An Evaluation of Seller Reputations and Prices' Mechanism – Empirical study of HuaJia's artist data analysis

MSc in Management Thesis

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Abstract

Since the digital art commission market is a new business model in the art industry, the discovery of potential mechanisms for setting digital art commission prices is considered limited. This research explores the mechanism between an artist's reputation level (proxied by the number of followers) and artwork prices in the online digital art commission market for an exploratory study of developing the pricing estimation framework.

Adopting a quantitative approach, the study analysed sample data from 103 independent artists on the HuaJia platform. The *T-tests*, Pearson Correlation Tests (*PCT*), and Simple Linear Regression Models (*SLRM*) are applied in this study. The dataset applies logarithmic transformations as the right-skewed data distribution has been observed to enhance statistical reliability.

Empirical findings demonstrate that artists with high follower counts charge higher prices than artists with low follower counts, confirming that a positive correlation between the number of followers and artwork prices is observed. Although the correlation is statistically significant, the explanatory power for price variations (Low R^2 Results) solely described by follower count is limited. The result suggests that reputation is a multidimensional construct that cannot be fully captured by a single numerical metric.

To conclude, this study confirms that the follower count as a proxy for reputation is plausible and provides empirical references for independent artists to develop pricing and competing strategies across various reputation stages.

Key words: Digital Art, Reputation Level, Proxy Variables, Quantitative Method, Statistical Modelling, Exploratory Discovery, Pearson Correlation Test, Simple Linear Regression

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Contents

1. Introduction

Price is crucial in commercial transactions involving products and services. From a seller's perspective, pricing involved balancing customers' willingness to pay for certain products and services with the artist's need to generate revenue (Kotler et al., 2020). Mintzberg (2009) suggests that artists should use analytical data to formulate pricing strategies so that better revenue generation can be achieved under a disciplined management perspective, particularly for artwork production for independent artists. In this study, the artwork pricing framework is combined with *artwork price* and *artwork pricing*. *Artwork price* refers to the final transactional value, while *artwork pricing* describes the mechanism of price setting strategies and corresponding calculations.

Traditionally, artwork pricing does not depend primarily on production costs, as the production costs remain relatively stable during creation (Bai et al., 2013). Since the production costs play a limited role in determining prices, a possible key influencer of price is the selling methods, such as selling via galleries (Schönfeld & Reinstaller, 2007). Another factor of artwork price influencers is the shipping costs. Under the physical art's selling model, their existence is collectively affecting the price model of physical artwork (Angelini et al., 2022). Physical art transactions therefore involve substantial intermediatory factors, the auction agencies and galleries playing a major role in the transaction processes (Schönfeld & Reinstaller, 2007).

However, digital platforms are reshaping the art market by allowing independent artists to compete and earn income without shipping costs when trading digital artworks (Bogaerts, 2015; Li & Xiao, 2025). As the digital art industry reshapes pricing models compared to the physical artwork pricing models, a new analytical approach is needed, since digital art transactions are less influenced by intermediatory factors than physical art transactions. Artists can then adjust their pricing decisions based on revenue generation and self-promotion to adapt the new dynamics of digital art market (Art Trails Tasmania, 2026; Mintzberg, 2009). To provide a practical framework for independent artists, developing a price estimation tool may help them determine prices and evaluate their market position on digital platforms (Ajayi et al., 2025; Kotler et al., 2020).

While artists encounter challenges in estimating the optimal prices for their artworks, one solution is to use their reputation level as an indicator. DiRusso et al.'s (2011) statistical model provides a framework on the approaches of estimating the influencing factors into measurable variables. Although the authors' the model targets general online retail pricing, it serves as a reference for preliminarily estimating the price structure, suggesting that the reputation evaluation is applicable in broader markets. This discovery indicates that quantitative estimation methods are applicable to artwork pricing description. However, DiRusso et al. (2011) note that the model cannot be directly applied to digital art pricing, as it includes factors irrelevant to describing the digital art commission market. To further explore relevant factors, insights from DiRusso et al.'s (2011) statistic model can be combined with Ning's (2024) observations on physical art pricing. This combination offers an approach for developing a pricing framework for digital art commissions.

In summary, the current literature lacks empirical evidence for determining artwork pricing in the platform-based digital art commission market. This gap limits the applicability of analytical approaches in defining whether artists can reliably use their reputation as an indicator for balancing customers' willingness to pay and revenue generation. According to DiRusso et al. (2011) and Ning's (2024) arguments, the most reliable indicator observable to consumers is the artist's reputation level.

Among the various factors that may influence the artwork prices, this study aims to address the gap in explaining the artists' artwork pricing mechanism frame and integrating the impacts of prices due to their reputation in digital art commission industry. Hence, the research question is proposed as follows:

How an artist's reputation level influences their artwork price in digital art online commission market?

The purpose of this research is to explore the mechanism linking artists' reputation level to artwork prices. It also explores the pricing decisions of independent artist’s commission work, which are influenced by quantitatively framed reputation levels. Furthermore, this research will develop a pricing formula based on collected data and statistical models. Independent artists can access the proposed formula to set artwork prices according to their market position, which can increase the likelihood of receiving commission requests from consumers.

The remaining part of this research is divided into five main sections. Section 2 provides a comprehensive review on the literature regarding the artist’s reputation evaluation, the pricing scheme, and the proxy indicator of reputation level based on the evaluation and applications of psychological effects. After the proxy indicators are evaluated and developed based on the theories provided in Section 2, the research methodology will be outlined in Section 3, detailing the quantitative data collection and analysis methods with the application of statistical tools and theories applied in this research. Section 4 presents the empirical findings of the dataset, and the statistical result clarifications are also included in this section. Section 5 provides a comprehensive discussion on the key findings based on the dataset, where the research contribution, insights for independent artists, and the research constraints and potential mitigation solutions. Section 6 concludes this research and proposes a strategic roadmap for future research of the pricing mechanism of digital art commission industry.

Additionally, in data collection and analyses section, this paper divides the main research question into three research phases. Each phase applies the corresponding statistical tools based on proposed hypotheses to evaluate the potential relationship between reputation level and artwork price level for selected type of art commission.

2. Theory

2.1. Background – Current research on the art industry

Since pricing is based on the psychological estimations of the customer preferences, the seller's reputation level is a plausible consideration (Hinterhuber, 2008; Johansson et al., 2012). To understand how the artwork pricing frameworks are developed and which factors influence the framework, one approach is to observe current art industry practices and general platform-based price models.

As suggested in Kotler et al.'s (2020) marketing analysis techniques, an effective way to understand price and market structure in the digital art commission market is to analyse physical art trading dynamics for general insights. In the physical art trading market, Ning (2024) identifies three main factors influencing contemporary art pricing: the artwork's intrinsic characteristics in production processes (including labour time spent of artwork, complexity level, etc.), demand level (mainly referring to target market development and segmentation), and intermediary elements in transactions. The primary sales channel for artists is galleries or auction agencies, which increase the selling costs and consequently increase the final price of the artwork due to the intermediary involvement (Candela & Scorcu, 1997; Angelini et al., 2022). These mechanisms provide a foundational reference for understanding price estimation in digital platform-based markets.

Schroeder (2005) identifies personal branding strategies as an additional factor that influences physical art prices. In his research, personal branding strategies are beneficial for artists to develop customer retention when selling artwork. However, the hidden costs of personal branding investments are not specifically quantified in Schroeder's (2005) study.

Building on the findings from Angelini et al. (2022) and Suchomelova et al. (2017), the costs of artists' personal branding vary under different strategies for selling the artwork or developing customer groups, and these monetary costs may influence the final price structure of artwork. Although additional costs associated with personal branding may affect the price decision for artists, Rodner & Kerrigan (2014) suggest that personal branding in art can also serve as a form of capital or resource that supports pricing decisions.

In physical art trading, intermediatory entities such as auction agencies and galleries play an active role in price formation by considering broader market factors when artworks are sold (Rurale & Prokupek, 2025). Although artworks sold through these channels are often priced higher, this mechanism also allows professional collectors to evaluate artworks during the purchasing process, including observing the purchasing behaviour of other buyers. According to Beckert & Rössel (2013), these observations may contribute to evaluating an artist's reputation and market position based on reactions of other customers who visit galleries or agencies. Therefore, these findings from the physical art trading market suggest that reputation can plausibly contribute to estimating artwork prices, which provides a foundation for this study.

Additionally, pricing models developed for online retail platforms provide a useful reference for understanding price factors in platform-based product trading, as digital artwork is identified as a virtual product (Li & Xiao, 2025). DiRusso et al.'s (2011) statistical model identifies several factors associated with selling prices, including *seller reputation*, *number of ratings*, and *featured merchant status*. The three customer-related influencers provide additional insights for quantitatively explore the artwork pricing based on artist's reputation. Since DiRusso et al.'s (2011) model directly incorporates online platform price factors, their findings suggest that artwork prices are possible to be quantitively evaluated under certain conditions.

2.2. Boundary refinements – Selection of the pricing model

According to Helmold's (2022) conceptual framework, since the digital art commission industry is considered a niche market and artworks are treated as complementary products rather than necessity goods, a value-based pricing approach is preferred because art provides additional values to consumers in pricing. To apply theories and observations from previous studies, understanding how the platform affects independent artists is recommended (Lee & Lee, 2019). As Lin et al. (2025) argue, online art commission platforms function as information-sharing systems, where artists can develop their reputation through social interactions for self-branding. Customers use the platform to contact artists for potential art commission requests, while comment sections and artists' data analytics on the platform allow users to access the artwork values (Lin et al., 2025).

Since the platform acts as a major facilitator of social interactions between artists and followers, the payment methods may vary depending on monetisation approaches. Oliver (2024) argues that value-based pricing can be applied in two forms: subscription-based models (which continuously provide artwork for customers to access over a pre-set period), and one-off payment models (which deliver artworks upon request).

The subscription-based payment model has a long historical background, with applications in creative and publication industries since the seventeenth century (Clapp, 1931). It is therefore expected that artists in platform-based services may adopt this model, as it provides stable income under contractual production arrangements (Meyn et al., 2023). Studies by Kang et al. (2024) also suggest that this payment model may contribute to follower growth and enhance competitive positioning in digital art markets.

In comparison, the one-off payment model is a traditional and widely accepted pricing mechanism in many retail services (Clark et al., 2024). The model provides unlimited access to products or services, which attracts customers who are more sensitive to ownership rights (e.g., buying a software instead of subscribing to avoid the periodic payments). According to Kjus (2022), providers using one-off payments are able to focus on project management without excessive pressure from external platforms such as algorithmic pressure on production volume. In the art commission industry, this allows artists to better manage customer requirements for artwork and improve customer retention.

Under ideal conditions, Oliver (2024) suggests that a hybrid payment method combines the advantages of both subscription and one-off systems. However, studies by Kjus (2022) and Clark et al. (2024) indicate that artists typically adopt only one dominant model due to mutually exclusive labour constraints.

Specifically, accepting the subscription-based model require contracts with other stakeholders. The subscription model requires continuous content production for subscribers' retention, whereas one-off payment models allow for greater flexibility for artists to polish artwork upon customers' requests and reduce exposure to aspirational labour pressures compared to subscription models (Clark et al., 2024; Kjus, 2022; Wong, 2020).

Based on these discoveries, this study focuses specifically on the one-off payment model and excludes subscription-based payments when estimating the independent artists' price frameworks. This boundary is defined based on evidence suggesting that one-off payment systems reflect independent artists' pricing behaviour on online commission-based platforms across multiple factors (Duffy, 2017; Kjus, 2022).

Under this framework, independent artists using one-off payment models are more likely to develop value-based pricing strategies by analysing variables that affect customer retention. At the same time, this model reduces exposure to fatigue and algorithmic pressure, enabling more sustainable promotional strategies (Duffy, 2017; Wong, 2020). To further understand pricing determinants, psychological pricing effects are introduced as an additional analytical lens (Kienzler & Kowalkowski, 2017).

2.3. Psychology Analyses – The dynamic of value addition

Kienzler & Kowalkowski (2017) explore theoretical dimensions applied in exploring pricing factors. The author's research on the pricing strategies shows a trend towards interdisciplinary studying, as pricing involves psychological and social considerations. Their findings also highlight the increasing importance of consumer perspectives in pricing studies, where psychological analysis plays an active role in understanding pricing behaviours.

To examine psychological factors that may affect price structure, analysing customer behaviour and preferences serves as the primary approach (Kotler et al., 2020). In the context of digital art commission and related business models on platforms, Lee & Lee's (2019) case study on *Saatchi Art* shows that customer comments directly affect the valuation and price dynamics, suggesting that comments and social interactions can serve as indicators in reputation estimations. Additionally, Bishop (2025) and Christodoulou & Styliaras (2013) argue that independent artists' self-branding techniques are rooted in influencer culture and social networking, which directly influence price tactics, development strategies, and customer engagement.

Although the online art commission industry can be considered as a retail service (Lee & Lee, 2019; Lin et al., 2025), current research lacks a fully established price evaluation framework applicable to independent artists, as the existing models require further validation under specific conditions. A closely related reference in this context is Lee & Lee's (2019) qualitative study on *Saatchi Art*. While their research provides a relevant foundation for the research question, its qualitative method and limited statistical support for estimating the pricing model restrict the applicability of its findings. To address this limitation, this study provides empirical data and a replicable quantitative analysis framework based on theoretical assumptions regarding customer-artist transactional relationships and artwork pricing in digital art markets (Ghanad, 2023).

2.4. Social Proof Effect – Reputation formation through follower accumulation

Although the feasibility of estimating reputation based on customers' psychological effects has been discussed, the underlying psychological factors and influence mechanisms have not yet been fully revealed. To further understand how the customers' behaviours are influenced when purchasing a product or service, the Social Proof Effect is a possible explanation on the follower-reputation correlation in creative work industry (Lee et al., 2024; Lopez, 2015; Park & McCallister, 2023). As the authors define, the Social Proof Effect posits that individuals tend to look for the behaviours or choices of others rather than relying solely on their own decisions, especially in purchasing goods or services.

Makrydakis (2024) demonstrates that the customers often look to others to determine the price based on the artists' reputation, illustrating how the Social Proof Effect drives customer decisions. Park & McCallister (2023) suggest that customers evaluate the quality of an artist's artwork based on reputation, because artwork quality is difficult to assess objectively when it is not quantitatively defined.

By combining the studies of Lin et al. (2025), Makrydakis (2024), and Park & McCallister (2023), a framework for reputation estimation based on follower group size can be established. This framework further contributes to price estimations. Since information asymmetry exists when customers consider purchasing artwork commissions, the count of followers serves as a tangible metric of reputation, as argued by Park & McCallister (2023). Furthermore, Gabor (1973) suggests that potential clients utilize this effect as a heuristic approach to evaluate the artist’s quality, thereby reducing uncertainty while deciding. Consequently, high social proof attracts more customer engagement for artists, as the artists’ credibility increases with follower size, their artworks may achieve higher market valuation (Park & McCallister, 2023; Yang, 2024).

Lin et al.’s (2025) discoveries on social-based mechanisms are also supported by Yang’s (2024) and Ridwan et al. (2026). Yang (2024) and Ridwan et al. (2026) further explain social-based mechanism by providing additional analyses of the online artwork transactions. Drawing on Lee & Lee (2019) and Ning (2024), who define artwork as a customized product, the authors argue that artistic productions lack generalised evaluation criteria for expected artwork prices. Artists’ reputation and comments from previous customers thus serve as sources for customers to form heuristic approaches in price estimation.

Additionally, the Social Proof Effect contributes to artists’ reputation by fostering customer trust, which facilitates customer retention and follower growth. Ridwan et al.’s (2026) studies confirm that this effect acts as a fundamental determinant in mitigating information asymmetry and building initial reputation capital. In the follower-artist dynamic, this observation suggests that social proof signals act as a cognitive factor that effectively reduces consumer uncertainty when evaluating artists who do not yet have established reputational records.

2.5. Supplementary Applications – How theories are practically applied in follower-price estimation mechanism?

Integrating the signalling mechanism with Osburg et al.'s (2022) analytical framework, signalling theory functions as a conceptual intermediary in customer-artist communication under information asymmetry regarding artwork prices. Specifically, direct communication between customers and artists is limited, as the artwork value depends on subjective evaluations. The authors suggest that the number of followers an artist has is selected as the representative signal of artwork value. After customers receive the signal (i.e., the number of followers), they can interpret the estimated artwork price accordingly.

Furthermore, Chenavaz & Eynan's (2021) findings on the dynamic adaptation of the Veblen Effect by sellers (i.e., artists) provide a supplementary perspective on the reputation-price estimation mechanism. Their findings suggest that the reputation level may also be dynamically influenced by evaluations based on follower groups, such as follower count variations over time. Similarly, artists may also adjust their pricing strategies according to the feedback received from customers and their perceived reputation level. Some artists may set relatively higher prices, possibly to create a sense of exclusivity for added value. However, in the context of this study, this concept serves only as a potential supplementary explanation for the empirical observations in Section 4.

While the customers want to purchase a customized artwork from the online platform, they are unable to estimate the products' prices directly because artwork price prediction is relatively subjective to customers (Lee et al., 2024; Ning, 2024). To explore the price estimation framework, customers' purchasing influencing factors is an approach for artists to estimate the position. According to Kumar & Pandey's (2017) and Seltzer's (2021) studies, they suggest that the follower count following the artists correlates with the reputation level, as the number of the followers is considered a plausible proxy signal for customers to estimate the artists' reputations.

Therefore, applying the Social Proof Effect may help customers develop an initial understanding about the products or services even when product prices remain unclear, customers can still estimate the approximate price level based on the artists' reputation because a larger follower count for artists indicates that an artist's artwork is generally accepted and the artwork quality is considered at a satisfactory level (Bishop, 2025; Christodoulou & Styliaras, 2013; Makrydakis, 2024). Specifically, the authors suggest that the Social Proof Effect explains the mechanism of how accumulated followers may enhance the perceived reputation level.

However, there is limited empirical evidence to validate whether the theories can be applied in the digital art commission industry. Although Kienzler & Kowalkowski (2017) reveal the importance on the customer psychological analysis, current marketing schemes are unable to identify the key factors of artists' pricing, as the market is relatively new and underexplored, and the applicability of the theories to such a market remains unknown. Studies by Chenavaz & Eynan (2021) and Rodner & Thomson (2013) focus mainly on theoretical developments concerning customer psychology that influences price frameworks, but they lack practical applications or case analyses to support their arguments. Similarly, Lin et al. (2025) discuss that their findings focus only on a broad approach of the dynamics of artwork prices, which does not provide a platform-specific analysis.

To further determine the application of these theories and enhance the generalisability under digital art commission industry, this paper will conduct further data analysis on specific digital art commission transactions. The research aims to provide empirical evidence on the applicability of combined analytical theories for estimating artists' reputation levels based on identified indicators and explaining the correlation mechanism of artwork prices.

2.6. The Hypotheses Extractions

In summary, the current literature reveals a broad body of research, but with limited empirical specification and insufficient case-based evidence on digital art commission trading mechanisms. Therefore, conducting empirical data analysis on a specific platform with quantitative methods can enhance the explanatory power of theories based on the customer data analyses. This approach complements existing literature discoveries by providing practical applications in market contexts (Bryman, 2016).

Therefore, the general hypothesis of the research question in Section 1 is:

The number of followers is related to the price level of artists who post the artwork commission offers on the platform, and the two variables are positively related. (i.e., a higher number of followers is associated with higher artwork price).

To further validate the general hypothesis above and the correlations between the two variables, this study divides the research question into three research phases, and each sub-section (phases) will apply different statistical tools that will be described in Section 3:

P1 (Phase 1): Whether there is a significant difference in mean price between artists with high *number of followers* and artists with low *number of followers*.

P2 (Phase 2): Whether there is a significant correlation observed between the *number of followers* and *artwork price*.

P3 (Phase 3): To what extent an increase in *numbers of followers* influences variations in *artwork price*.

To conduct the three research phases under a theoretical background with justification for the correlation between the artists' reputation level (indicated by *number of followers* in this study) and the *artwork price*, the proposed hypotheses for answering questions in three research phases above will be:

H1: *For artists with high follower counts, the artwork prices are significantly higher than those with low follower counts.*

H2: *There is a positive correlation between artists' number of followers and artwork prices. (i.e., higher follower counts are associated with higher prices.)*

H3: *The growth of an artist's follower base exerts a positive marginal effect on artwork pricing; specifically, an incremental increase in the number of followers leads to an increase in price.*

3. Methodology

3.1. Research Methods, Sources of Data and Approaches

To understand the pricing decisions of independent artists' commission work under the same product category, this study applies a quantitative research method to identify the relationships between artists' *number of followers* and their *artwork price* with the support of R programming language. The analysis aims to determine whether these factors are related under the predefined conditions of the selected platform through empirical evidence (Slater & Gleason, 2012).

According to the findings from Lin et al. (2025), this study adopts the Social Proof Effect as a theoretical framework to explain the potential mechanism between an artist's *number of followers* and *artwork price*. The Social Proof Effect contributes to explaining the phenomenon of how the reputation level observed by customers affects their preferences by encouraging customers to rely on heuristic judgements when subjectively estimating prices (Gabor, 1973; Park & McCallister, 2023). Furthermore, the findings on the association between artists' reputation level and the *number of followers* provide theoretical support in quantifying the artists' reputation level for the upcoming data analysis procedure (Kumar & Pandey, 2017).

For the platform selection, this study selects *HuaJia* (2026) as the main observation platform for data extraction. This platform is selected because *HuaJia* features a one-off payment method, which satisfies the preliminary condition for exploring the relationship between reputation level and artwork price with the collected data. Additionally, this platform provides an opportunity to validate whether the *number of followers* is applicable to be a proxy estimator of the reputation level (Seltzer, 2021), which further enables the analysis of how reputation level influences final prices on online commission platforms within China's market context.

Barroga et al. (2023) and Bryman (2016) suggest that quantitative research tests the theories using empirical data to confirm, reject or refine their boundary specifications. The authors also suggest that statistics plays a crucial role while in quantitative research, as the statistical methods contribute to theoretical generalisation in the target group by optimizing between analytical efficiency and quality. In other words, the researchers do not need to analyse all the samples in the target group while conducting data analysis, instead, a decent sample size is sufficient to explain the general distribution of the target data and conclude the discoveries (Barroga et al., 2023). Therefore, as the authors argue, this paper will then apply statistical methods to validate the research hypotheses for determining the correlations between the *number of followers* and *artwork prices* on the selected platform.

3.2. Notes and Data Size While Sampling

To address the research questions and develop the final statement addressing the research problem, an initial data collection process will be conducted in this paper. The dataset of artists' *artwork price* and *number of followers* from *HuaJia* is sampled through the platform's real-time listing system to gather 120 observations for statistical analysis, as this method can simulate the random sampling under limited access to the full dataset (Piña-García et al., 2016).

Additionally, a sample size of 120 is statistically acceptable and provides robustness for the statistical analyses conducted in this research. According to Guan et al.'s (2023) evaluation, the minimum sample size requirement for linear regression analyses is 58, and doubling this threshold may help mitigate potential skewness effects in statistical modelling and increase explanatory power of the statistical model results.

To further guarantee the sampling and analysis feasibility of the dataset, this study applies the sequential sampling technique on a real-time basis while collecting the data as this method optimizing the balance among efficiency, cost, and quality under the current digital art commission industry background (Piña-García et al., 2016; Wald, 1945). Specifically, the first step of data collection is to collect the *number of followers* and *artwork price* data of 240 artists; the next step is to select the odd-numbered rows. After this process, a dataset containing 120 artists will be saved for the upcoming data cleansing step to evaluate the feasibility of theoretical applications on a single digital art commission platform.

For artists who have fewer than 10 followers, their data will be removed, because a lower follower count is insufficient to apply the influencer effects while pricing the artwork (Bishop, 2025; Christodoulou & Styliaras, 2013; Makrydakis, 2024).

During the sampling process, there are potential factors that may affect the artwork prices while artists post the commission advertisement (*HuaJia*, 2026). Therefore, to reduce the potential errors, the data are selected under the same conditions listed as follows, along with a controlling framework for other parameters in this research:

a) Time of the digital art production: The production time for artwork commission is capped at a maximum of 7 days to deliver the final version to consumers.
b) Copyright licencing: The dataset’s artwork is all under the same condition of “no commercial use of the artwork” (*HuaJia*, 2026).
c) Type of art: The dataset will solely include artwork prices labelled or described as “single character, half-body style illustration”.
d) Working frequency: The dataset includes only artwork described as “not applying any template” to control producing parameters and reduce sampling errors while selecting samples for analyses and *Simple Linear Regression Model (SLRM)* applications (Martin, 2021).

Factors affecting the price structure that are not listed above will be neglected and incorporated into the error term (ϵ_i) of the *SLRM* (Martin, 2021).

3.3. Statistical Hypotheses and Tools

To conduct the analysis for **P1**, the *T-test* will be applied to determine whether there is a significant difference between the *high number of followers* artist group and the *low number of followers* artist group (King & Eckersley, 2019). The dataset will be divided based on the first and third quartile values of the *number of followers* variable. This division method is applied to facilitate a preliminary cross-group comparison to examine the differences based on the bottom and top tiers of artists’ follower count distribution through dichotomization, although this method carries a risk of losing information from the full dataset (MacCallum et al., 2002). In this study, a modified version of

MacCallum et al.'s (2002) dataset classification approach will be applied. The bottom 25% of artists in *number of followers* are categorized as the *low-follower* group, and the top 25% are categorized as the *high-follower* group.

To conduct the statistical analysis for **P2**, the *Pearson Correlation Test (PCT)* is applied to evaluate the relationships between these two variables with a general approach (Schober et al., 2018). Following Berman's (2016) analytical framework, the proposed model for applying the *PCT* is:

$$r = \frac{\sum(Followers_i - \overline{Followers})(Price_i - \overline{Price})}{\sqrt{\sum(Followers_i - \overline{Followers})}\sqrt{\sum(Price_i - \overline{Price})}}$$

(Note: In the equation above, the value $\overline{Followers}$ and $\overline{Price}$ means the mean values of these two variables.)

Following the analyses for **RQ1** and **RQ2**, the result of the correlation test will then be incorporated into the proposed *SLRM* to answer **RQ3** as:

$$Price_i \ = \beta_0 + \beta_1 Followers_i + \epsilon_i$$

Where β_1 represents the slope coefficient of the model and serves as a key parameter for addressing **P3** and providing the estimated price function (Martin, 2021). To further validate the results in RQ3, a robustness check will be conducted to reduce the potential influences of outliers on the regression results during regression analysis (Martin, 2021).

Since this study adopts a quantitative research approach, it applies statistical tools and analytic theories. To enhance the rigour of statistical applications, the hypotheses in Section 2.6 are adjusted as follows:

For comparing higher- and lower-follower groups in terms of average artwork price **(P1)**, the hypotheses are:

> Null hypothesis (H_0): There is no significant difference in the mean price between the *high-follower* and *low-follower* groups.
>
> Alternative hypothesis (H_1): There is a significant difference in the mean price between the *high-follower* and *low-follower* groups.

The hypotheses for identifying the relationship between the two variables **(P2)** will be:

Null hypothesis $H_0: r = 0$: There is no correlation between the *number of followers* and *artwork price*.

Alternative hypothesis $H_1: r \neq 0$: There is a correlation between the *number of followers* and *artwork price*, either positive or negative.

For examining the extent of change between the two variables **(P3)**, the hypotheses are:

Null hypothesis $H_0: \beta_1 = 0$, the *number of follow*ers does not statistically influence the *artwork price*, and there is no linear function to predict the relationship between *number of followers* and *artwork price*.

Alternative hypothesis $H_1: \beta_1 \neq 0$, the *number of followers* statistically influences the *artwork price*, and there is a linear function to predict the relationship between *number of followers* and *artwork price*.

3.4. Evaluations of Current Methodology

While this research applies a quantitative approach to evaluating how artists' reputation levels influence artwork price determination on the *HuaJia* platform, the strengths and limitations are interrelated.

As data are collected from the online platform, a key advantage is that the *number of followers* can be directly observed through platform-based user interactions and is commonly used as a proxy indicator of reputation (Kumar & Pandey, 2017). In this exploratory research, user behaviours on the platform on the platform – such as following preferred artists – generate measurable data that can be retrieved for subsequent analyses (Ball et al., 2015). After collecting data of artists' *number of followers* and *artwork price*, the methods allow flexible demonstration of statistical results through tables or figures for presenting the key takeaways from the empirical observations (Tukey, 1973).

Conversely, a key weakness of the current methodology is that additional analyses are required on the association between statistical results and their implications when exploring how artists' reputation levels influence prices. Since this paper applies quantitative research to explore the correlation between quantified reputation (by *number of followers*) and price, the application of statistical analyses requires further explanation to interpret the meaning of the statistical results for a more advanced understanding in this research (Ghanad, 2023).

Under the exploratory research conditions, based on Saunders et al.'s (2023) study design framework, selecting *HuaJia* as the data source is a practical choice for examining the relationship between artists' reputation level and artwork prices. The authors also include mitigation approaches in case the data extraction process contains difficulties. For example, given that digital art commission operates across various platforms, selecting an accessible platform improves the efficiency of data collection and reduces technical constraints for this study. This supports the development of an initial understanding of the relationship between artists' reputation level and artwork prices, and facilitate the examination of variations between these two variables.

3.5. AI applications

This research involves the application of generative AI tools (ChatGPT & Gemini) and AI search engines (Google AI search) to support the retrieval of academic resources, generate initial research ideas, validate academic writing, assist with programming, and evaluate statistical data collection procedures. The specific sample prompt is accessible in Appendix H.

4. Data Collection and Analysis

4.1. Initial Data Processing and Observations of Results

After applying the data sampling procedure and statistical design in Section 3, a total of 120 artists' follower counts and artwork price data of "single character, half-body illustration" artwork have been collected and analysed. The dataset is then cleansed based on the criteria as follows:

a. Artists who have lower than 10 followers.

b. Artists who do not provide the alternative prices with the artwork fit the criteria in Section 3.1.

Specifically, in category b above, if the artwork in the dataset is labelled or described as anything other than "single character, half-body illustration" in the artists' commission advertisement, the price is adjusted to the alternative artwork price corresponding to "single character, half-body illustration" category by accessing the artists' homepages to retrieve the alternative price that fits the criteria of "single character, half-body style illustration". If no price fits the criteria, these artists are removed from the original dataset.

During the data cleansing process, some data were removed based on the criteria mentioned in Section 3.1. *Table 1* below reveals the data cleansing process after collecting data from 120 artists:

Steps	Data selection criteria	Sample size
1	Original dataset	120
2	Remove the artists under two conditions: 1. Artists who have lower than 10 followers. 2. Artists in the dataset do not provide the alternative prices with the artwork fit the criteria in Section 3.1	17
Final	Modified dataset for conducting statistical analyses	103

Table 1: Data Cleansing Process

After the data validation and cleansing process, there are 103 out of 120 artists retained in the original dataset based on the data cleansing criteria (see Table 1), with 14.1% of artists' data removed (see Appendix B for the original data).

Figure 1 below presents the scatter plot of the final dataset, consisting of 103 artists' *number of followers* and *artwork price* where the artwork is labelled as "single character, half-body illustration".

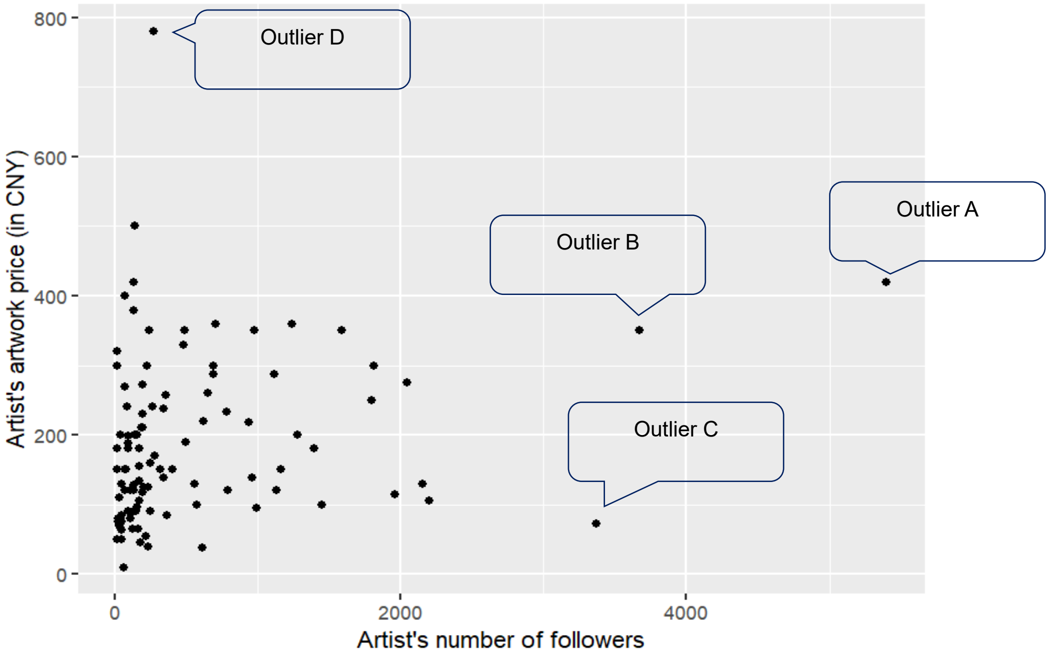


Figure 1: The Scatter Plot of Dataset including Outlier Notes

Table 2 below presents the mean, median, and standard deviation value of the variables: *Artist's number of the followers*, and *Artist's artwork price (in CNY)*.

Variables	Median	Mean	Std. Dev.
Artist's number of followers	195	548.6	837.1
Artist's artwork price (in CNY)	150	187.4	119.8

Table 2: The preliminary results of mean, median, and standard deviation.

According to Doane & Seward's (2011) discoveries, the results in Table 2 show a skewed distribution of data points in both variables: *number of followers* and *artwork price (in CNY)*. Referring to the outputs in Table 2, both the *number of followers* and *artwork price* have mean values greater than their median values, which also suggests the claim that the dataset is right-skewed and the data spread is wide. The scatter plot in Figure 1 provides further visual evidence of the skewed dataset, as most data points are concentrated in the lower-left corner, while the remaining data points are distributed across the remaining areas of the plot. Therefore, based on the preliminary analysis, it is highly recommended to apply logarithmic transformations to the dataset when analysing the *Pearson Correlation Coefficients* to determine the correlation (**P2**) and fitting *Linear Regression Line* (**P3**) for mitigating the skewness of the data and improving the reliability of the linear regression model when exploring the variations between the *artist's number of followers* and *artist's artwork price* (Wooldridge, 2019).

Apart from the data distribution findings, this research suggests that the 103 sampled artists have a wide range in the *number of followers* and *artwork price*, and that the degree of variation in *number of followers* is higher than the variation in *artwork price*. In other words, the plot reveals heteroscedasticity and a curvilinear trend with a plateau when observing the data distribution (Rosopa et al., 2013). Despite dataset varying significantly between the top-right region (higher values) and the bottom-left region (lower values), this paper selects four artists' data for further validation of the correlation between the two variables, which are considered outliers based on the plot output.

Outlier A refers to the artist with the highest *number of followers* in the dataset. This artist, with over 5,000 followers, charges 420 CNY for a "single character, half-body illustration" artwork commission. According to the first and third quartile values reported in Appendix C, Outlier A charges the top-quartile price (420 CNY), as 420 CNY exceeds the dataset's 3rd quartile value for *artwork price*, which is 254 CNY. Similarly, Outlier B has the second-highest followers (3,668) compared to the other artists in the dataset, and charges 350 CNY per artwork. This price also falls within the top 25% of *artwork price* for "single character, half-body illustration" commissions. Based on these findings, it is reasonable to argue that a higher *number of followers* is associated with higher *artwork price*.

While Outliers A and B show the same correlation pattern (the greater the *number of followers*, the higher the *artwork price*), the artist who is located at Outlier C does not follow this pattern. The artist at Outlier C has the third-highest *number of followers* in the dataset, but their price falls within the bottom 25% of all observations (the actual price is 78 CNY, which is even lower than the first quartile value of *artwork price*, 99 CNY). With this observation, it is plausible that artists do not necessarily charge high prices for artwork commissions, even though a large follower base may generally support higher pricing decisions within the mid-to-upper price ranges of the dataset.

Additionally, the artist at Outlier D differs from the correlation pattern observed in Outliers A & B. Outlier D represents the highest *artwork price* in the dataset, while their *number of followers* is positioned between the top 25% and the top 50% of all observations (mid-to-upper follower count). This phenomenon suggests that whether an artist charges a higher price is not solely determined by the *number of followers*. Instead, other underlying factors may contribute more to explaining pricing behaviour for artists in the medium-top tier (i.e., between the 25th and 50th percentiles) in the range of *number of followers*.

Based on the outputs from the initial analyses and the scatter plot observations, a dichotomization approach will be applied for the subsequent *T-test* analysis by selecting the top 25% and bottom 25% of artists in terms of follower counts (MacCallum et al., 2002).

(The executive summary, mean, median, standard deviation, and quartile values of the two variables are available in Appendix D)

4.2. Analyses for P1:

Using the *T-test* method, this study rejects the null hypothesis for **P1**, as the P-value (0.01148) is statistically significant. The P-value in this research is lower than the threshold for rejecting the null hypothesis in statistical analyses in general social studies (the most applied condition in rejecting the null hypothesis is a P-value lower than 0.05) (Wasserstein & Lazar, 2016). Therefore, the *T-test* result accepts the alternative hypothesis of:

For artists who have high follower counts, their artwork price is significantly higher than artists with low follower counts.

Figure 2 below provides an overview of the differences between the top 25% bottom 25% of artists in terms of *number of followers*:

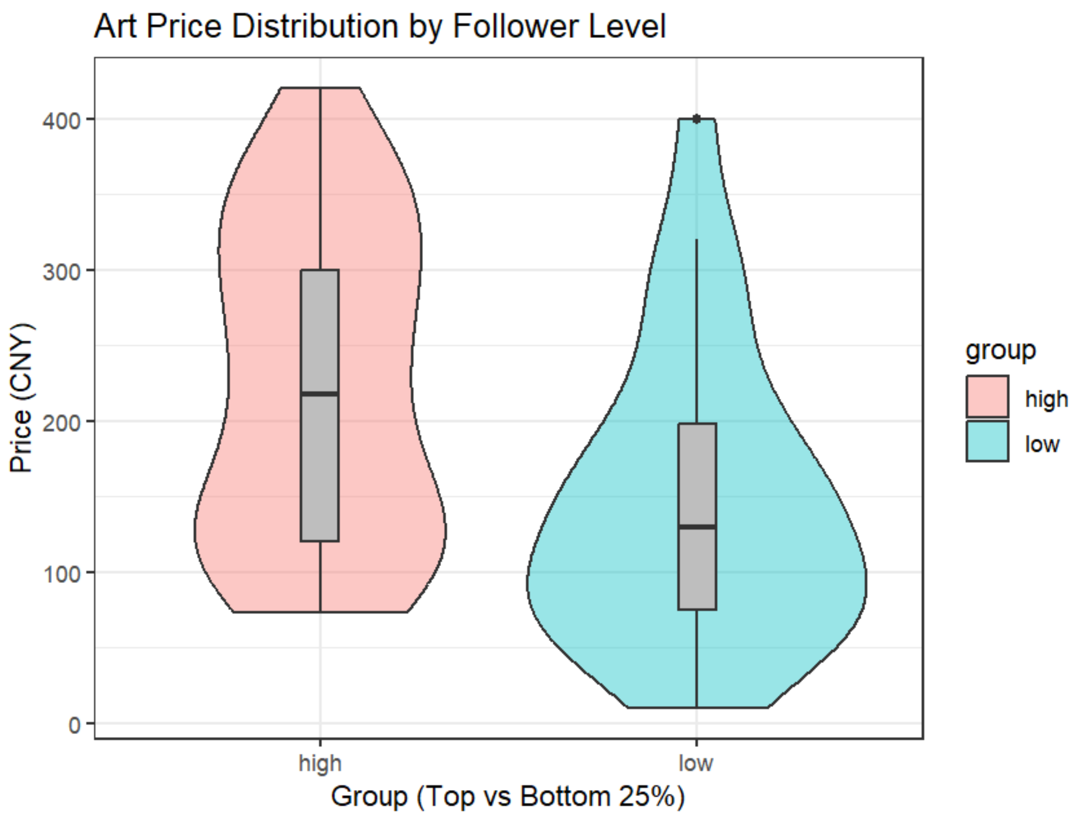


Figure 2: Art price distribution in different groups in follower count

The violin plot with an embedded boxplot suggests that the median value of *artwork price* in the *high-follower* group is significantly higher than that in the *low-follower* group. Approximately 75% of artwork prices in *high-follower* group exceed the *low-follower* group's median value. In the low-follower group, there is an outlier point in the violin plot. This outlier point reveals that there is an artist in the *low-follower* group who charges 400 CNY for the artwork, which exceeds the upper quartile price (300 CNY) in the *high-follower* group's artwork price range.

The violin plot reveals the distributions of *artwork price* within the two groups. Among artists in the *high-follower* group, the distribution of the *artwork price* is slightly more even, whereas the distribution in the *low-follower* group is highly clustered around the lower quartile (the bottom 25% of the *artwork price*). Though the distributions differ, a significant overlap in the *artwork price* is observed in the range between 100 and 400 CNY. The visual overlap in the price range suggests that artists within this range may be accepting art commissions at relatively budget-friendly (in customers' perspective) price levels in order to complete a higher number of commissions despite belonging to the *high-follower* group. Alternatively, some artists may by applying niche pricing based on other competitive advantages or value-adding features, even though they belong to *low-follower* group.

In a real-life scenario, this statistical result confirms that the bottom 25% artists in terms of *number of followers* have a generally lower price level than the top 25%. With the 95% confidence interval, the mean price difference for *high-follower* group and *low-follower* group is somewhere between 17.76 and 133.27 (in CNY). In other words, an artist who is positioned at the top-tier (top 25%) in *number of followers* is highly likely to charge a higher price in "single character, half-body illustration". Additionally, the price distribution and overlapping observations in the plot suggest that even though artists in the *high-follower* group have more flexibility in deciding artwork price, the overlapping price range demonstrates that the artwork pricing decisions do not solely depend on the *number of followers*.

The results confirm that there is a significant difference in average artwork price between the top 25% and bottom 25% of artists in terms of *number of followers*, and that the price distribution varies. However, this result raise another concern, which is whether the findings from the high-low group comparison can be generalised to an overall correlation trend when the middle 50% artists in terms of *number of followers* are also considered. To address this issue, the *PCT* method for evaluating the correlation power of the dataset will be applied in Section 4.4, where the analysis range expands to include the middle 50% of artists in terms of *number of followers*.

Group	High-follower	Low-follower
Sample count (under 25% quartile)	25	25
Mean	223.2	147.7
95% Confidence Interval in two group's differences-Low	17.76	
95% Confidence Interval in two group's differences-High	133.27	
t-test statistic	2.6294	
p-value	0.01148*	
Degree of freedom-df	47.637	

Table 3: Summary of T-test table

(Note: The asterisks in P-value row in Table 3 refers to the statistical significance level: * p<0.05; ** p<0.01; *** p<0.001)

Numerical categories of *artwork price*	Artists in *high-follower* group ($n = 25$)	Artists in *low-follower* group ($n = 25$)
Minimum	73	10
1st Quadrant	120	75
Median	218	130
3rd Quadrant	300	198
Maximum	420	400
Mean	223.2	147.7

Table 4: Summary table for two group's price comparisons

(Note: The detailed RStudio outputs for this research phase are available in Appendix E.)

4.3. Statistical Model Modification Under Right-Skewed Dataset

When applying the *SLRM* or the *PCT*, there are two different specifications of data – the original dataset and the logarithmic transformed dataset – can be used to determine the statistical results for **P3**. As the dataset in this study reveals a right-skewed distribution according to the analyses in Sections 4.1 and 4.2, subsequent analyses require additional modifications to the data frame to enhance the feasibility of data analysis results (Cowan et al., 2026), as well as to use the original dataset as a reference for robustness checks when determining correlations and proposing statistical models.

4.3.1. Condition A: Applying SLRM - Linear

If the *number of followers* has a normal distribution and does not have any significant outlier points for the sampled artists in the dataset, it is more appropriate to apply the SLRM directly to identify the direct statistical relationships of **P3**.

Under this condition, the model will not encounter the statistical risk of a higher *number of followers* creating boundary effects on the *artwork price*, as discussed in Cowan et al. (2026). Burton (2021) also argues that a less skewed dataset helps maintain the validity of the standard linear regression model, as the regression line is not compromised by fitting extreme points. When the dataset approximates an ideal normal distribution, the SLRM can be estimated using ordinary least squares method as the core approach of the proposed model, implying that the SLRM is statistically robust for discovering correlations (Burton, 2021).

Therefore, the proposed linear regression model used in this study is the same as that introduced in Section 3.1, where:

$Price_i$ means the i-th artist's *artwork price*;
$Followers_i$ means the i-th artist's *number of followers*;
ϵ_i means the other unobserved factors affecting the price value in the proposed model.

4.3.2. Condition B: Applying SLRM - Logarithmic

If the *number of followers* has a wider range (i.e., top artists with more than 10,000 followers and other artists with 10-50 followers), and the price range among artists with similar level of *number of followers* varies significantly, it is more appropriate to apply a logarithmically transformed data frame within the linear regression model (Xiao et al., 2011). The rationale for applying the transformed model is that a highly skewed dataset reduces the validity of the standard liner regression model.
P3 is therefore modified into the elasticity analysis approach to describe the variations with the applications of the linear regression analysis formulations as follows:

P3': *How much percentage variation in artwork price is associated with a 1% variation in the number of followers?*

According to Wooldridge (2019), a "log-log" model is feasible for estimating elasticity in percentile terms between the *number of followers* and *artwork price*, even though the original dataset is skewed, which helps mitigate skewness in the distribution of the dataset and enables the applications of *SLRM* with the modified dataset. Therefore, the proposed transformed linear regression model for conducting this paper's study will be:

$$\ln(Price_i) = \beta_0 + \beta_1 \ln(Followers_i) + \epsilon_i$$

The description of variables ($Price_i$, $Followers_i$, and ϵ_i) are the same as those in the original regression model. The hypotheses for **P3'** are modified based on the contents mentioned in Section 3.1 as below:

Null hypothesis for **P3'** H_0: $\beta_1 = 0$, meaning that percentage changes in the *number of followers* do not statistically influence percentage changes of *artwork price*, and there is no function to predict the percentile changes between the *number of followers* and *artwork price*.

Alternative hypothesis for **P3'** H_1: $\beta_1 \neq 0$, meaning that percentile variations in the *number of followers* statistically influence percentage variations of *artwork price*, and there is a function to predict the percentage changes between the *number of followers* and *artwork price* with the coefficient of β_1.

4.4. Analyses for P2:

After applying the *PCT* method in this research, the statistical result reveals that there is a relationship between artists' *number of followers* and *artwork price* in the dataset. In other words, this paper rejects the null hypothesis in Section 3.3:

There is no correlation between the number of followers and artwork price.

The original dataset (Figure 3 on next page) reveals that there is a statistically significant correlation between the two variables, with a P-value of 0.03, which is lower than the most common significance threshold of 0.05 (Berman, 2016). However, the correlation coefficient is 0.21, which suggests that the two variables are weakly correlated even though the statistical significance supports the correlation exists between them (Schober et al., 2018). Apart from the correlation coefficient and p-value, the rug plot of both variables (*number of followers* and *artwork price*) reveals a right-skewed distribution, as most observations are clustered near the lower range of both variables.

As the rug plot indicates skewness through the clustered data distribution, the result requires a robustness check on functional forms, since there are some significant outliers that may affect the correlation results between two variables (Martin, 2021). The robustness check will be conducted by logarithmically transforming the original dataset. According to Wooldridge's (2019) statistical research framework, the alternative (logarithmic) version of the correlation analysis is applied to mitigate the skewness risks, and the logarithmic dataset is used for analysing the correlation between the two variables in terms of percentage changes.

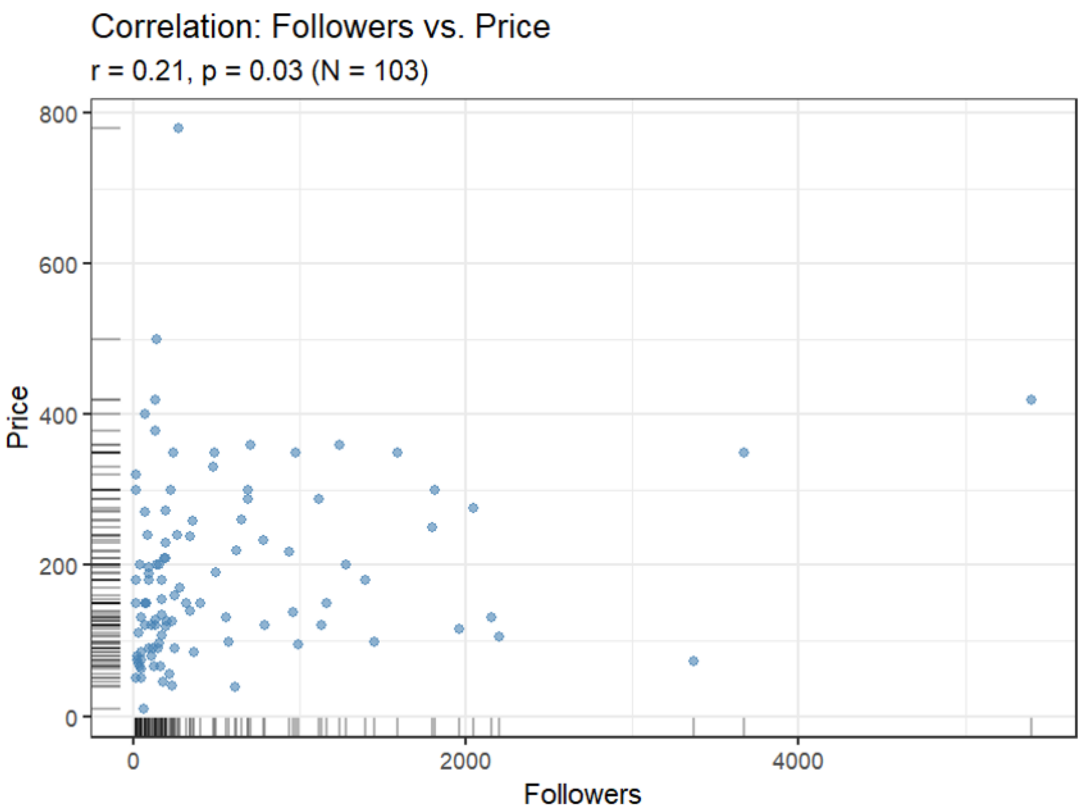


Figure 3: Correlation result and distribution in original dataset

In Figure 4, after transforming the dataset to the logarithmic form, the data distribution becomes normally distributed in the rug plot, which increases the reliability of the correlation analyses while applying the *PCT* compared to the original form (Cowan et al., 2026). Compared with the original dataset, the correlation coefficient increases to 0.282, which slightly increases the degree of correlation between the two variables for explaining in terms of percentage changes (Xiao et al., 2011). The P-value also decreases to 0.0039, which increases the statistical significance level for identifying the correlations between the two variables based on Wasserstein & Lazar's (2016) study. However, the correlation coefficient is still considered weak, as the value (r=0.28) is insufficient for achieving the minimum requirement for claiming a stronger correlation between two variables in *PCT* (As a reference, r value with greater than or equal to 0.4 is considered as moderate correlation) (Schober et al., 2018).

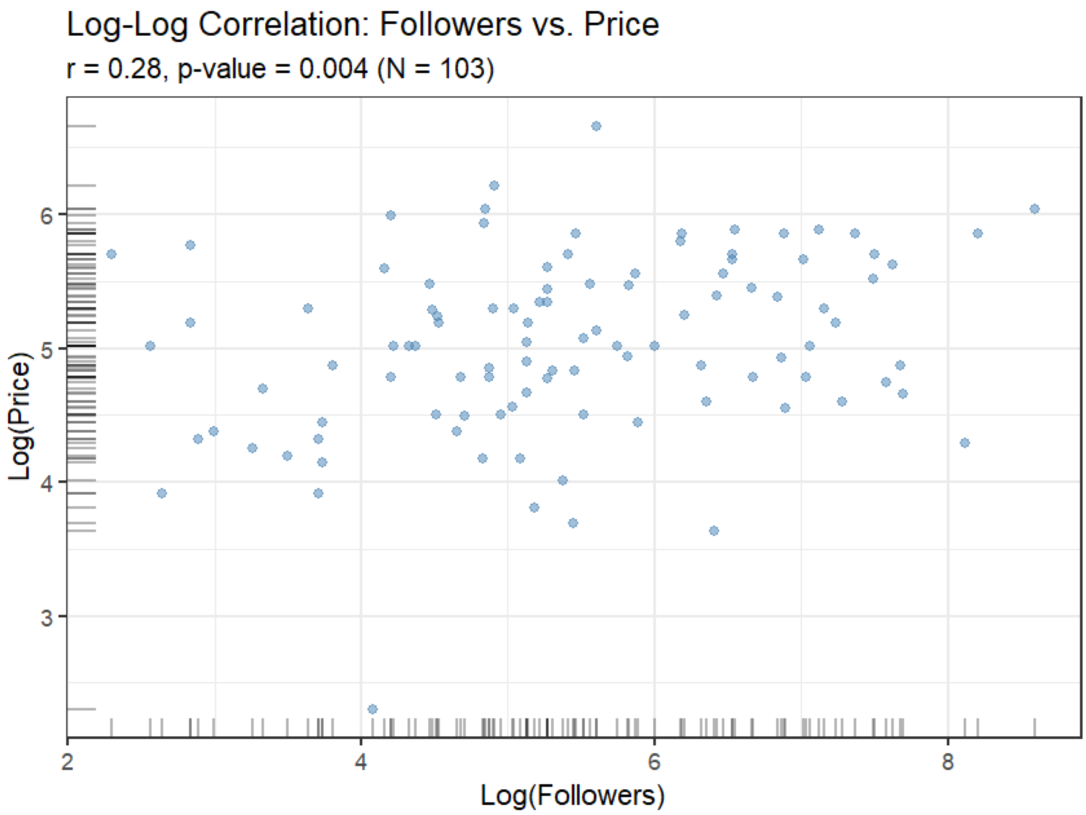


Figure 4: Correlation result and distribution in logarithmic dataset

Additionally, the statistical results confirm that the correlation coefficient for the original dataset falls between 0.0214 and 0.3913 with a 95% confidence interval. The confidence interval range suggests that the correlation between two variables is positive, meaning that artists with larger follower counts tend to charge higher prices for artworks. Similarly, the correlation coefficients based on the logarithmically transformed version of the original dataset falls between 0.0094 and 0.4510 with 95% confidence interval. The confidence interval's range is positive under the elasticity framework, suggesting that artists with higher follower counts are associated with higher prices on a percentage basis (Wooldridge, 2019).

Table 5 below includes the core numeric results for *PCT*:

Studies Conducted	*PCT*-normal	*PCT*-logged
Sample count	103	103
Correlation Coefficient	0.214	0.282
P-value	0.0299^{*}	0.0039^{**}
95% Confidence Interval of Coefficient – lower bound	0.0214	0.0094
95% Confidence Interval of Coefficient – upper bound	0.3913	0.4510

Table 5: PCT results with comparison between original dataset and logarithmic dataset

(Note: The asterisks in P-value row in table 5 refers to the statistical significance level: * p<0.05; ** p<0.01; *** p<0.001)

In summary, both the two model's findings provide significant evidence for estimating the correlation between the two variables through the scatter plots and distributions (the original version demonstrates the absolute correlation, while the logarithmic version demonstrates the elastic correlation). The results above support the hypothesis that growth in artists' *number of followers* is associated with the growth of artists' *artwork price*. However, the magnitude of the association between the two variables has not yet been determined. To determine this magnitude, the *SLRM* will be applied in this paper to provide a precise estimated relationship between the *number of followers* and *artwork price*.

(Note: The detailed RStudio outputs for this research phase are available in Appendix F.)

4.5. Analyses for P3/P3' and Model Output Comparisons:

Based on the graph provided in Section 4.1 and the analyses mentioned in Section 4.4, the right-skewed distribution of the dataset suggests that a robustness check is appropriate using two versions of the dataset (i.e., the original and the log-transformed versions) when applying the *SLRM*. Therefore, the *SLRM* estimations differ when accessing the correlation between artists' *number of followers* and *artwork price*.

The regression model results confirm the correlation and provide estimations of the changes in artists' *artwork price* as their *number of followers* increases, in both absolute and percentage terms.

In Figure 5, the regression model based on the original dataset suggests that for every 1,000-unit increase in artists' *number of followers*, their *artwork price* increases by 31 CNY accordingly. The P-value of this linear model is approximately 0.03, which once again provides evidence of the statistical significance of the correlation between the two variables. However, the R-squared result suggests that the proposed model has limited the explaining power in describing variations on the artist's *artwork price* based on the *number of followers*. The R-squared value equals 0.046, which means that only 4.6% of the variations in *artwork price* can be explained by the *number of followers* (Bryman, 2016). The grey-shaded area near the regression line represents the confidence band of the linear model. As the artists' *number of followers* increases, the width of the confidence band (the visual shading area in Figure 5) for the dependent variable also increases correspondingly, forming a funnel-shaped pattern. The funnel shape of confidence band is caused by the skewness of the data; the data point distributions for *high-follower* group is varied, according to the analytical results in Sections 4.1 & 4.2 (outlier data points and two-group *T-Test* results).

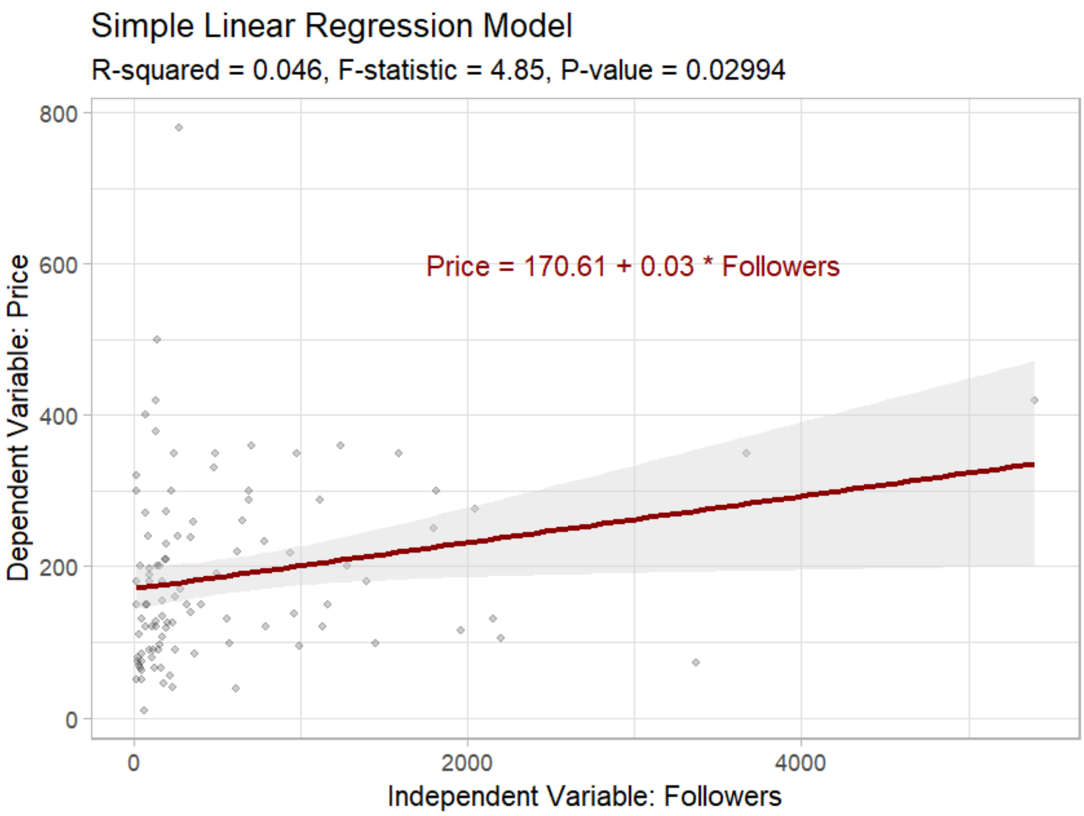


Figure 5: SLRM result in original dataset

Compared with the results in absolute terms, and applying Xiao et al.'s (2011) insights into logarithmic model applications, the estimated elasticity between artists' *number of followers* and *artwork price* indicates that when an artist's *number of followers* increases by 1%, *artwork price* increases by approximately 0.135%. The P-value of this model is approximately 0.004, which represents a higher level of statistical significance for identifying the correlation between the two variables. The R-squared value increases to 0.08, meaning that 8% of the variation in the logged *artwork price* can be explained by the logged *number of followers*, although this still indicates limited explanatory power (Bryman, 2016). The grey-shaded area in Figure 6 indicates an hourglass-shaped confidence band. The reduction in the confidence bands' width suggests that the influencing power of outlier points in the original dataset has been reduced following logarithmic transformation.

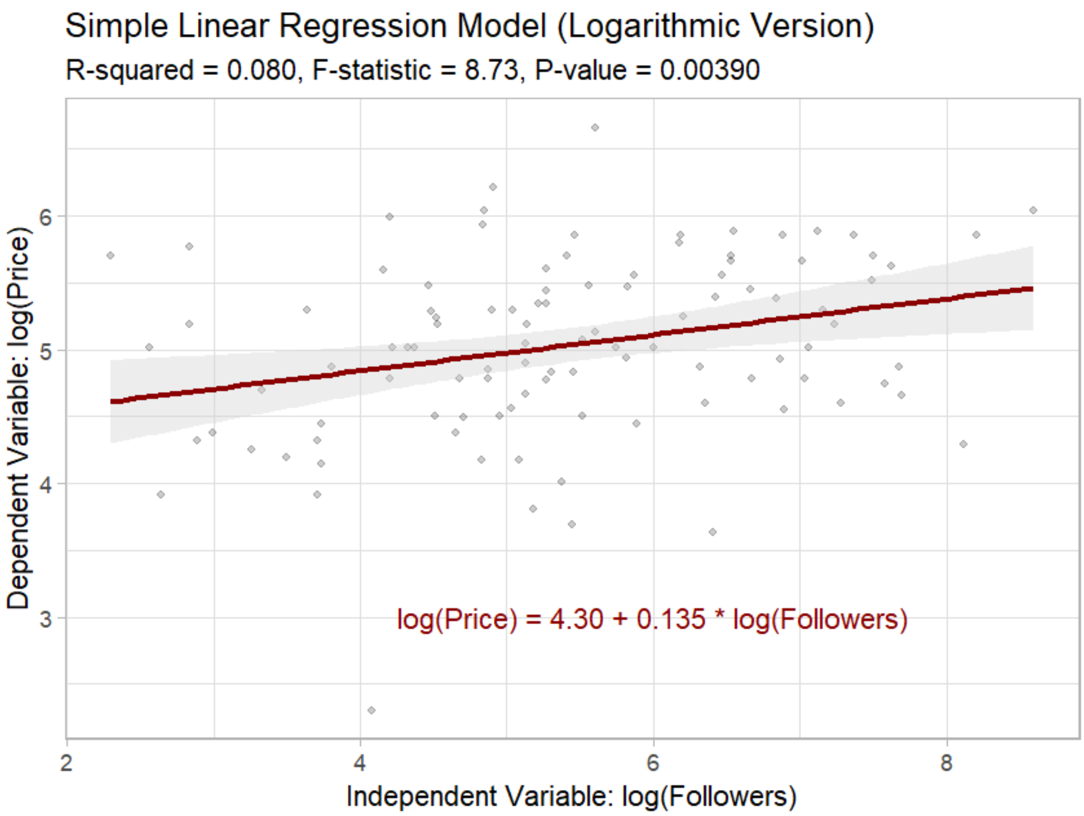


Figure 6: SLRM result in logged dataset

Table 6 below reveals the summarized statistical results of *SLRM* applications, including a robustness check based on different versions of the dataset. In the table, the comparison of the results reveals that the logarithmic version of dataset performs better in *SLRM* estimations than the original version. As the P-value of logarithmic version of the dataset in *SLRM* fitting decreases to 0.0039, the level of statistical significance (P-value) increases, which supports the rejection of the null hypothesis for **P3** (Wasserstein & Lazar, 2016). The goodness of fit (R-squared) also slightly increases from 0.046 to 0.080. The increase in R-squared indicates that the *SLRM-logged* version provides a relatively better explanation of the variations between the two variables, although both models still have limited explanatory power in estimating variations in an artist’s *artwork price* based on their *number of followers*. Based on visual comparison, the hourglass-shaped confidence band performs better than the funnel-shaped confidence band, as the logarithmic transformed model produces a more stable structure and a narrower confidence band of the *artwork price* across the predictor range.

Additionally, the difference in intercept values (β_0) in Table 6 provides a useful initial reference for baseline price analysis in artwork pricing estimations and an overview of price levels among lower-follower artists. In the linear specification, the regression model suggests that 170.61 CNY acts as the baseline price for the model's theoretical lower bound. Conversely, the log specification suggests that the intercept value of 4.301 represents the estimated $\ln(Price)$ at the base of the log-transformed scale. After exponentiation, 73.77 CNY is obtained as the baseline price for the model's theoretical lower bound and the predicted starting price (Martin, 2021). The log-transformed version significantly reduces the estimated baseline price, suggesting that the linear model's intercept is likely upward-biased due to the right-skewed distribution in the dataset, whereas the log model provides a more robust estimate of the baseline price by mitigating the influence of extreme high-value observations (Wooldridge, 2019).

Therefore, the logarithmic version of the dataset is more reliable for describing the dynamics in artwork pricing, as the logarithmic transformation in the dataset reduces heteroscedasticity effects according to the observations and analyses above (Rosopa et al., 2013).

Models applied	*SLRM*-normal	*SLRM*-logged
Independent Variable	$Followers$	$\log(Followers)$
Regression Coefficient (β_1)	0.031	0.135
Standard Error	0.014	0.046
P-value	0.0299^{*}	0.0039^{**}
Intercept (β_0)	170.61	4.301
Goodness of fit (R^2)	0.046	0.080
F-statistic	4.849	8.73
Sample count	103	103

Table 6: Comparison of the level-level SLRM and log-log SLRM model

(Note: The asterisks in P-value row in Table 6 refers to the statistical significance level: * p<0.05; ** p<0.01; *** p<0.001)

(Note: The detailed RStudio outputs for this research phase are available in Appendix G.)

5. Discussion

5.1. Executive Summary of Observations

The analysis results in Section 4, obtained using R scripts by RStudio and relevant statistical theories and analytical frameworks (King & Eckersley, 2019; Martin, 2021; Schober et al., 2018), confirm that the alternative hypotheses in all three research phases (**P1**, **P2**, and **P3**) are accepted.

Specifically, the accepted hypotheses are:

P1: *There is a significant difference in the mean price between the high-follower and low-follower groups.*

P2: *There is a correlation between the number of followers and artwork price, and the variables are positively correlated ($r = 0.21$ in original form and $r = 0.28$ in logged form).*

P3 & P3': *The number of followers influences the final prices under two specifications: one based on absolute variations in the original data frame, and the other based on percentile variations in the logged data frame. There are two versions of the estimation functions to predict the changes between number of followers and artwork price in both numerical and in percentiles. ($\beta_1 = 0.031$; $\beta_1' = 0.135$)*

As the alternative hypotheses are all accepted in three research phases, the null hypothesis of no observed correlation is rejected. However, the discoveries in phases 2 and 3 suggest that the correlation between the two variables does not provide sufficient explanatory power on describing how the variation of the artist's *number of followers* influences the *artwork price*.

In summary, the final answer to this paper's research question is:

> *There is a confirmed relationship between artists' reputation level (represented by artist's number of followers) and artwork price, but the number of followers alone is insufficient to fully describe variations in artwork price. A partial correlation has been discovered between variation in an artist's artwork price and their reputation (represented by artist's number of followers).*

This discovery implies that artists' perspective on their reputation levels are not single-dimensional, and that the follower count is only a weak proxy when estimating reputation levels. Since the dataset provides a partially related result while answering the research question, the statistical model for demonstrating the correlation between an artist's *number of followers* and *artwork price* has several limitations. The sources of incapability will be discussed further in the next section.

5.2. The Hidden Factors – The reasons of "partial correlation"

The correlation coefficient in the original dataset is approximately 0.21, indicating a weak correlation. Additionally, the estimated *SLRM* only has a goodness of fit of 0.046, meaning that changes in the *number of followers* explain only 4.6% of the variation in the *artwork price*. After applying logarithmic transformation to the dataset to reduce the heteroscedasticity, the output remains unpersuasive in explaining the percentage of variance of artists' *artwork price* based solely on the estimated reputation level, as proxied by *number of followers*. This section expands the discussion of the digital art online commission industry to further explore the potential applications of artists' reputation levels based on estimations derived from the Social Proof Effect in the platform-specific market (Lin et al., 2025; Rodner & Thomson, 2013).

Other observations regarding artists' pricing behaviour are also worth mentioning. Substantial price variation is observed among low-follower-count artists. A potential explanation for this phenomenon is different segmentation and strategic developments when artists select the prices of artwork commissions. Specifically, artists with a higher *number of followers* do not necessarily charge the highest prices, which is a counterintuitive finding in price prediction. The linear regression model and its confidence band suggest that there is a boundary effect of the follower group size. As an artist's *number of followers* increases, their *artwork price* varies significantly rather than maintaining similar patterns (Cowan et al., 2026). According to the visual characteristics of the grey-shaded area (representing the confidence band) in the linear regression model using the original dataset, the larger estimated confidence band suggests that latent variables in the linear model for estimating artists' reputation levels are important considerations for artists with a high number of followers.

This discovery also suggests that artists' reputation level based solely on follower count is insufficient to explain the pricing behaviour. One possible explanation is that follower count is considered as a form of visibility capital for increasing artists' potential pricing range rather than directly determining prices. The presence of highly followed artists charging relatively low prices indicates that pricing decisions may also be influenced by external market factors and artists' internal workload. Park et al. (2024) suggest additional factors to explain the decoupling phenomenon, such as the artist's workload, artwork characteristics, individual market strategies, commission volume preferences, and audience characteristics.

From an economic standpoint, this pattern is consistent with the idea that follower counts serve as of a social proof signal in early stages of reputation formation. However, the explanatory factors observed in the data distribution become less informative once artists reach a level of established market recognition. At this point, pricing may be constrained more by capacity limits, client segmentation, and strategic positioning rather than by the observing indicator of numerical follower count changes (Ning, 2024; Park et al., 2024).

As Rodner & Thomson (2013) and Lin et al. (2025) describe, the Social Proof Effect suggests that the *number of followers* is a plausible variable for preliminarily estimating reputation level. The reputation level proxied by the *number of followers* has proven applicable while the *number of followers* is relatively low, based on the dataset's distributions. However, for artists with higher follower counts, the proposed interpretations for developing pricing models and quantifying artists' reputation reduce the explanatory power when the Social Proof Effect is applied to discuss high-follower artists' reputation and how their reputation contributes to the artwork price.

Therefore, as the *number of followers* increases to a certain level, a new possibility emerges: pricing behaviour among artists with higher follower counts may be better explained by other internal or external factors that were previously hidden.

5.3. Implications

5.3.1. Theoretical Contribution

Based on the results in Section 5.1, this research provides empirical evidence describing how artist reputation influences artwork pricing decisions within digital art commission platform transactions. The data and analyses presented in this study offer an exploratory examination of one potential determinant of an independent artist's artwork price, under the condition that reputation is proxied by follower count. While Chenavaz & Eynan (2021) and Rodner & Thomson (2013) discuss the relationship between artist reputation and artwork price based on estimation indicators, this study contributes empirical evidence from the context of the digital art commission industry.

This study also evaluates whether the Social Proof Effect, as discussed by Lin et al. (2025), provides plausible theoretical explanations for reputation estimation based on customers' heuristic assessments of artist reputation and the corresponding variations in artwork prices. The discussion of the partially supported findings suggests that artist reputation may be better understood as a multidimensional construct rather than a concept represented solely by follower count. In addition, the observed patterns in the dataset indicate that the relationship between reputation and artwork price may not be fully linear. The substantial variation in artwork price among *high-follower* artists implies that the explanatory power of follower count as a reputation proxy becomes more limited at higher reputation levels. This finding further suggests that the explanatory relevance of the Social Proof Effect may vary across different market conditions and reputation levels.

The research method applied to identify the relationship between artists' follower counts and artwork prices is sufficient to describe the dynamics of digital art commission platforms within a statistical framework. The statistically significant results indicate that the methodological approach is applicable to exploring relationships between other potential numerical or categorical variables associated with artist reputation, such as customer feedback ratings (Ning, 2024).

Furthermore, this research serves as an exploratory step towards understanding artwork pricing in digital art commission platform transactions. The methodological and empirical foundations for future research can be applied in potential studies. The proposed approach may be extended by incorporating additional variables, conducting comparative studies across different markets, and further developing the price and reputation models quantitatively.

5.3.2. Insights for Artists

This paper has not only explored the pricing influencers of artwork price within the emerging trading environment of digital art commission platforms, but has also provided evidence for analysing strategies that independent artists can adopt to increase their profits under a value-based pricing approach. One suggested technique for increasing profit is raising the selling price per transaction, as defined by Helmold (2022) in Section 2. To increase artwork selling prices and expand potential customer groups, follower count can serve as a key observable indicator for artists to develop pricing and community strategies. This takeaway is supported by the empirical findings, given that customers' psychological expectations can be applied as a core theoretical lens for estimating reputation.

According to the results in Section 4, it is recommended that artists with lower follower counts focus on personal branding to move away from highly competitive market segments. Artists with fewer followers tend to have limited bargaining power, as they operate within more competitive *low-follower* group segments. Under such conditions, adopting a value-added pricing strategy based on the follower count is less feasible, as it requires a stronger level of differentiation in artistic output. Therefore, artists with a lower follower base are recommended to expand their follower communities, as indicated by the dataset distribution. A higher follower count is associated with higher unit prices in individual commission transactions and greater pricing flexibility.

However, the relationship between follower count and pricing outcomes is not linear across all levels of reputation. The dataset also suggests that once artists reach a sufficiently high follower base, further increases in follower count become less effective in raising artwork prices. The dataset is collected on 06/05/2026 and follows a time-based sampling design; therefore, the observed market dynamics suggest that *high-follower* artists should prioritise alternative revenue strategies rather than focusing solely on follower growth. Due to this boundary effect and the observed decoupling phenomenon between reputation and revenue at higher follower levels, community development strategies for *high-follower* artists should shift towards strengthening a distinctive artistic style and personal branding as a form of value creation (Suchomelova et al., 2017).

In summary, these findings indicate that the role of follower count in pricing strategies depends on the existing level of artist reputation. Artists are also recommended to develop their follower communities to support customer retention, but with differentiated strategies depending on their current follower level. The combined psychological mechanisms of the Social Proof Effect and the Veblen Effect provide a behavioural guideline for understanding how visibility and perceived status influence customer purchasing decisions.

5.4. Current Research's Constraints and Potential Improvements

Although this research applied parameter-control techniques to mitigate the effects of omitted variables while identifying the relationship between the two variables, the findings remain less persuasive in explaining artwork price variations solely based on the number of followers on the selected digital platform. Furthermore, the selection of both the platform and market context influences the generalisability of the findings, as differences in market characteristics may reduce the external validity and broader applicability of the proposed model (Stremersch et al., 2023). Therefore, the current study presents several limitations regarding the generalisability of its findings, the research methods employed to identify additional determinants of artwork prices, and the statistical model used to explain the relationships between the variables.

5.4.1. Boundaries and Generalisability

As this research exclusively selected *HuaJia* as the focused platform for analysing and estimating the potential relationship between artists' reputation levels and artwork prices, with the number of followers serving as the sole indicator of reputation, the findings are only applicable within the context of the selected platform when examining factors that influence artwork pricing. Furthermore, as described in Section 3, several parameter-control techniques were implemented and applied during the data collection process. While these controls helped reduce the influence of confounding factors, they also narrowed the scope and generalisability of the reputation-price relationship explored in this study.

The study focuses solely on *HuaJia*, a platform that primarily serves artists and customers in China and operates predominantly through one-off payments for digital art commissions. According to Stremersch et al. (2023), consumer preferences and market characteristics vary across countries and regions. Such variations are also likely to exist in digital art commission markets. For example, *Patreon* (2026) adopts a subscription-based payment mechanism rather than a one-off transaction model. Consequently, the relationship between follower-based reputation and artwork price identified in this study may not be directly applicable to platforms such as *Patreon* (2026), as their payment structures differ substantially from the market conditions under which this research was developed.

Furthermore, the data sampling strategy adopted in this study reduced the variability of the collected sample. The sampling process relied on the sequential selection of artists based on the platform's time-based listing system. Although this approach represented a practical compromise in response to privacy restrictions and technical limitations, it did not provide comprehensive coverage of the platform's historical artist population. To address this limitation, future studies may consider collecting data from multiple listing categories and alternative grouping mechanisms available on the platform, thereby increasing the representativeness of the sampled artists.

To further evaluate the boundaries of the findings presented in this study, future researchers are encouraged to investigate digital art commission platforms operating in other countries and regions. Such studies would help assess the applicability of the proposed findings across diverse market environments and contribute to a broader understanding of the relationship between artists' reputation levels and artwork pricing.

5.4.2. Combined Method – The Need for a Mixed-Methods Approach

Although follower count has been widely adopted as a direct indicator of artist reputation in previous studies (Chenavaz & Eynan, 2021; Rodner & Thomson, 2013), the current study does not evaluate other factors that may also contribute to variations in artwork prices. As suggested by the literature listed above, follower count is a numerical indicator that can be collected relatively easily during the data sampling process without requiring subjective evaluations of artistic quality. Consequently, this study focuses on examining the relationship between follower-based reputation and predefined categories of artwork prices.

Although Ning (2024) proposes several potential variables that may explain artwork prices, many of these variables remain difficult to identify solely through quantitative data collection. To gain a deeper understanding of artists' pricing decisions and their considerations during commission negotiations, qualitative research may provide valuable insights into how artists determine and justify their artwork prices from their own perspectives (Fossey et al., 2002).

The findings of this study suggest that artist reputation cannot be fully explained by follower count alone. While follower count may function as an observable indicator of reputation, the results imply that reputation itself may be a multidimensional construct influenced by additional factors that were not captured in the current statistical model. Therefore, qualitative methods may serve as a complementary approach for identifying latent dimensions of artist reputation and other factors that contribute to artwork pricing decisions (Fossey et al., 2002; Lim, 2025).

Furthermore, observations from the collected dataset indicate that artists' pricing decisions vary across different reputation levels. This finding reinforces the need to further investigate the underlying factors that shape artist reputation and influence the relationship between reputation and artwork prices. Through interviews and other qualitative approaches, and by focusing on other similar digital platforms, future researchers may be able to identify factors that are difficult to observe directly through numerical data alone (Matović & Ovesni, 2023).

The insights generated from qualitative research may subsequently contribute to the theoretical development of additional variables for future quantitative studies. After identifying and conceptualising these factors, researchers may incorporate them into statistical models to evaluate their influence on artwork prices and to improve the measurement of artist reputation. Ultimately, a combined research approach may contribute to the development of a more comprehensive pricing framework for the online art commission industry (Gelo et al., 2008).

5.4.3. Model – The Proposed Statistical Model's Constraints

To directly examine the relationship between artist reputation level and artwork prices on the selected platform, this research introduces a quantitative proxy variable (i.e., follower count) to represent artist reputation within the statistical model (Seltzer, 2021). While the results suggest that the quantified reputation variable is statistically significant in explaining variation in artwork prices, the regression coefficient indicates limited explanatory power in accounting for the variance of the dependent variable. This implies that additional factors also influence artwork prices beyond artist reputation or other observable market parameters (Candela & Scorcu, 1997; Angelini et al., 2022).

Some of the artwork pricing factors proposed by Angelini et al. (2022) and Ning (2024) are not included in this study, as the primary objective is to examine the relationship between artist reputation and artwork prices within a quantitative framework. To maintain statistical reliability and reduce the influence of confounding factors during data collection, the inclusion of additional variables is postponed in this research design. These omitted variables are integrated into the error term (ϵ_i) in the statistical model (as defined in Section 3).

According to the results presented in Sections 4.4 and 4.5, the number of followers as a single independent variable is insufficient to explain variations in artwork prices. The low R-squared values (0.046 in the original dataset and 0.080 in the logged dataset) and the relatively wide confidence intervals (as illustrated by the funnel-shaped distribution in Figure 5) indicate weak explanatory power for the proposed linear model. This suggests that using follower count alone as a proxy for reputation limits the robustness of the model and fails to capture a broader set of influencing factors.

To incorporate additional variables derived from qualitative findings or other numerical indicators within the platform, Pederson (2017) proposes the Multiple Regression Model (*MRM*) as an alternative approach. The MRM allows multiple independent variables to be included in the analysis, providing a more flexible framework for modelling artist reputation and estimating its effect on artwork price. This approach can be applied in future research to improve hypothesis testing and strengthen the empirical analysis of pricing mechanisms.

As Pederson (2017) further suggests, the *MRM* provides greater flexibility in incorporating additional variables and reduces estimation error compared to a single linear regression model. Based on this study's findings, the key advantage of *MRM* over *SLRM* lies in its improved robustness in capturing price variation patterns within the digital art commission industry.

In addition, Pederson (2017) notes that *MRM* enables the inclusion of broader pricing determinants beyond artist reputation alone. External factors identified by Angelini et al. (2022) – such as artwork complexity, transaction or intermediary costs, and other market-related conditions – can also be incorporated into future models. These variables may further enhance the development of a more comprehensive artwork pricing framework and provide stronger empirical validation across different market contexts and countries.

6. Conclusion

This research provides a solution to the research question regarding the factors influencing pricing in the digital art commission industry. The central research question addressed in this study is:

How does an artist's reputation level influence their artwork prices in the online digital art commission market?

To answer this question, three research phases were conducted. In Research Phase 1 (**P1**), the results revealed that the mean artwork price in the artist group with a higher *number of followers* is greater than that of the artist group with a lower *number of followers*. Research Phase 2 (**P2**) identified a statistically significant but weak correlation between artists' follower counts and their artwork prices. Research Phase 3 (**P3**) constructed linear regression models to provide empirical quantitative validation of the relationship between these two variables. The model results suggest that artists' follower counts can predict artwork price; however, the model demonstrates limited explanatory power despite its clearly identified statistical significance.

Combining the findings from the three research phases, they suggest that an artist's reputation level, as represented by follower count, is positively associated with variations in artwork prices. However, the relatively weak explanatory power of the statistical model indicates that additional factors are also involved in determining artwork prices within the digital art commission market. Hence, an artist's reputation level only partially explains variations in artwork price, as it shows a positive but weak explanatory power. Therefore, the conclusion is:

This study finds that the artist's reputation level has a statistically significant but weak influence on artwork prices in the online digital art commission market.

To further explore how artist reputation influences artwork pricing, an empirical analysis of artists on *HuaJia* was conducted using statistical methods and a predefined proxy variable (follower count) to represent artist reputation within the theoretical framework. Based on the partial acceptance of the proposed hypotheses and the collected data, this study suggests that artist reputation cannot be fully measured by follower count alone. Instead, reputation appears to be a more complex and multidimensional construct that combines numerical indicators with broader social dynamics.

Although the proxy variable presented in this study is statistically related to artwork price, follower count alone is unable to provide sufficient explanatory power for predicting price variations. Nevertheless, this study provides an initial framework for applying similar quantitative methods to identify and evaluate additional variables that influence pricing decisions on digital art commission platforms. The findings therefore contribute to the ongoing development of both theoretical and analytical frameworks for understanding artwork pricing in online creative markets.

Beyond answering the research question, this study also provides practical insights for independent artists. The findings suggest that developing and maintaining follower communities may contribute to higher revenue potential, particularly when different growth strategies are applied depending on the artist's existing follower base. In this context, follower count serves as a useful indicator for artists when evaluating their market position. However, artists also recognise that reputation is a complex construct that extends beyond numerical popularity and involves community-building activities such as audience retention, interaction, and engagement (Schroeder, 2005).

The contributions of this research can be summarised in several aspects. First, this study provides empirical evidence supporting the application of customer psychology theories in explaining how artist reputation influences pricing decisions in practice. Second, the methodological design of this research provides a quantitative analytical framework for examining artwork pricing mechanisms, including the evaluation of reputation-related factors and other external influences that affect pricing decisions. Finally, this study finds that the follower count is positively associated with artwork prices, which provides a reference for artists for developing their pricing strategies. While follower count, as a representation of an artist's reputation, is not a comprehensive measure, the statistical findings provide artists with a useful reference point for pricing decisions.

Ultimately, this study serves as an exploratory step towards developing a data-driven understanding of pricing mechanisms within the online art commission industry. The findings contribute to the broader effort to quantify the relationship between artist reputation and artwork pricing while highlighting additional unexplained factors. Furthermore, this research provides a foundation for future studies that aim to expand and refine the proposed pricing framework.

Future research may extend this work by examining digital art commission markets operating under different market structures and payment mechanisms to evaluate the generalisability of the findings. Researchers may also develop artwork pricing models by incorporating additional variables derived from artists' preferences, customer behaviour, or other dimensions of reputation that are not captured in the present study.

However, the findings of this research should be interpreted within clearly defined boundary conditions. As discussed in Section 5.4, the proposed pricing model does not directly apply to subscription-based platforms, where artists rely more heavily on personal branding, work-life balance, and long-term customer relationships (Duffy, 2017). Such subscription-based mechanisms are commonly observed in industries such as music and video platforms, where revenue generation differs significantly from direct commission-based transactions (Meyn et al., 2023). Therefore, future studies may need to adopt alternative analytical approaches when investigating consumer psychology and pricing behaviour under these market conditions.

As an exploratory study, this research contributes to the understanding of artist pricing mechanisms by proposing a quantitative approach for representing artist's reputation level and examining its relationship with artwork price through the estimations and applications of customer purchasing psychology. The findings provide a useful reference for artists operating within platform-based commission markets when making pricing decisions and competing for revenue opportunities. With future research developments, this framework contributes to a more data-driven decision-making for artists participating in creative industry (Mintzberg, 2009).

References

Angelini, F., Castellani, M., & Pattitoni, P. (2022). Artist Names as Human Brands: Brand Determinants, Creation and co-Creation Mechanisms. *Empirical Studies of the Arts*, vol. 41, no. 1, pp.80-107, https://doi.org/10.1177/02762374211072964

Art Trails Tasmania. (2026). Why Art Commissions Are a Powerful Income Stream for Artists – Part 1, https://arttrailstasmania.com.au/why-art-commissions-are-a-powerful-income-stream-for-artists-part-1/ [Accessed 24 April 2026]

Ajayi, A. O., Johnson, O. C., & Goodness, A. D. (2025). Investigating Artwork Pricing as A Challenge to Artists and The Way Out. *Iconic Research And Engineering Journals*, vol. 9, no. 3, pp.1176-1186 https://doi.org/10.64388/IREV9I3-1710788-290

Bai, J., Guo, J., & Mandel, B. (2013). Going Global: Markups and Product Quality in the Chinese Art Market [pdf], https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr614.pdf

Ball, A., Ranim, M., & Levy, Y. (2015). Examining users' personal information sharing awareness, habits, and practices in social networking sites and e-learning systems. *Online Journal of Applied Knowledge Management*, vol. 3, no. 1, pp.180-207, https://www.iiakm.org/ojakm/articles/2015/volume3_1/OJAKM_Volume3_1pp180-207.pdf [Accessed 3 June 2026]

Barroga, E., Matanguihan, G. J., Furuta, A., Arima, M., Tsuchiya, S., Kawahara, C., Takamiya, Y., & Izumi, M. (2023). Conducting and Writing Quantitative and Qualitative Research. *Journal of Korean medical science*, vol. 38, no. 37, https://doi.org/10.3346/jkms.2023.38.e291

Beckert, J., & Rössel, J. (2013). THE PRICE OF ART: Uncertainty and reputation in the art field. *European Societies*, vol. 15, no. 2, pp.178-195, https://doi.org/10.1080/14616696.2013.767923

Berman, J. J. (2016). Chapter 4 - Understanding Your Data, *Data Simplification*, Burlington: Morgan Kaufmann, pp.135-187, https://doi.org/10.1016/B978-0-12-803781-2.00004-7

Bishop, S. (2025). Influencer creep: How artists strategically navigate the platformisation of art worlds. *New Media & Society*, vol. 27, no. 4, pp.2109-2126, https://doi.org/10.1177/14614448231206090

Bogaerts, L. (2015). The Informational Potential of Art E-Commerce Platforms for Art Investors, Master thesis, Erasmus School of History, Culture and Communication, Erasmus University Rotterdam, https://thesis.eur.nl/pub/32696/Bogaerts-Laura.pdf [Accessed 24 April 2026]

Bryman, A. (2016). Social Research Methods, 5th edn, Oxford: Oxford University Press

Burton, A. L. (2021). OLS (Linear) Regression. In J. C. Barnes and D. R. Forde (eds), *The Encyclopedia of Research Methods in Criminology and Criminal Justice*, Hoboken: Wiley, pp.509-514, https://doi.org/10.1002/9781119111931.ch104

Candela, G., & Scorcu, A. E. (1997). A Price Index for Art Market Auctions. *Journal of Cultural Economics*, vol. 21, pp.175-196. https://doi.org/10.1023/A:1007442014954

Chenavaz, R. Y., & Eynan, A. (2021). Advertising, goodwill, and the Veblen effect. *European Journal of Operational Research*, vol. 289, no. 2, pp.676-682, https://doi.org/10.1016/j.ejor.2020.07.043

Christodoulou, S., & Styliaras, G. (2013). Web 2.0 and digital art communities: applications and potentialities. *International Journal of Web Based Communities*, vol. 9, pp.535-553, https://doi.org/10.1504/IJWBC.2013.057218

Clapp, S. L. C. (1931). The Beginnings of Subscription Publication in the Seventeenth Century. Modern Philology, vol. 29, no. 2, pp.199-224, https://doi.org/10.1086/387957

Clark, A. D., Myers, T. C., Steury, T. D., Krzton, A., Yanes, J., Barber, A., Barry, J., Barua, S., Eaton, K., Gosavi, D., Nance, R., Pervaiz, Z., Ugochukwu, C., Hartman, P., & Stevison, L. S. (2024). Does it pay to pay? A comparison of the benefits of open-access publishing across various sub-fields in biology. *PeerJ*, *12*, e16824. https://doi.org/10.7717/peerj.16824

Cowan, K., Marder, B., Lavertu, L., & Li, J. (2026). (How) Does the Number of Followers Impact the Success of Influencer Marketing? A Construal Level Perspective, *Journal of Advertising Research*, vol. 66, no. 1, pp.4-23, https://doi.org/10.1080/00218499.2025.2482276

DiRusso, D. J., Mudambi, S. M., & Schuff, D. (2011). Determinants of prices in an online marketplace. *Journal of Product & Brand Management*, vol. 20, no. 5, pp.420-428, https://doi.org/10.1108/10610421111157946

Doane, D., & Seward, L. (2011). Measuring Skewness: A Forgotten Statistic?. *Journal of Statistics Education*, vol. 19, no. 2, https://doi.org/10.1080/10691898.2011.11889611

Duffy, B. E. (2017). (Not) Getting Paid to Do What You Love: Gender, Social Media, and Aspirational Work, [e-book] New Haven: Yale Scholarship Online, https://doi.org/10.12987/yale/9780300218176.001.0001

Fossey, E., Harvey, C., McDermott, F., & Davidson, L. (2002). Understanding and evaluating qualitative research. *Australian and New Zealand Journal of Psychiatry*, vol. 36, no. 6, pp.717-732, https://doi.org/10.1046/j.1440-1614.2002.01100.x

Gabor, A. (1973). Price and consumer behaviour – A review. *Omega*, vol. 1, no. 3, pp.279-296, https://doi.org/10.1016/0305-0483(73)90105-9

Gelo, O., Braakmann, D., & Benetka, G. (2008). Quantitative and Qualitative Research: Beyond the debate. *Integrative Psychological and Behavioral Science*, vol. 42, pp.266-290, https://doi.org/10.1007/s12124-008-9078-3

Ghanad, A. (2023). An Overview of Quantitative Research Methods. *International Journal of Multidisciplinary Research and Analysis*, vol. 6, no. 8, https://doi.org/10.47191/ijmra/v6-i8-52

Guan, T., Alam, M. K., & Rao, M. B. (2023). Sample Size Calculations in Simple Linear Regression: A New Approach. *Entropy*, vol. 25, no. 4, p.611. https://doi.org/10.3390/e25040611

Helmold, M. (2022). Performance Excellence in Marketing, Sales and Pricing: Leveraging change, lean and innovation management, Cham: Springer, https://doi.org/10.1007/978-3-031-10097-0

Hinterhuber, A. (2008). Customer value-based pricing strategies: why companies resist. *Journal of Business Strategy*, vol. 29, no. 4, pp.41-50, https://doi.org/10.1108/02756660810887079

HuaJia. (2026). 找画师, 上画加 – 网易画加美术约稿平台 (Seeking Artists, Use HuaJia – NetEase HuaJia Art Commission Platform), https://huajia.163.com/ [Accessed 6 May 2026]

Johansson, M., Hallberg, N., Hinterhuber, A., Zbaracki, M., & Liozu, S. (2012). Pricing strategies and pricing capabilities. *Journal of Revenue and Pricing Management*, vol. 11, pp.4-11, https://doi.org/10.1057/rpm.2011.42

Kang, J., Su, C., Lan, J., & Chen, L. (2024). Effects of the Subscription-Based Partitioned Pricing Strategy of Digital Content Platforms on User Willingness to Purchase. Journal of Theoretical and Applied Electronic Commerce Research, vol. 19, no. 4, pp.3305-3330. https://doi.org/10.3390/jtaer19040160

Kienzler, M., & Kowalkowski, C. (2017). Pricing strategy: A review of 22years of marketing research. *Journal of Business Research*, vol. 78, pp.101-110, https://doi.org/10.1016/j.jbusres.2017.05.005

King, A. P., & Eckersley, R. J. (2019). Statistics for Biomedical Engineers and Scientists, Amsterdam: Elsevier. https://doi.org/10.1016/C2018-0-02241-0

Kjus, Y. (2022). Twists and turns in the 360 deal: Spinning the risks and rewards of artist–label relations in the streaming era. *European Journal of Cultural Studies*, vol. 25, no. 2, pp.463-478, https://doi.org/10.1177/13675494211044731

Kotler, P., Armstrong, G., Harris, L. C., & He, H. (2020). Principles of Marketing, 8th edn, Harlow: Pearson.

Kumar, S., & Pandey, M. (2017). The impact of psychological pricing strategy on consumers' buying behaviour: A qualitative study. *International Journal of Business and Systems Research*, vol. 11, no. 1-2, p.101, https://doi.org/10.1504/IJBSR.2017.080843

Lee, J. W., & Lee S. H. (2019). User participation and valuation in digital art platforms: the case of Saatchi Art. *European Journal of Marketing*, vol. 53, no. 6, pp.1125-1151, https://doi.org/10.1108/EJM-12-2016-0788

Lee, K., Park, J., Goree, S., Crandall, D., & Ahn, Y.-Y. (2024). Social signals predict contemporary art prices better than visual features, particularly in emerging markets. *Scientific Reports*, vol. 14, no. 1, https://doi.org/10.1038/s41598-024-60957-z

Li, D., & Xiao, J. (2025). Artistic interventions: Art, community, and media in China and beyond. *Global Media and China*, vol. 10, no. 1, pp.3-18, https://doi.org/10.1177/20594364241286782

Lim, W. M. (2025). What Is Qualitative Research? An Overview and Guidelines. *Australasian Marketing Journal*, vol. 33, no. 2, pp.199-229, https://doi.org/10.1177/14413582241264619

Lin, Y., Ng, J., Sun, G., & Wang, Y. (2025). Social Proof, Scarcity, and Discounts: Experimental Evidence on Digital Nudges in E-Commerce. *Advances in Economics, Management and Political Sciences*, vol. 240, no. 1, pp.40-57, https://doi.org/10.54254/2754-1169/2025.BL29479

Lopez, S. (2015). Value-based Marketing Strategy, Wilmington: Vernon Press.

MacCallum, R. C., Zhang, S., Preacher, K. J., & Rucker, D. D. (2002). On the practice of dichotomization of quantitative variables. *Psychol Methods*, vol. 7, no. 1, pp.19-40, https://doi.org/10.1037/1082-989x.7.1.19

Makrydakis, N. (2024). The crucial role of psychological techniques in digital marketing to influence consumer behavior. *International Journal of Management and Commerce*, vol. 5, no. 2, pp.6-10, https://www.researchgate.net/publication/378140252_The_crucial_role_of_psychological_techniques_in_digital_marketing_to_influence_consumer_behavior

Martin, P. (2021). Linear Regression: An Introduction to Statistical Models. Los Angeles: SAGE Publications. https://doi.org/10.4135/9781529682731

Matović, N., & Ovesni, K. (2023). Interaction of quantitative and qualitative methodology in mixed methods research: integration and/or combination, *International Journal of Social Research Methodology*, vol. 26, no. 1, pp.51-65, https://doi.org/10.1080/13645579.2021.1964857

Meyn, J., Kandziora, M., Albers, S., & Clement, M. (2023). Consequences of platforms' remuneration models for digital content: initial evidence and a research agenda for streaming services. *Journal of the Academy of Marketing Science*, vol. 51, pp.114-131, https://doi.org/10.1007/s11747-022-00875-6

Mintzberg, H. (2009). Managing, New York: Free Press.

Ning, D. (2024). Analysis of Factors Influencing Artwork Pricing. *Advances in Economics, Management and Political Sciences*, vol. 120, pp.17-22, https://doi.org/10.54254/2754-1169/120/20242352

Oliver, P. G. (2024). Digital transformation and the DIY artist: Balancing artistic integrity and economic sustainability in the digital domain. *DIY, Alternative Cultures & Society*, vol.2, no. 2, pp.207-223, https://doi.org/10.1177/27538702241251886

Osburg, V.-S., Yoganathan, V., McLeay, F., & Diallo, M. F. (2022). (In)compatibilities in sustainable luxury signals, *Ecological Economics*, vol. 196, https://doi.org/10.1016/j.ecolecon.2022.107430

Park, J., Lee, Y., Yang, D., Park, J., & Jung, H. (2024) Artwork pricing model integrating the popularity and ability of artists. *AStA Advances in Statistical Analysis*, vol. 108, pp.889-913, https://doi.org/10.1007/s10182-024-00504-3

Park, S., & McCallister, J. (2023). The Effects of Social Proof Marketing Tactics on Nudging Consumer Purchase. *Journal of Student Research*, vol. 12, no. 3, https://doi.org/10.47611/jsrhs.v12i3.4887, https://www.researchgate.net/publication/378163135_The_Effects_of_Social_Proof_Marketing_Tactics_on_Nudging_Consumer_Purchase [Accessed 28 April 2026]

Patreon. (2026). Where Creator Communities Thrive – Patreon, https://www.patreon.com/ [Accessed 3 June 2026]

Pederson, J., (2017). Multiple Regression, in *The SAGE Encyclopedia of Communication Research Methods*, Thousand Oaks: SAGE Publications, Inc., pp.1041-1045, https://doi.org/10.4135/9781483381411.n360

Piña-García, C. A., Gershenson, C. & Siqueiros-García, J. M. (2016). Towards a standard sampling methodology on online social networks: collecting global trends on Twitter. *Applied Network Science*, vol. 1, no. 3. https://doi.org/10.1007/s41109-016-0004-1

Ridwan, N. H., Alrizqi, Da. G., & Mildayanti, M. (2026). The Influence of Social Proof on Consumer Trust in New Online Stores. *East Asian Journal of Multidisciplinary Research*, vol. 5, no. 2, pp.623-642, https://doi.org/10.55927/eajmr.v5i2.24.

Rodner, V. L., & Kerrigan, F. (2014). The Art of Branding - Lessons from Visual Artists. *Arts Marketing: An International Journal*, vol. 4, no. 1-2, pp.101-118, https://doi.org/10.1108/AM-02-2014-0013

Rodner, V. L., & Thomson, E. (2013), The art machine: dynamics of a value generating mechanism for contemporary art. *Arts Marketing: An International Journal*, vol. 3, no. 1 pp.58-72, https://doi.org/10.1108/20442081311327165

Rosopa, P. J., Schaffer, M. M., & Schroeder, A. N. (2013). Managing heteroscedasticity in general linear models. *Psychological Methods,* vol. 18, no. 3, pp.335-351, https://doi.org/10.1037/a0032553

Rurale, A., & Prokupek, M. (2025). Understanding price formation in the art market through expert interviews. *Multidisciplinary Business Review*, vol. 18, no. 2, pp.44-56, https://doi.org/10.35692/07183992.18.2.4

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2023). Research Methods for Business Students, 9th edn, Harlow: Pearson https://www.researchgate.net/publication/240218229_Research_Methods_for_Business_Students

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia & Analgesia*, vol. 126, no. 5, pp.1763-1768, https://doi.org/10.1213/ANE.0000000000002864

Schönfeld, S., & Reinstaller, A. (2007). The effects of gallery and artist reputation on prices in the primary market for art: a note. *Journal of Cultural Economics*, vol. 31, pp.143-153, https://doi.org/10.1007/s10824-007-9031-1

Schroeder, J. E., (2005). The artist and the brand. *European Journal of Marketing*, vol. 39, no. 11-12, pp.1291-1305, https://doi.org/10.1108/03090560510623262

Seltzer, R. G. N. (2021). The Perilous Use of Proxy Variables. *Evaluation & the Health Professions*, vol. 44, no. 4, pp.428-435, https://doi.org/10.1177/0163278720903358

Slater, M. D., & Gleason, L. S. (2012). Contributing to Theory and Knowledge in Quantitative Communication Science. *Communication Methods and Measures*, vol. 6, no. 4, pp.215-236. https://doi.org/10.1080/19312458.2012.732626

Stremersch, S., Gonzalez, J., Valenti, A., & Villanueva, J. (2023) The value of context-specific studies for marketing. *Journal of the Academy of Marketing Science*. vol. 51, pp.50-65, https://doi.org/10.1007/s11747-022-00872-9

Suchomelova, A., Prochazka, J., & Durinik, M. (2017). Personal Interest Branding: Source of Price Premium. *Journal of International Consumer Marketing*, vol. 29, no. 1, pp.27-34, https://doi.org/10.1080/08961530.2016.1236309

Tukey, J. W. (1973). Exploratory data analysis, Reading, MA: Addison-Wesley

Wald, A., (1945). Sequential Tests of Statistical Hypotheses. *The Annals of Mathematical Statistics*, vol. 16, no. 2, pp.117-186, https://doi.org/10.1214/aoms/1177731118

Wasserstein, R. L., & Lazar, N. A. (2016). The ASA Statement on *p*-Values: Context, Process, and Purpos. *The American Statistician*, vol. 70, no. 2, pp.129-133, https://doi.org/10.1080/00031305.2016.1154108.

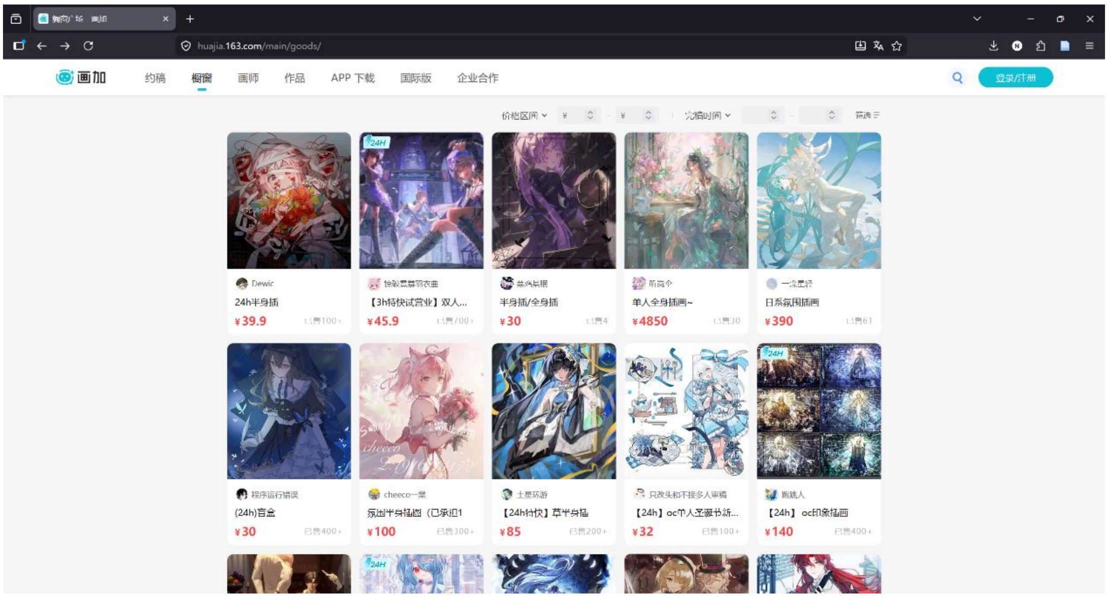
Wong, M. (2020). Hidden youth? A new perspective on the sociality of young people ‘withdrawn’ in the bedroom in a digital age. *New Media & Society*, vol. 22, no. 7, pp.1227-1244, https://doi.org/10.1177/1461444820912530

Wooldridge, J. (2019). Introductory Econometrics. 7th edn, Boston: Cengage

Xiao, X., White, E. P., Hooten, M. B., & Durham, S. L. (2011). On the use of log-transformation vs. nonlinear regression for analyzing biological power laws. *Ecology*, vol. 92, no. 10, pp.1887-1894, https://doi.org/10.1890/11-0538.1

Yang, R. (2024). Social psychology research in the commercial art market: challenges and opportunities. *Environment and Social Psychology*, vol. 9, no. 10, https://doi.org/10.59429/esp.v9i10.3126

Appendix A: Images of selected platform webpages



Sample User Interface of *HuaJia*’s (2026) commission posts, the prices above vary significantly from 30CNY to 4850CNY.

Appendix B: Original dataset

Note: in the main content of this research paper, some of the values have been removed due to the reasons mentioned in ***Sections 3 & 4***.

Artist No.	Artist's number of followers	Artist's artwork price (in CNY)
1	273	170
2	648	260
3	355	258
4	487	350
5	33	66
6	18	75
7	92	188
8	554	130
9	67	120
10	10	300
11	1586	350
12	68	150
13	194	210
14	136	500
15	105	80
16	259	240
17	67	400
18	248	90
19	1811	300
20	977	350
21	108	120
22	42	85
24	79	150
25	689	300
27	126	379
28	232	40
29	3668	350
30	2043	276
31	989	95
32	1279	200
33	237	350
34	935	218
35	615	220
36	1394	180
38	404	150
40	42	63
41	482	330
42	249	160
43	171	180
44	41	75
45	338	238
46	169	106
47	216	55
48	111	89
49	38	200
50	131	128
51	87	240
52	131	120
53	195	118
54	575	99
55	45	130
56	5397	420
57	2202	105
58	362	85
59	687	288
60	2150	130
61	494	190
62	958	138

Artist No.	Artist’s number of followers	Artist’s artwork price (in CNY)
63	202	125
64	76	150
65	271	780
66	169	155
67	155	200
68	1111	288
69	20	80
71	127	420
72	134	200
73	1163	150
74	233	125
75	1446	99
76	162	65
77	125	65
79	1961	115
80	13	150
81	93	180
82	312	150
83	41	50
86	59	10
89	224	300
90	782	233
91	89	198
92	1797	250
93	26	69.9
95	153	96
96	194	230
98	1241	360
99	142	90
101	64	270
102	178	45
103	28	110
104	700	360
105	608	38
106	169	134
107	185	210
108	91	90
111	194	273
112	1132	120
113	790	120
114	336	139
116	17	180
117	14	50
119	17	320
120	3366	73

Appendix C: R scripts for *Data Analysis Section*

```
# This script is executed under R 4.5.3 environment.
# This script requires tidyverse & readxl packages to execute
properly


library(readxl)
library(tidyverse)

ds=read_excel("C:/Users/Natha/OneDrive/MMgt-LU/MGTN59/Dataset.xlsx",
              sheet = "Sheet2Neat")

# Preliminary actions:
ds_sorted = ds %>% arrange(`Artist’s number of followers`)
summary(ds_sorted)
sd_x=sd(ds_sorted$`Artist’s number of followers`, na.rm= TRUE)
sd_y=sd(ds_sorted$`Artist’s artwork price (in CNY)`, na.rm=TRUE)
sd_x
sd_y
ggplot(ds, aes(x=`Artist’s number of followers`,
               y=`Artist’s artwork price (in CNY)`)) +
         geom_point()


# Part 1: t-test
n_25pa=floor(nrow(ds_sorted) * 0.25)
bottom_25=ds_sorted %>% slice(1:n_25pa)
top_25=ds_sorted %>% slice((nrow(ds_sorted)-
n_25pa+1):nrow(ds_sorted))

bottom_25$group = "low"
top_25$group = "high"

ds_topbtm <- rbind(bottom_25, top_25)

t_test_sol <- t.test(`Artist’s artwork price (in CNY)` ~ group,
                     data = ds_topbtm)
print(t_test_sol)

# Part 1’s graph
ggplot(ds_topbtm, aes(x=group, y=`Artist’s artwork price (in CNY)`,
                      fill=group)) +
  geom_violin(alpha=0.4) +
  geom_boxplot(width=0.1, fill="grey") +
  theme_bw() +
  labs(title="Art Price Distribution by Follower Level",
       x="Group (Top vs Bottom 25%)",
       y="Price (CNY)")




# Part 2: Pearson Correlation Test
cor_sol=cor.test(ds_sorted$`Artist’s number of followers`,
                 ds_sorted$`Artist’s artwork price (in CNY)`,
                 method = "pearson")
print(cor_sol)

# Part 2’s graph
```

```
ggplot(ds_sorted, aes(x = `Artist’s number of followers`,
                      y = `Artist’s artwork price (in CNY)`)) +
  geom_point(alpha = 0.6, color = "steelblue") +
  geom_rug(alpha = 0.3) +
  theme_bw() +
  labs(title = "Correlation: Followers vs. Price",
       subtitle = "r = 0.21, p = 0.03 (N = 103)",
       x = "Followers",
       y = "Price")

#Part 2’s alternative(log-log):
cor_sollog=cor.test(log(ds_sorted$`Artist’s number of followers`),
                 log(ds_sorted$`Artist’s artwork price (in CNY)`),
                 method = "pearson")
print(cor_sollog)

# Part 2’s alternative version graph
ggplot(ds_sorted, aes(x = log(`Artist’s number of followers`),
                      y = log(`Artist’s artwork price (in CNY)`))) +
  geom_point(alpha = 0.5, color = "steelblue") +
  geom_rug(alpha = 0.3) +
  theme_bw() +
  labs(title = "Log-Log Correlation: Followers vs. Price",
       subtitle = "r = 0.28, p-value = 0.004 (N = 103)",
       x = "Log(Followers)",
       y = "Log(Price)")



# Part 3: SLRM with Robustness check
# Normal version
model_normal=lm(`Artist’s artwork price (in CNY)` ~
                  `Artist’s number of followers`,
                data=ds_sorted)

summary(model_normal)
# Graph
ggplot(ds_sorted, aes(x = `Artist’s number of followers`,
                     y = `Artist’s artwork price (in CNY)`)) +
  geom_point(alpha = 0.2, size = 1) +
  geom_smooth(method = "lm", color = "darkred", fill = "lightgray") +
  annotate("text", x = 3000, y = 600,
           label = "Price = 170.61 + 0.03 * Followers", color =
"darkred") +
  theme_light() +
  labs(title = "Simple Linear Regression Model",
       subtitle = "R-squared = 0.046, F-statistic = 4.85, P-value =
0.02994",
       x = "Independent Variable: Followers",
       y = "Dependent Variable: Price")
# Logarithm version
model_log=lm(log(`Artist’s artwork price (in CNY)`) ~
               log(`Artist’s number of followers`),
             data=ds_sorted)

summary(model_log)
# Graph
ggplot(ds_sorted, aes(x = log(`Artist’s number of followers`),
                      y = log(`Artist’s artwork price (in CNY)`))) +
  geom_point(alpha = 0.2, size = 1) +
  geom_smooth(method = "lm", color = "darkred", fill = "lightgray") +
```

```
  annotate("text", x = 6, y = 3,
           label = "log(Price) = 4.30 + 0.135 * log(Followers)",
           color = "darkred") +
  theme_light() +
  labs(title = "Simple Linear Regression Model (Logarithmic
Version)",
       subtitle = "R-squared = 0.080, F-statistic = 8.73, P-value =
0.00390",
       x = "Independent Variable: log(Followers)",
       y = "Dependent Variable: log(Price)")
```

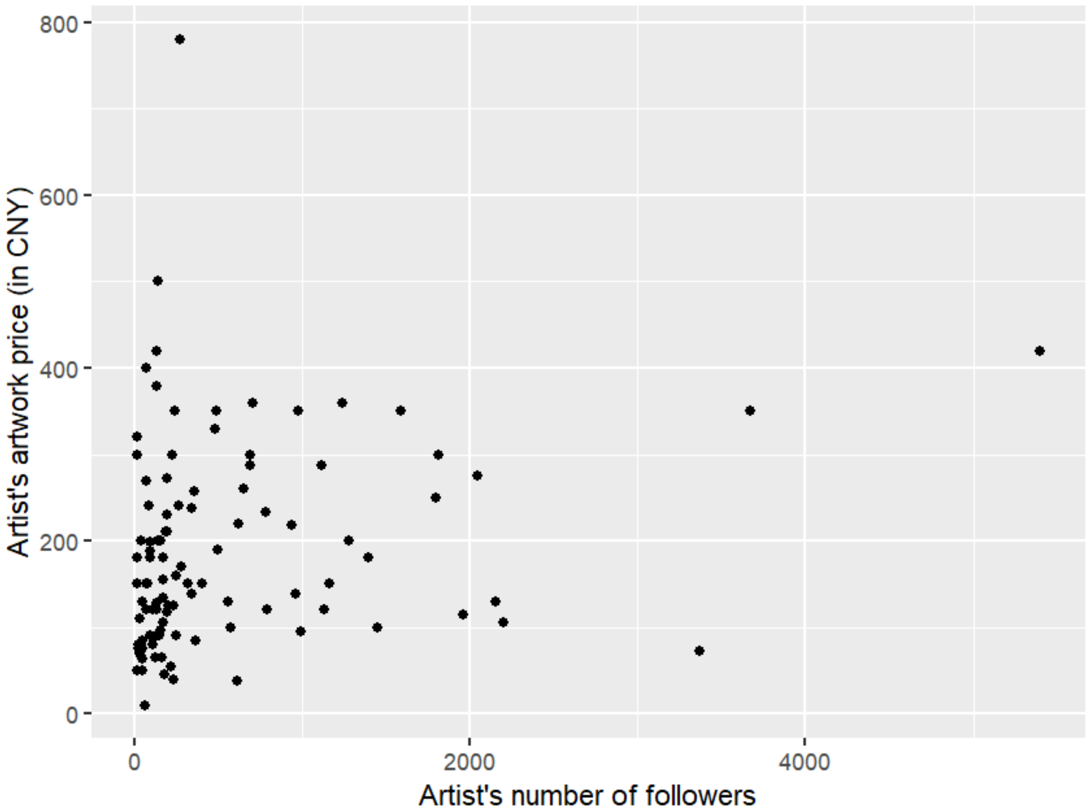
Note: The file path in command read_excel refers to the locally saved dataset, and the file itself can be retrieved and previewed in Appendix B above.

Appendix D: Basic statistical analyses tables and scatter plots (For Section 4.1)

```
  Artist No.       Artist's number of followers Artist's artwork price (in CNY)
 Min.    :  1.00   Min.    :  10.0              Min.    : 10.0
 1st Qu.: 28.50   1st Qu.:  91.5               1st Qu.: 99.0
 Median : 56.00   Median : 195.0               Median :150.0
 Mean   : 57.28   Mean   : 548.6               Mean   :187.4
 3rd Qu.: 84.50   3rd Qu.: 667.5               3rd Qu.:254.0
 Max.   :120.00   Max.   :5397.0               Max.   :780.0
```

```
> sd_x
[1] 837.0784
> sd_y
[1] 119.7565
```

Note: sd_x refers to the standard deviation of "Artist's number of followers", and sd_y refers to the standard deviation of "Artist's artwork price (in CNY)"




```
> summary(top_25)
   Artist No.      Artist's number of followers Artist's artwork price (in CNY)    group
 Min.   : 11.00   Min.   : 689                 Min.   : 73.0                   Length:25
 1st Qu.: 31.00   1st Qu.: 977                 1st Qu.:120.0                   Class :character
 Median : 60.00   Median :1279                 Median :218.0                   Mode  :character
 Mean   : 61.04   Mean   :1663                 Mean   :223.2
 3rd Qu.: 90.00   3rd Qu.:1961                 3rd Qu.:300.0
 Max.   :120.00   Max.   :5397                 Max.   :420.0
> summary(bottom_25)
   Artist No.      Artist's number of followers Artist's artwork price (in CNY)    group
 Min.   :  5.00   Min.   :10.00                Min.   : 10.0                   Length:25
 1st Qu.: 22.00   1st Qu.:20.00                1st Qu.: 75.0                   Class :character
 Median : 55.00   Median :41.00                Median :130.0                   Mode  :character
 Mean   : 58.64   Mean   :44.04                Mean   :147.7
 3rd Qu.: 91.00   3rd Qu.:67.00                3rd Qu.:198.0
 Max.   :119.00   Max.   :89.00                Max.   :400.0
```

Appendix E: Full *T-test* summary and figures (For Section 4.2)

```
        Welch Two Sample t-test

data:  Artist's artwork price (in CNY) by group
t = 2.6294, df = 47.637, p-value = 0.01148
alternative hypothesis: true difference in means between group high and group low is not equal to 0
95 percent confidence interval:
  17.76089 133.28711
sample estimates:
mean in group high  mean in group low 
           223.200            147.676 
```

Figures of the two-sample ***T-test*** result:

Appendix F: Full *Pearson Correlation Test* summary results (For Section 4.4)

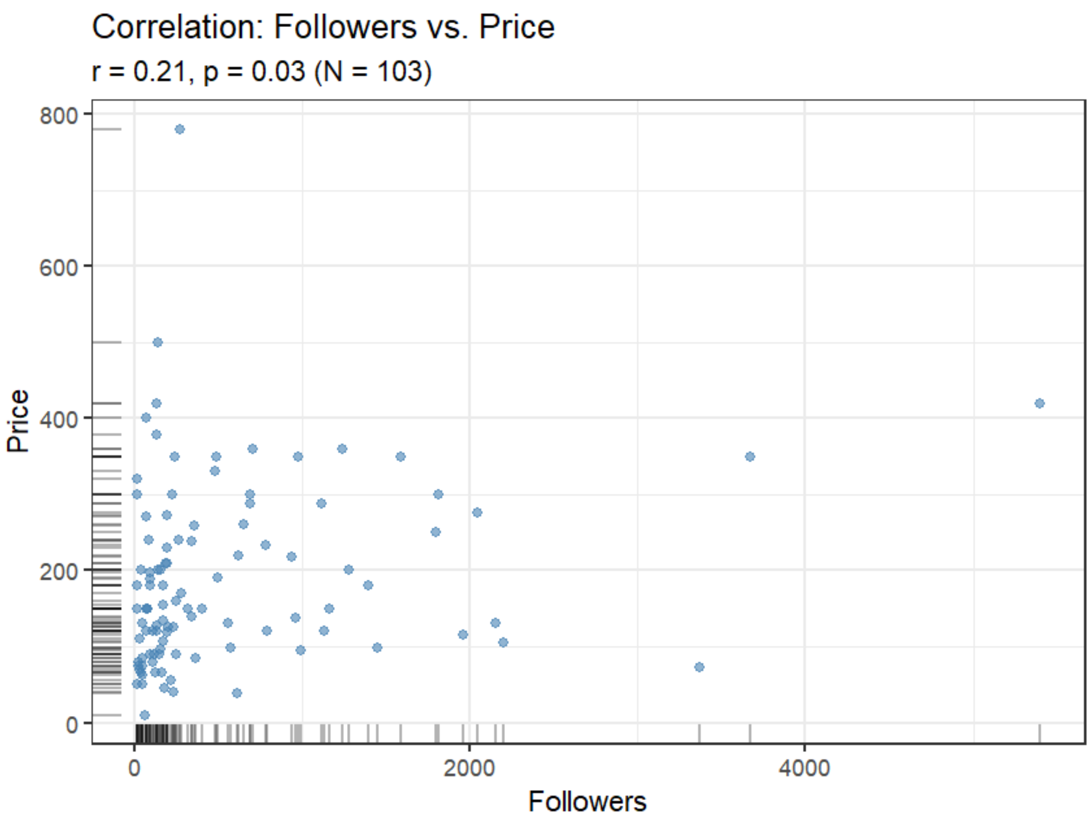
Note: The results below had applied two different datasets, tables and charts in **Series A** is using the original value of dataset, and outputs in **Series B** is using the logarithmic value of dataset.

Executive summary in **Series A:**

```
        Pearson's product-moment correlation

data:  ds_sorted$`Artist's number of followers` and ds_sorted$`Artist's artwork price (in CNY)`
t = 2.202, df = 101, p-value = 0.02994
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.02138959 0.39134361
sample estimates:
      cor
0.2140283
```

Plot with data distribution bar in **Series A**:

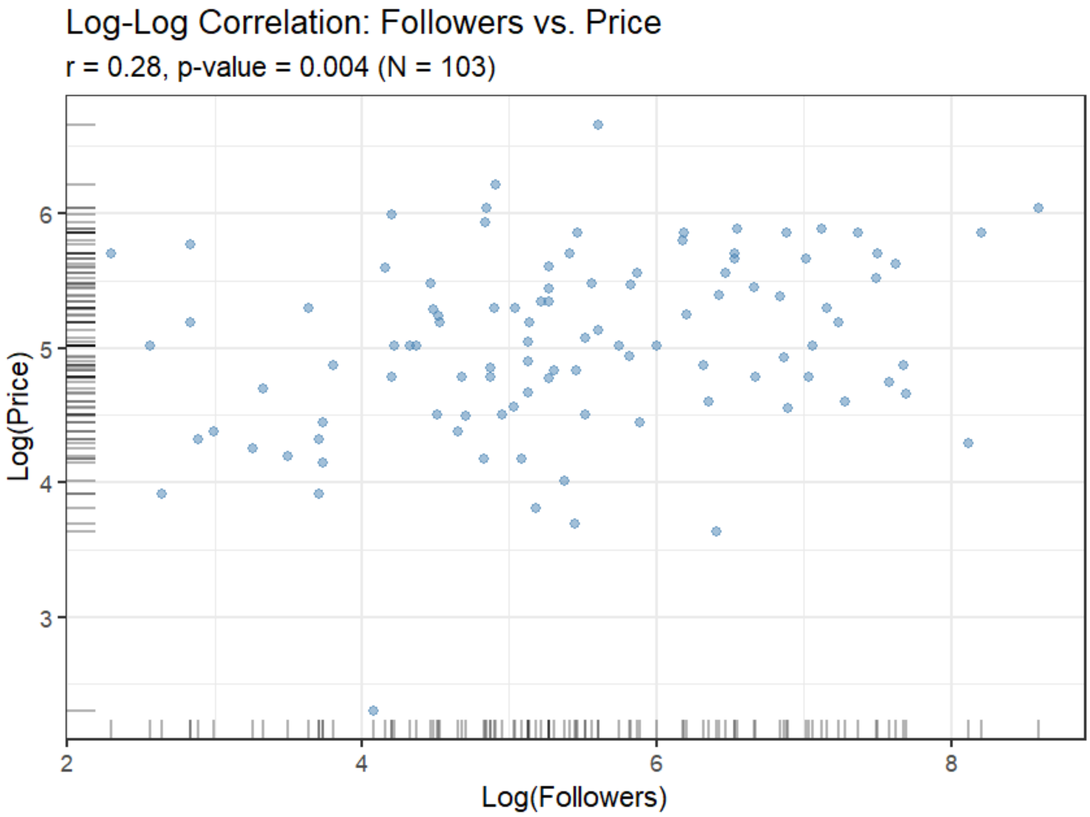


Executive summary in **Series B:**

```
        Pearson's product-moment correlation

data:  log(ds_sorted$`Artist's number of followers`) and log(ds_sorted$`Artist's artwork price (in CNY)`)
t = 2.9547, df = 101, p-value = 0.003895
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.09365354 0.45097346
sample estimates:
     cor
0.282066
```

Plot with data distribution bar in **Series B**:



Appendix G: Dataset comparison of P3's Simple Linear Regression Model (SLRM) and full SLRM reports (For Section 4.5)

Note: The results below had applied two different datasets, tables and charts in **Series A** is using the original value of dataset, and outputs in **Series B** is using the logarithmic value of dataset.

Executive summary in **Series A**:

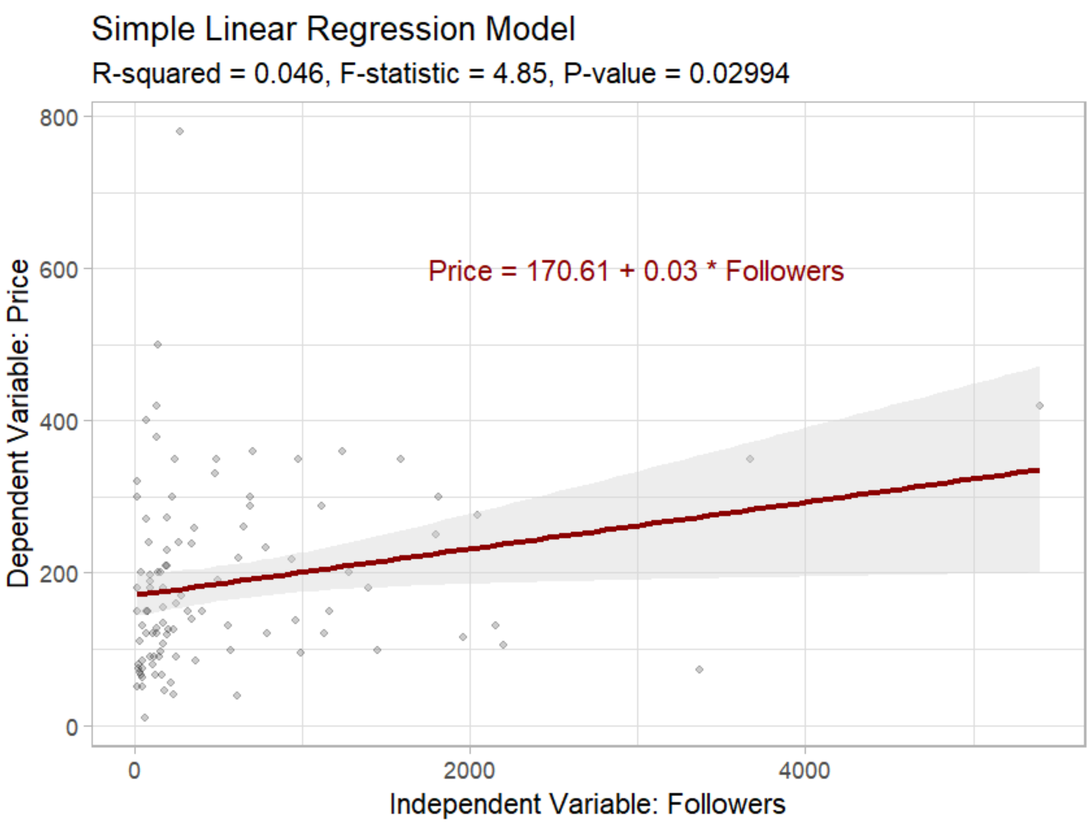
```
Call:
lm(formula = `Artist's artwork price (in CNY)` ~ `Artist's number of followers`,
    data = ds_sorted)

Residuals:
    Min      1Q  Median      3Q     Max
-200.67  -86.08  -22.93   64.10  601.09

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    170.60774   13.87007  12.300   <2e-16 ***
`Artist's number of followers`   0.03062    0.01391   2.202   0.0299 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 117.6 on 101 degrees of freedom
Multiple R-squared:  0.04581,	Adjusted R-squared:  0.03636
F-statistic: 4.849 on 1 and 101 DF,  p-value: 0.02994
```

Regression line and relationship formula plot in **Series A**:



Executive summary in **Series B**:

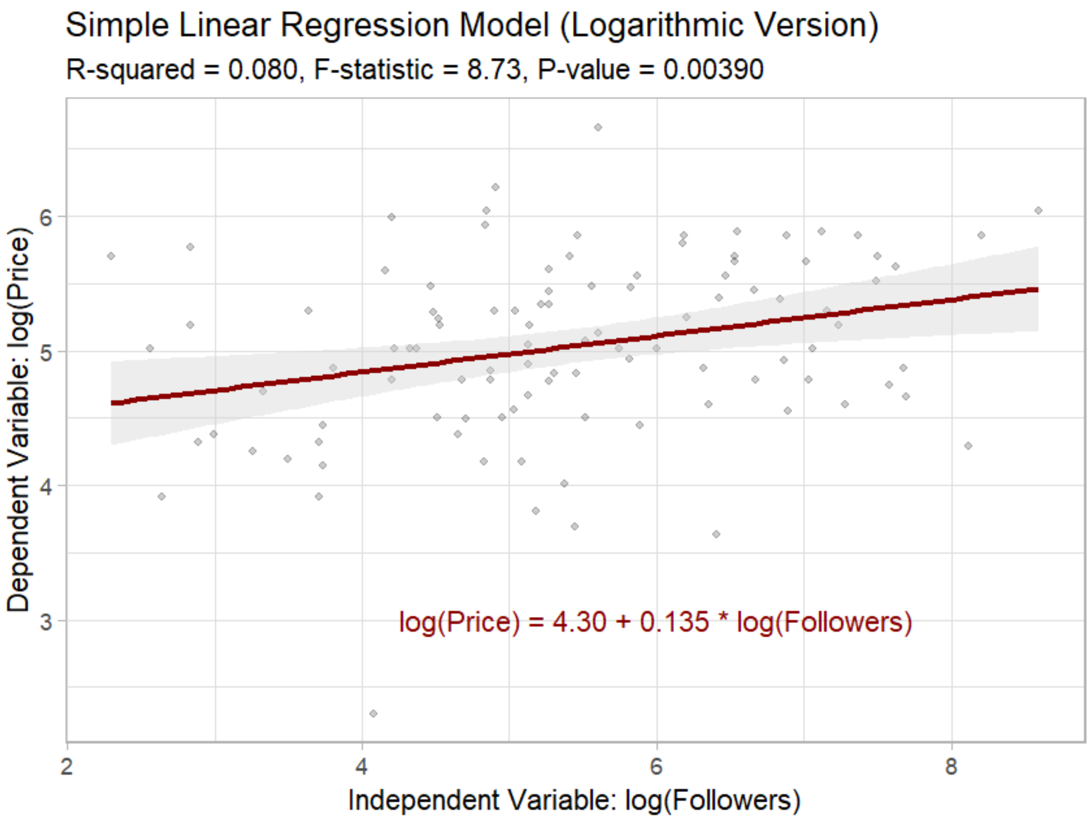
```
Call:
lm(formula = log(`Artist's artwork price (in CNY)`) ~ log(`Artist's number of followers`),
    data = ds_sorted)

Residuals:
     Min       1Q   Median       3Q      Max
-2.54941 -0.43250  0.04934  0.42714  1.60145

Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                           4.3014     0.2557  16.824  < 2e-16 ***
log(`Artist's number of followers`)   0.1350     0.0457   2.955  0.00389 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6486 on 101 degrees of freedom
Multiple R-squared:  0.07956,	Adjusted R-squared:  0.07045
F-statistic:  8.73 on 1 and 101 DF,  p-value: 0.003895
```

Regression line and relationship formula plot in **Series B**:



Appendix H: Generative AI Tools Applications

This research involves the application of generative AI tools (ChatGPT & Gemini) and AI search engines (Google AI search) for supporting the fetching of academic resources, discovering initial research ideas, validating academic writing, supporting programming, and evaluating the statistical collection procedures. The representative prompts and practical applications are as follow:

Fetching academic resources: *I have an argument of [argument], find some academic papers which is applicable as the evidence.* (Note: all academic resources are further evaluated by author by reading the journal/book/article page.)

Discovering initial research ideas: *Since I am planning to conduct quantitative research of digital art commission industry, how can I start on developing my literature review framework?*

Validating academic writing: *Please check out my content [paragraph], evaluate the critical grammar errors, word selection errors, and logical disconnection errors.*

Supporting programming: *Something wrong in generating the graph in R, [code], evaluate the bugs.*

Evaluating the statistical collection procedures: *Since I am applying the sequential data collection method, how to solve the issue of "there is a data line is not applicable" while collecting dataset?*

Apart from the listed applications above, the core research development in methodology, the analyses of theories as the main approach for developing the questions, the data analyses, and the discussion arguments and explanations are considered as the author's own work.