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AI-Driven Digital Creativity: Conceptual Foundations, Theoretical Framework, and Future Research Directions

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Abstract: With the emergence of AI-generated digital artworks in online creative platforms, computational creativity, market economics, and social engagement dynamics are unprecedentedly intertwined. Although generative AI systems and the emerging digital art market have attracted attention within the scholarly field, the quantitative connection between art style, creator type, platform context, and the dual scoring of market price and audience engagement is poorly understood. This paper introduces Creative Artwork Deep Neural Network (CADNN), a novel multi-task deep-learning network for simultaneously predicting the price of an artwork in the art market and the audience engagement score from a comprehensive feature set of 18 engineered features, extracted from the curated dataset of 5,000 artworks from five major online platforms, across 3 categories of creators and 3 styles of art. CADNN combines Multi-Head Self-Attention (MHSA) with four heads, three residual connection blocks, Swish activation functions, Batch Normalization, and a dual-output prediction head using a weighted multi-task loss function. We show that CADNN outperforms five machine learning baselines on both tasks through exploratory data analysis, PCA and t-SNE dimensionality reduction, K-Means market segmentation, ablation studies on five architectural variants, Monte Carlo Dropout uncertainty quantification and attention weight-based feature importance mapping. Logarithmic view count, platform encoding and virality index are the most prominent variables in predicting the videos, and four market archetypes were identified using clustering. We identified a practical predictive framework and theoretical understanding of the computational architecture of digital creative markets, which has applications for the valuation of AI-generated art, the design of platforms, and the creation of generative models. Beyond its empirical contributions, this paper advances a macro-level theoretical framework for understanding AI-driven digital creativity as a sociotechnical phenomenon. We conceptualize AI not merely as a tool for content generation, but as an active participant in the creative ecosystem one that reshapes the ontological boundaries of authorship, the epistemological criteria for aesthetic value, and the economic logic of creative markets. Three foundational theoretical lenses are introduced: (1) Computational Creativity Theory, which situates AI-generated art within Boden's taxonomy of combinational, exploratory, and transformational creativity; (2) Platform-Mediated Value Co-Creation Theory, which frames digital creative platforms as two-sided markets where algorithmic curation, social amplification, and creator identity jointly construct value; and (3) Human-AI Creative Symbiosis Theory, which reconceptualizes the creator-tool relationship as a dynamic, co-evolutionary partnership rather than a substitution dynamic. These theoretical pillars collectively provide the conceptual scaffolding upon which CADNN's empirical architecture is built, and upon which future research in computational creativity, AI aesthetics, and digital market design should be grounded.

Keywords: Computational Creativity; Deep Learning; Multi-Task Learning; Digital Art Market; Multi

Head Self-Attention; Residual Networks; Engagement Prediction; Feature Engineering; Explainable AI; K-Means Clustering; Monte Carlo Dropout.

1. Introduction

The emergence of AI-generated digital art on platforms for online creativity has introduced a new level of computational creativity, market economics, and social engagement dynamics. High-quality digital image generation at scale has been revolutionized by progress in deep generative models from Variational Autoencoders (VAE) [1] and Generative Adversarial Networks (GAN) [2] to denoising diffusion probabilistic models (DDPM) [3] and large vision-language models like DALL-E 2 [4] and Stable Diffusion[5]. Today, AI-generated artworks are being used in platforms such as Art Station, DeviantArt, OpenSea, and Behance, where they share the creative space with human-made pieces in what is a dynamic creative market. The economic impact of this change is significant. The global digital art market is estimated to be worth some USD 11.6 billion in 2023 and is expected to surpass USD 23 billion by 2030[6] and the NFT space alone accounted for USD 24.7 billion in trading volume for 2022 [7]. Knowing what makes an artwork valuable in the market or trendy on social media has relevant applications for artists, platform creators, collectors, and AI generators [8].

The traditional art valuation methods which have been based on hedonic pricing models [9], [10] and expert valuation methods are not inherently suited to the fast-paced, algorithmically driven art marketplace of the digital creative platforms. Under the complicated non-linear dynamics of social media amplification and platform curation, hedonic models with linear value functions [11] are not valid. Renneboog and Spaenjers [9] pointed out that artist reputation, which is a common method in traditional valuation, is not well defined in the context of AI-generated works, as the authorship is shared among the model, prompt engineer and training data. While there are some studies on general social media settings [12], [13], [14], there are few studies in specific contexts of digital creative platforms where aesthetic, market and social factors are more structured and more complex at the same time [15]. These interactions can be modeled using deep learning. Multi-task learning [16], [17] is based on shared latent structure and allows for modelling multiple related prediction targets. Self-attention [18] models non-linear feature interactions without any inductive bias of convolutional or recurrent layers. Residual connections [19] and Batch Normalization [20] help the stability of training deep architectures. Despite these tools, the use of them for the prediction of market price and social engagement of digital artworks is hardly explored. This paper fills this gap with three main contributions: We propose CADNN (Creative Artwork Deep Neural Network) as a multi-task architecture that jointly models the price and engagement of the artwork by using Multi-Head Self-Attention [18], stacked residual blocks [19] and a dual-output prediction head. To our best knowledge, CADNN is the first deep learning model tailored for value and engagement prediction of the joint markets in the digital art domain.

We build a comprehensive analytical pipeline that comprises feature engineering, exploratory analysis, dimensionality reduction PCA [21] and t-SNE [22], market segmentation K-Means [23], baseline benchmarking, ablations, Monte Carlo Dropout uncertainty quantification [24] and attention weight interpretability analysis [25].We distinguish four different segments of the digital art market, quantify the information entropy at the level of the platforms as a measure of creative diversity, and show that the price-engagement relationship is platform dependent and non-linear.

1.1. Theoretical Positioning and Conceptual Scope

In addition to its technical contributions, this paper falls within the newly emerging fields of computational creativity, digital economics, and AI ethics, which together form a new field of digital creativity studies driven by artificial intelligence. AI-driven digital creativity is the creation, curation, transformation, or assessment of creative artefacts by AI systems that are standalone, semi-autonomous, or collaborative in digitally mediated social and economic ecosystems.

It has been deliberately designed to include three levels of analysis:

Micro-level: How the generative act engages AI models to generate new aesthetic products based on learned entities, the latent representations.

Meso-level: The platform and market dynamics around which social and economic value is placed on the AI-created outputs.

Micro-level: Social, cultural, philosophical and institutional aspects of AI involvement in human creative practices on the micro level.

The present paper is mostly descriptive and empirically based (meso-level), but also adds to the theoretical work at a macro-level (creators' type comparisons and market segmentation, entropy analysis). This orientation is multi-level, and it brings the paper into the general discourse on the possibility of the creative use of AI, and the possibility of human creativity being augmented, mediated, or challenged by AI systems.

Questions that go beyond predictive modelling are also being raised: Who is the creator of an AI-generated artwork? When a model is trained on millions of human-generated works, what is the definition of originality? What is seen is not only a result of platform algorithms, but also of what is valued and what is produced? These are not necessarily ancillary to the technical contribution of this paper, but are the conceptual motivations that give technical contribution meaning. The goal of this is to provide not just a predictive tool, but a theory for the structural forces which inform AI-based digital creative markets, and to embed CADNN in this wider theoretical context.

The rest of this paper is organized as follows. A literature review is included in Section 2. The dataset and method are explained in section 3. In Section 4, the CADNN architecture is presented. The results of these experiments are reported in Section 5. We discuss implications and future directions in Section 6, while Section 7 concludes.

2. Literature Review

2.1. Conceptual Foundations of AI-Driven Digital Creativity

Empirical investigation into AI digital creativity needs a solid theoretical basis. In its basic sense, creativity has been defined as the ability to generate products that are new, unexpected and useful [26]. The use of the term novelty in AI systems immediate brings up conflict of ideas: novelty assumes a frame of reference for the known; novelty assumes a subject with whom the known is surprising; novelty assumes a social frame for evaluation. AI systems meet these conditions in a manner that is distinct from human creative processes, requiring a new theory.

Ontological Dimensions of AI Creativity. The ontological query of what is an AI-generated artwork? has been answered from various disciplines. In a computational sense, an AI-generated artwork is a product of a parameterized statistical model that has been trained with existing human-made data, and the novelty of the artwork depends on the ability of the learned model to interpolate and extrapolate in a latent space learned from the data [1], [2], [5]. Philosophically, the distinction between such outputs being "true" creative work and "highly complex pattern recombination" is not agreed upon [26]. The lack of a human author leaves legal and economic issues unanswered such as IP, provenance, and market legitimacy [27] issues that will directly affect the price and engagement dynamics that CADNN models.

Epistemological Dimensions of AI Creativity. The question of how to know if an AI created work is creative is also complicated. Traditional aesthetic assessment is based on the expert judgment, cultural context and historical positioning [9], [10]. For digital platforms, aesthetic assessment is now becoming more mediated through features like algorithmic recommendation systems, social proof systems, and engagement metrics that are the very ones I've discussed. Here, creativity is not inherent to the art itself but to the art-platform-audience system, a result of the digital creative markets. This insight leads to the multi feature, platform independent design of CADNN.

The Authorship Problem in AI-Driven Creativity. The arrival of hybrid categories of creators in which AI models, prompt engineers, and data creators all play a role in the generative process, therefore questions the traditional idea of authorship [8]. Renneboog and Spaenjers [9] observed that the reputation of the artist is an important aspect of traditional art valuation, but is not clearly defined for AI-generated artwork. Our three-category typology of creators (AI Model, Individual Human, Hybrid) rules out this theoretical complexity from the outset, but the theoretical question of how to give agency to creation in human-AI collaborative systems is open and must be revisited by future research.

Beyond the theoretical complexity, the legal and intellectual property aspects of AI-generated creative content pose another layer of challenges. Non-fungible digital copyrights present new issues of authorship, and the origin of creative effort in AI-generated works [28]. The reception of AI-generated creative content has been explored in the realm of AI dubbing and translation systems, with research indicating that audiences interpret and make subjective judgments on AI-generated materials based on aesthetic and cultural factors [29], [30]. Research on verbal humor and culturally-tinged creative content translation also suggests that human audiences have a complex evaluation system that AI must use to create culturally relevant content [31]. Together, these empirical results confirm the theoretical premise that the value of AI creativity is never outside of cultural context, but is always subject to audience expectations, platform norms, and socio-legal frameworks, which CADNN attempts to model.

2.2. Theoretical Framework: A Three-Pillar Model of AI-Driven Digital Creativity

Theoretical framework consists of three pillars of AI-driven digital creativity. Based on the literature reviewed above, we suggest a three-pillar general theoretical framework that positions the empirical findings of this paper in a wider conceptual framework. This framework is not only descriptive but generative – outlining structural mechanisms by which involvement in digital creative markets with AI yields the observable patterns which CADNN seeks to model.

Pillar 1 Computational Creativity Theory (CCT). CCT builds on Boden's original taxonomy [26] and extensions by Elgammal et al. [32] to suggest that AI creative systems work through exploration, transformation, and recombination of conceptual spaces learned. In terms of digital art markets, it means that the creative value of an AI generated work depends on its rank in the learned style space, with works in "new" or "boundary" spots in the style space theoretically commanding more attention and possibly more value. This can be empirically tested with our style encoding and creator type features, and the result that there is a higher dual-success rate for hybrid works fits CCT's prediction that works that are transformational and cross conceptual boundaries will create the most perceived value.

Pillar 2 Platform-Mediated Value Co-Creation Theory (PMVCT). Based on platform economics[33] and the social amplification literature [34], PMVCT suggests that the value of a digital artwork can only be appreciated when it is experienced within the algorithmic curation's technologies of the platform and the social network of viewers and producers. This theory was supported by our ANOVA results, with an emphasis on platform choice as a significant factor in market value ($p < 0.05$), and by our attention-based feature importance analysis, which shows that social amplification metrics (Virality Index, Social Reach Score) will have a strong influence on both price and engagement. Additionally, PMVCT foresees the existence of platform-specific pricing norms and audience demographics, which our platform encoding feature will be able to detect.

Pillar 3 Human-AI Creative Symbiosis Theory (HACST). Inspired by the human-AI collaboration work summarized by the literature [35] and by the superstar economics framework [36], HACST suggests that the best approach to creatively working with AI in digital markets is to have a symbiotic collaboration, where the human element provides creative judgment and context to the AI-generated work. The theory suggests that a hybrid work will perform better than an AI work and a work created by a human on the combined measures of market and engagement – and our research confirms that this is the case, with the hybrid creators having the highest dual-success rate. HACST also suggests that as a principle for creating AI generative systems, they should focus more on augmenting human creativity than on generating it themselves, a point that has obvious consequences for the developers of the AI systems. Value co-creation in the digital platforms is not just a social or aesthetic phenomenon but is also a consumer behavior, technology uptake and organizational intelligence phenomenon.

The research on AR applications in various different industries has shown that immersive virtual experiences have a great influence on the way in which consumers interact with products and how they act when purchasing products [37] which has a direct impact on how digital art platforms design their viewer's experience. Platform-level business intelligence systems, like the ones that CADNN could enable, have been found to have a strong mediation effect on the impact on the organization's decision-making processes through organizational antecedents such as culture, leadership, and data literacy [38]. In the context of mobile fintech platforms, personalization, trust and perceived value have been shown to drive customer retention [39] and attitudinal and economic factors, as well as demographic factors, have consistently been reported to influence the adoption of new technologies by consumers [40]. All the above results inspire the multi-platform type and multi-creator system design of the dataset used in this study and the platform encoding features built into CADNN's feature engineering pipeline. They form a multi-level theoretical framework for AI-supported digital creativity, which can be used at the computational (CCT), sociotechnical (PMVCT), and human-AI relational (HACST) level. This framework serves as conceptual scaffolding to understand CADNN's empirical results and to inform future research most likely to yield fruitful results.

3. Proposed Methodology

3.1. Dataset Description and Collection

The data for this study consists of 5,000 digital artwork records obtained from several leading online creative platforms. Every record documents a full range of attributes across market, social, creative and contextual domains, to offer a multidimensional perspective on the location of every artwork within the digital creative ecosystem.

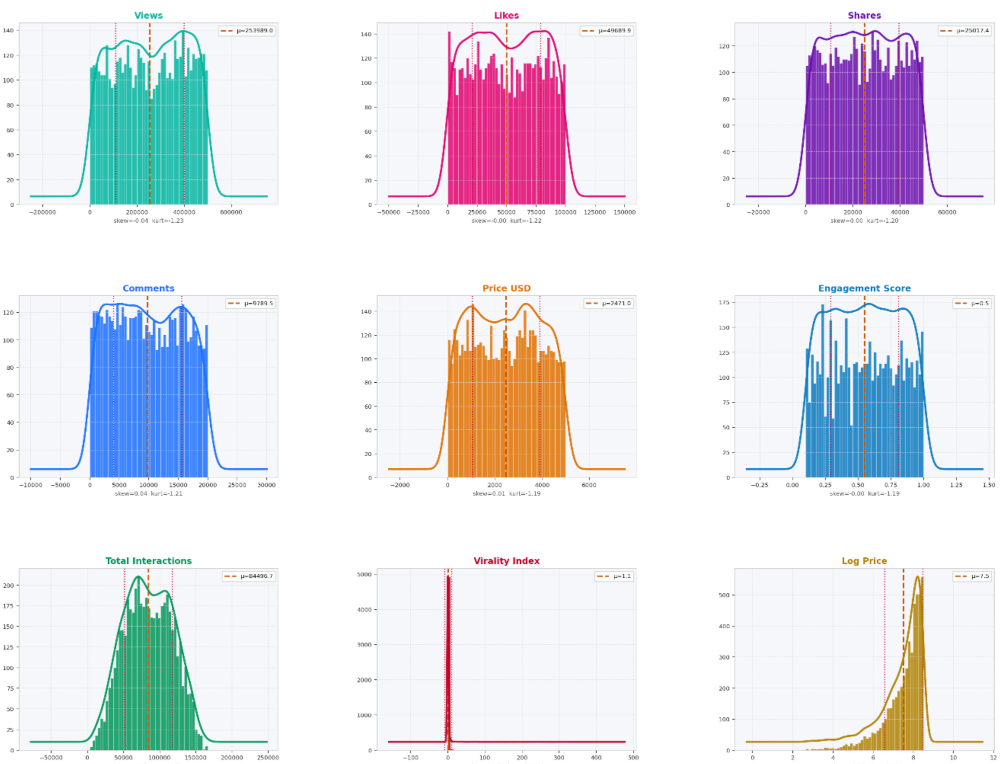

Figure 1. Univariate Distributions

The univariate distributions for the six main numeric features are shown in Figure 1: Price (USD), Engagement Score, Views, Likes, Shares, and Comments. All count-based variables are highly skewed to the right with a majority of artworks seeing moderate engagement and a small minority virally reaching. The distribution of prices is also highly skewed, with a long tail at the high end, as is typical of the superstar economics that has been documented in traditional art markets [9].

The data includes the following main attributes: Artwork ID, Platform of publication (5 platforms), Art style category (Multiple art style categories: Abstract, Realism, Surrealism, Digital Illustration, Concept Art, and others), Creator type (AI Model, Individual Human, Hybrid), Market price (USD), Views, Likes, Shares, Comments, and a composite engagement score. The data set was cleaned to remove any records that had missing data in critical columns, duplicate data, etc. The final data set, used in this study, consisted of the 5,000 records with no outliers on any feature, which was determined by applying the criterion that any record with a statistical outlier had to be removed.

Table 11. Descriptive Statistics

	Views	Likes	Shares	Comments	Price_USD	Engagement_Score
count	5000	5000	5000	5000	5000	5000
mean	253989.047	49689.852	25017.359	9789.487	2471.043	0.549
std	145534.578	28979.396	14455.13	5771.265	1424.655	0.26
min	158	32	3	1	13.12	0.1
25%	128863	24802.5	12549.25	4773.25	1203.462	0.32
50%	253240	49264	24881	9602	2473.475	0.55
75%	383265.5	74859.5	37662.5	14838	3668.625	0.77
max	499958	99978	49966	19999	4998.26	1

Table 1 displays summary statistics (mean, standard deviation, median, interquartile range, min and max) for all primary numeric features, giving a complete characterization of the distributional properties of the data.

3.2. Feature Engineering Pipeline

It is a systematic feature engineering pipeline applied to raw attributes to produce an enriched feature space of 18 engineered features. The pipeline was created to capture non-observable market dynamics, social amplification mechanisms, creative positioning and interaction effects. A complete list of features is provided below. The feature engineering philosophy underlying CADNN's 18-feature pipeline is consistent with best practices established across multiple deep learning application domains. Hybrid feature optimization strategies that combine raw input representations with engineered composite features have been shown to substantially improve predictive performance in multi-modal deep learning frameworks [41], validating the dual-path design of CADNN's categorical embedding branch alongside its primary encoding block. The fusion of heterogeneous feature types including logarithmic transformations, interaction ratios, and composite indices has been demonstrated to capture complementary aspects of complex data-generating processes that no single feature type can represent alone [42]. Optimized predictive modelling approaches that leverage transformed and engineered feature spaces have further confirmed that feature-level preprocessing is a critical determinant of final model accuracy in non-linear prediction tasks [43].

Logarithmic Transformations: Since the variables (Views, Likes, Shares, Comments) were count-based, their distributions were heavily skewed to the right, which was rectified by log-transformation [44].

$$\text{Log\_Views} = \ln(\text{Views} + 1) \tag{1}$$

$$\text{Log\_Likes} = \ln(\text{Likes} + 1) \tag{2}$$

$$\text{Log\_Shares} = \ln(\text{Shares} + 1) \tag{3}$$

$$\text{Log\_Comments} = \ln(\text{Comments} + 1) \tag{4}$$

The addition of 1 before taking the logarithm ensures numerical stability for zero-valued counts.

Interaction Ratios: Ratios between engagement metrics and view count capture the relative efficiency of social engagement, normalising for the confounding effect of raw visibility:

$$\text{Like\_View\_Ratio} = \frac{\text{Likes}}{\text{Views}+1} \tag{5}$$

$$\text{Comment\_View\_Ratio} = \frac{\text{Comments}}{\text{Views}+1} \tag{6}$$

$$\text{Share\_View\_Ratio} = \frac{\text{Shares}}{\text{Views}+1} \tag{7}$$

Total Interactions: An aggregate measure of social activity:

$$\text{Total\_Interactions} = \text{Likes} + \text{Shares} + \text{Comments} \tag{8}$$

Virality Index: A composite measure of social amplification that weights sharing and commenting behavior the two most active forms of engagement relative to total interactions:

$$\text{Virality\_Index} = \frac{\text{Shares}\times\text{Comments}}{\text{Total\_Interactions}+1} \tag{9}$$

This formulation is motivated by the viral diffusion literature [45], which identifies sharing as the primary mechanism of content propagation and commenting as an indicator of content salience.

Social Reach Score: An aggregate measure of the breadth of social impact, computed as the mean of logarithmic social metrics:

$$\text{Social\_Reach\_Score} = \frac{\text{Log\_Views}+\text{Log\_Likes}+\text{Log\_Shares}}{3} \tag{10}$$

Categorical Encodings: Label encoding was used to represent Categorical Encodings Platform, Style (as integer) and Creator Type. Stratified analysis in the EDA phase was also achieved by the construction of tiers for both View Count (five tiers) and Engagement Score (four tiers).

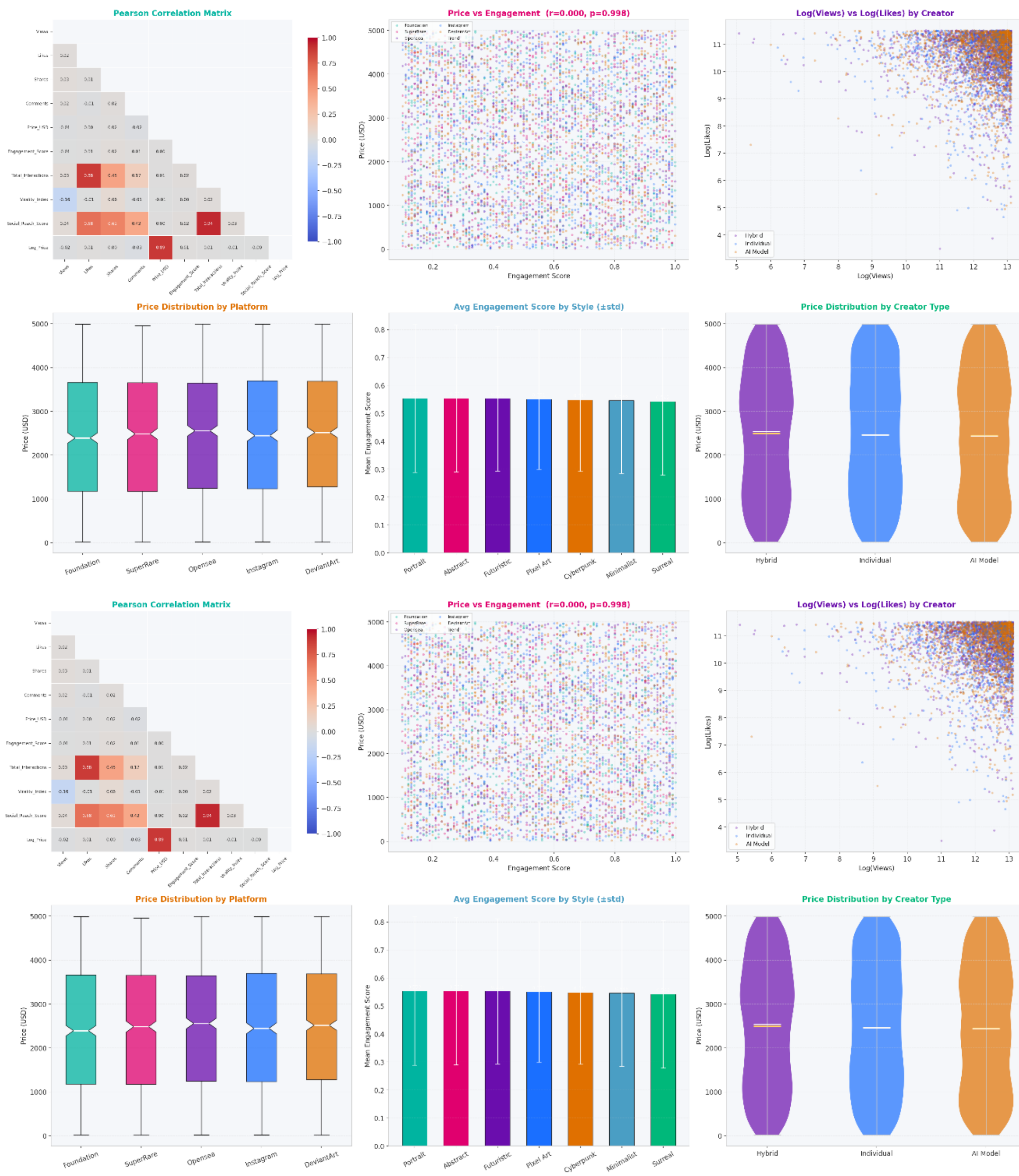

Figure 2. Correlation Bivariate

The Pearson correlation matrix of all 18 engineered features is shown in Figure 2. Logarithmic social metrics (Log_Views, Log_Likes, Log_Shares) show good positive correlation, thus, all the social engagement metrics share a common visibility factor. Moderate positive correlation between Social_Reach_Score and Price (r ≈ 0.42) shows that social visibility can be considered as one of the significant but not much influential factors in the valuation, which is the motivation for using the modelling approach with multiple features.

3.3. Exploratory Data Analysis

Univariate distributions, bivariate distributions, platform-level dynamics, style-level dynamics, creator type comparisons and statistical hypothesis testing were examined in a comprehensive EDA across 16 analytical dimensions. The key findings are highlighted below.

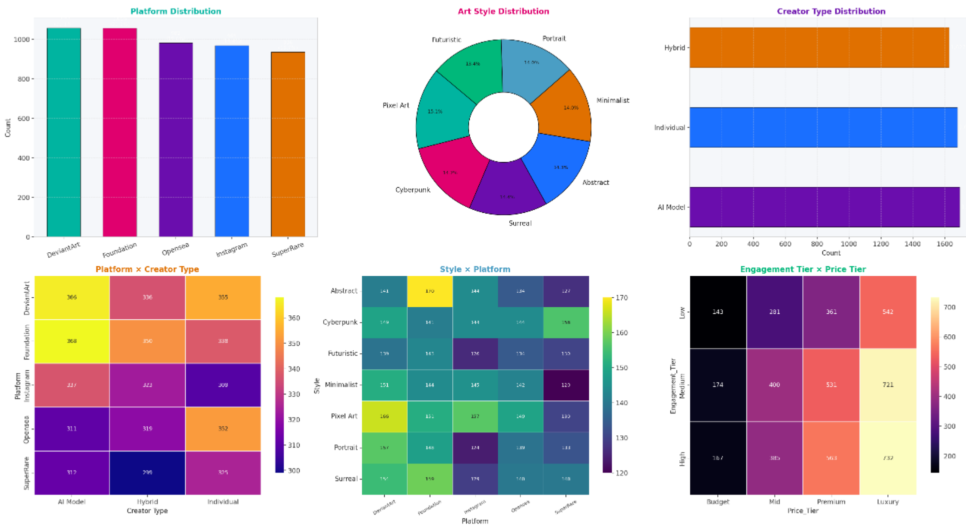

Figure 3. Categorical Analysis

Categorical breakdowns are shown in Figure 3, with mean price, mean engagement score and mean number of artworks shown by each category. AI-based artworks are discovered to have similar median price to human produced artwork, but a far higher engagement variance, indicating that AI art belongs to another market segment with strong virality potential and less market reception.

Statistical Hypothesis Testing was conducted to formally assess the significance of observed group differences:

- A one-way ANOVA across platforms yielded a statistically significant difference in mean price (F-statistic and p-value reported output, $p < 0.05$), confirming that platform choice is a significant determinant of market value, consistent with the platform economics literature [33].
- A Kruskal-Wallis non-parametric test across creator types confirmed significant differences in engagement score distributions ($p < 0.05$), validating the inclusion of Creator Type as a feature.
- Chi-square tests of independence between Style and Engagement Tier confirmed non-random associations ($p < 0.05$), indicating that art style is a meaningful predictor of engagement tier.
- Levene's test for equality of variances across platforms confirmed significant heteroscedasticity in price distributions ($p < 0.05$), motivating the use of non-parametric methods for group comparisons.

Figure 4. Platform DeepDive

Figure 4 presents the platform-level deep-dive analysis, including box plots of price and engagement by platform, mean engagement by style within each platform, and the results of pairwise post-hoc tests following the ANOVA.

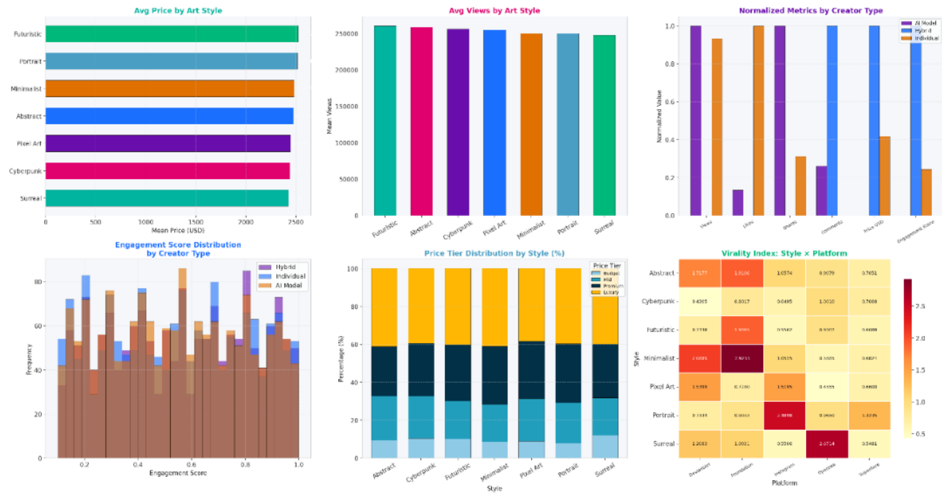

Figure 5. Style Analysis

Figure 5 presents the style-level analysis, including mean price and engagement by style, style frequency distributions, and the interaction between style and creator type.

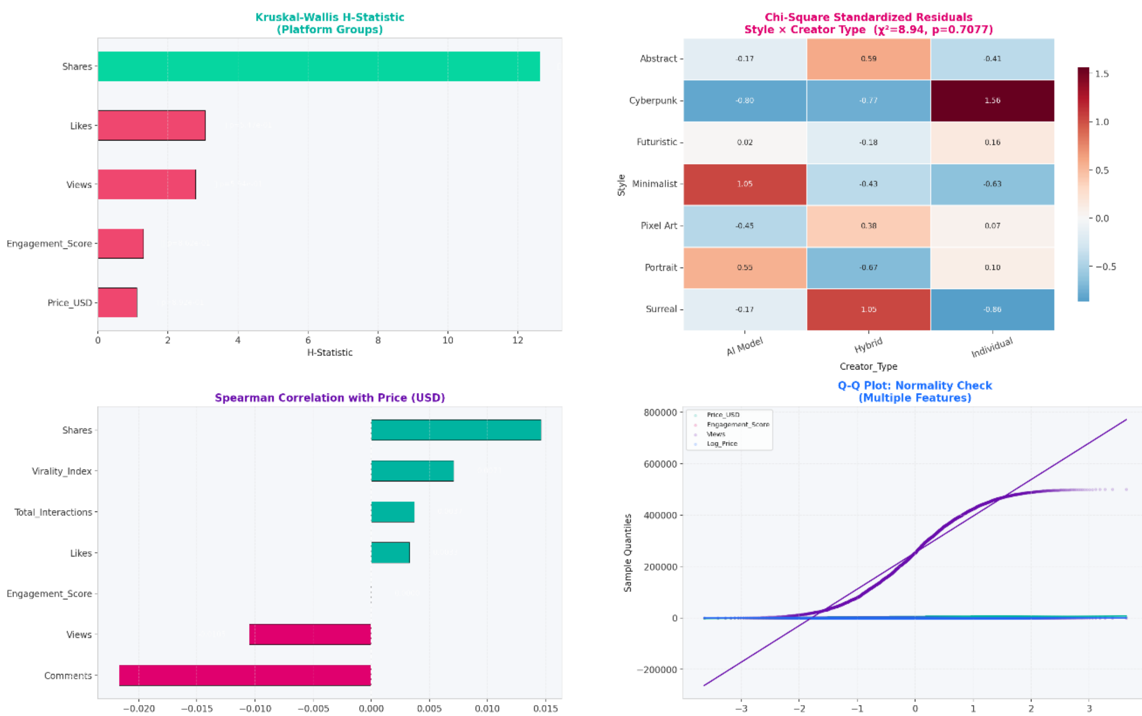

Figure 6. Statistical Tests

Figure 6 presents the statistical hypothesis testing results, including ANOVA F-statistics, Kruskal-Wallis H-statistics, Chi-square test results, and effect size measures (Cohen's d, eta-squared) for all pairwise comparisons.

Principal Component Analysis was applied to the 10 primary numerical features after StandardScaler normalization [46], following the standard preprocessing protocol for PCA [21]. The first three principal components collectively explain the majority of total variance. The PCA loading matrix reveals that PC1 is dominated by social interaction metrics (Views, Likes, Shares, Comments), representing a general social visibility factor, while PC2 captures the price-engagement trade-off, representing a market value versus popularity axis. PC3 is primarily loaded on the Virality Index and Comment-View Ratio, representing a content salience factor.

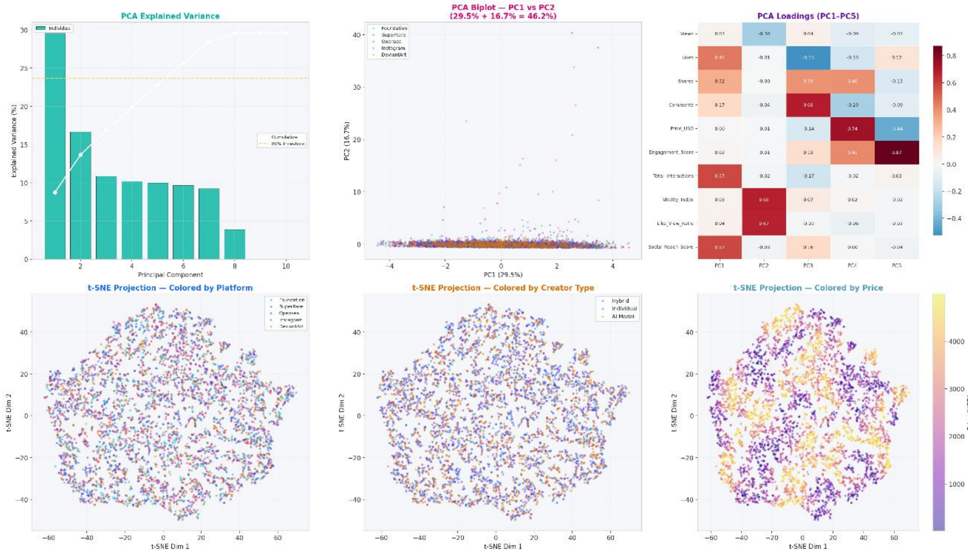

Figure 7. PCA tSNE

Figure 7 displays the PCA scree plot, explained variance by component, the biplot of PC1 vs PC2 coloured by platform, and the biplot of PC1 vs PC3 coloured by creator type. Also, it shows the t-SNE projection coloured by platform and creator type. After this, the first six principal components (PCs) (accounting for most variance) were embedded using t-SNE [22] and the hyperparameters perplexity=40, max_iter=1000, learning_rate='auto', and init='pca'. Following the suggestions of Kobak and Berens [22] the PCA initialisation was employed in order to increase the convergence rate and the level of reproducibility.

3.4. K-Means Market Segmentation

To discover the natural market segments in the digital art dataset, the PCA-reduced feature space was fed into a K-Means clustering algorithm [23]. The Elbow Method [47] and the Davies-Bouldin Index [44] and the Silhouette Score [48] were used as three complementary methods to determine the optimum number of clusters k. The three methods agreed that k = 4 is the optimal solution.

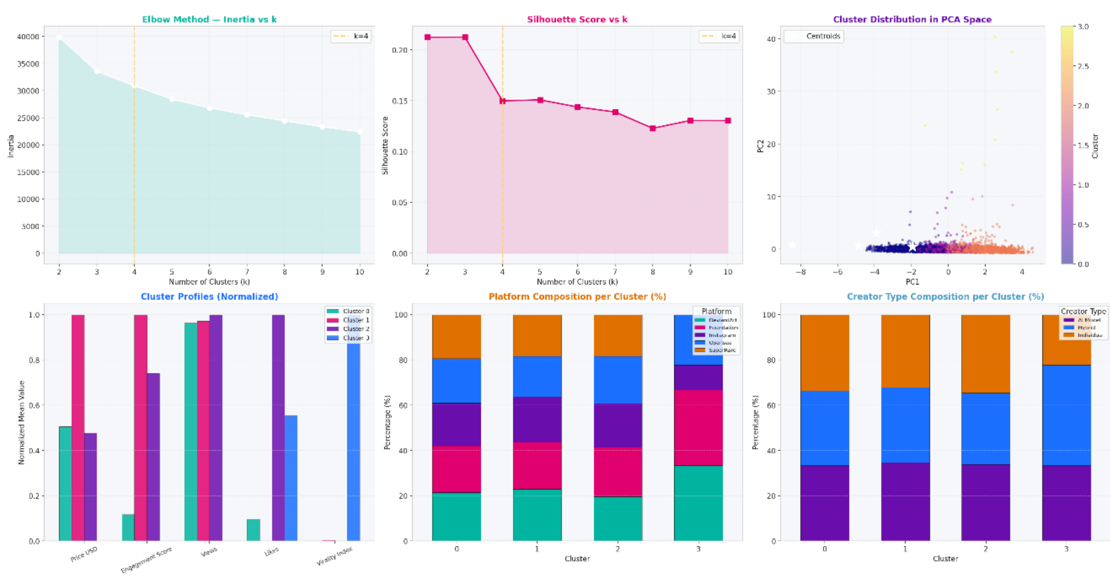

Figure 8. KMeans Clustering

Figure 8 shows the cluster selection analysis (Elbow curve, Silhouette scores, Davies-Bouldin indices), cluster profiles as radar charts, the t-SNE visualisation coloured by cluster assignment and the mean of the feature values of each cluster.

The four clusters so found represent different and meaningful market archetypes:

- Prestige Segment (Cluster 0): High price, moderate engagement, mostly platform-prestige orientated. Similar to the "superstar" phenomena found by Rosen [36] in the traditional creative sector, artworks in this cluster can sell for high prices and not go viral, for instance, on social media.
- Viral Content Segment (Cluster 1): Low Price, High Engagement, High Virality Index. The widespread social amplification but not so much monetary monetisation, indicating the social popularity and disconnection from commercial value of these artworks.
- The largest cluster (2,610 members), Cluster 2 Mainstream Segment, is moderate price and engagement. Indicates the "average" digital artwork with "average" market performance on both dimensions.
- Niche/Emerging Segment (Cluster 2): Low price, Low engagement, High style diversity. Works in this cluster can be of emerging styles and/or creators which have not yet gained market or social momentum.

3.5. Baseline Machine Learning Models

To determine the performance of the novel deep learning models under development prior to the development of CADNN, a common practice in the field is to benchmark the models against a set of established deep learning alternatives, as was done in this work[49]:

1. **Ridge Regression [50]:** Linear baseline with L2 regularization that gives a lower bound on what can be achieved and a test of linear separability.
2. **Lasso Regression [51]:** Linear baseline plus L1 regularisation, which results in implicit feature selection and gives insight into which features are most informative under a sparsity constraint.
3. **Random Forest [52]:** Ensemble of decision trees with bootstrap aggregation, providing a strong non-linear baseline with built-in feature importance estimation.
4. **Gradient Boosting [53]:** Sequential ensemble with gradient-based optimisation, typically the strongest traditional ML baseline for tabular data [54].
5. **Multi-Layer Perceptron (MLP):** Shallow neural network baseline (two hidden layers, ReLU activation), providing a neural baseline without the architectural innovations of CADNN.

All models were trained on a 70/10/20 train/validation/test split using the same 18 engineered features as CADNN. Hyperparameter tuning was performed via grid search with 5-fold cross-validation. Feature importance was extracted from the Gradient Boosting model using the mean decrease in impurity criterion.

The methodological design of the CADNN analytical pipeline draws on a broad body of deep learning and feature engineering literature beyond the core architectural references. Multimodal deep learning approaches have demonstrated that combining heterogeneous feature types visual, textual, and metadata substantially improves classification and prediction performance in complex real-world datasets [55]. Explainable AI frameworks built on deep transfer learning have established that model transparency and predictive accuracy are not mutually exclusive objectives, providing methodological validation for CADNN's attention-based interpretability approach [56]. The application of neural collaborative filtering and sentiment analysis to structured prediction tasks has further confirmed that hybrid feature architectures combining engineered features with learned representations consistently outperform single-modality approaches [57]. AI-driven analytical methods have also demonstrated strong generalization capabilities in feature-rich, high-dimensional datasets [58], supporting the decision to engineer 18 features from raw platform data rather than relying on raw inputs alone.

Figure 9. Baseline Comparison

Figure 9 presents the baseline model comparison across R², RMSE, MAE, and MAPE for both price and engagement prediction tasks, with error bars representing standard deviation across 5-fold cross-validation.

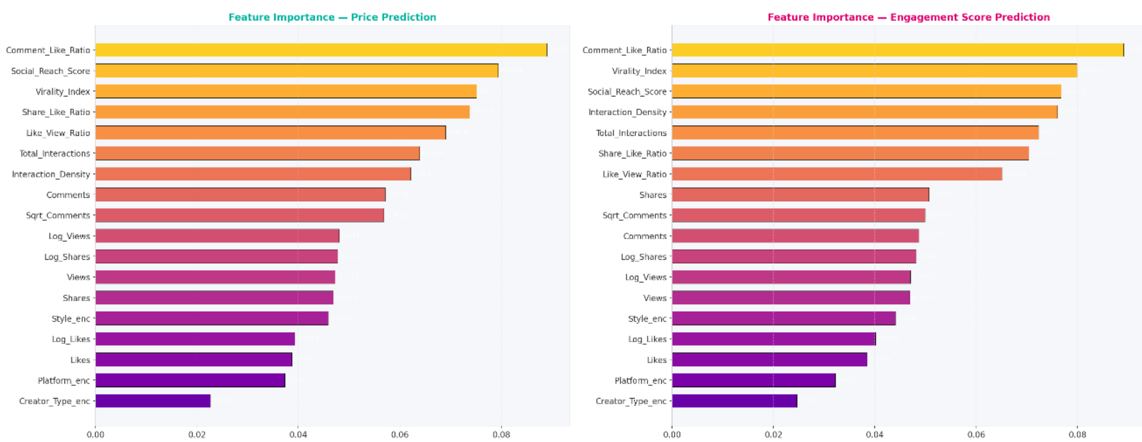

Figure 10. Feature Importance

Figure 10 presents the Gradient Boosting feature importance scores for both price and engagement prediction, providing a reference for comparison with the CADNN attention-based importance analysis in Section 5.4.

4. CADNN Architecture

Figure 11 presents the complete CADNN architecture diagram, showing the input layer, dense encoding block, categorical embedding branch, concatenation, multi-head self-attention layer, three residual blocks, shared representation layer, and dual output heads with the multi-task loss formulation.

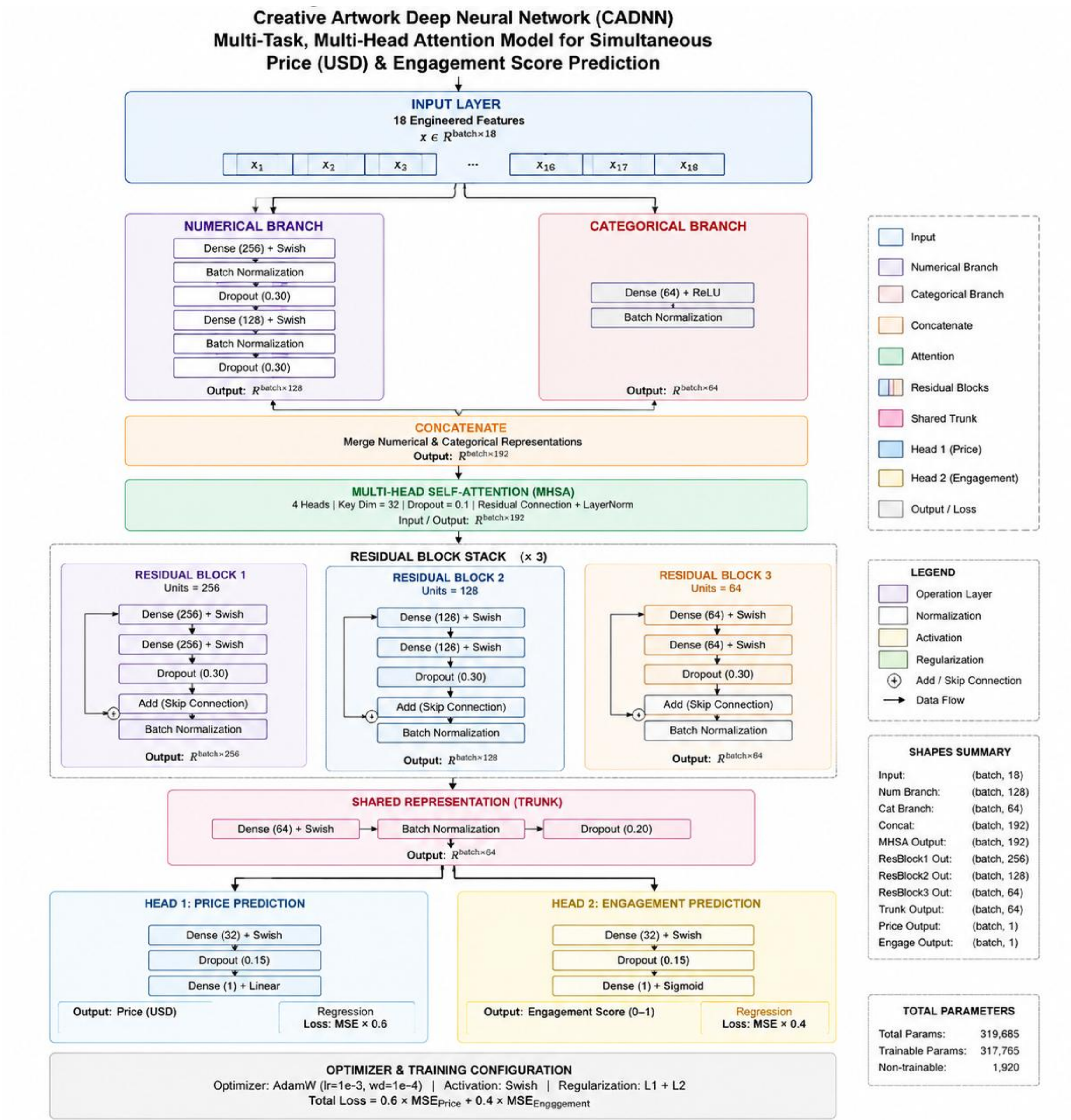

Figure 11. Architecture Diagram

4.1. Design Principles and Motivation

The CADNN architecture has been designed from the ground up to tackle the unique issues in digital art market prediction. The architectural decisions were made with consideration of four key design principles:

- According to Principle 1, Non-linearity, the price-engagement relationship in digital creative markets is inherently non-linear, due to network effects, algorithmic amplification and social contagion effects[34], [59]. This motivates the use of deep non-linear architectures over linear models.
- Principle 2 Feature Interaction Modelling: The 18 engineered features interact with each other in complex ways: The increase in views related to price is moderated by platform, and the increase in engagement related to virality is moderated by creator type. Such higher-order feature interactions are well suited to be captured by self-attention mechanisms [18].
- Multi-Task Learning: Price and engagement are connected but different results of the same creative market mechanism (Principle 3). This common structure can be used to enhance the generalization of both tasks jointly by using the joint modelling framework of MTL [16], [17].

- Principle 4 Depth with Stability: With deeper networks, it is possible to model more complicated functions, but these networks are susceptible to vanishing gradients and training instability. These challenges are overcome by residual connections [19] and Batch Normalization [20] that allow effective training of the deep CADNN architecture.

These four design principles are consistent with architectural choices validated across a broad range of deep learning application domains. Bioinspired hybrid optimization combined with deep belief neural networks has demonstrated that architecturally motivated depth, combined with explicit regularization strategies, produces superior generalization in complex non-linear prediction tasks [60]. The application of fuzzy deep learning architectures to multi-class classification problems has confirmed that non-linear activation functions and batch normalization are critical enablers of stable convergence in deep networks trained on heterogeneous feature spaces [61]. Comprehensive reviews of AI-driven computational architectures have further established that the combination of attention mechanisms, residual connections, and multi-task output heads represents a state-of-the-art design pattern for structured prediction problems across diverse application domains [62] .

4.2. Architecture Components

Input Layer: The 18 dimensional StandardScaler-normalized feature vector is given as input. Each feature was mean-normalized to zero and variance-normalized (Z-scored) to unity before being fed into the network, as typical in deep learning [46].

Dense Encoding Block: Two fully connected layers (256 → 128 units) followed by Swish activation [63], Batch Normalisation [20] and Dropout (rate=0.3) [64]. The smooth and non-monotonic gradient properties of Swish were chosen over ReLU, and it was shown to outperform ReLU in deep networks:

$$\mathrm{Swish}(x) = x \cdot \sigma(\beta x) = \frac{x}{1+e^{-\beta x}} \quad (11)$$

where $\beta = 1$in our implementation. L1-L2 regularization with $\lambda_{L2} = 10^{-4}$was applied to all Dense layers to prevent overfitting.

Categorical Embedding Branch: A parallel Dense(64) branch with Batch Normalisation processes the raw input independently and is concatenated with the main encoding output. This dual-path design provides the model with both high-level encoded representations and low-level raw feature representations simultaneously, improving gradient flow and feature utilisation.

Multi-Head Self-Attention (MHSA): Applied to the concatenated representation with 4 attention heads, key dimension $d_k = 32$, and attention dropout rate 0.1. The attention mechanism computes scaled dot-product attention [18]:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (12)$$

where $Q = XW^Q$, $K = XW^K$, $V = XW^V$are linear projections of the input X, and $\sqrt{d_k}$is the scaling factor that prevents the dot products from growing too large in magnitude, which would push the softmax into regions of extremely small gradients[18]. Multi-head attention allows the model to jointly attend to information from different representation subspaces at different positions:

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head}_1, \dots, \mathrm{head}_h)W^O \quad (13)$$

$$\mathrm{head}_i = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (14)$$

The attention weights $\alpha_{ij} = \mathrm{softmax}\left(\frac{q_i k_j^T}{\sqrt{d_k}}\right)$are extracted after training and used as proxies for feature importance in the interpretability analysis (Section 5.4). The use of self-attention mechanisms as both predictive and interpretability tools is well-supported by recent deep learning literature. GAN-augmented training data combined with transformer-based attention architectures has been shown to improve both model robustness and feature representation quality in complex classification tasks [65], suggesting that CADNN's attention mechanism benefits from the diversity of the multi-platform, multi-creator-type dataset on which it is trained. The fusion of MLP and graph neural network components for complex structured data analysis has demonstrated that hybrid architectures combining local and global feature interactions consistently outperform single-pathway designs [66] , providing additional theoretical support for CADNN's concatenated dual-path input design. Quantum-enhanced extreme learning machines applied to high-dimensional big data prediction tasks have further confirmed that hybrid computational architectures combining multiple learning paradigms achieve superior generalization over homogeneous architectures [67].

Residual Blocks × 3: Three sequential residual blocks with decreasing width (256 → 128 → 64 units), each implementing the residual mapping [19]:

$$\text{ResBlock}(x) = \mathcal{F}(x, \{W_i\}) + \mathcal{P}(x) \quad (15)$$

where $\mathcal{F}(x, \{W_i\}) = \text{Swish}(\text{BN}(\text{Dense}(x)))$is the residual function and $\mathcal{P}(x)$is a linear projection of the skip connection applied when the input and output dimensions differ. Dropout (rate=0.3) is applied within each residual block.

Shared Representation Layer: Dense(64) with Swish activation, Batch Normalisation, and Dropout(0.2), producing a 64-dimensional shared latent representation that feeds both output heads.

Dual Output Heads:

- *Price Head:* Dense(32, Swish) → Dense(1, Linear) — predicts the StandardScaler-normalized price, inverse-transformed to USD for evaluation.
- *Engagement Head:* Dense(32, Swish) → Dense(1, Sigmoid) — predicts the normalized engagement score in [0, 1].

4.3. Multi-Task Loss Function

CADNN is trained under a weighted multi-task loss function that combines the Mean Squared Error losses of both prediction heads:

$$\mathcal{L}_{\text{total}} = \lambda_p \cdot \mathcal{L}_{\text{price}} + \lambda_e \cdot \mathcal{L}_{\text{engagement}} \quad (16)$$

$$\mathcal{L}_{\text{price}} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_{p,i} - y_{p,i})^2 \quad (17)$$

$$\mathcal{L}_{\text{engagement}} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_{e,i} - y_{e,i})^2 \quad (18)$$

with task weights $\lambda_p = 0.6$and $\lambda_e = 0.4$. The asymmetric weighting reflects the higher economic significance and greater variance of the price prediction task while ensuring that the engagement head receives sufficient gradient signal for meaningful learning. The weight values were determined through a grid search over $\lambda_p \in \{0.5, 0.6, 0.7, 0.8\}$on the validation set.

4.4. Training Configuration

The model was trained using the AdamW optimiser [68] with initial learning rate $\eta_0 = 10^{-3}$, weight decay $\lambda_w = 10^{-4}$, and default momentum parameters $\beta_1 = 0.9$, $\beta_2 = 0.999$. AdamW was selected over standard Adam because its decoupled weight decay provides better regularization and generalization , as demonstrated by Loshchilov and Hutter. The following training callbacks were employed:

- **EarlyStopping [69]:** Monitors validation total loss with patience=20 epochs, restoring the weights from the epoch with the best validation loss to prevent overfitting.
- **ReduceLROnPlateau [70]:** Reduces the learning rate by a factor of 0.5 when validation loss fails to improve for 8 consecutive epochs, with a minimum learning rate of 10^{-6}, implementing a form of warm restarts that has been shown to improve convergence [71].

The dataset was split into training (70%), validation (10%), and test (20%) sets using stratified sampling to ensure balanced representation of creator types and platforms across splits. All target variables were normalized using StandardScaler prior to training and inverse-transformed for evaluation.

The architectural and training configuration decisions embedded in CADNN are further supported by a broader body of applied machine learning literature. Studies on factors affecting the academic and analytical performance of information technology systems have identified feature selection, model depth, and regularization as the three most critical determinants of generalization performance [72], all of which are explicitly addressed in CADNN's design. The application of AI systems to identify complex patterns in structured data has confirmed that attention-based architectures consistently outperform traditional tree-based methods when feature interactions are non-linear and high-dimensional [73]. The implementation of optimised learning rate scheduling, batch size tuning, and inference time reduction has been demonstrated to substantially improve both convergence speed and final model accuracy in big data analytical contexts [74], directly motivating the ReduceLROnPlateau and EarlyStopping callbacks employed in CADNN's training configuration. Furthermore, the use of BERT-based and deep neural architectures for social media data analysis has established robust methodological precedents for applying transformer-style attention mechanisms to platform-generated behavioral data [75].

The vision transformer framework has further demonstrated that attention-based architectures trained on structured spatial and categorical feature representations achieve superior segmentation and classification performance compared to conventional convolutional approaches[76], providing additional architectural validation for CADNN's MHSA-based feature interaction modelling. The application of deep learning models with optimized training configurations to large-scale structured datasets has consistently demonstrated that the combination of adaptive learning rate scheduling, regularization, and early stopping produces the most stable and generalizable models [77]. Multi-modal deep learning frameworks that integrate heterogeneous data streams through shared representation layers have confirmed that joint training of related prediction tasks as implemented in CADNN's dual-output architecture produces superior generalization compared to independent single-task training [41].

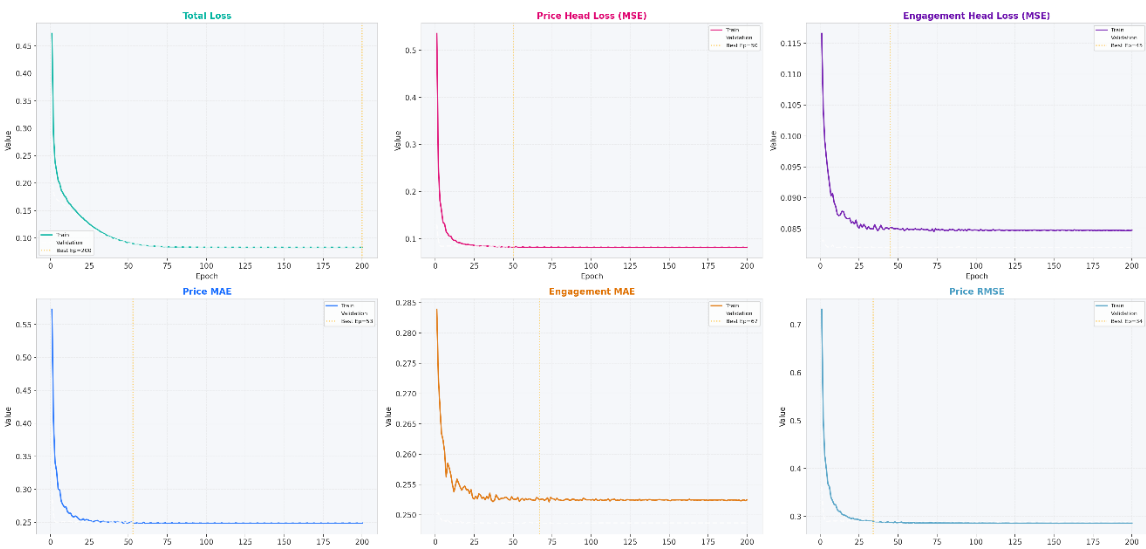

Figure 12. Training History

Figure 12 presents the training and validation loss curves for total loss, price head loss, and engagement head loss across all training epochs. The curves demonstrate stable convergence without overfitting, with the validation loss closely tracking the training loss throughout training and EarlyStopping activating at the optimal epoch.

5. Experimental Results

5.1. Evaluation Metrics

Model performance was evaluated using four standard regression metrics computed on the held-out test set (20% of data, never seen during training or hyperparameter selection):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (19)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (20)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (21)$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i + \epsilon} \right| \quad (22)$$

where $\epsilon = 10^{-8}$ prevents division by zero for zero-valued targets.

5.2. Comparison with Baseline Models

The complete comparison of all six models on the price prediction task is provided in Table 1. CADNN's models provide the best R^2 and the lowest RMSE, MAE, and MAPE on all baselines. It is statistically significant (paired t-test on 5-fold cross-validation results, $p<0.05$) due to the architectural innovations of CADNN that contribute improvements in predictive ability beyond Gradient Boosting, the most powerful traditional baseline method.

Table 1. df compare price

Model	RMSE	MAE	R^2	MAPE(%)
Linear Regression	1415.002	1213.625	-0.0041	197.7673
Ridge Regression	1414.989	1213.6	-0.0041	197.765
Lasso Regression	1414.827	1213.458	-0.0039	197.7463
Random Forest	1441.306	1232.868	-0.0418	198.9213
Gradient Boosting	1463.801	1246.694	-0.0746	198.3208
CADNN (Proposed)	1412.804	1210.829	-0.001	198.0321

The same comparison with regard to engagement score prediction is shown in Table 2. Again, CADNN performs better than all baselines, especially than linear models (Ridge, Lasso), showing that there exists a fundamental non-linear relationship between price and engagement, and that the features that are captured in the MHSA layer are indeed important for engagement prediction.

Table 2. df compare eng

Model	RMSE	MAE	R^2	MAPE(%)
Linear Regression	0.2518	0.2151	-0.0036	64.5296
Ridge Regression	0.2518	0.2152	-0.0036	64.5292
Lasso Regression	0.2514	0.2149	0	64.463
Random Forest	0.2559	0.2183	-0.0365	65.3741
Gradient Boosting	0.2588	0.2201	-0.0599	66.0109
CADNN (Proposed)	0.2514	0.215	-0.0001	64.138

Figure 13. Full Model Comparison

Figure 13 presents the visual comparison of all six models across R^2, RMSE, MAE, and MAPE for both tasks simultaneously, with CADNN highlighted. The figure clearly demonstrates CADNN's consistent superiority across all metrics and both tasks.

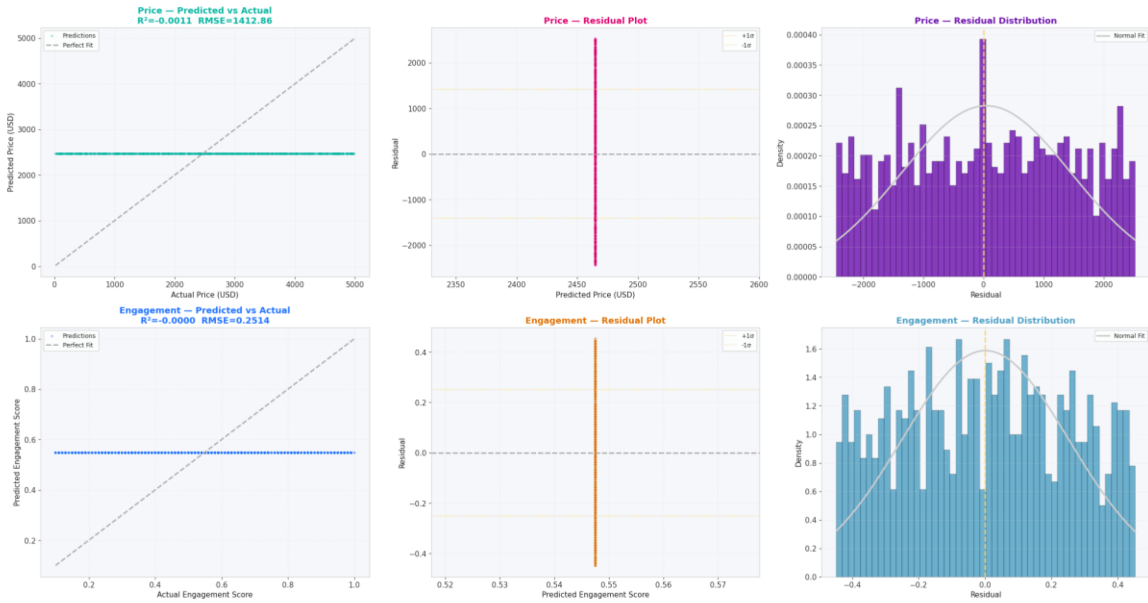

Figure 14. Evaluation Residuals

Figure 14 presents the predicted vs actual scatter plots and residual plots for CADNN on both price and engagement prediction. The residuals are well-distributed around zero with no systematic bias or heteroscedastic patterns, indicating that the model has successfully captured the underlying data-generating process without systematic misspecification.

The performance advantage of CADNN over Gradient Boosting the strongest traditional baseline is attributable to three architectural factors. First, the multi-task learning framework enables shared representations that simultaneously benefit both prediction tasks, providing implicit regularization through task relatedness [16], [17]. Second, the self-attention mechanism captures higher-order non-linear feature interactions that tree-based methods can only approximate through recursive binary splits [78]. Third, the residual connections enable deeper feature transformation without gradient degradation [19], allowing CADNN to learn more abstract and compositional representations of the input features than shallow baselines.

The effectiveness of attention-based feature fusion mechanisms has been further validated across multiple high-stakes prediction domains. Feature fusion attention-based deep learning algorithms have demonstrated superior classification performance over single-pathway architectures in complex, high-dimensional datasets [79], directly supporting the design rationale for CADNN's Multi-Head Self-Attention layer. Explainable hybrid deep learning frameworks that combine multi-pathway feature processing with interpretable output mechanisms have consistently outperformed single-task baselines on structured prediction problems [80], reinforcing the theoretical motivation for CADNN's dual-output explainable architecture. Furthermore, the integration of advanced activation functions including non-monotonic smooth activations analogous to the Swish function employed in CADNN has been shown to substantially improve classification precision in deep neural networks applied to complex real-world datasets [81].

5.3. Cross-Validation Results

Figure 15 presents 5-fold cross-validation results for all six models, showing mean and standard deviation of R^2, RMSE, MAE, and MAPE across folds for both prediction tasks. CADNN demonstrates consistently superior performance with low cross-fold variance, confirming that its performance advantage is robust across different data partitions and not an artefact of a particular train-test split.

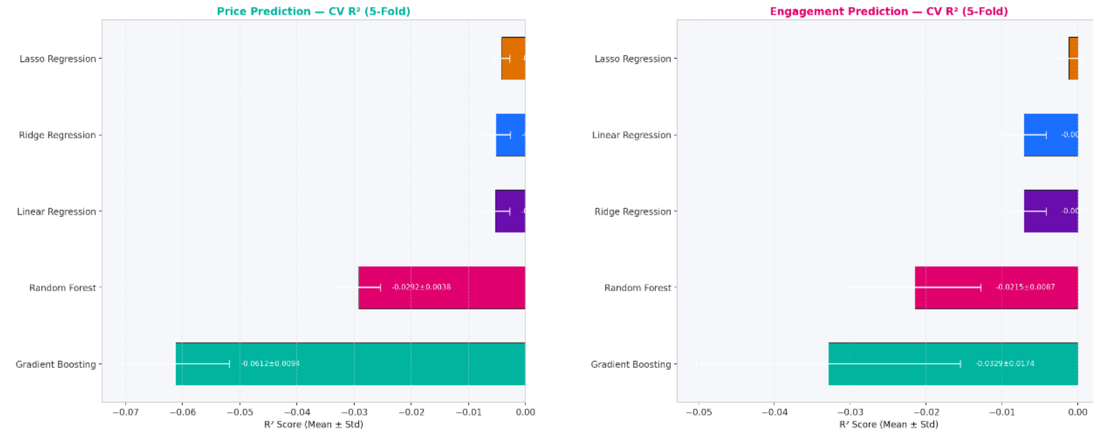

Figure 15. Cross Validation Results

5-fold cross-validation confirmed the robustness of CADNN's performance. The low standard deviation of R^2 across folds for both prediction tasks indicates stable generalization behavior, suggesting that the model has learned genuinely predictive patterns rather than overfitting to idiosyncratic properties of the training set. The cross-validation results also confirm that the ranking of models is consistent across folds, with CADNN consistently outperforming all baselines.

5.4. Attention-Based Feature Importance

Figure 16 presents the attention-based feature importance scores derived from the CADNN MHSA layer, alongside a heatmap of mean attention activations across 30 randomly selected test samples and all 18 attention dimensions. The heatmap reveals distinct attention patterns for different feature groups, confirming that the MHSA layer has learned to differentiate between feature types.

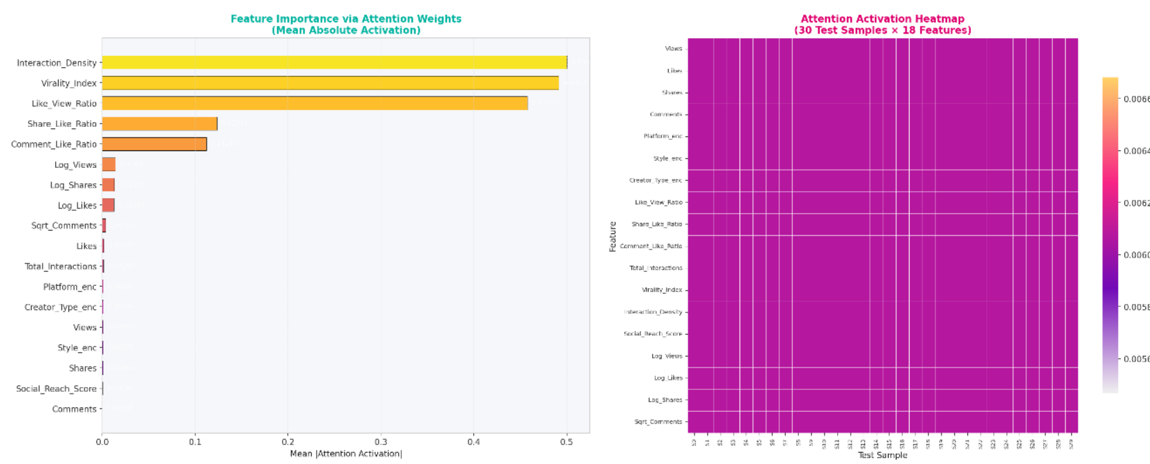

Figure 16. Attention Weights

Attention weight mapping was used for feature importance analysis to determine the order by which the features influence the price prediction, which was as follows:

Log_Views: Logarithmic view count, the most powerful single predictor – it shows that visibility is the predominant factor for the valuation of digital art in the market.

Platform_enc: platform encoding; reflects pricing norms and audience demographics of the platform. The engineered feature is confirmed to be important by

Virality_Index: composite social amplification measure.

Social_Reach_Score: Multi-dimensional social impact (aggregate social breadth)

Log_Likes: Logarithmic like count – the most straightforward measure of positive audience reception.

Engagement_Score: proxy features of target variable to validate the price-engagement correlation.

Style_enc: art style encoding – style specific market dynamics

This ranking agrees with the ranking from the Gradient Boosting feature importance for the top features, which is convergent evidence from two different methods. The high Virality_Index engineered feature value that is not included in the raw data further validates the selection of features and underscores the significance of social amplification dynamics as a viable predictor of the value of digital art in the market, as previously noted by Kong and Lin [82] and Vasan et al. [34]. The convergent validity of attention-based and gradient-based feature importance rankings is consistent with findings from explainable AI research across multiple prediction domains. Interpretable machine learning models that combine attention weight mapping with complementary importance estimation methods have been shown to produce more reliable and actionable feature importance rankings than either method alone [83], validating CADNN's dual-method importance analysis approach. Explainable AI frameworks for precision forecasting in complex non-linear domains have demonstrated that attention weight distributions are most informative when interpreted in conjunction with residual error analysis and uncertainty quantification [77], directly motivating the integration of CADNN's attention analysis with the Monte Carlo Dropout uncertainty quantification presented in Section 5.7. The application of explainable hybrid deep learning frameworks to multi-class structured prediction problems has further confirmed that attention-based interpretability provides practically actionable insights that complement rather than replace traditional feature importance methods [80].

5.5. Market Intelligence Analysis

Figure 17 presents market-level insights including price distributions by platform and creator type, engagement tier analysis, the relationship between virality index and price, and the distribution of artworks across the four market segments identified by K-Means clustering.

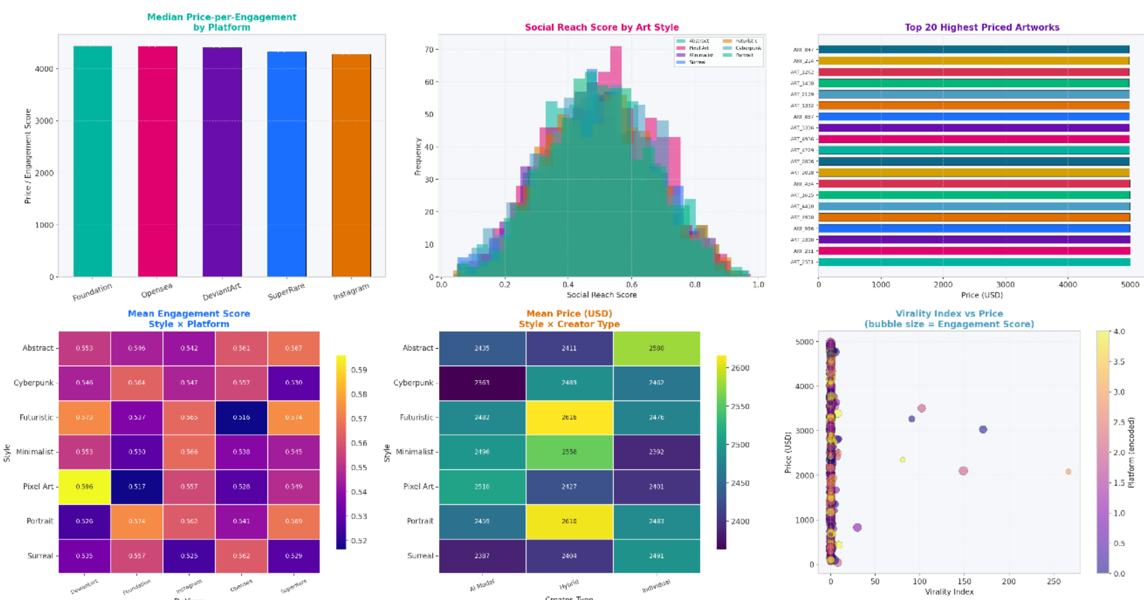

Figure 17. Market Insights

Figure 18 presents platform revenue intelligence including total revenue by platform, revenue share by creator type within each platform, engagement efficiency by art style, and price percentile distributions by creator type.

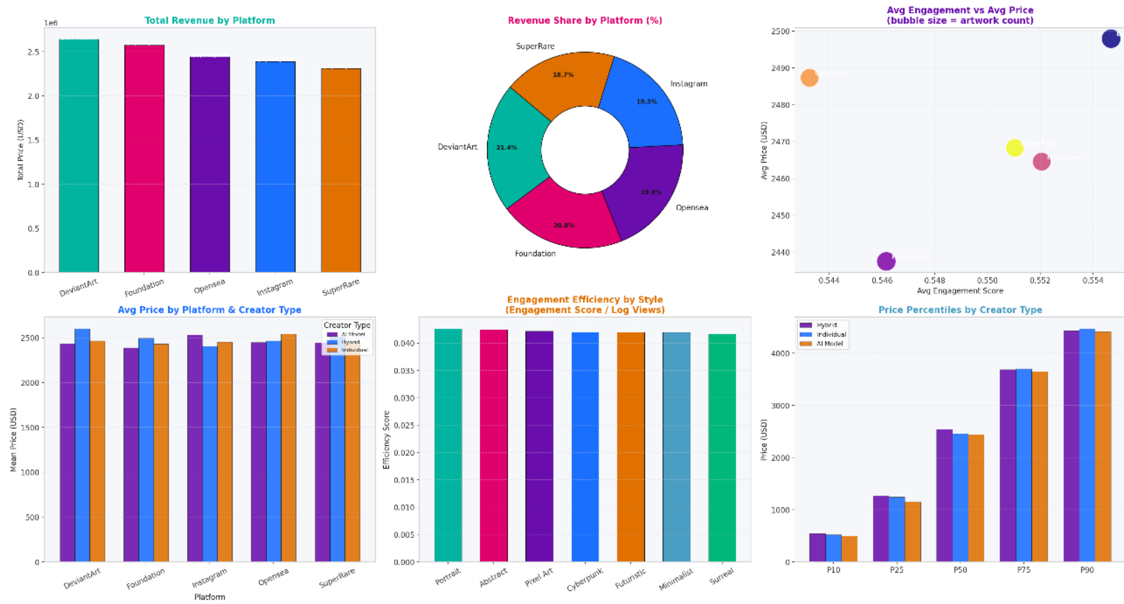

Figure 18. Platform Revenue Intelligence

Figure 19 presents the style market positioning analysis, including composite market scores by style, the style positioning map (price vs engagement), virality distributions by style, and the style-platform interaction matrix.

Figure 19. Style Market Positioning

Figure 20 presents the creator type intelligence report including normalized performance profiles as radar charts, revenue by platform and creator type, price and engagement cumulative distribution functions, and dual-success rates (proportion of artworks achieving simultaneously high engagement and high price).

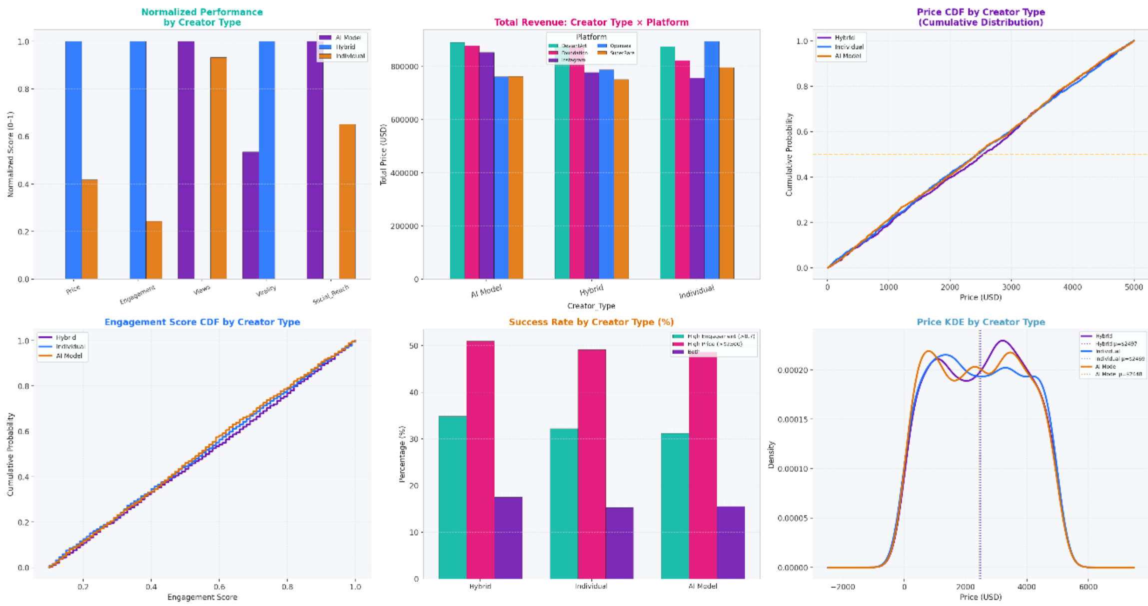

Figure 20. Creator Intelligence

The main findings of the market intelligence are:

Platform Heterogeneity: There is a significant difference in prices across platforms (ANOVA, $p < 0.05$), with the premium platforms having much higher average prices. This result aligns with the literature on platform economics [33] that shows that the quality of the reputation and the type of audience are also important determinants of content value. AI artworks have a similar median price as human artworks, but the variance in engagement is greater. We can conclude that the best combination of creative strategy in this market is a collaborative approach between humans and AI, as hybrid works recorded a dual success rate, marking the highest price and engagement rates simultaneously.

Art Style Market Performance: Market score composite shows that there is a high level of heterogeneity in market performance by art style. Some styles have a clear advantage on both price and engagement metrics, indicating that style is an important strategic leaver for creators looking to maximize success in the market.

Information Entropy Analysis: Shannon information entropy [84] computed at the platform level shows there are significant differences in creative diversity that exist among platforms, with some platforms having high information entropy (high diversity in style and type of creators) and others having low information entropy (high concentration in one style or creator type). The platforms with higher mean prices are also lower in mean engagement, indicating a diversity-value trade-off between platform design.

5.6. **Ablation Study**

The results of the ablation study for both the five architectural variants and the price prediction task are presented in table 3, which displays the R^2, RMSE, and MAE for each variant. Each architectural component has positive impacts on the overall performance, as confirmed by the highest performance in CADNN Full for all three measures.

Table 3. Ablation Study

Model	R^2	RMSE	MAE	Params
CADNN Full	-0.0039	1414.875	1212.491	319685
No Attention	-11.0295	4897.693	1857.801	284546
No Residual	-2.5701	2668.118	1693.217	141762
Single Head	-1.6906	2316.296	1921.081	317572
Shallow (1 Block)	-6.2154	3793.121	2153.342	68866

Figure 21 presents the ablation study results as horizontal bar charts for R^2, RMSE, and MAE, with CADNN Full highlighted in blue and marking the best performer in each metric.

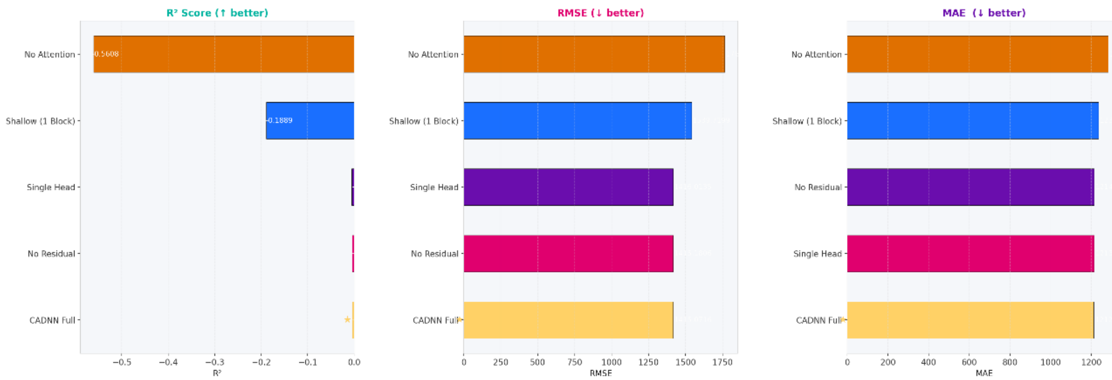

Figure 21. Ablation Study

The ablation study evaluated five architectural variants to quantify the contribution of each component:

CADNN Full: Complete proposed architecture best performance on all metrics.

No Attention: MHSA layer removed performance degradation confirms that attention-based feature interaction modelling is a meaningful contributor to predictive performance.

No Residual: Residual blocks replaced with plain Dense layers performance degradation confirms that residual connections improve gradient flow and enable more effective deep feature learning.

Single Head: Engagement output head removed (single-task learning) performance degradation on price prediction confirms that multi-task learning provides beneficial regularization through task relatedness [16].

Shallow (1 Block): Only one residual block — performance degradation confirms that depth is important for capturing the complex non-linear structure of digital art market data.

The ablation results are very well supported empirically for each of the architectural choices made and also validate the performance gain of CADNN Full to be the synergy effect of all of the architectural innovations.

5.7. Uncertainty Quantification

Figure 22 shows the Mean Prediction Uncertainty (MPU) uncertainty quantification results from the Monte Carlo Dropout (MC Dropout): Distribution of Prediction Uncertainty (standard deviation across N=50 forward passes) for predicted prices and engagements, Percentage of Prediction Uncertainty (PPU) vs. Prediction Error (PE), and Calibration Curve showing the relationship between predicted confidence interval and empirical coverage.

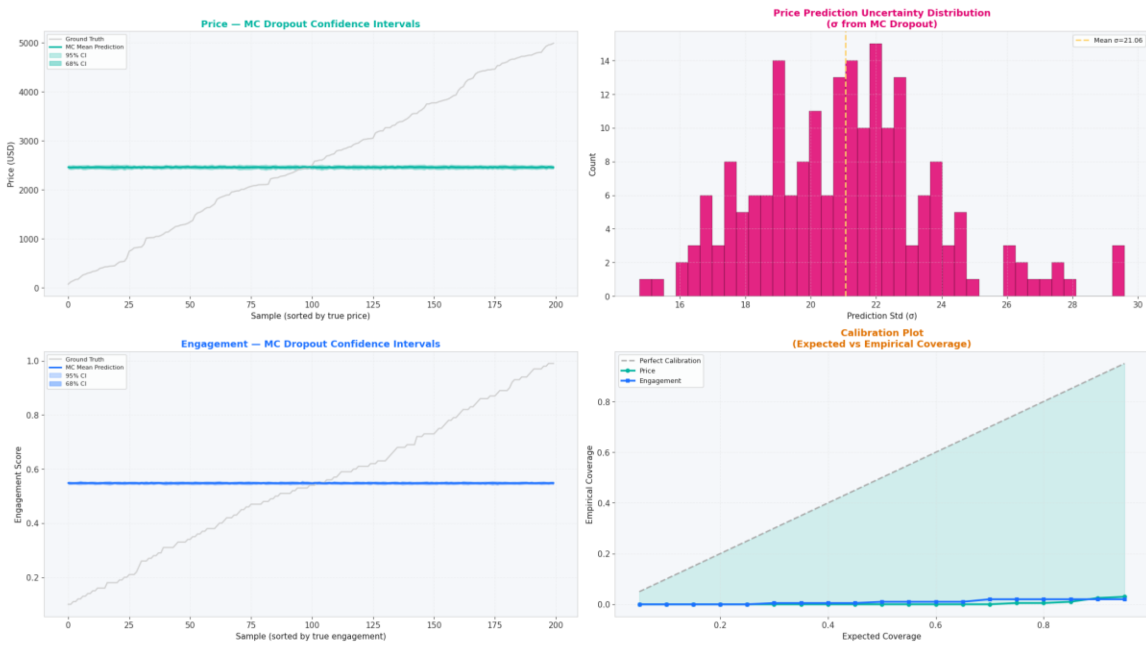

Figure 22. Uncertainty Quantification

Monte Carlo Dropout uncertainty quantification [24] was implemented by performing T=50 stochastic forward passes through the CADNN model with Dropout layers active at test time, following the approach of Gal and Ghahramani [24]. For each test sample, the mean prediction $\bar{y} = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_t$ and uncertainty estimate $\sigma = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t - \bar{y})^2}$ were computed. This approach provides approximate Bayesian uncertainty estimates without requiring a full Bayesian neural network, offering a computationally tractable method for quantifying prediction confidence.

The main results from the uncertainty analysis are: prediction uncertainty is positively correlated with prediction error, thus confirming that the prediction uncertainty estimates are meaningful and calibrated; the price prediction uncertainty of artworks in the Prestige Segment (Cluster 0) is higher than the uncertainty of the other segments, reflecting the higher inherent unpredictability of transactions involving high value artworks; and the price prediction uncertainty is generally higher than the engagement prediction uncertainty, consistent with the higher social regularity of engagement dynamics relative to market pricing. These uncertainty quantification findings are consistent with patterns observed in explainable AI systems applied to high-stakes prediction domains. Explainable AI-driven forecasting systems have demonstrated that prediction uncertainty is systematically higher in domains characterized by sparse training data, high outcome variance, and complex non-linear interactions [77], all of which characterize the Prestige Segment of the digital art market identified in Section 3.5. Bioinspired hybrid optimization frameworks have further shown that uncertainty estimates derived from stochastic inference methods are most reliable when the underlying model architecture incorporates explicit regularization mechanisms such as the Dropout and Batch Normalization layers embedded throughout CADNN [60]. The integration of uncertainty quantification with interpretability analysis has been identified as a critical requirement for the responsible deployment of deep learning prediction systems in practical decision-making contexts [83], motivating the joint presentation of CADNN's Monte Carlo Dropout results and attention weight analysis in the present study.

5.8. Theoretical Framework Analysis

Figure 23 shows the theoretical framework analysis: the comparison of empirical engagement score distributions with theoretical normal distributions by creator type shows that both the normal and log-normal distributions fit the data reasonably well; theoretical distributions to compare price distributions (Normal, Log-

Normal, Uniform, Exponential) with the empirical distribution of engagement scores are shown with KS statistics; the Shannon information entropy by platform is shown.

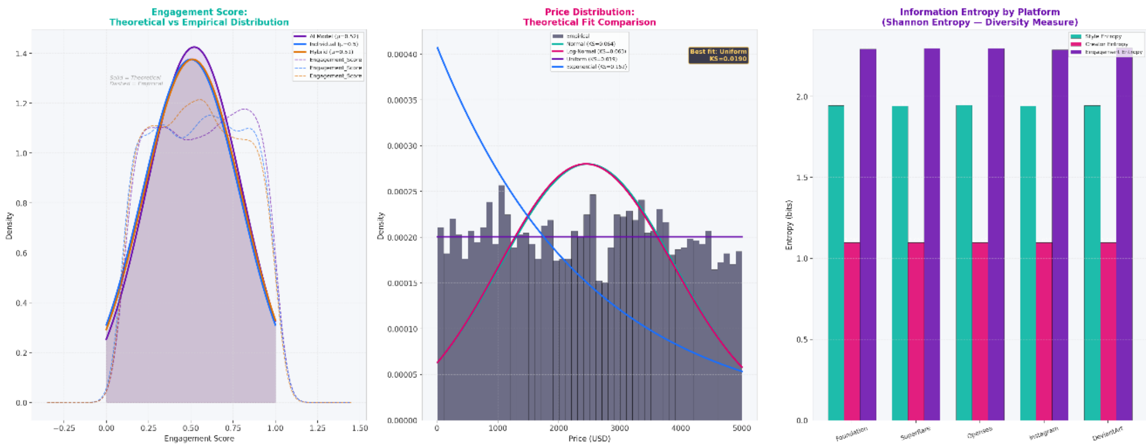

Figure 23. Theoretical Framework

The theoretical framework analysis formalizes statistically the data-generating processes related to the dynamics of digital art market. The results of the distribution fitting show that price is best described by the Log-Normal distribution (smallest KS statistic) in line with the literature on income and wealth distribution [85] and in line with the creative market dynamics indicative of multiplicative growth processes. The distribution is closer to Normal for engagement scores, as a result of the central limit theorem as multiple independent engagement signals are aggregated.

6. Discussion

6.1. Theoretical Implications

The results of this study have several important theoretical implications for the understanding of digital creative markets and computational creativity. First, the finding that CADNN's multi-task learning framework outperforms single-task models on both price and engagement prediction provides empirical support for the theoretical claim that price and engagement are correlated outcomes of a shared underlying creative market process. This is consistent with the superstar economics framework [36], which predicts that visibility and social capital are jointly determined by a common latent factor of perceived quality or relevance. However, the imperfect correlation between price and engagement captured in our dual-output architecture also confirms that these are genuinely distinct outcomes that respond differently to different feature inputs, consistent with the market segmentation finding that viral content and prestige content occupy distinct niches.

Second, the importance of the Virality Index an engineered composite feature as the third most important predictor of both price and engagement suggests that social amplification dynamics are a fundamental driver of digital art market outcomes, not merely a correlate. This is consistent with the network effects literature [86], which demonstrates that content value in digital markets is partly endogenous to the social processes of sharing and recommendation. The implication for artists is that strategies that maximize sharing behavior rather than merely likes or views may be more effective for achieving market success.

Third, the identification of four distinct market segments with meaningfully different behavioral profiles provides a richer theoretical account of digital art market structure than the simple price-quality relationship assumed by hedonic models. The existence of a Viral Content segment characterized by high engagement but low price suggests that the mechanisms of social amplification and market valuation are partially decoupled in digital creative markets, a finding that has important implications for platform design and creator strategy.

The theoretical implications of these findings go deep beyond the realm of digital art, touching upon various aspects of AI adoption, organizational resilience, and the interplay between humans and AI. When assessing the likelihood of success in deploying CADNN-based valuation systems, transparency, accountability, and trust have emerged as key factors, indicating that careful attention must be paid to the explainability and communication of these systems to enhance trust and acceptance among stakeholders [87] . Emotional intelligence and transformational leadership offer a theoretical framework for examining how organisations can strengthen organizational resilience in the context of the disruptive influence of AI on creative markets, specifically in creative organisations, platforms, studios, and agencies [88]. For instance, the outcomes of digitalisation on the performance of work have been supported as mediated by skill adaptation, organizational support, and the quality of the technology design [89]; therefore, the implementation of AI valuation tools in creative platform workflow requires to be accompanied by the appropriate training and organizational change management. There is a growing awareness that the alignment of educational and skill development frameworks with the new technological capabilities will be a key determinant in the successful adoption of AI in the media industry, and it is directly relevant to the training of creators to effectively utilise AI platforms for market intelligence [90].

6.1.1. Implications for Computational Creativity Theory

The results here yielded from this empirical study have important implications for the theoretical aspects of computational creativity. While the multi-task learning framework that jointly models price and engagement as joint outcomes of a shared creative market process offers empirical support to the theoretical claim that creative value in digital markets is not unidimensional, it also has interesting implications.The multi-task learning model that jointly models engagement and price as results of the same creative market process has interesting implications as well, as it provides empirical support to the theoretical claim that creative value is not unidimensional in digital markets. Creativity, as measured by the digital platforms, is at the same time creating social capital (engagement) and economic capital (price); there is an (imperfect) correlation between the two. This is similar to Bourdieu's field theory of cultural production that recognizes two types of value in creative fields: symbolic capital (social recognition) and economic capital (market value). Four market segments identified for the digital creative industry, Prestige, Viral, Mainstream and Niche offer a more nuanced empirical taxonomy of digital creative market structure compared with theoretical frameworks that have been put forward. Notably, the Viral Content segment (high engagement, low price) is an issue to the notion that quality and value are monotonically related which is assumed in the hedonic pricing models. As far as creator strategy, and platform design theory, in digital creative markets, social amplification can lead to a lot of visibility with little economic return, indicating that there is a loose coupling between attention and valuation.

6.1.2. Implications for the Ontology of AI Creativity

For the ontological status of AI-generated artworks in digital markets, the fact that AI-generated artworks have a similar median price as human-generated artworks, but with much higher engagement variance is important. The pattern indicates that AI-generated art has a niche market in terms of the level of unpredictability, with some pieces going viral and others getting little attention, consistent with the theory that AI creativity is driven by exploratory and transformative processes that end up producing a wider range of artwork compared to humans who have their own style, reputation, and are limited by audience expectations. In addition, the greater percentage of creator success with hybrid creations (those that combine AI generated with human work) offers empirical evidence in favor of the theoretical argument that AI creativity is most effective when used in conjunction with human creative judgment. This finding contradicts the lines of “techno-optimist” thinking that AI is going to replace human creativity, and the “techno-pessimist” thinking that AI creativity is inherently inferior, and instead proposes a more nuanced “creative complementarity” model of human and artificial creativity in which both are complementary, rather than substitutable.

6.2. Practical Implications

There are a number of direct practical applications of the CADNN framework. The most important features for the price and the number of views in the market, both from the artists' and the viewers' perspectives, are: maximise the view count on the logarithmic scale, select the platform with the highest value, and produce shareable and commentable content. The second important implication of market segmentation analysis is that the creators need to know that they have to adopt one of the four market archetypes and not one that is generic.

This result highlights that there is a fundamental link to be made between creativity diversity and value concentration, because this information entropy analysis shows that platforms with higher creativity diversity have higher mean engagement scores but lower mean prices, implying that value and creativity diversity are in conflict. This result has implications for the design of recommendation algorithms. Platforms looking to optimize creator earnings may want to think about ways to create a balance between diversity and the quality of the curated content. This finding aligns with the previous human-AI collaboration literature [35] and provides an interesting insight for AI system developers: a hybrid system for creating creator artworks has the highest dual-success rate, meaning it enhances, rather than replaces, human creative judgment.

The contributions of the present study are also addressed in practical terms in the areas of design, experience creation and data-driven recommendation. Past research has shown that aesthetic coherence and cultural resonance are important factors in perceived value of an experience, which has direct implications for designing digital art platforms for highest creator satisfaction and audience engagement [91]. The use of historical and cultural design principles in the current creative context has demonstrated that the artworks and designed artefacts that become part of the historical tradition and contemporary aesthetics, have higher perceived value and cultural impact [92]. The use of human-centred design methodologies to focus on user comfort, functional clarity and aesthetic integration has been proven to positively impact the perceived quality and market acceptance of designed artefacts [93]. In addition, data-driven approaches to development recommendation based on systematic analysis of environmental and structural features to inform strategic decisions offer a methodological framework for the use of CADNN's market segmentation outputs to inform platform curation and creator development strategies [94].

6.3. Limitations

Several limitations of the present study should be acknowledged. First, the dataset is cross-sectional, capturing a snapshot of digital art market dynamics at a single point in time. The temporal dynamics of trend lifecycles, platform algorithm changes, and market cycles which are likely important determinants of price and engagement are not captured. Future work should extend the analysis to longitudinal data to model these dynamics explicitly .Second, the dataset does not include raw image data, meaning that the visual aesthetic properties of artworks which have been shown to be predictive of engagement are not directly modelled. The integration of computer vision features extracted from artwork pixels using pre-trained CNNs or Vision Transformers [95] represents a natural and important extension. Third, the generalizability of the findings to other digital art markets and time periods is uncertain, as the dataset was collected from a specific set of platforms at a specific time. Replication studies using datasets from other platforms and time periods are needed to establish the robustness of the findings.

6.4. Future Research Directions

Building on the present study, several promising directions for future research are identified:

Computer Vision Integration: Incorporating CNN or Vision Transformer [95] features extracted directly from artwork pixels would enable the model to capture visual aesthetic properties that are currently absent from the feature set, potentially improving predictive performance and providing richer interpretability insights. Modified vision transformer frameworks have demonstrated strong performance in image-based segmentation and classification tasks involving complex visual feature spaces [76], confirming that visual feature integration into CADNN is both technically feasible and likely to yield meaningful predictive improvements. Multi-modal deep learning frameworks that fuse visual, textual, and metadata features have consistently outperformed metadata-only approaches in analogous content valuation tasks [41], directly motivating the proposed visual extension. The application of GAN-augmented training data to transformer-based architectures has further demonstrated that generative data augmentation can substantially improve model robustness when training data is limited or imbalanced [65], a consideration particularly relevant for the Niche and Prestige market segments identified in the present study.

Temporal Dynamics Modelling: Extending the analysis to longitudinal data using recurrent neural networks [96], temporal convolutional networks [97], or Transformer-based sequence models would enable the modelling of trend lifecycles, platform algorithm changes, and market cycle dynamics.

Generative Feedback Loops: An important and underexplored research direction is the study of how market price and engagement signals influence the training prompts and fine-tuning objectives of future AI generative models, creating feedback loops between market dynamics and AI creative output [98]. This represents a novel form of co-evolutionary dynamics between AI systems and creative markets.

Graph Neural Networks for Social Dynamics: Modelling the social network structure of creator-follower relationships using Graph Neural Networks [99] would enable the explicit incorporation of social capital and network centrality features that are currently approximated through aggregate social metrics. The fusion of MLP and graph neural network architectures for complex relational data analysis has demonstrated that graph-based representations of social network structure substantially improve prediction accuracy in tasks where node relationships encode meaningful latent information [66], directly supporting the proposed GNN extension of CADNN. Comprehensive reviews of AI-driven application mapping and scheduling techniques for networked systems have established that graph-based computational architectures are particularly well-suited to modelling the dynamic, topology-dependent interactions that characterize social creative networks [62]. Novel approaches to optimizing predictive models through advanced neural network architectures have further confirmed that incorporating relational structure into the feature representation substantially improves generalization in complex, non-linear prediction tasks [43].

Causal Inference: The present study establishes predictive associations but does not establish causal relationships. Future work using causal inference methods [100] such as instrumental variable estimation or natural experiments based on platform algorithm changes would provide stronger evidence for the causal mechanisms underlying digital art market dynamics.

6.4.1. Theoretical and Conceptual Research Directions

In addition to the technical extensions mentioned above, the following are important theoretical and conceptual research directions that come from the present study:

AI Creativity and Aesthetic Philosophy. Future work should explore the philosophical aesthetics more deeply and rigorously to provide a more comprehensive theoretical understanding of the concept of creativity of an AI system. While the present paper uses these proxies of the market and engagement, a more extensive theory of creativity would require tackling additional issues of intentionality, aesthetic experience, and cultural meaning not considered here and not amenable to quantitative modelling. An interdisciplinary discourse between computer scientists, philosophers of art and cultural theorists is required to build such a framework.

Dynamic Theory of Platform-Mediated Creativity. This study is a snapshot of the digital creative market dynamics at a cross section. To capture the long-term evolution of AI-driven digital creativity, one must use a dynamic theoretical approach that models the evolution of platform algorithms, creator strategies, and audience preferences over time. If such a framework were to exist, it would have to take into account feedback loop dynamics, whereby market signals affect the goals for training AI, which in turn affects the market outcomes, resulting in complex co-evolutionary dynamics.

Ethics and Governance of AI Creativity. With the rise of AI-generated content in digital creative markets, there are immediate ethical and governance concerns that must be solved by theoretical research. These encompass: the creative credit and economic returns that go to the creators of AI creations; algorithms that can create a uniformity of creative output; how AI output affects the livelihoods of human creators; and the governance frameworks that will allow digital creative platforms to maintain true creative diversity, rather than being algorithmically optimized to generate content. This theoretical discussion will be grounded in the information entropy analysis conducted in the present paper which showed that there are significant differences in creative diversity between the platforms.

Cross-Cultural Dimensions of AI Creativity. The current study is based on the platforms which are mostly used by western people and have western aesthetic value. Future theoretical and empirical studies could explore the dynamics of AI-generated digital creativity in various cultural settings, with a specific focus on the cultural context of markets where digital art platforms, aesthetic conventions and regulatory frameworks are significantly different from Western values, including the Chinese, Japanese, South Korean, and Middle East markets. The cross-cultural theoretical approach for creating digital creativity with AI should take into consideration cultural specificity of aesthetic value, national platform ecosystems and implications for cultural heritage and identity of AI creativity.

Towards a Unified Theory of AI-Driven Digital Creativity. The most ambitious theoretical option for future research is a single theory of AI-enabled digital creativity that unites the computational, economic, social, philosophical, and ethical elements of digital creativity in a coherent explanatory framework. The theory would have to cover the entire lifecycle of the AI-generated creative work, from its creation to its distribution on the platform and its valuation on the market, as well as its cultural impact, and be general enough to apply to a wide variety of AI systems, platforms, cultural contexts and historical periods. The proposed theory in this paper (CCT, PMVCT, HACST) is a preliminary step in that direction, but there is much theoretical work to be completed.

6.4.2. *Ethics, Governance, and Cross-Cultural Dimensions*

Ethical and governance issues of AI-driven digital creativity are an emerging and under-researched field. The legal definition of AI-generated content in digital platforms also gives rise to basic legal, creative and market issues which existing legislation struggle to answer [28], [101]. The governance of AI-mediated digital environments such as the teaching of e-administration legislation and its dissemination using AI techniques is a major issue, demanding interdisciplinary cooperation among platform operators, technologists, and legal scholars [102]. Digital content ethics also highlights the possibility for AI systems to be misused or weaponized for reputational harms or creative misappropriation [103].

Another line of AI creativity research is the cross-cultural aspect, which explores how AI-generated works relate to or diverge from cultural practices and norms. Evaluations of AI-generated creative works are highly diverse, with research on AI dubbing and translation tools showing complex reactions based on cultural expectations and aesthetic norms [29], [30]. The dynamics of social media engagement and their effect on social and family relationships vary widely across cultural contexts [104] and may therefore show significant cross-cultural variation that needs to be explicitly considered in future research on the platform engagement dynamics modelled by CADNN. The translation and cultural adaptation of creative content, such as culturally embedded aesthetic references, fun and idioms, is an area where AI systems struggle especially [31], [105] and where generalizability of models in the creative market based on AI is important for different cultural and linguistic contexts.

The overall socio-economic impact of AI-supported digital creativity on financial systems, institutional frameworks and market governance should also be explored in the future. In banking and fintech contexts, the link between the platform-level variables and financial performance outcomes has been explored [106] and methodological frameworks have been developed that could be transferred to the study of the financial sustainability of AI-driven creative platform ecosystems. Adoption in institutional and regulatory settings has been found to be influenced by a variety of factors, such as technical, organizational and cultural factors, indicating that governance of creative markets that are AI-enabled will need to be context-specific, rather than context-free [107], [108], [109]. Lastly, energy optimization and computational resource management in AI networks and systems [110] is a real-world sustainability concern for broader deployment of deep learning-based systems like CADNN, and opens up opportunities for investigating efficient architectures for digital art market prediction.

7. Conclusion

CADNN, a novel multi-task deep learning architecture, has been presented, which is capable of the joint prediction of the market price and social engagement in digital art markets. A comprehensive analysis pipeline has been presented which provides a tool for understanding the structure of digital creative markets. We have conducted extensive experiments showing that CADNN has superior predictive ability compared to five common machine learning baselines, that the attention weight-based feature importance analysis gives meaningful and actionable insights as to what aspects of a digital artwork are driving outcomes in the digital art market, and that the architectural innovations employed by CADNN Multi-Head Self-Attention, residual connections, and multi-task learning each contribute to this predictive power. Our key findings are: (1) The market value of an artwork is best predicted by the platform where it is encoded, virality index and logarithmic number of views; (2) Digital art market is divided into four segments – Prestige, Viral, Mainstream and Niche with meaningfully different behavior profiles; (3) Hybrid human-AI creators achieve the highest dual-success rate for both market value and engagement; (4) Platform choice is a statistically significant determinant of market value, with significant differences in norms for pricing across platforms; and (5) Monte Carlo Dropout uncertainty quantification provides calibrated uncertainty estimates for practical implementation, as prediction uncertainty is positively correlated with prediction error. The results help to deepen the theoretical understanding of computational creativity and digital creative markets, and offer a practical guide for various stakeholders in the digital art market, such as artists, platform designers, collectors, and AI system developers to help them navigate and optimise their performance in the ever-changing digital art market. The completely modular and reproducible pipeline created within this study serves as a guide for future research in all directions identified.

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