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Aesthetic Experience and Popularity Ratings for Controversial and Non-Controversial Artworks Using Machine Learning Ranking

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Abstract: Currently, a substantial portion of images snapped at exhibitions and galleries on social media demonstrates that aesthetic experience is not restricted to the confines of cultural institutions. The primary objective of this paper is to examine whether the content or aspect of an artwork influences the aesthetic experience of the viewer and to measure the artwork's social media popularity. To compare controversial works of art with those whose design, qualities, or intended message are non-controversial, we first sought out controversial works. A variety of artworks were revealed on Instagram; thus, the objective was to identify a non-controversial artwork published in the same year as each controversial artwork. We adhered to the complete procedure for cleansing, standardizing, and transforming the data to ensure comparability. Popularity was measured using a ranking algorithm and quantitative approaches for the recognition and statistical measurement of emotions. In addition, the exhaustive literature survey on models of aesthetic experience revealed no link between the experience of art and its social media popularity. Considering this, we have proposed, among other things, a new framework for interacting with art that integrates these parameters. According to the findings, controversial artworks elicited stronger emotions than non-controversial artworks. Furthermore, investigations have determined the three most popular works of art in each category. Under the scrutiny of social media, these results may inspire future research on the popularity of museum artworks and the design of aesthetic experiences.

Keywords: aesthetic experience; machine learning; ranking; popularity; social media; museums; public art; emotion; controversial art

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1. Introduction

Art origins, appreciation, and involvement currently coexist with technological advances and social media applications. New fields of science have emerged because of the rapid spread of the digital age and the pervasive and viable development of software and social media applications [1]. Data science is one example of a discipline that has grown in prominence since 2010 [1]. Instagram was introduced at the same time. Instagram skyrocketed in popularity due to its retro aesthetic and a myriad of built-in tools for creating images resembling Polaroids captions from the 1970s [2]. Personal self-branding profiles progressively gave way to business and commercial accounts. A large number of influencers are photographed in museums and iconic landmarks daily to promote goods and services. Travel, style, and food bloggers and photographers frequently promote opulent lodgings, restaurants, apparel, and other goods [2]. The presence of readily accessible and, at times, extremely cheap digital devices, such as smartphones, has profoundly altered the interactions of individuals with art [3]. Concerning museum-based art, Hunter [4] stated in her study on museum selfies that museum selfies had the potential to positively disrupt museum poetics, allowing viewers to become involved and activating the age-old tropes of artworks coming to life. Thus, the viewer assumes the role of performer and is actively involved in co-creating a new narrative with the objects.

Regarding how they would be exhibited and communicated to the public, controversial artworks pose a conundrum, not only for spectators but also for scientific practices. Although the adjective "controversial" does not identify specific works of art, it describes their content and meaning. According to our bibliographic investigation, no formal definition for this category could be found. Equally, contemporary artworks have shown vast potential over the past few decades, compelling researchers to examine whether they can be legitimately identified as "art" and what other factors influence spectator evaluation [5]. In fact, it has been observed that visitors tend to prefer ancient art for didactic reasons, while they prefer contemporary art for emotional and aesthetic gratification [6]. However, viewers may often choose to witness extremely controversial art exhibitions. The "This is not a body" exhibition at the Musée Maillol in Paris in 2022 was a recent and notable example. The majority of the forty realistic sculptures on display are nude. This is the exhibition's thirteenth visit since its 2016 debut at the Bilbao Museum of Fine Arts. On specific dates and times, 800 individuals are permitted to observe the statues without clothing. The goal was to make visitors feel like they were an integral part of the story. This was a highly tactile and inventive method of handling objects [7]. However, occasionally art can be excessive and elicit a wide range of emotions. The performance "Rhythm 0" by the controversial artist Marina Abramovic, which took place at Studio Mora in Naples in 1974, was an extreme and notable example due to its violent context. The duration of the performance was six hours, and the artist provided the audience with "Instructions. There are 72 objects on the table that one can use on me as desired. Performance I am the object. During this period, I take full responsibility". On a table were 72 objects, some of which were dangerous, such as a weapon, a saw, chains, scissors, knives, pins, needles, and razors. Additionally, there were other everyday items such as cosmetics, perfume, a coat, an apple, etc. Participants were permitted to use whatever they wished in any manner. Various reactions and aggressive or harassing behaviors were observed [8]. Similarly, art can provoke within the context of filmmaking productions. The dinner sequence in "The Square" is an example of this. It is about Terry Notary's performance as a monkey at a lavish gala to frighten a group of benefactors. As the performance continued, the monkey's aggression towards the audience intensified. Such a scene may elicit intensely negative emotions in the viewer, as well as the question of where the boundaries lie and how to stop this tragedy [9]. "Mother and Child (Divided)" by Damien Hirst [10] is another illustration. The insides of a bisected cow and calf preserved in formaldehyde and transparent cases are visible to visitors.

Numerous studies [11,12] have investigated how context, either space (museum, gallery, laboratory, public art) or content (such as the International Affective Picture System (IAPS) image dataset), influences art appreciation. The exhibitions' significance and influence can be attributed to the visitors' involvement with them. The literature refers to this sociocultural phenomenon as the "museum effect" [13]. The contribution of social media to this issue is critical. Through museum photographs, individuals' identities can be determined [14]. Their online distribution offers a new perspective on the conventional conceptions of the artworks. However, most studies do not evaluate any of the variables we examined in this study. Using empirical data from social media, the objective is to investigate the aesthetic experience and measure the popularity of controversial and non-controversial artworks. The remainder of the paper is structured as follows: Section 2 explains the literature review. The aim of this investigation is articulated in Section 3. Section 4 describes the materials and methods used in the research. Section 5 presents the study's implementation and findings. Section 6 presents the discussion, while Section 7contains the conclusion and the limitations of the study.

2. Literature Review

2.1. Studying the Aesthetic Experience

There appear to be a variety of definitions of "model" in the literature, each of which is determined by the field to which it pertains. The Merriam-Webster [15] dictionary defines a model as "a description or analogy used to help visualize something (such as an atom) that cannot be directly observed". There are many different sorts of models, including conceptual models, exploratory models, and data models. This section reviews some fundamental psychological models of the viewer's experience with art. Many scientific models reflect a certain portion or facet of the world, which serves as the model's target system [16]. The psychological models presented below have structural commonalities. They contain three components. Consider these features: (1) Inputs that enhance the experience, such as personal traits, previous experiences, sociocultural status [17], and other artwork aspects [18], (2) input processing mechanisms, and (3) multiple intellectual and behavioral effects (outputs) of processing art, including positive or negative affect, physiology, actions, appraisals, meaning-making, novelty, transcendence, aesthetic, self-adjustment, social, and health outcomes [19].

We begin by briefly reviewing some of the core aesthetic experience models. The objective of Chatterjee's [20] model was to examine the cognitive and neurological aspects of the viewer. Hence, he concentrated on three stages of human visual recognition based on visual studies: "early", "intermediate", and "late" [20,21]. Moreover, he concurred that, like any other visual stimuli, the visual features of artworks are received and processed by several brain regions [21]. Primarily, he thought that early and intermediate vision perceive the formal and most significant parts of an artwork, whereas later vision processes the content [20]. The model of Leder et al. [22,23] consisted of five stages, namely: (1) "perceptual analysis" (low-level visual features); (2) "implicit memory integration" (previous experiences, expertise, schema); (3) "explicit classification" (content, style); (4) "cognitive mastery" (interpretations, associations, links to prior knowledge); and (5) "evaluation" (judgement and aesthetic emotions). The procedure is circular and can be repeated if the viewers are unsatisfied or if another element catches their eye. After a quick discussion of aesthetic experience's components, the next part discusses emotions.

Aesthetic experience is multi-layered, affected by the qualities of the artwork, the viewer's personality, and the context. A list of art criteria includes canvas, multisensory, and multidimensional objects [24], and immediacy and tangible presence, such as with gold [25] or everyday objects [26]. Larger artworks may be more enticing [27]. In cases involving famous artworks or exact duplicates, original artworks are the most desirable [28]. Brushstrokes or fingerprints reveal the artist's labor and touch [29]. Moreover, there is the question of whether objects qualify as art [30]. Personal qualities are as important in art as any other factor. These art skills distinguish novices from experts [31]. People with a higher income and education are regular museum visitors. Single or group visits generate less interest than single visits [32]. Context influences a person's engagement with art, such as displaying and hanging paintings or a sculpture in the room's center [33]; using cases or ropes as borders [34], labels, and audio instructions [24]; and the use of warm or cold lighting [35]. Architecture, design, and cultural influences reassure visitors [36]. Other factors include mobility patterns [35], museum fatigue [37], and the position of the body during viewing, such as standing, walking, or sitting [38]. Viewing distance [39] and time spent viewing art [11] are also relevant.

2.2. Theories and Taxonomies of Emotions

A few years ago, several approaches treating emotions were offered. The objective was to formulate a linguistically and theoretically fruitful definition [40,41]. In this section, we attempt, as much as possible, to give a birds' eye view of the emotional concern but cannot cover the entire original theory of emotions. Defining "emotion" has been and may still be the most challenging task for science. William James proposed in 1884 that primary emotions (fear, anger, joy) each have their own physical state [42]. The term "émotion" has French origins and first appeared in the English language around the seventeenth and eighteenth centuries. It did not specify mental states until the mid-19th century [43–45]. To bring a more theoretical and historical approach, ancient Greek terms such as passion, sentiment, affection, affect, disturbance, movement, perturbation, upheaval, or appetite are used to convey a kind of emotion [40]. Scherer [46] defined emotion as "an episode of interrelated, synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism" [47,48].

It is normal to inquire about the emotions we are conveying. Paul Ekman detailed basic emotions and their acquaintances. He identified enjoyment, disgust, fear, surprise, and anger as basic emotions [49]. Each emotion has unique symptoms, physiology, and triggers. Facial expressions dominate [50]; this is because facial expressions of emotions are universal. Multiple facial expressions accompany each emotion [49]. Emotions are usually triggered by objects, people, events, or a mix of these in terms of aesthetic experience. Regardless of the object causing the emotions, Kenny [51] stressed that "any X that I can have emotion E about is a particular object of E, whereas the formal object of E is the property which I implicitly ascribe to X by virtue of having E about X". A growing body of literature has examined the interesting concept of aesthetic emotions. Aesthetic emotions can occur because of the viewer's perception and evaluation of an aesthetic stimulus. They are defined by four features: (1) aesthetic evaluation or appreciation of events or objects, (2) prediction of a certain type of aesthetic appeal, (3) association with a subjective feeling of pleasure or displeasure, and (4) prediction of liking or disliking of the event or object [52].

In addition to Paul Ekman, several scientists have identified basic emotions, including Richard and Bernice Lazarus [53] and Cowen and Ketler [54]. Other scholars have sought to categorize and model emotion taxonomies. Robinson [55] classified the emotions as either positive or negative. Using the aforementioned criteria, the following sorts of emotions emerged: object-related, future appraisal, event-related, self-appraisal, social, and cathected. Each of these categories includes a collection of positive and negative emotions. Another classification proposed a tree-structured list of primary, secondary, and tertiary emotions that are interconnected. On the first level of the emotion hierarchy, a few categories (love, joy, anger, sadness, fear, and perhaps surprise) are most effective in everyday situations [56,57]. Finally, Plutchik [58] developed a wheel of eight emotions, namely joy, trust, fear, surprise, sadness, disgust, anger, and anticipation. The wheel is divided into four pairs: the primary dyad, the secondary dyad, the tertiary dyad, and the opposing emotions. There are also triads of emotions, and often multiple potential combinations are possible.

2.3. An Interdisciplinary Approach of Popularity

For decades, defining popularity, like emotions in the abovementioned section, has been and remains a challenge for philosophers and sociologists. However, with the proliferation of social media platforms and the rapid sharing of information, it is apparent that this term has taken on new interpretations. According to the Cambridge Dictionary [59] and The Britannica Dictionary [60], popularity is "the fact that something or someone is liked, enjoyed, or supported by many people". The adjective "popular" is etymologically associated with the old French word "populaire" ("public commonly known") and taken directly from Latin "popularis" ("belonging to the people, general, common; devoted to or accepted by the people; democratic"), and was first seen in 1601 [61]. Popularity is about an individual, although it can only be comprehended in groups. As a concept, it relies on the emotions and evaluations it prompts. In a nutshell, it requires a group of people to support someone [62]. Consequently, popularity cannot exist in another scenario.

There is a substantial corpus of literature that investigated popularity via sociometric variables. The term "popularity" was often used in the classical approach proposed by Bukowski [63] to refer to "the ranking of children or adolescents in their peer groups (classroom or grade) based on a hierarchy or status criterion (positive criterion or desired attribute)". According to this practice, the individuals at the top of the rating list are dubbed popular. For numerous decades, this method was employed in popularity research. Coie et al. [64] discovered four dimensions through sociometric research: acceptance, rejection, preference, and influence based on who was "most liked" or "liked least" (likability). Subsequent surveys used "most popular" and "least popular" instead of the earlier terms [65,66]. As a side effect, popularity has been introduced as a fifth sociometric component in addition to the other four. Hence, popularity "is a dimension of power, prestige, or visibility derived from popularity nominations of who is most or least popular". Parkhurst and Hopmeyer [66] differentiated sociometric and perceived popularity. Their idea is ambiguous since they defined popular as both "sociometric" (liked and accepted) and "perceived" (popular and high ranked). Moreover, they used a sociometric method to assess popularity, which confounded the interpretation [63]. Other scholars proposed judgmental [67], reputational [68], and consensual popularity [69]. Nevertheless, these efforts did not yield a universal, objective term.

As we have seen, aesthetic experience entails emotional judgment of the artworks. While exploring popularity, we found similarities with art experience. These are emotions and judgment. According to Moreno [70], an individual's judgment determines sociometric popularity and this is called "Emotional judgment", which enables better comprehension of "an individual's private sentiments of attraction or repulsion about another that are not necessarily shared with the group or by the group". Contrary to perceived popularity, "judgments are reputational" [63,70]. Simonton [71] linked an artist's popularity to their creativity. Other researchers such as Van de Rijt et al. [72] and Rindova et al. [73] argued that "fame" depends on "large-scale public attention" and social culture. Moreover, fame may be derived by achievements or social status [74]. To provide further insight, Mitali and Ingram [75] analyzed the artists' popularity. A study of 90 twentieth century artists revealed that an artist's social network predicts popularity. The extant literature review found that artists having a diverse social network are more likely to be popular.

2.4. Machine Learning Applications in Cultural Analytics

A rising amount of research has addressed content or statistical analysis, social media emotion recognition, etc., but less so in the arts. Lev Manovich coined "cultural analytics" in 2007. This is not a strict or confined term because it can be adapted. As a concept, it includes "the use of computational and design methods— including data visualization, media and interaction design, statistics, and machine learning—for exploration and analysis of contemporary culture at scale" [1]. Therefore, we use the concept as a basis for our research. Gangrade et al. [76] used Thayer's psychological model to classify Instagram posts' sentiments. Other research has employed Naive Bayes (NB), Support Vector Machines (SVMs), Decision Trees (DTs), Random Forest (RF), Convolutional Neural Networks (CNNs), BiLSTM, L2, and Adam on large-scale Twitter data to detect pandemic emotions [77]. Using Instagram and Twitter data, we found in our most recent paper [78] that a public art installation that elicits intense emotions may gain popularity due to deliberate media-sharing activities and habits.

There is a vast amount of literature on ranking methods. Most studies ranked products, websites, news, or services. Recommendation systems also use ranking. Zhang, Wu, and Liu [79] ranked products online. They developed a novel approach using a hesitant fuzzy set (HFS) and a sentiment work framework to calculate overall performance. Belkacem et al. [80] rated social media news feeds using the Random Forest (RF) algorithm, providing personalized and non-personalized prediction models. They tested the model on Twitter data to forecast news feed relevance. Non-personalized models outperformed personalized ones. Based on social media engagement, Brison and Geurin [81] ranked US Olympic athletes as brand endorsers (likes, comments, total number of followers, etc.). They examined the link between follower engagement and brand mentions. Using text analysis of the tweets of 190 US Olympians during the 2018 PyeongChang Games, researchers revealed significant gender differences in engagement. Additionally, it was revealed that non-brand-related posts generated far more interaction than brand-related posts.

We previously discussed popularity. Then we examined popularity ranking. Qi et al. [82] combined a personalized score and the news popularity score to produce a ranking score that can provide users with personalized news and predict their popularity in real time. Koya and Chowdhury [83] developed a novel approach to analyzing and visualizing research datasets; the number of citations from the year of origin, overall number of citations, and impact factor of journals that publish articles citing datasets were used. A system to obtain datasets based on ranking variables was also recommended. In our recent study [84], we examined Instagram art memes and museum posts to assess the impact and popularity of classical art. Using supervised machine learning algorithms and emotion analysis, we identified the most prevalent emotions in each scenario. Then, we found the most popular artworks as memes and museum posts in the context of aesthetic experience using the LightGBM ranking algorithm and relevance scores in each group of artworks (91 total, N = 1222 for memes and N = 3304 for museum posts). Our tests revealed the top seven art memes, top twelve museum artworks posts, and top four common artworks in both cases.

3. Aim of the Current Study

Emotional stimulation is destined to become a crucial aspect of the operation of cultural organizations and an intriguing topic in cultural analytics. Several basic models of art experience (e.g., [22,23]) and emotions (e.g., [58]) have been provided in the literature review to underline the impact's depth. When examining the concept of popularity through the lens of aesthetic experience, however, a slew of concerns arises: (1) it is crucial to identify the primary factors that affect the aesthetic experience in the digital realm; (2) it is essential to anticipate the factors influencing the popularity of the artworks; and (3) a new framework is required to enhance the aesthetic experience and the popularity of art. To address all these issues, we provide a new approach that explores the aesthetic experience of controversial and non-controversial artworks in a variety of contexts. As seen below, this can be accomplished by conducting two studies.

Study 1. The aim is to develop a framework that will reshape the aesthetic experience of art viewers. The objective is to overcome the cognitive gaps left by similar models that do not incorporate social media platforms during viewing or do not clearly relate to emotions.

Study 2. By conducting experiments with machine learning techniques, we intend to evaluate the popularity and impact of art by setting up three (RQs) research questions:

RQ1. What is the popularity of controversial artworks?
RQ2. What is the popularity of non-controversial artworks?
RQ3. What emotions motivate individuals to share their aesthetic experience on social media?

The use of social media has had a tremendous impact on how we experience art in any context [3,85]. Most of the content we encountered on social media, notably Instagram, consists of photographs followed by brief descriptions [86]. Presently, there are a vast number of indoor (museums, galleries, etc.) and outdoor (archaeological sites, monuments, parks, shopping malls, etc.) displays of various forms of art. A quick search on social media will reveal posts marketing goods, clothes, devices, self-improvement courses, workout videos, health and wellness advice, and artworks [2]. According to the bibliographic search we undertook, no relevant approaches exploring controversial and non-controversial artworks using machine learning methods were found. Furthermore, we anticipate that our research will provide insight into how provocative or common artworks might become popular through social media applications such as Instagram. We also intend to provide social media and data scientists, museologists, artists, art experts, and researchers a glimpse of the aesthetic experience and popularity.

It became evident after conducting a bibliographic search that there is no universally accepted definition of controversial art. As individuals hold diverse values and beliefs, it seems that interpreting controversial works of art is largely a subjective endeavor. Nevertheless, controversial works of art may have political, religious, moral, or sexual implications. Therefore, each viewer will interpret them differently [87]. In addition, these are the actual criteria for rejecting or approving the artwork. However, spectators do not reject controversial art because they do not find it enjoyable, original, meaningful, or fascinating; rather, they evaluate it based on the emotions it elicits in them, such as hostility, rejection, self-affirmation, or aggression [88,89]. Sometimes art provokes particularly aggressive or even angry emotions in viewers. Some viewers believe that the controversial artworks were created intentionally to offend or anger them. Piss Christ by Andres Serrano and or Virgin in a Condom by Tania Kovats are examples of this type of work [90]. Given that contemporary art approaches the current political, social, or even climate crises with a critical eye, this can be a starting point for shifting the perspective of viewers towards these issues and a catalyst for social change [91–94]. It is important to note that the reactions of spectators may vary depending on their context, such as a gallery or laboratory [95]. Moreover, it should be mentioned that negative emotions are frequently encountered by viewers and do not undermine the aesthetic experience.

Due to the examination of our assumption, we intended to identify the most pertinent term, which is the controversial art genre commonly known as shock art. Considering what we have read in the literature, "Shock art is a subset of contemporary art that utilizes disturbing imagery, sounds or scents to provoke agitation, upset or disquiet in the viewer. Often, proponents and appreciators of shock art cite the ability of the genre to galvanize social critique, with the predominant use of unconventional materials in shock art challenging more commonplace craft techniques" [96]. Additionally, in the Merriam-Webster dictionary [97], the term "culture shock" means "a sense of confusion and uncertainty sometimes with feelings of anxiety that may affect people exposed to an alien culture or environment without adequate preparation", and this can be also applicable in the art domain.

4. Materials and Methods

Figure 1 depicts the entire data management process, which includes data collection, preprocessing, transformation, and evaluation. The purpose is to clarify the sequence of procedures followed in this social media data-driven study.

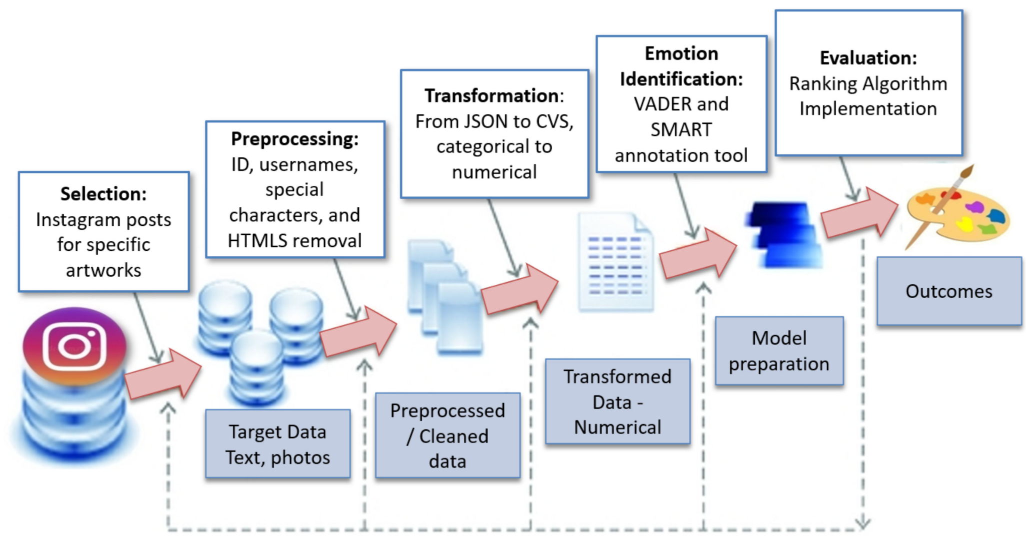

Figure 1. Data preparation process.

4.1. Searching for Artworks

The research is quantitative since it relies on actual numerical data from social media to examine the response of the viewers. We then proceeded to browse the Internet for artworks collectively to discover precisely what the controversial artworks are, who created them, when they were created, and where they are exhibited. To investigate the aesthetic experience of spectators in both scenarios, we carried out a similar experiment using non-controversial artworks. We examined the presence of the artworks on Twitter and Instagram, among other social media channels. Due to the textual nature of Twitter posts, Instagram was selected as the primary source for data collection. Furthermore, we searched for the artworks on both platforms, but Twitter did not provide sufficient data or any data at all for any of the specified artworks. After verifying that all the desired artworks were accessible on Instagram, we performed a geographical independent search for each artwork. In line with this strategy, we positioned the original viewer posts within each museum or location. Then, we generated lists of 14 controversial and 14 non-controversial art pieces. It is important to clarify that our list includes artworks that are exhibited in vivo (without a glass enclosure), in vitro (inside a glass enclosure), and in situ (in their physical position, for instance, monuments or ancient ruins).

As shown in Table 1, the artworks in both genres are arranged in chronological order, from the most classical or historical to the most contemporary.

Table 1. List of selected controversial and non-controversial artworks in chronological order.

ID	Controversial Artworks and Artists	Year	Non-Controversial Artworks and Artists
1	Fountain (Marchel Duchamp)	1917	The Gates of the Hell (Auguste Rodin)
2	Artist's Shit (Piero Manzoni)	1961	Orange, Red, Yellow (Mark Rothko)
3	Campell's Soup Cans (Andy Warhol)	1962	IKB 191 (Yves Klein)
4	Piss Christ (Andres Serrano)	1978	Tower (Keith Haring)
5	My Bed (Tracey Emin)	1998	Water Tower (Rachel Whitered)
6	Traffic Light Tree (Pierre Vivant)	1998	Angel of the North (Anthony Gormley)
7	La Nona Ora (Maurizio Cattelan)	1999	Maman (Louise Bourgeois)
8	Sylvie (Wim Delvoye)	2006	Gloud Gate (Anish Kapoor)
9	Forever Marilyn (Seward Johnson)	2011	Waiting for the Climate Change (Isaac Cordal)
10	Tree (Paul McCarthy)	2014	A Pound of Flesh for 50p/Melting House (Alex Chinneck)
11	Girl With Balloon/Love is In the Bin (Banksy)	2018	The London Mastaba (Christo)
12	Comedian (Maurizio Cattelan)	2019	ParaPivot (Alicja Kwade)
13	Rebel Without a Cock (Kembra Pfahler)	2019	Illuminated River (Leo Villareal)
14	Ballon Dog Blue (Jeff Knoons)	2021	Solid Sky at 550 Madison Avenue (Alicja Kwade)

It is also evident that the artworks have been chronologically arranged, which was not done by chance; it was our intent to identify a non-controversial work of art that was produced in the same year as each controversial artwork. We chose the listed non-controversial works on the same date since we were unable to locate enough relevant Instagram posts. Attempts were made to categorize the artworks as logically as possible, while keeping in mind the subjectivity of art observers and what exactly would be considered controversial or not. For the selection and categorization of the works into controversial and non-controversial types, we considered, in addition to the date, the nature, intent, and message of each artist's work. To compile the final list, we therefore investigated both online [98,99] and bibliographic sources [100] regarding their interpretation.

4.2. Preparing Data for Analysis

Data Collection

Instagram data were collected with the Instaloader Python library version 4.7.4 [101]. This is an easy-to-use open-source tool for downloading entire posts from Instagram, such as images or videos, along with their metadata (such as likes, comments, shares, text, saved to collection, tags, and other technical attributes). This solution also enables one to extract stories, biographical descriptions, IGTV (Instagram TV), highlights, hashtags, and reels from both public and private accounts. We obtained N = 6124 posts (N = 3662 for controversial artworks and N = 2462 for non-controversial artworks) using the Python script for geotags. We ran the script twenty-eight times, modifying the criteria each time, because it was practically impossible to download all the data at once because there were many artworks and locations. Given that Instagram restricts the data size that can be downloaded per day, we gathered the maximum number of Instagram posts permitted by the policy. Since it was enabled by Instaloader, we saved the posts to our Instagram collection per artwork and downloaded them as saved posts. Since the Instaloader retrieves posts in JSON (JavaScript Object Notation) format, they must be converted prior to being updated and approved. The technique is described in length in the next section.

4.3. Pre-Processing and Transformation

We created two separate datasets, one for controversial artworks and one for non-controversial artworks. The original csv (comma separated value) files displayed tabular data. Both datasets contained seven columns, including the artwork's id, comments, likes, saved to collection, has more comments, Facebook shares, and text emotion. The JSON (JavaScript Object Notation) strings were converted to csv (comma separated value) using Python modules from the Pandas library [102]. When necessary, we transformed categorical data to numeric, such as in columns saved to collection and has more comments when the values were binary (TRUE or FALSE). The remaining columns, including id, likes, comments, and Facebook shares, were initially formatted as numerals. To integrate the accompanying text with the posts in the datasets, we employed a different tactic. The original text order in each post were maintained. Using the OpenRefine software, we removed spelling errors ("MUSEum Dayzzzz" to "Museum Day"), special characters (@, #, &, %, ", +), stop words (and, the, to, etc.), punctuation (!, ;), and other symbols [103]. While translating posts from multiple different languages to English using the proper Python modules, we also converted all uppercase letters to lowercase. After cleaning the data, we were able to extract the emotions from the text.

4.4. Emotion Identification

In our previous work [84], we used the sEntiment Reasoner and the Valence Aware Dictionary (VADER) from Natural Language Toolkit (NLTK) to analyze emotions in social media discourse [104,105]. These practices enable text and emoji analysis. We also used the well-designed Sentiment Analysis and Cognition Engine SEANCE [106]. This application was insufficient, as found previously; it only accepts txt files and calculates polarity for the entire input, not per post. Both are rule-based and employed in natural language processing research. This may have substantial limits, such as recognizing exclusively positive, negative, and neutral emotions in the text. This is enough for a wide case overview. However, we believe that this categorization will be ineffective in our scenario.

To solve this, we incorporated emotions into our datasets using the annotated technique, which has been utilized in a large body of studies. SMART [107] was implemented to achieve this. It is an open-source online tool that enables incredibly straightforward data labeling to build efficient datasets for testing supervised machine learning. Several of the benefits include a user-friendly interface, parallel use by several users on team projects, self-hosted installation, and data protection. As input, we chose a spreadsheet (xlsx) that normally contains tabular data. SMART can accept a variety of file extensions, including csv, tsv, and xlsx. To add labels, the data must be organized into two or three columns with headings, plus an optional column with the id. Therefore, we uploaded a file including two columns: id and text. Then, we affixed emotion labels to every post. We chose emotions by studying Paul Ekman's [49] analysis of basic emotions and a taxonomy of emotions as proposed by Robinson [55]. These emotions included enjoyment, disgust, fear, surprise, and anger. Because automated approaches are incapable of combining multiple emotions from psychological models, we adopted this strategy.

5. Implementation and Results

This section presents a new framework of aesthetic experience and popularity and implements machine learning experiments to measure the popularity of controversial and non-controversial pieces of art.

5.1. Study 1. A New Framework of Art Experience

In museum-based art, aesthetic experience has garnered a great deal of attention. Several models portraying the viewer's involvement with art can be found in the literature [33], but they do not account for the use of social media prior to, during, and after a visit to an art exhibition. However, other perspectives failed to recognize the emotional connection as an intrinsic component of the art experience. Moreover, since Instagram's release in 2010, a reasonable amount of research has been conducted on its use in general, but less in a museum or gallery setting. This has prompted authors such as Suess [108] to give a comparable perspective through the paradigm of "Art Gallery Visitor Instagramming". Suess divided a museum visit into three stages based on physical presence: pre-visit, during visit, and post-visit. The first stage includes triggers such as Instagram posts from other museumgoers that inspire an individual to visit a museum. They are encouraged to take pictures, provide feedback, and share them on social media during or after their visit. The third stage is a circular process that focuses on the visit's impacts, such as uploading, commenting on, and sharing photographic content. As previously noted, psychological models do not include the concept of social media. Similarly, Suess's approach does not include the emotional aspect in any obvious sense. To bridge this gap, we present a new framework regarding the individual's prior exposure to art and the popularity of the art. We divided the procedure into three stages, as depicted in Figure 2 To be completely impartial, we took terms from various models describing the aesthetic experience. Due to the dissimilarity of our scenarios, we did not study the same aspects. We explain our concept in detail below.

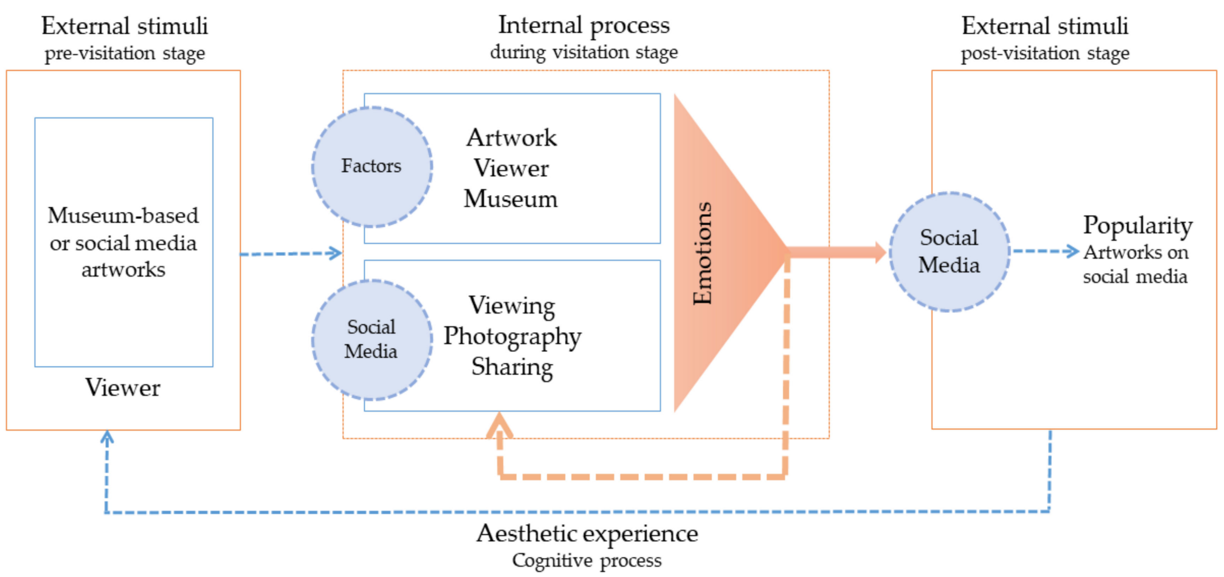

Figure 2. A new perspective of aesthetic experience and popularity of art.

In summary, we clarify the inadequacies of the models at the outset of this subsection, either in terms of the cognitive dimension of aesthetic experience or the use of social media during museum visits. Suess' paradigm inspired the stage names (pre-visit stage, during visit stage, and post-visit stage) as well as the sub-stages applicable to the viewer's social media activity. We also borrowed aesthetic experience aspects that trigger similar emotions in the viewer, such as space, artwork qualities, and personality (these factors are discussed in depth in Section 2.1). Regarding popularity, none of the preceding models are included. Sociometric popularity is related with emotions that individuals may share with others, according to the research. Moreno [70] illustrated this using the term "emotional judgments." In contrast to perceived popularity, which is based on evaluations and is hence widely shared with others, the conclusion of the model of Leder et al. [22] of aesthetic experience is "aesthetic judgments" and "aesthetic emotions". Although the relationship is vague, because Leder et al. [22] employed two unique notions as an outcome of the model, we might claim that popularity is a byproduct of aesthetic experience. This is the argument that Figure 1 intends to present.

Our goal was to illustrate the aesthetic experience of the individual and the popularity of the artworks in three stages, comprising pre-visit, during visit, and post-visit, as follows:

- Stage 1: Pre-visit stage

First, the person is exposed to external triggers before the visit. Digital artworks, artist social media posts, and museum posts are external stimuli. According to studies, smart device use has mediated visual and social experiences [109]. Art is also affected. Instagram's audience includes "exploration" users who search the home page and peruse algorithm-suggested content. The "associated" audience uses the app to maintain contacts. The "thematic" audience receives hashtags about certain people, items, places, emotions, or phrases. Moreover, "chatterbox" viewers may like commenting [85]. FOMO ("fear of missing out") is yet another kind of audience made up of users who monitor other users' online activity [85,110]. It may be the first step, but it is crucial because it includes the motivations that will drive the individual to potentially visit a museum, either to seek out the artwork or the location that observed. In any case, it is the viewer's initial encounter with the artwork that they may or may not be familiar with. In both instances, the viewer can share the art encounter on social media.

- Stage 2: During visitation stage

Second, the aesthetic experience is determined by the environment, the artwork's qualities, and the individual's personality [33]. That is when individuals engage, appreciate, judge, and generate emotions in response to artworks and their settings. This stage is an internal process. Several factors, along with social media activity, represent the viewer's intimate attachment. First impressions are intuitive [111], and combine visual sense, structure, style, meaning, and emotional response [111]. Social media apps enhance the art experience when viewing exhibits. Stylianou-Lambert [112] argues that taking photos in a museum can preserve the art encounter. Additional incentives include emotional gratification, educational interests, and amusement. After seeing these posts, users consider visiting. Budge [113] claimed visitors use Instagram to document their art encounters and promote exhibitions. She also stated that visitors' use of Instagram improves social cohesion and user socialization by communicating "I'm here. You can be here too" [114]. This stage concentrates on the most critical aspect of the aesthetic experience, which is the individual's presence in the museum while viewing an artwork. There, the observer will engage with and emotionally experience the artwork and its surroundings.

- Stage 3: Post-visitation stage

These emotions enhance social media sharing. The posts usually include emotional content. Sharing photos generates external stimulus that people like, comment on, and distribute. We placed social media networks and popularity as a third-stage outcome. As indicated, a public art installation that elicits intense emotions may gain popularity through social media sharing. When the monument was wrapped, social media reactions on both platforms increased [78]. In another study, we examined the nexus between museum visitor posts, emotions, and artwork and meme popularity. After detecting emotions with machine learning algorithms, ranking tasks revealed the most popular meme and museum post, which can enhance aesthetic experience and popularity [84].

Considering how Figure 1 could be used to reshape the concept of popularity, we argued that the aesthetic experience is an internal process in which individuals are exposed to external stimuli and are compelled to attend art places in which they engage and experience emotions, which they share online, and therefore generate new external stimuli that may gain popularity. This is also the main distinction between this study and others in the same field. After critical analysis, theoretical works neglected social networking. While other studies have focused on the role of social media during the museum visit, they did not address the viewer's emotional state. Similar surveys in laboratories or museums have relied on questionnaires, interviews, or other technologies. Social media studies in the arts evaluated user engagement or popularity, but not emotion. Kang, Chen, and Kang [115] explored the most liked artworks and the link between Instagram likes, comments, and the artist's creative process. Quantitative (Instagram data) and qualitative research was carried out (online questionnaires responded to by artists). Artists denied that their most liked work is also their favorite. They asserted their most popular artworks and followers' interaction will not affect their creativity. This study did not incorporate the emotional component and found no link with popularity.

5.2. Study 2. Machine Learning Experiments

Ranking items based on their relevance to a task is a challenge in machine learning. It is applied in query auto-completion [116], document retrieval [117] key term extraction [118], definition finding [119], product rating [120], sentiment analysis [121], and anti-Web spam [122]. Learning-to-rank (LTR) models handle ranking problems using supervised machine learning. Traditional machine learning (classification or regression) focuses on predicting single numerical or categorical instances at a time. The ranking approach uses a list to solve a problem. The goal is to rank the items based on relevance, rather than on final score [123]. We employed Microsoft's LightGBM algorithm for testing (RQ1, RQ2). We used a ranking approach to determine the most popular artwork in both scenarios based on relevance criteria. This innovative method enables us to rethink our research questions.

5.3. Data Handling

The next step involves data handling. The ranking requires two datasets. The LightGBM algorithm is numeral based. The data should be pre-sorted and stored in a csv (comma separated value) file. We built two datasets, one for controversial ($N = 3662$) and another for non-controversial ($N = 2462$) artworks, each with nine columns, namely id, label, comments, likes, saved to collection, media type, media count, has more comments, and Facebook shares. The "label" column depicts the impact of attributes on what is popular or not. As in our prior research on memes [84], we provide experiments that declared relevance equally. There are some previous examples. In their music popularity prediction experiments, Lee and Lee [124] utilized multiple popularity indicators extracted from song ranks measured using rank scores, including max rank and rank (the song's rank). They anticipated the most popular song on a 100-song chart would be 100 and the least popular would be 1. Chapelle and Chang [125] employed labels {0, 1, 2, 3, 4} for document retrieval ranking in their model, where positive numbers denoted higher relevance and negative numbers denoted lower relevance. In our most recent analysis [84], we assigned the values for this feature from 0 (absolute negative correlation) to 3 (absolute positive correlation). Each artwork was in a separate group. Using OpenRefine [103], all samples were properly allocated a value between 0 and 3 based on the number of interactions per post. We gave 3 to the most interacted-with posts. We gave 0 to the posts having the least engagement. Relevantly, the remaining medium values were assigned 1 and 2.

5.4. Implementation Parameters

LightGBM can perform classification, regression, and ranking by invoking the necessary learning-to-rank (LTR) functions. It is a Microsoft-powered training speed algorithm.

Low computing consumption, higher reliability, and data scaling are other benefits. We used LightGBM Ranker for our paper's questions. We ranked using Lambda Rank, which is useful for optimizing ranking functions such as nDCG, which is included in our script. The Normalized Discounted Cumulative Gain ranks samples based on their gain [126]. A relevant sample placed at the top of the predicted data has a higher gain than one placed at the bottom of the predicted data, which has a lower gain. LightGBM Ranker can rank pointwise, pairwise, or listwise [123]. The pointwise method examines one item at a time and trains a classifier or regressor to predict relevance. Item scores determine ultimate ranking [117]. Pairwise ranking classifies items into two categories (correctly ranked and incorrectly ranked) based on their optimal ordering [119]. The listwise technique evaluates the whole list of items to find their optimal order using nDCG or by minimizing a loss function [119]. In our case study, we used listwise ranking to find the most popular artworks based on two scenarios. We observed how LightGBM Ranker performed with our data in later experiments.

5.5. Data Exploration

As the total number of artworks used for ranking experiments in this problem is smaller than that in previous tests, it was considered proper to investigate the data distribution in both controversial and non-controversial artworks at this time. There is a total of 28 works of art, 14 of which are controversial and 14 that are not. The following two tables illustrate the distribution of values for the likes and comments features, which have the greatest variation compared to other features and can have a significant impact on the ranking. Table 2 depicts the distribution of data for two key features of the ranking dataset. As can be noted, it contains seven columns that define the total number of posts for each controversial work of art, the average number of likes, their maximum (max) and minimum (min) values, and their standard deviation (std). Most posts concern Andy Warhol's Campbell's Soup Cans. According to the distribution, the minimum amount of likes for an artwork is 0, while the maximum is 5810 for the sculpture Forever Marilyn, etc.

Table 2. Statistical description of the likes feature of the controversial artwork's dataset.

ID	Artwork	Count	av Likes	Max Likes	Min Likes	Std Likes
1	Artist's Shit	352	182.25	2065	1	293.96
2	Fountain	300	48.53	862	1	74.47
3	Campbell's Soup Cans	579	137.95	2369	1	306.51
4	Piss Christ	133	149.44	2623	2	310.05
5	Ballon Dog Blue	426	146.16	2869	4	264.18
6	My bed	160	75.52	955	1	131.61
7	Traffic Light Tree	214	105.58	920	4	94.05
8	La Nona Ora	278	83.17	1439	0	167.96
9	Sylvie	145	59.24	307	1	79.32
10	Forever Marylin	265	168.8	5810	0	519.94
11	Tree	128	98.65	1170	2	169.59
12	Girl with Balloon/Love is in the bin	237	221.15	5512	3	540.81
13	Comedian	299	206.89	5467	5	487.59
14	Rebel Without a Cock	146	102.46	1231	2	145.06

Table 3 depicts the comment feature's data distribution, which includes the total number of posts, the mean value of comments overall, the maximum and minimum values for each non-controversial artwork, and the standard deviation. According to the data, the minimum number of comments is 0 and the maximum number of comments is 1, related to the controversial artwork Comedian.

Table 3. Statistical description of the comments feature of the controversial artwork's dataset.

ID	Artwork	Count	av Comments	Max Comm	Min Comm	Std Comm
1	Artist's Shit	352	16.34	199	0	29.7
2	Fountain	300	4.81	48	0	8.10
3	Campbell's Soup Cans	579	13.81	303	0	31.14
4	Piss Christ	133	19.54	202	0	35.47
5	Ballon Dog Blue	426	15.42	202	0	28.11
6	My bed	160	75.52	102	0	16.94
7	Traffic Light Tree	214	8.08	41	0	7.85
8	La Nona Ora	278	2.54	42	0	5.30
9	Sylvie	145	2.33	26	0	4.23
10	Forever Marylin	265	13.77	193	0	31.58
11	Tree	128	8.63	102	0	15.39
12	Girl with Balloon/Love is in the bin	237	24.99	321	0	47.97
13	Comedian	299	18.63	321	1	37.41
14	Rebel Without a Cock	146	9.88	121	0	16.99

According to the data, the minimum number of comments is 0 and the maximum number of comments related to the artworks is 321, for Banksy's Love Is in the Bin and Mauricio Cattelan's Banana. In a similar vein, data regarding the non-controversial works of art are provided. Fourteen works of art of various genres were created in response to each other's controversy in the same year. Moreover, the two tables that follow depict the distribution of values for the most variable features, likes and comments, which may have a significant impact on the ranking tests. The two tables that follow indicate the distribution of values for the likes and comments features, which have the greatest variation among the other attributes and may have a major influence on the ranking of non-controversial artworks.

Table 4 portrays the data distribution for two key features of the ranking dataset. In addition, it contains seven columns comprising the total number of posts for each non-controversial work of art, the average number of likes, their maximum (max) and minimum (min) values, and the standard deviation (std). Most posts are about Maman by Louise Bourgeois. According to the distribution, the lowest number of likes for an artwork is 0, while the maximum is 6925 for Solid Sky by Alicja Kwade.

Table 4. Statistical description of the likes feature of the non-controversial artwork's dataset.

Id	Artwork	Count	av Likes	Max Likes	Min Likes	Std Likes
1	Orange, Red, Yellow	201	469.52	2241	0	472.50
2	The Gates of the Hell	209	50.22	624	1	87.54
3	IKB-191	389	133.41	4046	0	370.65
4	Tower	66	150.00	891	11	274.57
5	Solid Sky	124	224.86	6925	3	795.89
6	Water Tower	130	69.20	2062	1	222.19
7	Angel of the North	110	92.68	1761	2	246.96
8	Maman	391	102.47	1817	2	184.41
9	Cloud Gate	233	55.24	1279	0	106.88
10	Waiting for the Climate change	101	299.43	4966	7	861.66
11	Melting House	72	53.43	193	2	53.58
12	The London Mastaba	212	85.44	586	2	87.52
13	ParaPivot	108	154.04	3335	4	397.95
14	Illuminated River	116	127.30	2129	1	290.09

Furthermore, Table 5 depicts the comment feature's data distribution, which includes the total number of posts, the mean value of comments overall, the maximum and minimum values for each non-controversial artwork, and the standard deviation. According to the data, the minimum number of comments is 0 and the maximum number of comments related to the artwork IKB-191 is 335. As shown in the preceding table, the percentage of comments for the subsequent works of art is significantly lower.

Table 5. Statistical description of the comments feature of the non-controversial artwork's dataset.

ID	Artwork	Count	av Comments	Max Comm	Min Comm	Std
1	Orange, Red, Yellow	201	41.35	335	0	51.07
2	The Gates of the Hell	209	6.85	199	0	18.41
3	IKB-191	389	13.67	255	0	370.65
4	Tower	66	150.00	199	0	40.15
5	Solid Sky	124	5.96	206	0	22.22
6	Water Tower	130	5.13	99	0	12.65
7	Angel of the North	110	6.21	110	0	15.42
8	Maman	391	9.54	182	0	20.35
9	Cloud Gate	233	5.61	131	0	13.36
10	Waiting for the Climate change	101	16.42	199	0	41.51
11	Melting House	72	4.81	21	0	5.36
12	The London Mastaba	212	5.83	144	0	12.18
13	ParaPivot	108	10.70	167	0	26.91
14	Illuminated River	116	12.49	281	0	35.90

RQ1. What is the popularity of controversial artworks?

Considering the data structure and context, an additional ranking study was conducted to determine the most popular controversial and non-controversial works of art. This research query relates to controversial works of art. Due to the size of the sample and the number of discovered artworks, multiple datasets were produced to conduct the ranking experiment. Given the general technical limitations for data searching and downloading, a standard sample size (N = 3662) of controversial Instagram artworks was obtained. The dataset contained nine columns: ID, comments (count of comments per post), likes (count of likes per post), saved to collection (if the users saved the post to their Instagram account's private collection), media type (if the post is a feed, the carousel may contain up to ten photos or videos, which is the maximum number), media count (the number of photos or videos if the post is a carousel), has more comments (if the specific post has the most comments). In all datasets, approximately 80% (11 groups) were designated for training, whereas the remaining 20% (3 groups) were designated for validation testing, as it was desirable to include all posts from the same group. All the selected artworks were included in a testing set to determine their rating scores, despite the fact that the number of artworks is relatively small due to the previously described constraints. Therefore, in each iteration of the algorithm, the groups in the testing set were adjusted to three to ensure that all artworks in the testing set pass, and a final score was calculated by combining their individual scores. Five distinct datasets were constructed for this research query. This method helped each artwork pass the entire test set. Consequently, separate evaluation scores were extracted for each of them. To determine which group is the most popular, it is incorrect to determine which post is the most popular because a group may not be popular but have several popular posts. The objective is to determine which group is the most popular overall. Using the weighted average of all post scores for each group may be an appropriate criterion for determining the most popular group. However, because an excessive number of posts garnered negative ratings, a different method was implemented. Therefore, it was optimal to select 10% of the most popular posts. In a group of sixty posts, for instance, the average of the best six is chosen. With each algorithm run, the most popular artworks were thus identified. The final ranking is displayed in Table 6 below.

Table 6. The final list of controversial artworks by ranking outcomes.

The Final Rank of the Most Popular Controversial Artworks (N = 3662)				
	Artwork	**Artist**	**Group ID**	**Predicted Ranking Score**
1.	Comedian	Maurizio Cattelan	13	6.92
2.	Fountain	Marcel Duchamp	1	6.72
3.	Girl With Balloon (Love is In the Bin)	Banksy	12	6.65
4.	Forever Marilyn	Seward Johnson	10	5.69
5.	Campbell's Soup Cans	Andy Warhol	3	5.46
6.	Piss Christ	Andres Serrano	4	4.82
7.	Balloon Dog Blue	Jeff Knoons	5	4.00
8.	Tree	Paul McCarthy	11	1.32
9.	Sylvie	Wim Delvoye	9	1.23
10.	Rebel Without a Cock	Kembra Pfahler	14	1.20
11.	La Nona Ora	Maurizio Cattelan	8	0.73
12.	Traffic Light Tree	Pierre Vivant	7	0.38
13.	My bed	Tracey Emin	6	−0.44
14.	Artist's Shit	Piero Manzoni	2	−3.29

The scores of the most popular controversial artworks range from 6.92 (the highest-ranking value) to −3.29 (the lowest and negative ranking value) according to the ranking task's overall measurement data. Given that both datasets contained renowned works of art, this improved both the research questions and the model's reliability. As shown in the table, the three most popular controversial works are Comedian by Maurizio Cattelan, Fountain by Marcel Duchamp, and Girl with Balloon (Love is in the Bin) by Banksy. These works have been primarily characterized as controversial. We briefly examine the reason for this. Comedian was created by the well-known artist Maurizio Cattelan. It consists of three versions, of which two were sold at Art Basel Miami Beach for $120,000 each and the third was donated to the Guggenheim Museum. It is extraordinary that the fruit was purchased for only 30 cents at a Miami grocery store. The artwork consists predominantly of a fresh banana displayed with sticky tape on the wall. As a piece of conceptual art, it comes with the necessary certificates of authenticity and display instructions. Many questioned it, while others described it as an expensive selfie, a humorous minimalist work of art, or cynical [127]. Although the artwork has its own Instagram account, it is also featured on the cover of the New York Post [128]. Fountain by Marcel Duchamp is considered the most controversial work of art in the world to this day. It is a readymade sculpture of an inverted porcelain urinal bearing the signature "R. Mutt". It sparked a heated debate among art experts about what constitutes art and whether Fountain is art. Thus far, neither the narrative behind the sculpture nor its signature have been disclosed [129]. Similarly, the muralist Banksy painted Girl with Balloon. It is an artwork that was initially captured as a mural. It was also his only work to be transferred to paper and the only work in history that was destroyed in front of the public during its auction at Sotheby's using a special mechanism. It was damaged immediately after its sale for £18,582,000. The auto-destructive artwork was subsequently renamed Love is in the Bin [130]. Even the artist is controversial due to the political, capitalist, and consumerist subject matter of his works. As he has not disclosed his identity, it is assumed that on the day of the auction he was also present in the auction hall [131]. In contrast, the least renowned work of art is Artist's Shit by Piero Manzoni. It is also observed that, following the three most popular works of art, the next four are somewhat less popular, and that the remaining works follow a downward trend and produce negative results. This suggests that the latest artworks are unpopular.

RQ2. What is the popularity of non-controversial artworks?

We used the identical methodology in the subsequent ranking investigation. The present research query relates to controversial works of art. Due to the magnitude of the sample and the number of non-controversial artworks discovered (N = 2462), multiple datasets were also created to complete the current ranking experiment. In all datasets, approximately 80% (11 groups) were designated for training, whereas the remaining 20% (3 groups) were designated for validation testing, as it was desirable to include all posts from the same group. Moreover, to determine ranking scores for each of the selected artworks, they were all included in a testing set, despite the relatively small number of artworks due to the technical limitations of Instagram. In turn, in each iteration of the algorithm, the groups in the testing set were adjusted to three so that all artworks in the testing set succeed and a final score was calculated by combining their scores. To achieve this, five distinct datasets were constructed. It is notable that the same method of selecting the weighted average (10% of all posts) was used to determine the most popular group in this dataset. Each time the algorithm was executed, the most popular non-controversial artworks were identified. The final ranking is displayed in Table 7 below.

Table 7. The final list of non-controversial artworks by ranking outcomes.

The Final Rank of the Most Popular Non-Controversial Artworks (N = 2462)				
	Artwork	**Artist**	**Group ID**	**Predicted Ranking Score**
1.	Waiting for climate change	Isaac Cordal	10	9.61
2.	The Gates of the Hell	Auguste Rodin	1	9.16
3.	Solid Sky	Alicja Kwade	5	6.80
4.	Tower	Keith Haring	4	4.82
5.	Illuminated River	Leo Villareal	14	4.50
6.	ParaPivot	Alicja Kwade	13	3.72
7.	IKB 191	Yves Klein	3	3.57
8.	Maman	Louise Bourgeois	8	2.89
9.	Angel of the North	Anthony Gormley	7	2.54
10.	Water Tower	Rachel Whiteread	6	1.74
11.	The London Mastaba	Christo and Jeanne-Claude	12	1.32
12.	Orange, Red, Yellow	Mark Rothko	2	0.51
13.	Cloud Gate	Anish Kapoor	9	0.03
14.	Melting House	Alex Chinneck	11	−1.93

The scores of the most popular controversial artworks range from 9.61 (the highest-ranking value) to −1.93 (the lowest and negative ranking value) according to the ranking task's overall measurement data. According to the results, the first two artworks appear to be the most popular, with the third artwork following closely behind with a lower ranking score, and the remaining artworks demonstrating a particularly precipitous decline, culminating in a negative ranking. Based to the ranking, Waiting for climate change by Isaac Cordal, The Gates of Hell by Auguste Rodin, and Solid Sky by Alicja Kwade are the most popular works. As with the previous experiment's artworks, a concise explanation of the non-controversial artworks is provided in the lines that follow. The Waiting for climate change project is an art installation by Isaac Cordal that was exhibited in the summer of 2013 in the moat of the Château des Ducs de Bretagne, in Nantes, France. The installation comprised fourteen floating sculptures that moved in line with the wind and water currents. The real-size sculptures depicted figures in business attire. The objective was to demonstrate their apathy towards climate change, and specifically the rising water level [132]. The monumental sculpture The Gates of the Hell by Auguste Rodin depicts the first part of Dante Alighieri's Divine Comedy through 180 figures. It is exhibited in the Musée d'Orsay in Paris. It has been described as Rodin's most repulsive and incoherent sculpture, but it has not been deemed controversial [133]. Solid Sky by Alicja Kwade consists of a polished quartzite sphere weighing 22,000 kg and suspended in steel chains from the ceiling of the 550 Madison building in Manhattan. It is a work with political but not provocative implications, as the artist mentioned when comparing it to the planet Earth, and still remains as a symbol of capitalist corruption and a competitive world [134]. In these two cases, for both research queries, the models that emerged may have been unique, but the results were comparable, which is essential for the ranking's accuracy. Given that both datasets contained popular works of art, this improved both the research questions and the model's reliability.

RQ3. What emotions motivate individuals to share their aesthetic experience on social media?

Since the concept of controversial and non-controversial artworks was fundamental to this context, identifying the most popular works in each category was not the sole objective of this study. In addition, it intends to investigate the emotions elicited by these works in their viewers and analyzes these emotions through text processing of Instagram posts referencing these works. Art can have a significant impact on an individual's emotional state, inducing either positive or negative emotions, according to a review of the relevant literature. With very few exceptions, art receives no response from viewers. In fact, both the literature and the experiments demonstrate that the context and inherent qualities of art objects can affect an individual's aesthetic experience and engagement. Therefore, the text of the posts was kept in the same order as that of the other datasets so that it would be simpler to analyze and assign emotions using the annotated method and the SMART tool discussed in a previous section. Most studies evaluate emotions using the VADER lexicon from the NLTK tool, which categorizes emotions as positive, negative, or neutral. This procedure, however, does not meet the requirements of the research topic. For this purpose, we selected the emotions of disgust and surprise, as mentioned below. The posts that express no other emotion were marked as neutral.

5.6. Emotions Distribution of Controversial and Non-Controversial Artworks

The structure of the Instagram datasets was further investigated by analyzing their distribution. Both sets of data contained both the final ranking scores and the emotion attribute. The distribution of the three selected emotions (surprise, neutral, and disgust) across both datasets is depicted in Figure 3. The selection of emotions was based on user posts and is limited to three distinct emotions because other lexicon-based methods, such as NLTK, classify emotions into three equally categories, such as positive, negative, and neutral. Therefore, we conformed to this practice. The selection of emotions was based on Paul Ekman's theory of basic emotions and a broader taxonomy of eleven pairs of emotions consisting of three columns, where the kinds of emotion, for instance, are emotions related to object properties, event-related emotions, social emotions, etc. [55]. The other two columns contain positive and negative emotions. For our task, we selected the first category of emotions related to the object properties, and among the positive and negative emotions, we selected surprise and disgust, respectively. We used the neutral emotion for works that did not express any emotion or were partially insensitive.

According to the number of samples, the datasets are small because the emotion classification only pertains to the three most popular artworks in each dataset, as determined by ranking. The controversial artworks revealed a normal distribution of emotions, as depicted by the graph, with surprise represented in 430 posts, disgust in 232 posts, and neutral or ambiguous in 232 posts. Figure 3 reveals that in the dataset of non-controversial artworks, 75 posts contain the emotion of surprise, 24 posts contain the emotion of disgust, and 327 posts contain no emotion.

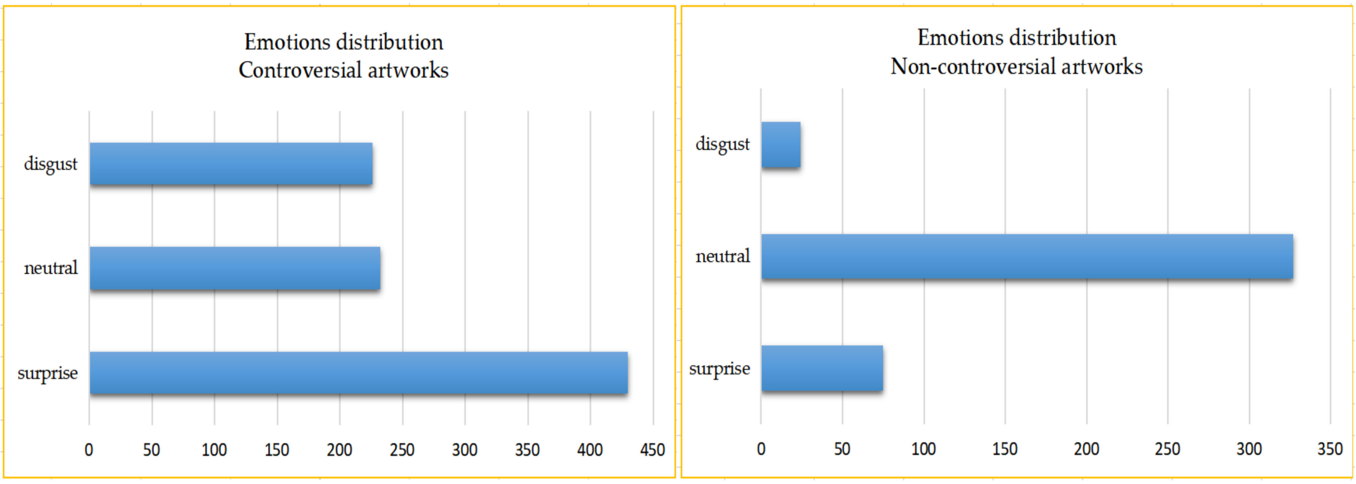

Figure 3. Emotion distribution of controversial and non-controversial popular artworks.

According to the data, the emotion distribution in controversial works of art is more typical. However, in the non-controversial works of art, the two most intense emotions, namely surprise and disgust, are significantly less frequent than in the first set of data, and the neutral emotion predominates. This may be due to several factors, but a review of the literature on the effect of art indicates that the inherent qualities of pieces, such as those found in controversial works of art, may be responsible for evoking strong emotions. Regarding the non-controversial works of art, which neither provoke nor possess particularities, this may also explain why attendees exhibited no emotion. In addition to the emotions, the graph below displays the score distribution for the top three works of art. The scores in the table are the result of adding all post-ratings for each piece of artwork. The total number of scores in the first dataset of the three most popular controversial artworks is greater than that in the second dataset of the three most popular non-controversial artworks, as indicated by the mean value in Table 8. This does not occur at all values and has no effect on the result, as it is a result of and dependent on the amount of data.

Table 8. Data exploration of the top three controversial and non-controversial popular artworks.

Controversial Artworks Final Scores (N = 888)					
Artwork	**Group ID**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Comedian	13	2.484981404	10.88238822	7.073537861	3.291500614
Fountain	1	3.572207427	10.97884701	6.720352801	2.631098511
Girl with Balloon	12	1.761229941	10.88238822	6.657787787	3.786313271
Non-Controversial Artworks final scores (N = 426)					
Artwork	**Group ID**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Waiting for climate change	10	4.954004609	10.67143134	9.615771934	2.235132131
The Gates of the Hell	1	7.247078366	9.751324437	9.166683576	0.712114018
Solid Sky	5	−3.137829148	9.751324437	2.923083106	4.644242865

As explained in the experiment, this also proves the premise that controversial artworks may elicit more intense aesthetic emotions, such as disgust or surprise, than non-controversial artworks. The potential for an artwork's qualities and the intense emotions it evokes to increase its popularity through social media engagement is a further argument in favor of the concept. As we observed, viewers were more surprised by the first scenario than the second. Based on extant research and previous experiments, it is highly likely that this is due to the inherent qualities and meaning of the artworks. Even though the qualities of non-controversial artworks were not as distinct as those of controversial artworks, observers did not experience strong emotions when viewing them. The present thesis was tasked with identifying the relationship between aesthetic experience and the popularity of art through a series of machine learning experiments. This final experiment confirms this link.

6. Discussion

Smart mobile devices are now universally adopted and used due to the vast array of features they offer. Mobility, usability, user settings, and broader social influence are a few of the aspects that impacts how their users deal with them [135]. Moreover, social media, such as Instagram, which was used in this study, coexists with other information platforms, and serves as a forum for young people's active discussions daily. A significant proportion of political figures are observed to use social media to promote their political agenda. On the other hand, youthful people appear to respond and express their opinions in this manner using hashtags, emoji, and negative words [136]. Similarly, young people can partake in discussions regarding art, particularly provocative art. This actual interaction, such as via likes, comments, and shares on other users' accounts or even other social networking platforms, can be a reliable indicator of the art's popularity. Compared to the aesthetic experience, there were fewer studies on the topic of popularity. Most of the research on aesthetic experience has concentrated on the viewer's experience with art in a laboratory or natural setting, such as a museum or gallery. Using specialized apparatus, other researchers compared the aesthetic experience of the viewer in a physical and virtual environment [137]. Although these studies are extremely intriguing, social media and the concept of popularity are absent. Some scholars [138] investigated content heterogeneity and popularity using data from a Facebook page with thousands of followers that posted the same image of an Italian vocalist each day. The objective was to compare its popularity to that of other news websites with heterogenous content, such as news. This study was neither about art nor employed ranking algorithms to measure the popularity of content. Furthermore, the endeavor to measure the popularity of the art using a ranking algorithm was intriguing because no other study followed the same methodology. The present study went a step further by incorporating the aesthetic experience of the viewer, considering the findings of Mitali and Ingram [75] regarding the renown of artists and how this stems from their social context and not their creativity. In addition, it presented a novel viewpoint of the role of social media in aesthetic experience and its contribution to the popularity of art.

7. Conclusions

This was the first attempt to rank and classify controversial and non-controversial artworks. Notably, according to the literature there is no universal definition of controversial art; therefore, what is provocative depends on a variety of factors, including the qualities of each work of art and the emotions it elicits in the viewer. We used Instagram data to investigate our idea. We chose Instagram because, due to certain limitations, Twitter did not contain the data we required to conduct these investigations, as previously mentioned. In addition, study data from Facebook cannot be accessed due to privacy concerns. Our analysis did not consider the viewer's gender, age, origin, education, or interests, as other studies on relevant topics did. We examined how people interacted with art in person and online. Due to the complexity of locating user demographics on social media, such as gender, age, and place of residence, this study did not concentrate on examining the user's personal characteristics. This is difficult given the fact that many Instagram users do not disclose their actual name, age, or country of residence on their accounts. Very frequently, we come across Instagram profiles that lacked a biographic description, regardless of whether the user posted a quote or information about their interests. Given these factors, we omitted this type of information. Regarding the recognition of emotions, the emotions of disgust, surprise, and neutral were utilized. It was observed that in the first scenario, surprise prevails over the other emotions, but the proportion of all emotions is greater than in the second dataset. In the second scenario, involving non-controversial artworks, an emotion of neutrality prevails, which seems reasonable given that the specific works of art lack as many distinctive characteristics as the controversial ones. This is exceptional because most academics limit their research to positive, negative, and neutral emotions based on automatic methods of emotion identification in social media text that were tested and discussed in previous sections. Moreover, it is intriguing that, according to the findings, certain controversial art pieces such as Comedian by Maurizio Cattelan or Girl with Balloon by Banksy have emerged as the most popular, as they have long piqued the interest of both the public and art experts. Considering how often these artworks were discussed on a global scale, the outcome was perhaps interesting. On the other hand, as regards the non-controversial works, it was not at all apparent which might be the most popular although some of them have preoccupied art experts. Consequently, we recognize the significance of the qualities of the works and their purpose, and how this could influence their popularity. Future research aims to expand the newly proposed framework by integrating additional factors derived from empirical studies of artworks and social media data. If possible, attempts will be made to include user attributes alongside popularity to obtain a greater grasp of the factors that can influence popularity.

This study had also conceptual and technical limitations, like others. Concerning theoretical constraints, we conducted extensive research on emotions, aesthetic experience, and popularity. The overview was not comprehensive. To construct our own framework, we solely used the most crucial components. It was hard to envision all the aspects that affect aesthetic experience and artwork popularity. Three segments illustrate the viewer's involvement with art and social media's mediation role. Another obstacle arose in our art quest. Initially, it was difficult to list controversial artworks and to identify non-controversial artworks released in the same year as the controversial ones. We selected 28 artworks (14 controversial and 14 non-controversial) because we were unable to locate sufficient Instagram posts for the other artworks on our initial list. This could have caused a negative balance in our machine learning trials; thus, we maintained a standard dataset. It is also important to discuss data gathering and processing challenges. Instagram's rate limit and API (Application Programming Interface) modifications made it difficult to obtain data. For instance, 100–300 posts took four hours to download. Large-scale data downloads are prohibited; hence, the procedure was phased. We obtained the maximum number of Instagram posts per day using geotags that are permanently or periodically displayed. Instagram blocked us frequently, so we had to create new accounts to obtain the data. As indicated in the data processing section, Instagram downloads JSON (JavaScript Object Notation) data. Each JSON (JavaScript Object Notation) dataset must be converted to csv (comma separated value) separately. Merging the datasets was a laborious task. We were fortunate to catch them. In addition, we attempted to gain insight into the future of the art popularity issue by increasing the sample size and combining more variables. Similarly, the implementation of the ranking was hampered by the lack of an established method for ranking the data on a predetermined scale. Consequently, relevance assessment was conducted to the greatest extent feasible, based on the data and similar studies that employed the relevance score.

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