

A Study of Aesthetics and Hedonics in Photography

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Introduction

Photography is a form of art, involving the practice of taking and processing photographs and “capturing the moment.” [8] Aesthetics in the realm of photography regards the nature and appreciation of beauty within this art form [5, 8, 16]. Usually the study of pleasure, or hedonics, is associated with aesthetics, as in the phrase “aesthetically pleasing.” However, aesthetics and pleasure are completely subjective, thus making it difficult to say that this specific feature of photography *always* makes it more beautiful or more ugly [2, 5, 15, 16, 18]. Rather, there are certain features and qualities of an image that *usually* make it more or less pleasing to the eye [2, 5, 16, 18]. There are a plethora of these features, such as lighting, contrast, and saturation, that professional photographers generally worry about when taking a photo, but are not things that are commonly thought about by the average viewer or amateur photographer. [5, 8, 16, 18] Despite such ambiguity and subjectivity regarding enhancing the aesthetic value and pleasurability of photography, this paper shows not only that there is a significant correlation between aesthetics and hedonics in photography, but also that there are certain visual features that *generally* increase or decrease how aesthetic something is.

Currently, in the field of photographic aesthetics, many experts are trying to create a computational analyzation method to determine the aesthetic value of photos. This includes a visual feature extraction method [8], a collaborative composition model [26], and a spatial recomposition model [5]. Online photo sharing communities provide a strong basis and dataset to analyze images for these studies [8, 23]. However, there are still many issues with computationalizing something that is psychologically subjective. Thus, the main topic of inquiry

for this paper regards finding what specific features of photography influence the aesthetic value of an image.

Literature Review

Recently, photography has become more prominent with an increase in digital technology. According to Nancy Van House [23], people are posting more and more photos on social media and generally, pictures that are more aesthetic, get more “likes” or are considered more favorable to look at [23]. However, a somewhat unexplored field of photography is its overall hedonic value, or pleasurability, specifically based on the aesthetic component. Before one can delve into aesthetic enhancement techniques and pleasurability, it is important to look at how notions of aesthetics have changed over time, especially with improved camera technology.

Susan Murray [18] discusses this recent transition in everyday aesthetics due to digital technologies. She focuses on a more basic level of aesthetics, concluding that while it is becoming more difficult to differentiate beginner and professional photography, there are still commonalities and similar values to follow as well as decisions such as subject choice, lighting, color, and framing [18]. Digital photography has significantly raised societal standards regarding image quality [18]. However, there is still an accompanying acceptance of what might be considered the “imperfect” image as well [18]. With online public photo-sharing, we find a modified material relationship to the everyday image, a decreasing gap between professional and amateur [18]. This leaves a unique sense of a community between viewers and photographers, as well as a new relationship between the collection, display, categorization, and distribution of the digital image [18]. While digital photography has not revolutionized photography or led to a loss of authenticity, it has significantly modified our relationship with photography, especially when

paired with social networking software, as well as increased societal expectations for, and interactions with, the image and an everyday aesthetic [18].

Van House [23] further discusses personal photography and the transformation from film to digital technologies within photography. With the ease and convenience of digital technologies, there is a substantial increase in the number and variety of images made [23]. Digital cameras and camera phones allow people to take spontaneous photos, any time, any place, and without prior planning [23]. With this shift to digital cameras and camera phones, it was noticed that people posted their personal photography a lot more and had considerably improved image quality [23]. Because of convenient and rapid viewing and sharing, images have become a greater part of people's lives [23]. Technology and social media increasingly publicize personal images; photos are less private and less ownership based as almost all photos posted online can be accessed by others [23]. In Van House's study, it was found that along with the traditional purpose of photography as a tool to remember an event, it also has significance regarding emotional relationships to someone or something, and is form of self-representation and personal expression [23]. It's increasingly become a form of art with strong emotional value [23].

A basis of knowledge for how aesthetics is perceived psychologically is an important foundation before looking at the computational approaches that have become increasingly popular. Belke et. al. [4] focuses more on this psychology of aesthetics, explaining why and how the brain perceives it. The study suggests the aesthetic appreciation is partially resultant of a perceiver's' higher-order-processing dynamics, meaning the higher a viewer's cognitive fluency is, the more enjoyable a picture or art is to look at [4]. Going off of this idea, Reber et. al. [20] further explains the correlation between processing fluency and aesthetics. These authors, too,

propose that aesthetic pleasure is a function of the perceiver's processing dynamics [4, 20]. The more fluently the perceiver can process an object, the more positive the aesthetic response is, as determined by psychophysiological findings [4, 20]. It is important to note that processing fluency is itself hedonically marked [4, 20]. Beauty is a subjective experience, however, objective properties of stimulus material and previous encounters with the stimulus are also incorporated into such processing experiences, thus affecting some viewers more emotionally than others [4, 20].

Furthermore, there has been significant research on how to enhance aesthetics and what aspects of an image make it more or less pleasing to look at. Many authors have worked towards finding a computational approach to aesthetics, an abstract, psychological concept. In "On Aesthetics and Emotions in Images: A Computational Perspective," Joshi et. al. [16], discusses an overview and history of the topic, describing many different models and factors in aesthetic photography, and showing how it has changed over time [16]. They reveal that aesthetic response depends upon several dimensions, such as composition, colorfulness, spatial organization, emphasis, motion, depth, or presence of humans [16]. Photographers generally abide by rules that distinguish professional shots from amateur ones [16, 18]. Some examples are the rule of thirds, the use of complementary colors, and close-up shots with high dynamic ranges [8, 16]. Furthermore, there are two key aesthetically relevant segment-based features; one computes the position of the visual attention center with respect to focal stress points in the image, while the second measures the ratio of weights of support and sky regions [16]. This correlates with work done by Datta et. al. [8]. In their paper, "Studying Aesthetics in Photographic Images Using a Computational Approach," the authors establish significant correlation between various visual properties of photography images and their aesthetic ratings,

with certain visual properties yielding higher influences on aesthetic quality than others [8]. This is based on their “method of choice” survey in which 3581 different photographs were rated on a seven-point Likert scale based on aesthetic value, and again from one to seven based on their originality [8]. (Originality ratings are based on the uniqueness of the images [8].) The authors discovered a positive, linear correlation between aesthetics and originality [8]. Moving on, they mostly focused on just the aesthetics score, using a feature extraction method to analyze 56 different features that could potentially make a photo more or less aesthetic [8]. They chose features based on common rules of thumb in photography and observed trends in the ratings [8]. Some of the prominent features analyzed included exposure of light, colorfulness, saturation, hue, the rule of thirds, familiarity to subject matter, wavelet-based texture, size and aspect ratios, region composition, and low depth of field indicators [8]. When looking at their regression results, it was found that the variance of the aesthetics scores over all 3581 samples was 0.69 [8]. The authors developed new feature methods relevant to photographic quality in order to analyze aesthetics: including a low depth-of-field indicator, a colorfulness measure, a shape convexity score and a familiarity measure [8]. Overall, the study is a significant step toward the highly challenging task of understanding the correlation of hedonics and photography aesthetics by a computational approach [8].

Additionally, in “A framework for photo-quality assessment and enhancement based on visual aesthetics,” Bhattacharya et. al. [5] developed a different model for computational aesthetics in which they also used a user study, another name for the method of choice. Their sample population rated different photos based on aesthetic value, this time on a five-point Likert scale, and then the authors analyzed the pictures after [5]. Their dataset consisted of 632 digital photographs with fifteen independent participants assigning the rankings [5]. To analyze the

pictures, they used a supervised learning-based scene classification method to accomplish two main goals [5]. For one, they assessed the aesthetic appeal of photographs based on visual weight [5]. Secondly, they strived to recompose the given image while still maintaining the scene integrity, meaning they tried to keep the background the same while only altering the subject [5]. Their research focuses on increasing aesthetic value with recomposition techniques, whereas the previous sources just analyze what existing features of the original images make them more or less aesthetic [5]. Overall, these authors introduced a new multimedia application that assesses the aesthetic quality of photography using geometric rules of composition [5]. Users are then able to make an informed decision on how to improve the photography using spatial recomposition [5]. In regards to predicting the attractiveness of unrated images when compared to respective human rankings, their approach achieved 86% accuracy [5]. Furthermore, 73% of the images recomposited with their application were ranked more attractive than their original counterparts by human raters [5].

Also in the realm of computational aesthetics was Zhang et. al. [26] with their research, “Strategy for aesthetic photography recommendation via collaborative composition model.” As the title states, they use a collaborative composition model to analyze pictures and make recommendations for subject poses to increase the aesthetic value [26]. They start by collecting professional photos from an online photo-sharing website to use as a reference dataset [26]. The dataset consisted of 232 photographs [26]. The images that were tested and compared were 50 images of scenes of landscape [26]. They analyzed the photos based on attention composition and geometric composition, looking at aesthetic representation based on these two factors [26]. After the aesthetic composition representation step, they moved on to reference candidate photos from the dataset using a collaborative composition model [26]. Based on all the information they

collect from this model, they then select a reference photo and create recommendations for more suitable poses and positions of the subject matter, guiding users to take more satisfactory photos. [26]. Zhang et. al. also incorporates a user study into their research, however they use it in a different way than the other authors [26]. Ten participants evaluated the 50 images by picking the pose and position they want to capture in the images [26]. They compared this with the recommendations to make it more subjective [26]. Each photo is then rated on a satisfaction scale of five to one, five being quite satisfactory and one being dissatisfactory [26]. When looking at the original images with the new recommended ones, the results show their method shows a 5 to 23% improvement in average satisfaction scores compared to other baseline methods [26]. Overall, this method is another effective method in improving the aesthetic quality of photographs [26].

More broadly than just aesthetics, there are many different aspects that make photography pleasurable. While my main focus is on aesthetics, some other factors include that photography can help enhance experiences, and can be used as a tool for identity, communication and memory [9, 10, 15]. Higgins [15] studies the value of hedonic experience, with a focus on how the strength of engagement of an experience can contribute to the pleurability, or displeurability, of that experience. Diehl et. al. [9] elaborates on the idea of how photography specifically enhances experiences, finding that compared to not taking photos, photo-taking can greatly increase enjoyment of positive experiences. It does so because photo-taking increases engagement [9]. Taking photos focuses more attention to the experience, particularly on aspects of the experience worth capturing [9]. Throughout multiple experiments, it is found that photo-taking enhances a diverse variety of experiences [9]. This shows how photography can make an experience more pleasurable, increasing the hedonic value [9].

However, when the focal experience is already engaging, there is no increased pleasure from taking photos [9]. Also, because taking photos heightens engagement with the experience, it was also found that not only does it boost positive experiences, but worsens negative ones as well [9]. Furthermore, Dijck [10] focuses on identity, communication and memory as positive results of photography. Rapidly increasing popularity in the use of camera phones supports and drives a new communicative use for personal photography [10]. Pictures are becoming the new basis for social interaction, specifically on social media [10]. The frequency of fusing photography with daily experiences and communication is part of a broader cultural transformation, involving individualization and intensification of experience. [10]. Digital photo cameras have also been seen as novel instruments of identity formation, particularly as they allow users to manipulate or edit their own images[10]. While photography is increasing regards as an instrument for identity construction, rather than one for recollection or reflection, this new role does not negate photography's traditional function [10].

Aesthetics and the pleurability of photography are becoming increasingly more important as photography continues to grow in popularity, especially on social media platforms, and it is valuable to explore the correlation between the two. There is a gap in the current body of knowledge regarding computational aesthetics in that no previous study looks specifically at high school students. Teenagers are an important group to look at as they comprise a large portion of social media users, and are thus exposed to numerous images on a daily basis.

Methods

The majority of this study is aligned with the studies prepared by Joshi and Datta [8, 16]. While the exact questions from their studies were not released, methods of data collection and data analyzation were alike. For my study, alike to Joshi and Datta's [8, 16], I gathered

quantitative and categorical data regarding aesthetics and hedonics in photography. Inference procedures included estimates of population means and proportions, correlation analysis, shape and spread analysis, as well as the use of descriptive statistics to evaluate if the population means and proportions were above or below certain threshold levels compared to the Joshi and Datta [8, 16] studies.

All photos for my method of choice survey were uploaded directly from a large online photo sharing community; *Flickr.com* [12]. While Joshi and Datta [8, 16] used *Photo.net* as their online database, other experts in the field, such as Murray [18], discuss *Flickr.com* as an ideal source to extract images for aesthetics rating purposes. Flickr allows users to browse through thousands of photographs, organized into “photostreams” by subject materials, colors, tags, and other methods of classification [12]. Nearly four million new images are uploaded daily [12]. When selecting photos for my survey, each image was very distinct in terms of prominent colors, contrast, lighting, subject material, as well as the quality of the photo. Such photo diversity was intended to minimize bias and avoid similar aesthetic scores.

This study falls under the field of experimental aesthetics in which there are three main methods of use, as described by Fechner’s *Zur experimentellen Aesthetik* [11]. One of the most notable methods, employed both in my study and in Joshi and Datta’s studies, is the method of choice [8, 16]. Subjects are asked to compare objects with respect to their pleasingness, or more simply, subjects rate photos on a Likert Scale based on aesthetic and pleasurability values [8, 16]. For my study, 100 high school students were asked to rate twenty distinct photographs on a scale of one to nine, first based on their aesthetics scores, and then again rate the same photos based on their pleasurability, or hedonics, scores.

Students were all from the same densely populated high school located in a suburban area of Southern California. The school is widely recognized for its academic excellence, with extremely high graduation and college acceptance rates. The school displays impressive diversity, with a minority enrollment of 72% and 52% enrollment from students whose families are economically disadvantaged. Because of this, it is believed these high school students can be an adequate proxy for the population of all high school students within the United States within regards to analyzing the aesthetic and hedonic value of photography. Students embody numerous ethnicities, all economic levels, and have various exposures to social media and photography. This high school was also chosen for convenience purposes, as this is where I attend. That made this study less costly and time consuming, which were important factors in making widespread data collection plausible.

Because there are so many students attending this high school, a stratified random sample was selected as the best method of data collection. The school was subdivided based on entry points of the students, and each entry point, or gate, was used as the stratum. These seven strata were chosen after studying the access students have to the school, and found that students can be exclusively distributed to a single point of initial entry each morning. Students only enter school once, which is why entrance points were chosen, versus exits, as students leave at various times each day based on each student's unique class schedule. Stratifying the school into seven entry points gave us representative samples of the entire student population to ensure everyone was equally likely to be selected. Within each stratum, random selection of subjects was conducted. Standing outside with a partner each morning for seven days (for the seven gates) between 7:00 a.m. and 8:20 a.m., we approached every third person entering each gate and

asked them to sign up to take the survey. To minimize nonresponse bias, a \$30 VISA gift card raffle was used as incentive to motivate students to participate.

Figure 1 depicts a map of the school, with each colored circle representing a different point of entry. The table shows the number of students that enter each gate, along with the percentage of total students, and the percentages used for this survey. Chi squared analysis was used to ensure that the distribution of students per gate was similar to the expected.

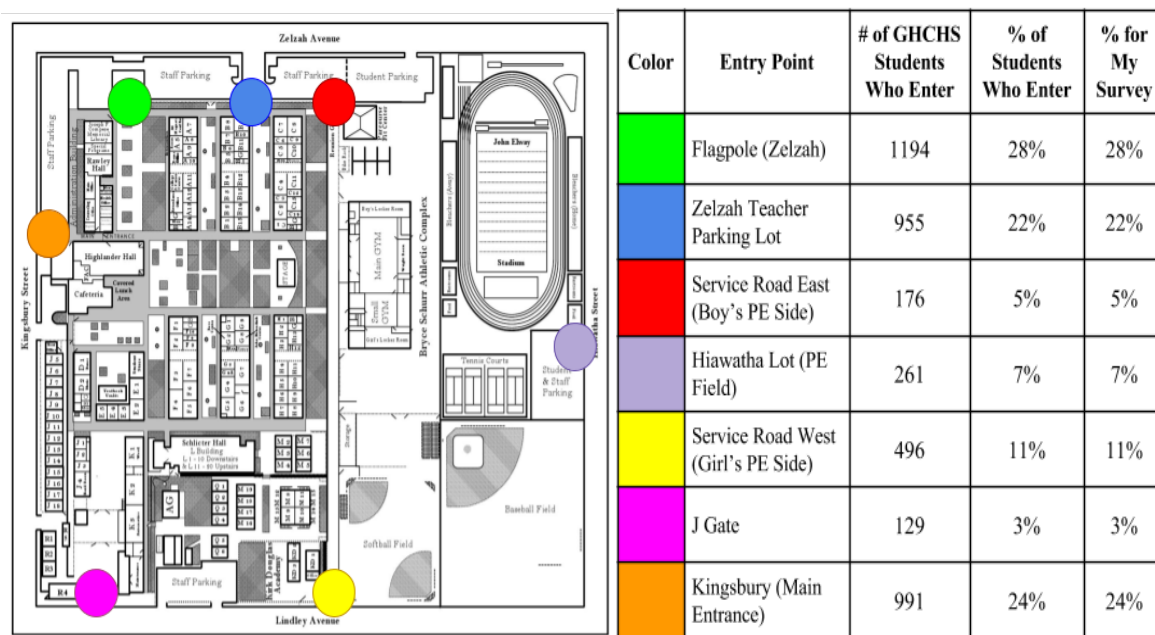


Figure 1

Regarding the data collection process and the survey delivery, students were given the survey in a natural setting. Rather than being asked to stop at the gate and take the survey when they entered campus, students instead wrote down their student ID number, and were emailed the survey later that day. Emailing the survey allowed them to complete it at their own leisure. The survey was non-disguised, as all students knew they were being observed during the data collection process. Furthermore, direct and structured observations were employed, as was also employed by Joshi and Datta [8, 16]. All subjects were anonymous. Mechanical collection was

used with Google Surveys. All questions were online, and the responses were then directly downloaded from Google's platform into an Excel Spreadsheet. Statistical analysis was conducted in Excel.

Along with careful selection of the images from Flickr, other components of the survey were cautiously designed to avoid bias and maximize response rate. Surveys were made available on student's school laptops so they could take it at their own convenience, ensuring adequate representation of the population and avoiding undercoverage bias. No leading questions were used and there was no attempt to influence any rankings on the pictures. Each picture was shown separately, so they could not be directly compared. Response bias was minimized by making the survey anonymous. Only basic demographic information (grade, gender, social media usage) was asked of the participants, so they do not have to worry about perceived judgement of their answers or being linked to their responses. Along with the raffle, to increase response rate, professional presentation of the survey along with clear and concise instructions were utilized. The survey was organized in a non-threatening way, starting off with initial demographic information before delving into aesthetics, then hedonics rankings. Questions were worded in a way that were not intimidating, narrowed to one dimension, accommodating to all answers, and had no answers dependent on previous questions. There was also an inclusion of neutral response choices. The variety of pictures was intended to provoke variability in answer responses as previously stated.

Overall, the purpose of this survey is to assess the correlation of aesthetics and hedonics in photography based on responses from high school students. Based on responses, it was also designed to be able to analyze what aspects of photography make images more or less aesthetic, or more or less pleasurable.

Findings

When employing the method of choice and analyzing ratings of photos, Joshi and Datta [8, 16] looked at aesthetics scores and originality scores, whereas this study looked at aesthetics scores and hedonics scores. They found that there was a strong correlation between the aesthetics and originality rankings for their data [8, 16]. As result of this finding, they chose to limit the rest of their study to aesthetics rankings only, since the value of the score of one can be approximated to the score of the other [8, 16]. Within my own study, I found a strong positive correlation between the aesthetics and pleasurability scores. For the twenty images, correlations ranged from 0.61 to 0.83, indicating a positive, linear correlation. As Joshi and Datta did, I will also limit my study to aesthetics scores only, as the value of hedonics can be approximated to the value of aesthetics if necessary.

To further analyze data, there were limitations in regards to computational analysis tools. Joshi and Datta were able to use a complex visual feature extraction method where each image was converted to *HSV* color space, thus producing two-dimensional matrices, I_h , I_s , and I_v , each with a dimension of $X \times Y$ [8, 16]. For each of their images, 56 visual features were extracted and analyzed to see what factors or trends lead to higher aesthetics rankings [8, 16]. However, I did not have access to this type of analyzation software. Thus, I will take an approach more along the lines of descriptive statistics, comparing shape and spread of my findings with theirs, based on this visual extraction method. For example, one of the features they analyzed was light exposure by using average pixel intensity [8, 16]. Through this, they found that pictures with high exposure (those that are too bright) and those with low intensity (too dark) generally have lower aesthetics rankings [8, 16]. While I can't compute average pixel intensity, I can look at my

images, specifically the ones that are too dark or too light, and see if these images have low aesthetics rankings, as discovered by Joshi and Datta.

To decide what features to extract, Joshi and Datta used some basic rules of thumb in photography [8, 16]. Based on these rules and their findings, out of the twenty images from my survey, I chose five main images to analyze, as they applied to multiple rules, and could thus be analyzed more holistically. However I will discuss some other images as applicable. I named each image by their subject, to make them easier to keep track of for the purposes of this paper. All images are displayed in Figure 2. The five main images, along with data regarding the aesthetics rankings for each are displayed in Figure 3.

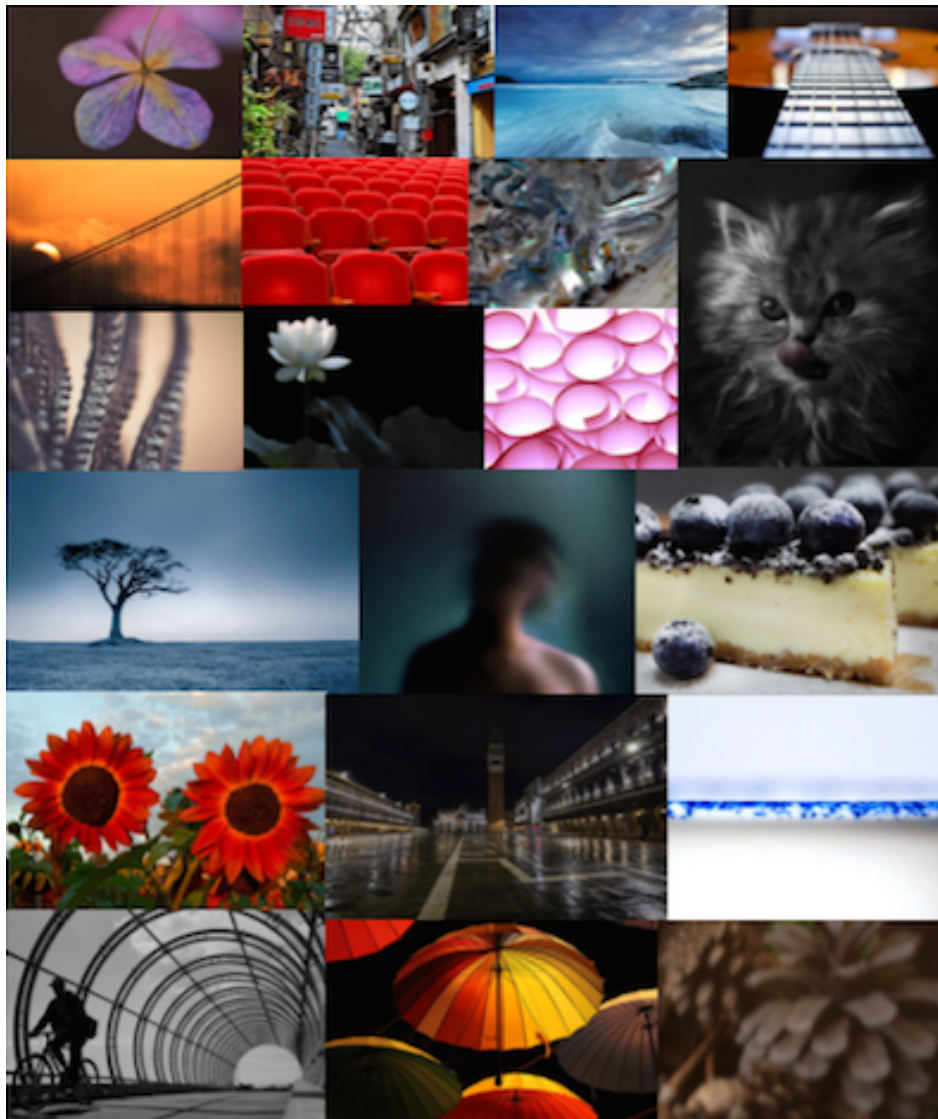


Figure 2

The rankings are based on a Nine-Point Likert Scale with the following criteria: 1=Very Ugly; 2=Ugly; 3=Somewhat Ugly; 4=Barely Ugly; 5=Neutral, 6=Barely Pretty; 7=Somewhat Pretty; 8=Very Pretty, 9=Very Pretty.

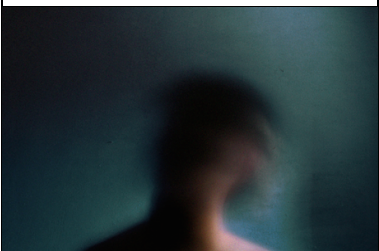
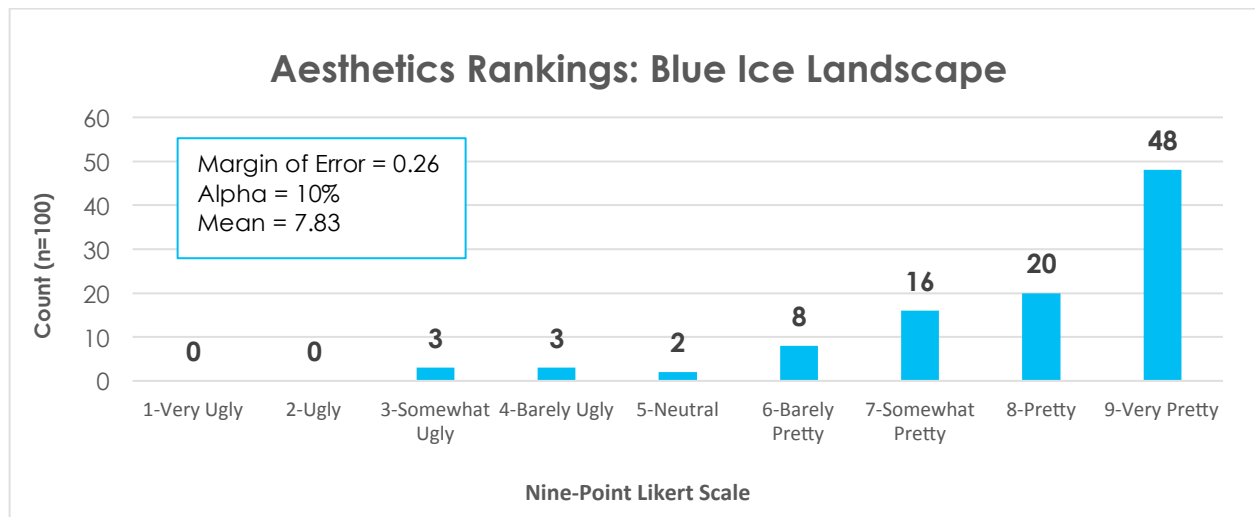
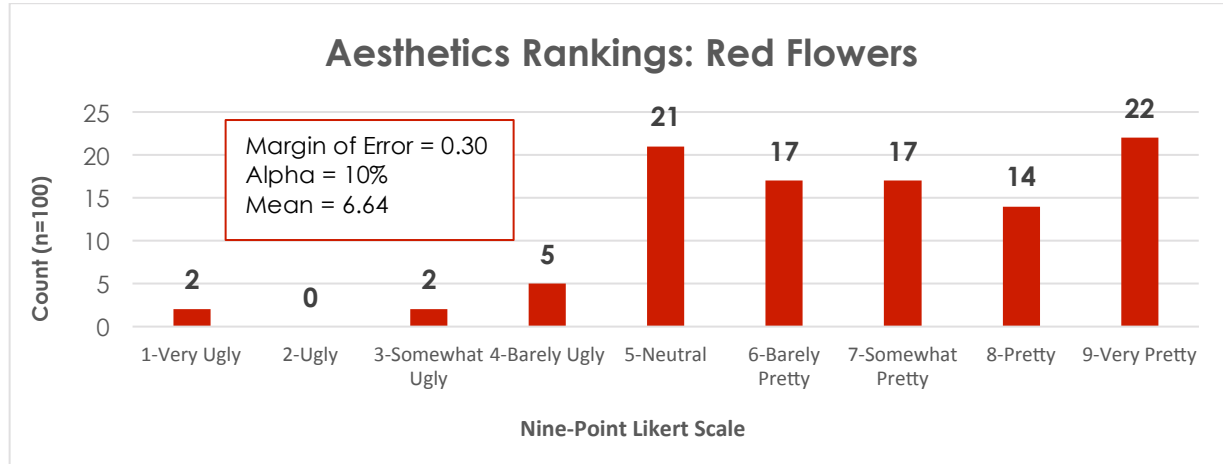
	Blue Ice Landscape Mean = 7.83 Median = 8 Mode = 8 Skewness = -1.48 Alpha = 10% Margin of Error = 0.25	- Prominent primary color throughout (blue) - High saturation - Clear, sharp image - Some contrast Predicted: High aesthetic ranking
	Pinecone Mean = 3.50 Median = 3 Mode = 1 Skewness = 0.69 Alpha = 10% Margin of Error = 0.36	- No prominent primary color - Low saturation - Blurry, out of focus image - Little contrast - Dark image Predicted: Low aesthetic ranking
	Red Flowers Mean = 6.64 Median = 7 Mode = 9 Skewness = -0.52 Alpha = 10% Margin of Error = 0.31	- Prominent primary color (red) - High saturation - Clear, sharp image - Some contrast Predicted: High aesthetic ranking
	Umbrellas Mean = 6.53 Median = 7 Mode = 8 Skewness = -0.91 Alpha = 10% Margin of Error = 0.31	- Prominent pure colors (yellow, red) - High saturation - Clear, sharp image - High contrast Predicted: High aesthetic ranking
	Blurry Man Mean = 4.24 Median = 4 Mode = 5 Skewness = 0.32 Alpha = 10% Margin of Error = 0.38	- No prominent primary colors - Low saturation - Blurry, out of focus image - Some contrast - Dark image Predicted: Low aesthetic ranking

Figure 3

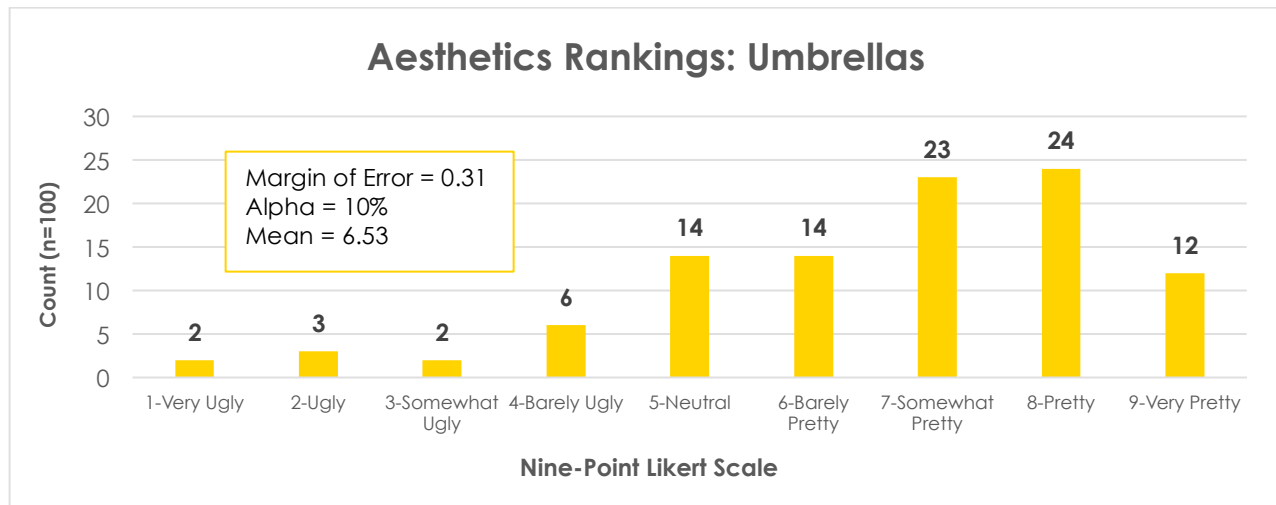
One accepted rule in nature photography, as described by Joshi and Datta, is that the purer the primary colors, such as red (sunsets, flowers), green (trees, grass), and blue (sky, ocean), the more striking the scenery is to viewers [8, 16]. That is, the higher the aesthetics rankings are and the more skew left the histogram graphs will be. The blue ice landscape, and the red flowers both exemplify bright, pure, primary colors and were predicted to have high aesthetics rankings, where the pinecone, with a more faded brown color, was expected to have a low ranking. The blue ice landscape image's ratings produced a unimodal graph with a Fisher skew statistic of -1.51, indicating highly skewed left. It's aesthetics ranking was 7.83, which was the highest mean ranking out of all 20 images, thus corresponding with the findings of Joshi and Datta.



The red flower produced similar results, a bimodal graph and a mean aesthetics ranking of 6.64.

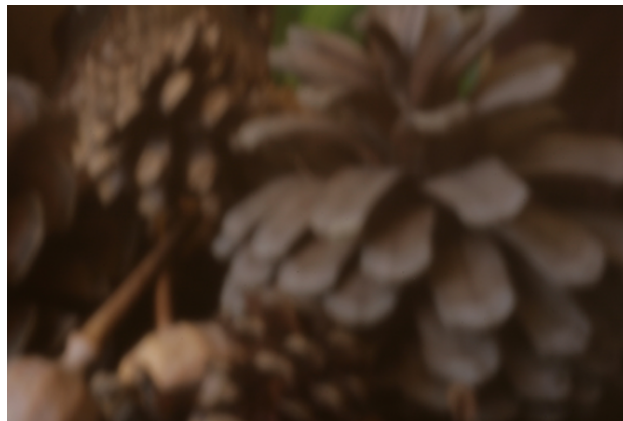
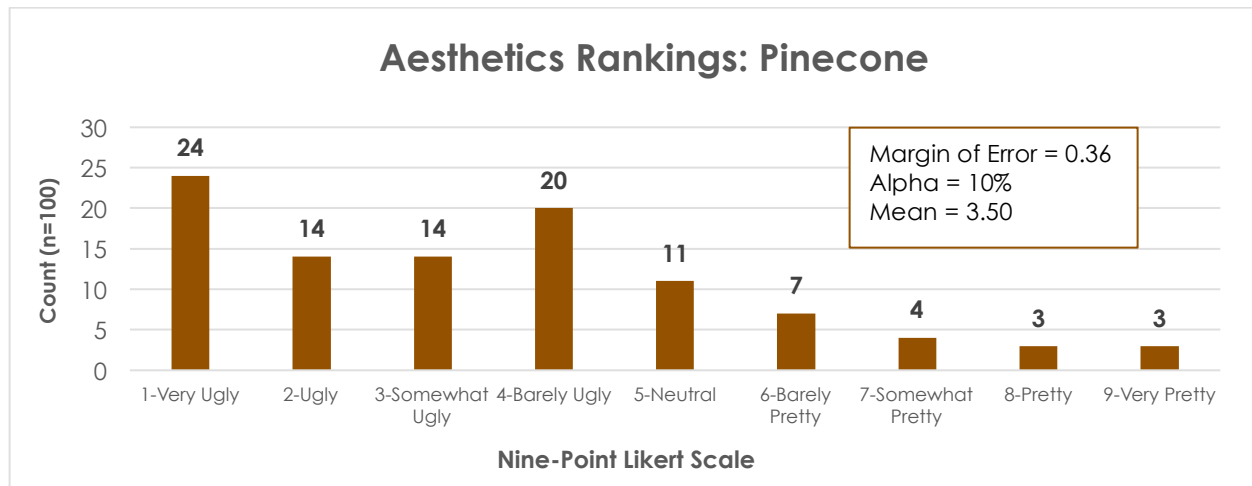


I believe the reason this score was not as high as the blue ice landscape is due to the fact there is also a prominent use of brown and green in the foreground, whereas blue is the sole prominent color in the other image. While this rule is in regards to nature photography, high saturation and pure colors are generally perceived as more aesthetic as well for all types of images [8, 16]. The image of the umbrellas also had a similar graph to the flowers and landscape, with a mean aesthetics ranking of 6.53.



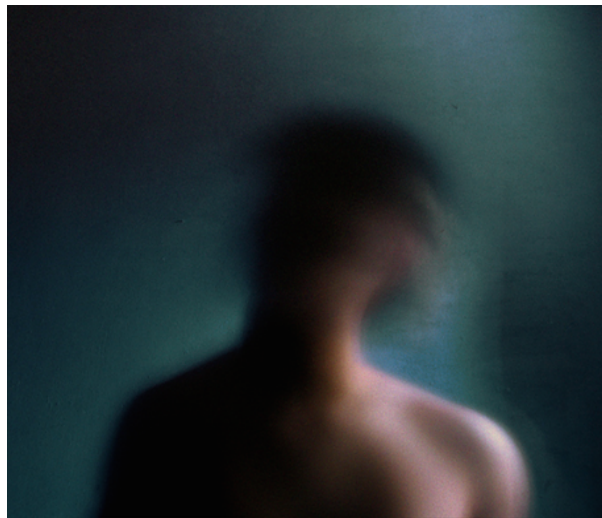
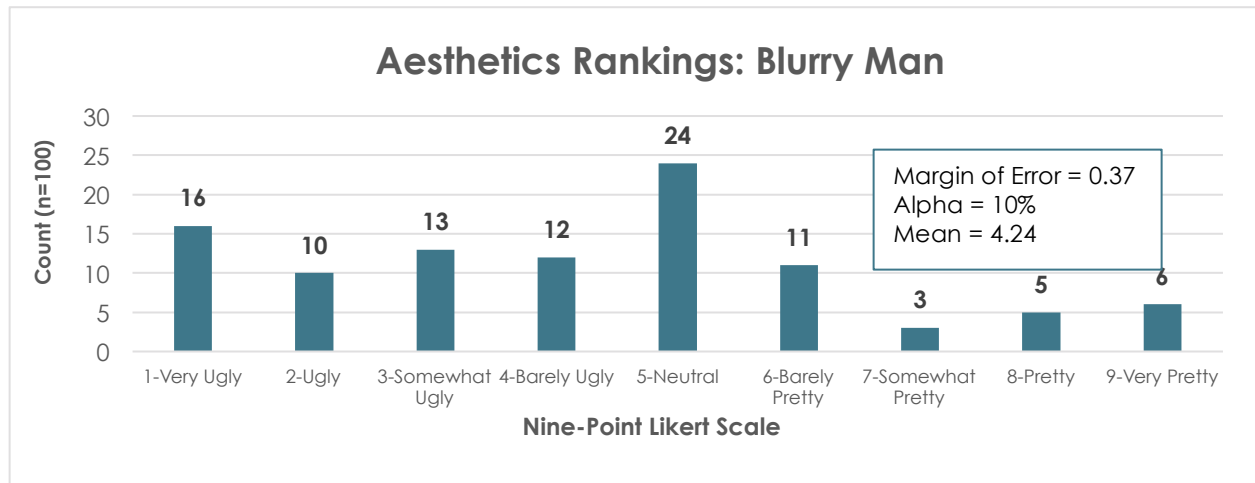
While depicting yellow and red as the prominent and bright colors, these colors are not widely present throughout the picture, but rather concentrated in the center with the outside being dark. This contributes to the slightly lower aesthetics score.

Furthermore, when looking at the data for the pinecone image, it was found to have a skewed right distribution with a mean aesthetics ranking of 3.50, the lowest mean aesthetics ranking of the 20 images.

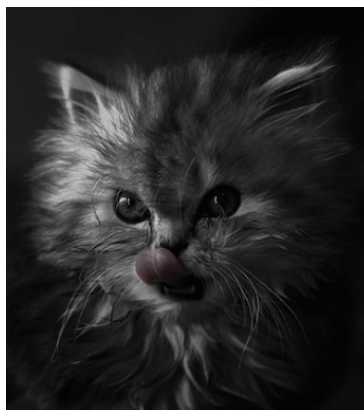


Along with a lack of prominent primary colors, there are other issues with the image of the pinecone that caused it to have a low ranking. Joshi and Datta also discuss that grainy, blurry, or out of focus pictures are generally perceived as less aesthetic [8,16]. Because the pinecone is quite out of focus, this further caused the low ranking. The image of the blurry man (aptly named) had a more neutral mean aesthetics ranking of 4.24. Again, this lower score is due to the low quality, or blurry nature of the image. Semantics is another key factor that affects how people visually perceive images [8, 16]. Because the image depicts a human, people are likely to feel more connected to the image, thus causing for a slightly higher score than the pinecone. It was also slightly more colorful than the image of the pinecone, with a blue-green toned

background, which could have caused a higher ranking as well.



Semantics affected the rankings of other images as well, such as the image of the cat, which had a mean aesthetics ranking of 5.81.



While the image is dark, has little contrast, and is not colorful, which should lead to a low aesthetic score, the image still proved to have a more neutral, medium ranking. Again, humans can see an animal and relate more emotionally to it, compared to not reacting as emotionally to an images of umbrellas. Thus, the aesthetic score for this image was higher than predicted, as people who love cats would rank it as highly aesthetic, despite the qualities that should lead to a less aesthetic score.

Another feature Joshi and Datta looked at was contrast [8, 16]. From their studies, they found that images are perceived as more aesthetic when there is high contrast or a clear distinction between the background and the subject [8, 16]. The picture of the blurry man is a dark subject on a pretty dark background, with little contrast between the two, thus also contributing to the image's lower mean aesthetics ranking. Again looking at the image of the umbrellas, it is obvious that there is high contrast between the bright red and yellow subject, with the dark, black background, suggesting a higher aesthetic ranking. However, this finding proves somewhat contradictory with what was discovered of the image earlier, as it was more medium high. This image is a prime example displaying how complex aesthetics is and why it is difficult to create a computational approach. While many visual features can be analyzed and predict high or low scores, because aesthetics is largely based on human emotions and perceptions, there are aspects that cannot be computed by technology. Even though Joshi and Datta extracted and analyzed 56 visual features for nearly 4,000 images, they too, admit that it is only a step towards computational aesthetics, and is not near perfect yet [8, 16]. For my study, just analyzing these key features for five main images shows how complex aesthetics is. However, it still provides foundational information for making images more pleasing and creating a basis for computational aesthetics.

Conclusion

Overall, this study provides a basis for increasing aesthetic quality of image and shows how complex the field of computational aesthetics truly is. While elements such as lighting, contrast, and saturation generally have an effect on increasing or decreasing the aesthetic value of an image, it is still something completely subjective, thus creating extreme difficulty in the computational process.

Despite such limitations in the field, this study still contributes valuable information regarding how to improve personal photography. Especially with increasing digital technology in society and smartphones with high quality cameras equipped, more and more people take pictures and more frequently. Understanding aesthetics and pleasurability in photography not only can help people improve their photo quality, but it can also help enhance experiences. Because of the correlation to hedonic value, the more aesthetic something is, the more pleasing people will find it to be to look at, thus increasing happiness among viewers. Furthermore, as discussed by Van House [23], the more beautiful something is, the more likely it is people will “like” it on social media. Knowing how to improve photo quality for the purposes of posting images on social media platforms can increase the photographer’s popularity as well, something many users thrive on. As Murray [18] found, the distinction between amateur and professional photography has been decreasing in recent years, and this study further helps close the gap, helping “amateurs” take better photos.

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Appendix 1

Excel Data as Presented in Excel

Sample Size: n=100

Design: Stratified random Sample

What is your gender?	Grade?	DSLR?	Instagram?	Snapchat?	Flickr?	Enjoy?	gate did you come into school this morning?	what time did you arrive at school this morning?
Male	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	8:07
Male	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	7:00
Male	11	Yes	No	Yes	No	Yes	Kingsbury (Main Entrance)	7:40
Male	12	No	Yes	Yes	No	No	Kingsbury (Main Entrance)	10:27
Female	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	7:05
Male	11	No	No	No	No	Yes	Kingsbury (Main Entrance)	7:22
Female	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	9:22
Female	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	9:25
Male	12	No	No	No	No	Yes	Kingsbury (Main Entrance)	9:20
Male	12	No	Yes	No	No	Yes	Kingsbury (Main Entrance)	8:20
Male	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	9:21
Male	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	7:20
Female	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	7:15
Female	12	Yes	Yes	No	No	Yes	Kingsbury (Main Entrance)	9:22
Male	12	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	8:13
Female	9	Yes	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	7:15
Male	9	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	7:20
Female	9	No	No	Yes	No	Yes	Kingsbury (Main Entrance)	7:05
Female	9	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	6:50
Female	9	No	No	Yes	No	Yes	Kingsbury (Main Entrance)	8:00
Female	9	No	Yes	Yes	No	Yes	Kingsbury (Main Entrance)	8:15
Male	9	No	No	No	No	Yes	Kingsbury (Main Entrance)	8:10
Male	9	No	Yes	No	No	Yes	Kingsbury (Main Entrance)	8:17
Female	9	No	No	No	No	Yes	Kingsbury (Main Entrance)	8:10
Male	10	No	No	No	No	Yes	Flagpole (Zelzah)	8:15
Male	9	No	No	No	No	Yes	Flagpole (Zelzah)	8:40
Male	10	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:07
Female	9	No	Yes	No	No	Yes	Flagpole (Zelzah)	7:15
Female	10	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	8:23
Male	10	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:00
Male	10	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:15
Male	12	Yes	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:45
Male	12	Yes	No	No	No	Yes	Flagpole (Zelzah)	8:05
Female	12	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	8:00
Female	12	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	8:00
Male	12	No	No	No	No	No	Flagpole (Zelzah)	7:50
Male	12	No	No	No	No	No	Flagpole (Zelzah)	8:00
Female	12	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:10
Female	12	Yes	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:20
Female	11	No	No	No	No	No	Flagpole (Zelzah)	8:00
Male	12	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:11
Male	9	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	8:00
Male	11	No	No	No	No	Yes	Flagpole (Zelzah)	7:20
Male	12	No	Yes	Yes	No	No	Flagpole (Zelzah)	8:20
Male	12	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:15
Female	12	No	Yes	Yes	Yes	Yes	Flagpole (Zelzah)	8:17
Male	12	No	No	Yes	No	Yes	Flagpole (Zelzah)	8:22
Female	11	No	Yes	Yes	Yes	Yes	Flagpole (Zelzah)	7:18
Female	9	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:30
Female	9	No	Yes	Yes	No	Yes	Flagpole (Zelzah)	8:05
Male	9	No	No	Yes	No	Yes	Flagpole (Zelzah)	8:15
Female	9	Yes	Yes	Yes	No	Yes	Flagpole (Zelzah)	7:20
Female	9	No	Yes	Yes	No	Yes	Hiawatha lot (PE field)	8:15
Female	10	Yes	Yes	Yes	Yes	Yes	Hiawatha lot (PE field)	8:15
Male	12	Yes	Yes	Yes	No	Yes	Hiawatha lot (PE field)	8:20
Male	12	No	Yes	Yes	No	Yes	Hiawatha lot (PE field)	8:10
Male	12	Yes	Yes	Yes	No	Yes	Hiawatha lot (PE field)	8:05
Female	11	No	Yes	Yes	No	Yes	Hiawatha lot (PE field)	8:15
Female	9	No	Yes	Yes	No	Yes	Hiawatha lot (PE field)	8:08
Male	9	No	Yes	Yes	No	Yes	Service road East (Boys PE side)	8:10
Male	10	No	Yes	Yes	No	Yes	Service road East (Boys PE side)	6:44
Female	10	No	Yes	Yes	No	Yes	Service road East (Boys PE side)	7:12
Male	10	No	Yes	Yes	No	Yes	Service road East (Boys PE side)	7:00
Female	12	Yes	Yes	Yes	No	Yes	Service road East (Boys PE side)	8:05
Male	11	Yes	Yes	Yes	No	Yes	Service Road West (Girls PE side)	7:20
Female	11	No	Yes	Yes	No	Yes	Service Road West (Girls PE side)	7:15
Female	11	No	Yes	Yes	No	Yes	Service Road West (Girls PE side)	7:20
Female	12	Yes	Yes	No	No	Yes	Service Road West (Girls PE side)	8:20
Female	12	No	Yes	Yes	No	Yes	Service Road West (Girls PE side)	8:15
Male	12	No	Yes	Yes	No	Yes	Service Road West (Girls PE side)	8:10
Female	9	No	Yes	No	No	Yes	Service Road West (Girls PE side)	6:40
Male	9	No	No	Yes	No	No	Service Road West (Girls PE side)	7:08
Male	9	No	No	No	No	No	Service Road West (Girls PE side)	7:25
Female	9	No	Yes	Yes	No	Yes	Service Road West (Girls PE side)	7:20
Female	9	No	No	No	No	Yes	Service Road West (Girls PE side)	7:15
Female	9	No	Yes	Yes	No	Yes	J Gate	8:10
Male	10	No	Yes	Yes	No	No	J Gate	7:10
Male	9	Yes	No	No	No	Yes	J Gate	7:23
Male	10	No	Yes	Yes	No	No	Zelzah Teacher Parking Lot	7:23
Male	9	No	No	No	No	No	Zelzah Teacher Parking Lot	7:20
Female	10	No	Yes	Yes	No	No	Zelzah Teacher Parking Lot	7:20
Male	12	No	Yes	No	No	No	Zelzah Teacher Parking Lot	7:45
Male	10	No	Yes	No	No	Yes	Zelzah Teacher Parking Lot	8:15
Male	10	Yes	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:00
Male	12	Yes	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:20
Male	11	No	No	Yes	No	No	Zelzah Teacher Parking Lot	7:45
Female	12	Yes	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:10
Female	12	Yes	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:15
Male	9	No	Yes	Yes	Yes	Yes	Zelzah Teacher Parking Lot	8:00
Female	12	Yes	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:05
Male	12	No	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:11
Female	12	No	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	7:18
Male	12	No	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	7:00
Female	12	No	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:00
Male	11	No	No	Yes	No	Yes	Zelzah Teacher Parking Lot	8:40
Male	12	No	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	6:40
Female	10	No	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	7:20
Female	9	Yes	Yes	No	No	Yes	Zelzah Teacher Parking Lot	7:00
Female	9	No	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:22
Female	9	No	Yes	Yes	No	Yes	Zelzah Teacher Parking Lot	8:10

Gender		
Female	47	47.0%
Male	53	53.0%
Total	100	100.0%

Grade		
9	31	31.0%
10	15	15.0%
11	11	11.0%
12	43	43.0%
Total	100	100.0%

Zelzah Teacher Parking Lot	22	22.0%
J Gate	3	3.0%
Service Road West (Girls PE side)	11	11.0%
Service road East (Boys PE side)	5	5.0%
Hiawatha lot (PE field)	7	7.0%
Flagpole (Zelzah)	28	28.0%
Kingsbury (Main Entrance)	24	24.0%
Total	100	100.0%

Do you own a DSLR camera?		
Yes	20	20.0%
No	80	80.0%
Total	100	100.0%

Do you use Instagram?		
Yes	77	77.0%
No	23	23.0%
Total	100	100.0%

Do you use Snapchat?		
Yes	76	76.0%
No	24	24.0%
Total	100	100.0%

Do you use Flickr?		
Yes	4	4.0%
No	96	96.0%
Total	100	100.0%

Mean	6.909090909	Mean	5.81	Mean	7.83	Mean	7.31	Mean	6.46
Standard Error	0.165014013	Standard Error	0.2214256	andard Error	0.1537777	andard Error	0.171561	andard Error	0.165014013
Median	7	Median	6	Median	8	Median	8	Median	8
Mode	7	Mode	6	Mode	9	Mode	8	Mode	6
Standard Deviation	1.641868703	Standard Deviation	2.2142559	Standard Deviation	1.5377774	Standard Deviation	1.715615	Standard Deviation	1.641868703
Sample Variance	2.695732839	Sample Variance	4.9029293	Sample Variance	2.3647477	Sample Variance	2.9433333	Sample Variance	2.695732839
Kurtosis	1.480431944	Kurtosis	-0.7409601	Kurtosis	1.884916	Kurtosis	2.343535	Kurtosis	1.480431944
Skewness	-1.136207787	Skewness	-0.2389121	Skewness	-1.51106	Skewness	-1.47571	Skewness	-1.136207787
Range	8	Range	8	Range	6	Range	8	Range	8
Minimum	1	Minimum	1	Minimum	3	Minimum	1	Minimum	1
Maximum	9	Maximum	9	Maximum	9	Maximum	9	Maximum	9
Sum	684	Sum	581	Sum	783	Sum	731	Sum	684
Count	99	Count	100	Count	100	Count	100	Count	99
Confidence Level(90.0%)	0.274014221	Confidence Level(90.0%)	0.3676531	Confidence Level(90.0%)	0.255331	Confidence Level(90.0%)	0.284859	Confidence Level(90.0%)	0.274014221

[illegible]

y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy	y DispleasucpleasSrMeotrreBarBy
5	3	5	3	8	5	3	4	3	3
8	8	5	6	6	9	1	5	8	8
7	7	2	1	1	2	1	6	5	1
2	3	3	9	5	3	3	3	4	1
8	7	5	3	9	7	6	8	5	7
9	9	5	5	5	7	6	8	7	9
9	9	5	9	4	7	3	8	9	1
6	2	7	1	4	9	5	8	3	6
4	5	4	3	5	2	2	7	6	9
8	5	5	5	1	7	1	3	8	4
9	9	1	1	9	1	1	2	9	1
4	1	3	6	7	5	2	6	7	6
8	2	8	8	8	9	2	9	5	6
8	9	7	1	4	4	4	6	9	5
5	1	1	1	9	1	1	1	1	1
9	9	6	1	6	3	3	6	9	8
8	5	4	4	7	3	3	4	8	4
7	9	7	6	6	9	8	8	9	6
4	3	5	6	6	5	1	6	3	5
7	3	3	3	5	9	4	8	9	8
6	7	4	3	2	4	1	6	7	5
5	9	5	1	3	5	2	5	4	5
5	4	5	1	3	9	2	4	3	2
7	5	7	2	8	9	2	6	9	6
7	9	5	5	6	7	5	9	7	4
7	8	5	5	9	9	6	6	9	8
7	9	6	4	5	5	5	6	7	5
7	4	5	2	3	7	5	5	5	5
2	7	1	9	8	5	6	7	8	4
8	9	9	5	4	9	7	7	9	4
6	8	7	1	5	6	5	6	6	6
5	7	1	2	5	5	2	6	6	1
9	2	6	1	5	7	1	4	4	6
8	8	5	4	5	7	3	7	8	7
8	4	3	2	5	7	4	9	8	6
7	8	1	1	1	8	9	3	8	7
8	8	6	2	5	8	8	4	8	6
9	9	9	2	9	9	6	9	6	7
7	6	6	4	4	8	2	6	6	7
7	5	5	2	5	7	3	6	7	7
9	3	3	2	3	3	3	8	6	9
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7	5	4	2	1	7	2	7	8	5
7	6	8	1	9	9	1	8	7	7
8	9	5	9	9	5	5	9	9	4
8	9	7	1	7	9	1	9	9	7
2	3	2	2	5	6	3	3	7	3
7	8	8	1	8	7	4	9	4	7
8	8	9	5	7	9	5	9	8	5
9	7	1	9	9	9	2	9	6	1
9	1	8	3	4	9	5	7	6	9
9	9	8	5	8	9	5	8	8	8
7	5	5	1	8	9	4	9	8	8
9	9	1	9	2	3	1	9	2	1
7	7	8	7	7	8	2	7	8	7
8	4	7	3	6	5	4	6	6	7
3	8	7	4	9	1	1	8	7	2
5	9	8	2	4	9	2	5	9	5
7	6	3	1	5	8	4	3	5	1
8	8	8	5	8	8	5	7	9	6
8	8	5	2	7	9	4	7	8	8
9	9	9	1	4	9	8	6	9	6
6	9	4	1	3	2	4	5	9	4
5	6	6	3	2	8	1	7	9	2
8	3	1	3	1	9	7	8	9	1
4	7	6	3	6	9	2	4	7	2
8	8	9	4	6	6	3	8	9	4
5	1	1	1	9	9	8	2	9	1
5	9	6	1	5	9	1	8	8	6
9	8	8	7	2	9	5	8	8	6
7	6	9	1	8	7	1	7	2	1
8	5	5	2	5	8	4	5	6	6
6	5	1	1	3	9	2	6	7	5
7	9	9	2	5	9	1	9	9	5
8	7	6	1	5	7	3	5	6	9
9	9	9	6	9	8	8	8	8	9
9	9	3	1	5	5	2	9	8	3
7	5	6	1	4	9	3	6	9	4
7	7	5	2	7	4	6	4	7	3
8	6	8	5	5	7	5	3	6	4
2	2	2	5	7	2	1	2	7	1
4	4	4	4	4	4	4	4	4	4
8	5	6	5	8	7	5	7	9	5
9	5	6	7	8	4	1	5	6	3
7	6	8	2	7	8	7	7	7	5
8	8	8	6	4	9	5	6	9	9
9	2	6	1	3	9	1	9	8	7
4	6	6	6	2	8	5	6	6	4
3	9	4	1	5	4	1	6	5	8
8	8	5	1	7	5	2	5	3	8
9	7	1	4	1	9	1	9	7	1
9	5	1	7	5	7	2	9	8	4
3	6	2	4	2	3	1	6	7	6
5	1	4	1	9	9	1	9	1	9
8	5	9	7	3	9	5	6	9	8
4	2	5	1	9	6	1	6	7	7
8	9	9	9	9	1	1	9	8	1
8	8	8	4	9	8	5	7	9	5
9	7	7	5	8	7	4	8	9	3
9	9	7	1	7	9	3	9	9	9
9	9	3	1	5	8	3	5	6	4
3	9	4	1	5	4	1	6	5	8
8	8	5	1	7	5	2	5	3	8
9	7	1	4	1	9	1	9	7	1
9	5	1	7	5	7	2	9	8	4
3	6	2	4	2	3	1	6	7	6
5	1	4	1	9	9	1	9	1	9
8	5	9	7	3	9	5	6	9	8
4	2	5	1	9	6	1	6	7	7
8	9	9	9	9	1	1	9	8	1
8	8	8	4	9	8	5	7	9	5
9	7	7	5	8	7	4	8	9	3
9	9	7	1	7	9	3	9	9	9
9	9	3	1	5	8	3	5	6	4
3	9	4	1	5	4	1	6	5	8
8	8	5	1	7	5	2	5	3	8
9	7	1	4	1	9	1	9	7	1
9	5	1	7	5	7	2	9	8	4
3	6	2	4	2	3	1	6	7	6
5	1	4	1	9	9	1	9	1	9
8	5	9	7	3	9	5	6	9	8
4	2	5	1	9	6	1	6	7	7
8	9	9	9	9	1	1	9	8	1
8	8	8	4	9	8	5	7	9	5
9	7	7	5	8	7	4	8	9	3
9	9	7	1	7	9	3	9	9	9
9	9	3	1	5	8	3	5	6	4
3	9	4	1	5	4	1	6	5	8
8	8	5	1	7	5	2	5	3	8
9	7	1	4	1	9	1	9	7	1
9	5	1	7	5	7	2	9	8	4
3	6	2	4	2	3	1	6	7	6
5	1	4	1	9	9	1	9	1	9
8	5	9	7	3	9	5	6	9	8
4	2	5	1	9	6	1	6	7	7
8	9	9	9	9	1	1	9	8	1
8	8	8	4	9	8	5	7	9	5
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9	7	1	4	1	9	1	9	7	1
9	5	1	7	5	7	2	9	8	4
3	6	2	4	2	3	1	6	7	6
5	1	4	1	9	9	1	9	1	9
8	5	9	7	3	9	5	6	9	8
4	2	5	1	9	6	1	6	7	7
8	9	9	9	9	1	1	9	8	1
8	8	8	4	9	8	5	7	9	5
9	7	7	5	8	7	4	8	9	3
9	9	7	1	7	9	3	9	9	9
9	9	3	1	5	8	3	5	6	4
3	9	4	1	5	4	1	6	5	8
8	8	5	1	7	5	2	5	3	8
9	7	1	4	1	9	1	9	7	1
9	5	1	7	5	7	2	9	8	4
3	6	2	4	2	3	1	6	7	6
5	1	4	1	9	9	1	9	1	9
8	5	9	7	3	9	5	6	9	8
4	2	5	1	9	6	1	6	7	7
8	9	9	9	9	1	1	9	8	1
8	8	8	4	9	8	5	7	9	5
9	7	7	5	8	7	4	8	9	3
9	9	7	1	7	9	3	9	9	9
9	9	3	1	5	8	3	5	6	4
3	9	4	1	5	4	1	6	5	8
8	8	5	1	7	5	2	5	3	8
9	7	1	4	1	9	1	9	7	1
9	5	1	7	5	7	2	9	8	4
3	6	2	4	2	3	1	6	7	6
5	1	4	1	9	9	1	9	1	9
8	5	9	7	3	9	5	6	9	8
4	2	5	1	9	6	1	6	7	7
8	9	9	9	9	1	1	9	8	1
8	8	8	4	9	8	5	7	9	5
9	7	7	5	8	7	4	8	9	3
9	9	7	1	7	9	3	9	9	9
9	9	3	1	5	8	3	5	6	4
3	9	4	1	5	4	1	6	5	8
8	8	5	1	7	5	2	5	3	8
9	7	1	4	1	9	1	9	7	1
9	5	1	7	5	7	2	9	8	4
3	6	2	4	2	3	1	6	7	6
5	1	4	1	9	9	1	9	1	9
8	5	9	7	3	9	5	6	9	8
4	2	5	1	9	6	1	6	7	7
8	9	9	9	9	1	1	9	8	1
8	8	8	4	9	8	5	7	9	5
9	7	7	5	8	7	4	8	9	3
9	9	7	1</						

Not at all	Not at all	Not at all	Not at all	Not at all	Not at all	Not at all	
By Displeasure	By Displeasure	By Displeasure	By Displeasure	By Displeasure	By Displeasure	By Displeasure	
4	5	4	8	5	8	5	
1	7	5	6	4	8	5	
1	2	1	2	6	5	1	
8	7	4	7	8	7	4	
4	5	6	6	7	7	6	
2	9	5	8	7	9	4	
5	9	9	8	5	7	1	
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2	7	6	1	5	8	3	
4	6	8	3	6	6	8	
1	6	7	5	3	3	5	
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5	7	4	8	5	8	1	
1	5	4	2	3	9	5	
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3	5	4	3	4	4	3	
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1	7	6	8	6	6	5	
6	5	5	4	4	9	5	
7	8	9	7	6	5	9	
1	4	5	4	1	6	6	
5	5	5	4	5	6	5	
1	7	2	8	5	1	8	
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2	8	6	8	7	8	8	
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7	8	8	6	5	8	8	
2	5	6	8	1	6	1	
7	5	8	7	5	8	9	
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1	5	6	4	3	8	5	
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3	8	7	1	6	7	8	
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5	9	9	6	5	7	9	
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2	5	7	8	8	7	5	
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5	9	9	4	9	9	9	
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2	8	5	3	7	5	7	
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9	6	4	8	6	7	5	
1	5	6	3	2	9	5	
1	9	9	9	1	1	1	
8	5	8	9	9	9	6	
2	6	5	1	6	9	4	
7	9	9	7	1	1	8	
7	8	8	7	8	8	5	
4	7	8	4	7	9	4	
3	8	5	5	4	8	6	
Column1	Column1	Column1	Column1	Column1	Column1	Column1	
Mean	3.51	Mean	6.13	Mean	6.08	Mean	4.98
Standard Err	0.238045	Standard Err	0.217727	Standard Err	0.212574	Standard Err	0.238675
Median	3	Median	6	Median	6	Median	5
Mode	1	Mode	5	Mode	7	Mode	5
Standard Devia	2.380455	Standard Devia	2.17727	Standard Devia	2.125744	Standard Devia	2.386748
Sample Variar	5.666566	Sample Variar	4.740505	Sample Variar	4.518788	Sample Variar	5.696566
Kurtosis	-0.58566	Kurtosis	-0.16967	Kurtosis	-0.33571	Kurtosis	-0.72437
Skewness	0.684204	Skewness	-0.59543	Skewness	-0.45433	Skewness	-0.11687
Range	8	Range	8	Range	8	Range	8
Minimum	1	Minimum	1	Minimum	1	Minimum	1
Maximum	9	Maximum	9	Maximum	9	Maximum	9
Sum	351	Sum	613	Sum	608	Sum	498
Count	100	Count	100	Count	100	Count	100
Confidence Level(	0.472334	Confidence Level(	0.361512	Confidence Level(	0.352957	Confidence Level(	0.396294

Appendix 2

Statistical Analysis in Excel

Sample size: n = 100

<i>Question 1</i>		<i>Question 2</i>		<i>Question 3</i>		<i>Question 4</i>		<i>Question 5</i>	
Mean	6.909091	Mean	5.81	Mean	7.83	Mean	7.31	Mean	6.84
Standard Error	0.165014	Standard Error	0.221426	Standard Error	0.153777	Standard Error	0.171561	Standard Error	0.195257
Median	7	Median	6	Median	8	Median	8	Median	7
Mode	7	Mode		Mode	9	Mode	8	Mode	9
Standard Deviation	1.641869	Standard Deviation	2.214256	Standard Deviation	1.537774	Standard Deviation	1.715615	Standard Deviation	1.952569
Sample Variance	2.695733	Sample Variance	4.902929	Sample Variance	2.364747	Sample Variance	2.943333	Sample Variance	3.812525
Kurtosis	1.480432	Kurtosis	-0.74096	Kurtosis	1.884916	Kurtosis	2.343535	Kurtosis	0.535875
Skewness	-1.13621	Skewness	-0.23891	Skewness	-1.51106	Skewness	-1.47571	Skewness	-0.96702
Range	8	Range	8	Range	6	Range	8	Range	8
Minimum	1	Minimum	1	Minimum	3	Minimum	1	Minimum	1
Maximum	9	Maximum	9	Maximum	9	Maximum	9	Maximum	9
Sum	684	Sum	581	Sum	783	Sum	731	Sum	684
Count	99	Count	100	Count	100	Count	100	Count	100
Confidence Interval	0.274014	Confidence Interval	0.367653	Confidence Interval	0.255331	Confidence Interval	0.284859	Confidence Interval	0.324203
<i>Question 6</i>		<i>Question 7</i>		<i>Question 8</i>		<i>Question 9</i>		<i>Question 10</i>	
Mean	5.51	Mean	4.24	Mean	5.81	Mean	4.17	Mean	4.17
Standard Error	0.219961	Standard Error	0.228354	Standard Error	0.216816	Standard Error	0.209885	Standard Error	0.209885
Median	5	Median	4	Median	6	Median	4	Median	4
Mode	5	Mode	5	Mode	5	Mode	4	Mode	4
Standard Deviation	2.19961	Standard Deviation	2.283538	Standard Deviation	2.168158	Standard Deviation	2.098845	Standard Deviation	2.098845
Sample Variance	4.838283	Sample Variance	5.214545	Sample Variance	4.700909	Sample Variance	4.405152	Sample Variance	4.405152
Kurtosis	-0.78355	Kurtosis	-0.56198	Kurtosis	-0.54872	Kurtosis	-0.75181	Kurtosis	-0.75181
Skewness	-0.20834	Skewness	0.315877	Skewness	-0.32061	Skewness	0.265426	Skewness	0.265426
Range	8	Range	8	Range	8	Range	8	Range	8
Minimum	1	Minimum	1	Minimum	1	Minimum	1	Minimum	1
Maximum	9	Maximum	9	Maximum	9	Maximum	9	Maximum	9
Sum	551	Sum	424	Sum	581	Sum	417	Sum	417
Count	100	Count	100	Count	100	Count	100	Count	100
Confidence Interval	0.365221	Confidence Interval	0.379157	Confidence Interval	0.359999	Confidence Interval	0.34849	Confidence Interval	0.34849
<i>Question 11</i>		<i>Question 12</i>		<i>Question 13</i>		<i>Question 14</i>		<i>Question 15</i>	
Mean	6.64	Mean	7.48	Mean	5.34	Mean	3.5	Mean	6.34
Standard Error	0.185058	Standard Error	0.155362	Standard Error	0.2438	Standard Error	0.215322	Standard Error	0.183248
Median	7	Median	8	Median	5	Median	3	Median	6.5
Mode	9	Mode	8	Mode	5	Mode	1	Mode	7
Standard Deviation	1.85058	Standard Deviation	1.553621	Standard Deviation	2.437999	Standard Deviation	2.153222	Standard Deviation	1.832479
Sample Variance	3.424646	Sample Variance	2.413737	Sample Variance	5.943838	Sample Variance	4.636364	Sample Variance	3.35798
Kurtosis	0.11248	Kurtosis	3.344054	Kurtosis	-0.98373	Kurtosis	-0.13981	Kurtosis	0.140969
Skewness	-0.51909	Skewness	-1.58636	Skewness	-0.24336	Skewness	0.690715	Skewness	-0.61812
Range	8	Range	8	Range	8	Range	8	Range	8
Minimum	1	Minimum	1	Minimum	1	Minimum	1	Minimum	1
Maximum	9	Maximum	9	Maximum	9	Maximum	9	Maximum	9
Sum	664	Sum	748	Sum	534	Sum	350	Sum	634
Count	100	Count	100	Count	100	Count	100	Count	100
Confidence Interval	0.307269	Confidence Interval	0.257962	Confidence Interval	0.404803	Confidence Interval	0.357519	Confidence Interval	0.304263
<i>Question 16</i>		<i>Question 17</i>		<i>Question 18</i>		<i>Question 19</i>		<i>Question 20</i>	
Mean	6.53	Mean	5.85	Mean	5.85	Mean	6.93	Mean	4.9
Standard Error	0.188805	Standard Error	0.238419	Standard Error	0.238419	Standard Error	0.1981	Standard Error	0.228079
Median	7	Median	6	Median	6	Median	8	Median	5
Mode	8	Mode	7	Mode	7	Mode	8	Mode	5
Standard Deviation	1.888054	Standard Deviation	2.384186	Standard Deviation	2.384186	Standard Deviation	1.980996	Standard Deviation	2.280794
Sample Variance	3.564747	Sample Variance	5.684343	Sample Variance	5.684343	Sample Variance	3.924343	Sample Variance	5.20202
Kurtosis	0.561945	Kurtosis	-0.84364	Kurtosis	-0.84364	Kurtosis	0.494959	Kurtosis	-0.92274
Skewness	-0.91122	Skewness	-0.41633	Skewness	-0.41633	Skewness	-1.10227	Skewness	-0.08809
Range	8	Range	8	Range	8	Range	8	Range	8
Minimum	1	Minimum	1	Minimum	1	Minimum	1	Minimum	1
Maximum	9	Maximum	9	Maximum	9	Maximum	9	Maximum	9
Sum	653	Sum	585	Sum	585	Sum	693	Sum	490
Count	100	Count	100	Count	100	Count	100	Count	100
Confidence Interval	0.313491	Confidence Interval	0.395868	Confidence Interval	0.395868	Confidence Interval	0.328923	Confidence Interval	0.378701

Question 21

Mean	6.6
Standard Error	0.189097
Median	7
Mode	8
Standard Deviation	1.890967
Sample Variance	3.575758
Kurtosis	0.452994
Skewness	-0.84876
Range	8
Minimum	1
Maximum	9
Sum	660
Count	100
Confidence Interval	0.313975

Question 26

Mean	5.3
Standard Error	0.243501
Median	5
Mode	5
Standard Deviation	2.435014
Sample Variance	5.929293
Kurtosis	-0.81866
Skewness	-0.27628
Range	8
Minimum	1
Maximum	9
Sum	530
Count	100
Confidence Interval	0.404308

Question 31

Mean	6.41
Standard Error	0.202058
Median	6
Mode	6
Standard Deviation	2.020576
Sample Variance	4.082727
Kurtosis	-0.45243
Skewness	-0.51108
Range	8
Minimum	1
Maximum	9
Sum	641
Count	100
Confidence Interval	0.335495

Question 36

Mean	6.08
Standard Error	0.212574
Median	6
Mode	7
Standard Deviation	2.125744
Sample Variance	4.518788
Kurtosis	-0.33571
Skewness	-0.45433
Range	8
Minimum	1
Maximum	9
Sum	608
Count	100
Confidence Interval	0.352957

Question 22

Mean	4.81
Standard Error	0.279138
Median	5
Mode	9
Standard Deviation	2.791383
Sample Variance	7.791818
Kurtosis	-1.36212
Skewness	0.159881
Range	8
Minimum	1
Maximum	9
Sum	481
Count	100
Confidence Interval	0.463479

Question 27

Mean	3.44
Standard Error	0.245904
Median	3
Mode	1
Standard Deviation	2.459038
Sample Variance	6.046869
Kurtosis	-0.31478
Skewness	0.824377
Range	8
Minimum	1
Maximum	9
Sum	344
Count	100
Confidence Interval	0.408297

Question 32

Mean	6.94
Standard Error	0.205392
Median	7
Mode	9
Standard Deviation	2.05392
Sample Variance	4.218586
Kurtosis	0.456503
Skewness	-1.04539
Range	8
Minimum	1
Maximum	9
Sum	694
Count	100
Confidence Interval	0.341031

Question 37

Mean	4.95
Standard Error	0.259905
Median	5
Mode	8
Standard Deviation	2.599048
Sample Variance	6.755051
Kurtosis	-1.22864
Skewness	-0.04619
Range	8
Minimum	1
Maximum	9
Sum	495
Count	100
Confidence Interval	0.431544

Question 23

Mean	7.87
Standard Error	0.178464
Median	9
Mode	9
Standard Deviation	1.784643
Sample Variance	3.184949
Kurtosis	3.52205
Skewness	-1.95446
Range	8
Minimum	1
Maximum	9
Sum	787
Count	100
Confidence Interval	0.29632

Question 28

Mean	5.55
Standard Error	0.241784
Median	5
Mode	5
Standard Deviation	2.417842
Sample Variance	5.84596
Kurtosis	-0.98283
Skewness	-0.12147
Range	8
Minimum	1
Maximum	9
Sum	555
Count	100
Confidence Interval	0.401456

Question 33

Mean	5.08
Standard Error	0.249719
Median	5
Mode	1
Standard Deviation	2.49719
Sample Variance	6.23596
Kurtosis	-0.96672
Skewness	-0.21195
Range	8
Minimum	1
Maximum	9
Sum	508
Count	100
Confidence Interval	0.414631

Question 38

Mean	4.86
Standard Error	0.238692
Median	5
Mode	5
Standard Deviation	2.386917
Sample Variance	5.697374
Kurtosis	-0.86061
Skewness	-0.1128
Range	8
Minimum	1
Maximum	9
Sum	486
Count	100
Confidence Interval	0.396322

Question 24

Mean	6.93
Standard Error	0.193456
Median	7
Mode	8
Standard Deviation	1.934561
Sample Variance	3.742525
Kurtosis	0.106875
Skewness	-0.9754
Range	7
Minimum	2
Maximum	9
Sum	693
Count	100
Confidence Interval	0.321213

Question 29

Mean	6.68
Standard Error	0.241995
Median	7
Mode	9
Standard Deviation	2.419951
Sample Variance	5.856162
Kurtosis	-0.40108
Skewness	-0.84234
Range	8
Minimum	1
Maximum	9
Sum	668
Count	100
Confidence Interval	0.401806

Question 34

Mean	3.51
Standard Error	0.238045
Median	3
Mode	1
Standard Deviation	2.380455
Sample Variance	5.666566
Kurtosis	-0.58566
Skewness	0.684204
Range	8
Minimum	1
Maximum	9
Sum	351
Count	100
Confidence Interval	0.395249

Question 39

Mean	6.76
Standard Error	0.217014
Median	7
Mode	9
Standard Deviation	2.170137
Sample Variance	4.709495
Kurtosis	0.49493
Skewness	-1.04574
Range	8
Minimum	1
Maximum	9
Sum	676
Count	100
Confidence Interval	0.360328

Question 25

Mean	6.21
Standard Error	0.249968
Median	7
Mode	9
Standard Deviation	2.499677
Sample Variance	6.248384
Kurtosis	-0.83876
Skewness	-0.57653
Range	8
Minimum	1
Maximum	9
Sum	621
Count	100
Confidence Interval	0.415044

Question 30

Mean	3.38
Standard Error	0.213096
Median	3
Mode	1
Standard Deviation	2.130965
Sample Variance	4.54101
Kurtosis	-0.44482
Skewness	0.639104
Range	8
Minimum	1
Maximum	9
Sum	338
Count	100
Confidence Interval	0.353823

Question 35

Mean	6.13
Standard Error	0.217727
Median	6
Mode	5
Standard Deviation	2.17727
Sample Variance	4.740505
Kurtosis	-0.16967
Skewness	-0.59543
Range	8
Minimum	1
Maximum	9
Sum	613
Count	100
Confidence Interval	0.361512

Question 40

Mean	4.98
Standard Error	0.238675
Median	5
Mode	5
Standard Deviation	2.386748
Sample Variance	5.696566
Kurtosis	-0.72437
Skewness	-0.11687
Range	8
Minimum	1
Maximum	9
Sum	498
Count	100
Confidence Interval	0.396294