigoroudis, L. Noel, E. Galariotis, C. Zopounidis, E. Galariotis, and C. Zopounidis, “An ordinal regression approach for analyzing consumer preferences in the art market,” *European Journal of Operational Research*, vol. 290, no. 2, pp. 718–733, 2021.

[9] O. Chanel, “Is art market behaviour predictable?” *European Economic Review*, vol. 39, no. 3–4, pp. 519–527, 1995.

[10] C. Valsam, “Canadian versus American art: what pays off and why,” *Journal of Cultural Economics*, vol. 26, no. 3, pp. 203–216, 2002.

[11] L. Powell, A. Gelich, and Z. W. Ras, *Rough Sets*, pp. 480–494, “Springer International Publishing”, New York City, 2019.

[12] L. Renneboog and T. Van-Houtte, “The monetary appreciation of paintings: from realism to Magritte,” *Cambridge Journal of Economics*, vol. 26, no. 3, pp. 331–358, 2002.

[13] L. Powell, A. Gelich, and Z. W. Ras, “How to raise artwork prices using action rules, personalization and artwork visual features,” *Journal of Intelligent Information Systems*, vol. 57, no. 3, pp. 583–599, 2021.

[14] J. Prieto-Rodriguez and M. Vecco, “Reading between the lines in the art market: lack of transparency and price heterogeneity as an indicator of multiple equilibria,” *Economic Modelling*, vol. 102, Article ID 105587, 2021.

[15] H. Higgs, “Australian art market prices during the global financial crisis and two earlier decades,” *Australian Economic Papers*, vol. 51, no. 4, pp. 189–209, 2012.

[16] L. Renneboog and C. Spaenjers, “Buying beauty: on prices and returns in the art market,” *Management Science*, vol. 59, no. 1, pp. 36–53, 2013.

[17] R. Kraeussl and R. Logher, “Emerging art markets,” *Emerging Markets Review*, vol. 11, no. 4, pp. 301–318, 2010.

[18] A. Collins, A. Scorcu, and R. Zanola, “Reconsidering hedonic art price indexes,” *Economics Letters*, vol. 104, no. 2, pp. 57–60, 2009.

[19] F. Wang, “Which part of the Chinese art market is more worth investing in? Applying the quantile regression to analyze Chinese oil paintings 2000–2014,” *Emerging Markets Finance and Trade*, vol. 53, no. 1, pp. 44–53, 2017.

[20] L. Modugno, S. Cagnone, and S. Giannerini, “A multilevel model with autoregressive components for the analysis of tribal art prices,” *Journal of Applied Statistics*, vol. 42, no. 10, pp. 2141–2158, 2015.

[21] J. M. Quigley, “A simple hybrid model for estimating real estate price indexes,” *Journal of Housing Economics*, vol. 4, pp. 1–12, 1995.