# How do the attributes of colour in influencer photo posts contribute to the engagement of users?

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#### ABSTRACT

Previous research has provided valuable insights into the roles of colour in marketing, it is used as a force, to build brands and to differentiate. In psychology, it is found that people attach meanings to colour. Considering that a substantial portion of today's marketing is shifting towards social media platforms, this study explores the effects of colour composition on success on Instagram. Colour is already indicated to influence Instagram engagement. However, there is little research on how this works for social media influencers and their performance. To address this lack of understanding, in a sample of big social media influencers it was investigated how lightness, chroma and hue relate to engagement. These findings indicate that hue contributed significantly to post popularity. Future directions and limitations are also discussed.

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#### **Keywords**

Social media, Influencer, Colours, Engagement, Instagram, Social Network Analysis, Influencing Power

# TITLE

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# **INTRODUCTION**

Social media have become a ubiquitous platform for brand advertising and promotion, which has led to the emergence of a new phenomenon known as social media influencers. Businesses are investing heavily in influencer marketing, a practice that involves partnering with popular social media users, better known as influencers, to promote their products. (Cartwright, 2022) These influencers have gained a significant amount of following on social media platforms such as Instagram, YouTube, and TikTok, and have become a crucial part of marketing strategies for many brands (Hudders, 2021; Jayasinghe, 2021). Social media influencers are known to have a significant impact on consumer behavior, and they often use visual content elements such as images and videos to convey their message to their followers. Since social media importance is growing nowadays, researchers are trying to explain how these influencers became 'influential'. The influential power an influencer has gained comes in part from successfully engaging with its audience. Therefore, growth in engagement rates can be beneficial for social media influencers. Also, increased reach and visibility can be deployed to raise awareness about important issues, mobilize support, and encourage meaningful conversations among a wider audience. The opportunity to amplify the impact of socially responsible causes through improved engagement rates allows messages to reach a larger audience, creating a ripple effect as people share, comment, and react to the content. This can lead to greater attention, participation, and support for the cause, ultimately increasing its potential for positive change. How actually can engagement with users be achieved? So far. scholars have identified that factors such as credibility and attractiveness of influencers are crucial to the success of engagement in influencing (Sokolova, 2021). On the other hand, the perceived value from the experiences, knowledge, and resources that the influencers share could be a decisive factor to capture the attention and persuade followers (Lee, 2014). This perceived value can be defined in terms of perceived interest, usefulness, novelty, or quality of the influencers' content (Djafarova, 2017; Lou, 2019; Romero, 2011; Xiao, 2018). Regarding to quantitative attributes of the influencers' content, on the social media platform Instagram it is identified that users are more likely to respond to brighter and more saturated pictures (Yu, 2020). Still, a lot of variances of engagement have not been explained yet, which creates a gap in the understanding. Scholars are looking for additional factors the explain user engagement for influencers. Yu, (2020) already suggested that variations in the engagement of Instagram posts may be explained by colour. We are going to elaborate on this. Our research question is: "How do the attributes of colour in social media influencer photo posts on Instagram contribute to the engagement of users?" This paper focuses on a sample of popular images on Instagram to find out if colours are related to the success of an influencers' posts, which has not been empirically tested yet.

Despite the widespread use of social media influencers in marketing, there is limited research on the role of colour elements in enhancing user engagement rates on the platforms. Studies on social media influencing strategies, consumer engagement, impact of colour and their attributes on marketing have already been conducted. (Kwayu, 2018; Shi, 2013; Sokolova, 2021). In marketing, colour is a main aspect in building an authentic brand, it has been found to affect cognition and mood, which in turn influences consumer decision making (Shi, 2013). However, there is no comprehensive study which aligns these topics and is relating to the biggest influencers, which creates a gap. Understanding the mechanisms that drive the effectiveness of visual content elements could provide valuable insights that can be used to optimize influencer and marketing strategies. Social media influencers could potentially take advantage of this knowledge. Would it be useful for influencers to use certain colours attributes to increase their user engagement, build their brand and eventually increase their influential power?

One of the major issues that arise from the current lack of research is the difficulty in identifying the most effective colour elements that can be used by social media influencers to enhance their influence. Furthermore, social media influencers have a significant impact on consumer behavior, but the extent of this impact can vary depending on the demographics of the target audience. Understanding the role of colouring in social media influencer marketing can help brands and marketers tailor their marketing strategies to specific consumer segments. In conclusion, further research on the role of colours in enhancing the engagement of users in social media can function as a valuable contribution in the discussion toward how scientists can explain variance in engagement.

# **RESEARCH PROJECT RATIONALE**

There are several reasons to investigate on this subject. We believe that there is a gap in existing research: As mentioned in the problem analysis, there is limited research on the role of enhancing influencers' colours in user engagement, that is a shortcoming, since engagement is a big metric of the influential power a social media influencer has. In our field of study. International Business Administration, we already became familiar with the basic practices of marketing, digital marketing, and designing online business platforms. Since these topics appeal to our profession, and we may start a Master program that touches these topics, we think writing a thesis in this topic could help us develop valuable skills and knowledge that could be beneficial for our professional development The purpose of this study is to examine the impact of colour use on the engagement. An improved understanding of this relationship may help the development of influencer marketing strategies. Regardless of whether we discover interesting findings, we hope this research contributes to a better understanding of effective influencing Furthermore, we hope to make a worthy contribution to the current literature.

# **THEORY & HYPOTHESES**

Following to traditional communication theory (Rogers, 1962), a minority of users, called 'influential', excel in persuading others. This theory predicts that by targeting these influential in the network, one may achieve a

large-scale chain-reaction of influence driven by word-of-mouth, with a very small marketing cost (Katz, 1955), retrieved from (Cha, 2010). Recognizing the impact of eWOM (Electronic Word of Mouth) on consumers' attitudes and decisions, brands have started approaching social media influencers (i.e., influential social media users who managed to build a large audience of followers or subscribers), and incentivizing them to create and distribute relevant, authentic looking brand-related content, a practice that is called 'influencer marketing'. It refers to advertisers closing deals with influencers, which entail promotion in exchange for payment, free products or invitations to exclusive events. (De Veirman M. &., 2017) In return for free promotional goods or payment, brands ask these influencers to endorse their products on their social media profiles (on their feed or in their stories on Instagram, videos on YouTube and TikTok, or Facebook updates, etc.) and their channels in turn earn advertising revenue as a result of their large audiences. This form of marketing regarded as a form of advertising when (1) influencers receive a compensation (free products or financial payment) and (2) advertisers have control over the content, which also includes simple final approval of the post or general instructions regarding the post. In this research we also refer to Social Media Influencers as "SMIs". There is research that distinguishes Social Media Influencers and Celebrity Endorses as two separate definitions (Chang, 2020). Social media users tend to view SMIs who are knowledgeable in their specific fields as more convincing and authentic (Ao, 2023). In this research, we choose not to differentiate between these terms, because Celebrity endorsers are covered by the SMI definitions.

SMIs are "opinion leaders in digital social media who communicates to an unknown mass audience". This is what their "influential power" means (Uzunoğlu, 2014). They have a reputation of authority or expertise in a particular area and use that authority to engage with large numbers of social media followers (Gräve, 2019). On these platforms, growth can emerge very rapidly. Potential social media influencers can become top Influencers within six months (Tigar, 2018), therefore it might be interesting for certain brands to collaborate with the 'right' passionate influencer or potential

social media influencer and take advantage of their explosive growth. (Ouvrein, 2021)

In order for influencers to participate in influencer social media advertising, it is important to be in the picture with the relevant companies. For this to happen, influencers must build a certain dignity, they have to prove their ability to engage an audience. One way for them to do this is through growth of engagement with the audience they already have, increasing the number of interactions on their social media profile. On Instagram, there are multiple measures for engagement, e.g., number of followers, likes, views, comments, and shares.

The follower count is one of the many metrics which imply an influencers' capacity to, ultimately, influence. Following the social impact theory (Latan'e, 1996), the number of followers can be a critical factor in determining the amount of social influence exerted in a given social setting. Therefore, when no other diagnostic information is available, consumers tend to form perceptions of the influencing power of an influencer based on follower count. However, when diagnostic information is available, engagement rates such as likes, views and shares on influencer posts are metrics that are an accurate indicator for the actual influential power (Zhou, 2023). According to (Brodie, 2011) 'consumer-based engagement' (CBE) can be defined as collaborative, cocreated consumer experiences that generate a psychological state. On social media, consumer engagement refers to "an expression of consumers' cognitive and emotional attitudes via their brand-related engagement behaviors in social media" (Pentina, 2018). According to this definition, customer behavior and attitude toward brands are both included in participation on social media. In line with this, customer behaviors toward brands, goods, or services make up social media engagement. Users may then engage with a post by clicking the "like" button on the post or by leaving a comment on the post. The customers who are passionate enough to take action, and interact on social media are truly engaged (Yoon, 2018).

Another popular metric for evaluating audience engagement on Instagram posts are 'likes'. Together with commenting, it is proof of and genuine engagement in influencer marketing (Li, 2020; Gross, 2022). Liking can be a useful gauge of how well-received a post is (Hughes, 2019). Users who "like" a post by doubletapping it, do so because they found it appealing or intriguing in some way (Xie-Carson, 2023). Likes can also stand in for other types of interaction like comments or shares. Because these measures are frequently influenced by identical factors, such as the value of the content or the appeal of the visual components, a post that receives a lot of likes is likely to also receive a lot of comments. It is important to keep in consideration, nevertheless, that likes are not a perfect indicator of involvement. Users may like posts not because they were very interested in the content, but rather to promote a friend or influencer.

How actually can influencers grow their engagement, what is needed to gain more traffic? Above all, they got to be honest and trustworthy. It is proven that the consumers' perceptions of sources strongly influence the persuasion of advertising (for a meta-analysis see (Wilson, 1993)). Influencers have to realize that source credibility plays a critical role in how consumers evaluate brands and products, whereby a positive evaluation of the credibility of the source is likely to translate into positive advertising outcomes (Sternthal, 1978; Ohanian, 1991). Source credibility consists of two dimensions: trustworthiness and expertise. Trustworthiness refers to the honesty. believability, and morality of the endorser, while expertise refers to the endorser' competence, knowledge, and skills (Hovland, 1953; Sternthal, 1978; Erdogan, 1999; Flanagin, 2007). Both trustworthiness and expertise have been found to enhance advertising effectiveness (Amos, 2008).

Furthermore, the physical appearance or attractiveness of the source plays a major role in the endorsers' credibility and, consequently, persuasiveness (Kahle, 1985; Kamins, 1989; McCracken, 1989; Ohanian, 1991), retrieved from (De Veirman M. H., 2019).

The factors discussed in the studies mentioned above all relate to the right appearance and the behavior of the influencer. However, the full package consists of more than this. When considering not only the creator, but the content the creator creates there are several more impactful aspects that play a major role in engagement. Research has demonstrated that content that is likely to "go viral" and receive a substantial amount of engagement tends to provoke emotional arousal (Berger, 2014; Casas, 2019). This can work both ways, as a recurring finding in the viral media literature is that negativity works effectively in propagating political messages on social media (J. Lee and Xu 2018; Stromer-Galley et al. 2018).

For influencers, creating emotional arousal may not always be the best option. Therefore, we want to find something to explain engagement through an attribute than can be part of a picture. There is limited research that does this for SMIs, whereas for instance in politics, it is found that images featuring own faces only the most effective in spurring were engagement. Also, when a photo is perceived as "beautiful", it seems to increase the number of likes and comments on Instagram posts (Colliander, 2018). Another photo-variable is colour. Drawing on a corpus of one million images crawled from Pinterest, Bakhshi (2015) found that colour significantly impacts the spread (from person to person) of images and adoption of content on image sharing communities such as Pinterest. This drew our attention, so we started to look into that.

According to Singh (2011), colour can be a sublimely persuasive force as marketing tool, and as a functional component of human vision, colour can capture attention, relax or irritate the eyes, and affect the legibility of the text. More than 60 percent of customer assessments are based on colours (Singh S., 2006). Colours have always had a big impact on people's moods, emotions, sentiments, sensations, and perception. Psychology has shown that people attach meanings and emotionally respond to colour. For example, cross culturally, blue, green and white are associated with good, gentleness and calm, while black and red are strong, active and potent colours (Adams, 1973; Madden, 2000). Because of its universal effect, packaging designers even consider colour to be the most influential aspect of their design (Klimchuk, 2006; Meyers, 1998). Colour makes the brand, as it is a vital part of products, services, packages, logos, displays and collateral. It is a potent cue for product and brand differentiation (Schmitt, 1994), for creating and sustaining corporate identities (Garber Jr, 2000; Madden, 2000) and consumer perceptions (Grossman, 1999). For instance, it is a powerful cue assisting brand recall (Tavassoli, 2002). Red is associated with Coke, blue with Pepsi, pink with Barbie dolls and green with 7- Up (Cheskin & Masten Inc., 1987). As you can see, its strategic use could create specific associations across markets (Aslam, 2006). Therefore, colour remains a potent independent variable in managing corporate image consistency. However, this may not apply to all markets yet. For example, colour is difficult to use as a cue for recognizing a particular fashion brand as it has weak associations with top clothing brands (Kerfoot, 2003). This emphasizes the still exploring possibilities through good use of colour.

Cheskin & Masten Inc. (1987) asserted that while product quality is the primary factor in determining consumer satisfaction, imagery is the means by which the target population is drawn in through "sensation transference", suggesting that the emotional response brought on by the colours used in products, packages, and logos affects how customers view the company and the product. Given that our emotions and moods are unstable and that colours influence how we feel, managers must comprehend the significance of colour in marketing (Singh S., 2006). They can respond to this by utilizing knowledge of colour preferences of consumers. One piece of research in psychology has found that colour preferences are related to factors personality (Hyun, 2019), but also gender, ethnicity and age (Kauppinen-Räisänen, 2014). Men are found to prefer blue, African Americans like the range of red-purple-black, Caucasian Americans prefer blues and greens, adults favour the range of blue- red-green, whereas children like bluered-purple: introverts like cooler and calmer colour ranges, whereas extroverts prefer more 'exciting' colours.

Considering our research group and its audience, which is globally dispersed, we think we should investigate colour variables which are more general and always applicable. In our research, we want to dive deeper into quantitative variables, which we want to test empirically. Therefore, we decided to take the three main attributes every colour can de described by as independent variables. Our independent variables are the colour features (hue, saturation, and lightness). The LCH (Luminance, Chroma, Hue) colour space, which includes a means of recognizing and mapping a specific combination of the colour model, will be used to categorize the colours. Through notation, the colour space permits reproducible colour representations. Given that it corresponds to how the human eye perceives colour, the LCH colour space has a significant impact (Hsieh, 2018).

Lightness describes how bright a colour space is (Hsieh, 2018). Colours can be categorized as bright or dark when comparing lightness and can be quantified separately.

According to research (Gerald J. Gorn, 1997), brightness can have an impact on how relaxed people feel. In our research, we refer to 'lightness', which is the quantitative value of brightness. 'Brightness' or 'luminance' is only psychological because it is determined by the perception of colour. Given equally intense blue and green, the blue is perceived as much darker than the green.

The attribute of perceived colour known as chroma has to do with chromatic strength or 'colour saturation'. According to (Gerald J. Gorn, 1997), a colour has more pigment the higher its saturation.

Colour appearance characteristics are referred to as 'hue'. Technically speaking, hue refers to the wavelength of light that falls inside the visible spectrum and reflects different hues of red, blue, and yellow, among others (Hsieh, 2018). Additionally, other colours may be created by combining hues; for example, orange is created by combining red and yellow.

In comparable recent research (Yu, 2020) the role of colour psychology was tested by investigating what effect colour composition has in the popularity of tourism-related photographs on Instagram. One on the main findings of this studies was that blue and blueviolet (i.e., the blue colour system) contribute substantially to the number of "likes" on pictures related to art and culture. In contrast, the (Aramendia-Muneta, 2021) tourism photographs study, claims that the colour rose, which is a warm colour, attracted more likes. And Sharma (2023) found the warm colours red, yellow, and orange to predict a higher number of likes in food images. Comparatively little is known in terms of SMI photographs, so investigating how hue relates to engagement may be a worthy contribution to the excising influencer literature. Nevertheless, because blue possesses universal meanings (Amsteus, 2015) and is a colour to which individuals rarely react negatively (Singh S. , 2006), we chose cold colours as our positive predictor.

H1: The engagement (likes) of images on Instagram by influencers is associated with more use of cold, relaxing colours (e.g., blue, green), rather than warm, arousing colours (e.g., red, orange, yellow).

The perception is cold and warm colours are psychological, meaning that they are based associations we make. upon In the methodology, we will indicate how we will make this measurable. We expect posts were cold colours are dominant to have more engagement. We chose to formulate our hypotheses based on findings of this comparable research and not based on marketing literature, because from that perspective we found a wide range of assumptions while we want to keep the variations between what we compare it to as small as possible to strengthen our hypotheses.

As stated by Sokolik (2014), an experimental study in a natural setting in which they compared people's reactions to a warm colour and cool colour on a news site, they found that colours with a high degree of saturation increased click-through rates in online environments by arousing more individual attention. According to Yu (2020), gastronomy posts with a high saturation and brightness indicated they could positively predict the number of likes and comments. Also, Bakhshi (2015) reported that both high brightness and saturation promoted image diffusion on Pinterest. In addition to this, Banerjee (2018) found that brightness posed a positive effect on Facebook images. Moreover, people tend to associate brightness with positivity (Specker, 2018). Therefore, our second and third hypotheses are the following:

H2: The engagement (likes) of images on Instagram by influencers is positively associated with colour saturation.

H3: The engagement (likes) of images on Instagram by influencers is positively associated with colour lightness.

# METHODOLOGY

#### Data and sample

In order to test our hypotheses, we rely on a sample of Instagram posts. Because we want to investigate in influencers with not too much variety in number of followers, we selected posts made by the top 20 followed influencers in Instagram. The following of these accounts range from roughly 200 to 600 million followers. We did not choose a random sample of influencers, since we want the accounts to have somewhat the same degree of magnitude, because otherwise the values for the dependent variable would diverge too much. Generally, accounts with less followers tend to get less likes on their posts than accounts with more followers, because it reaches far fewer audience. From all these accounts, we select the 10 latest posts. We assess the impact relationships between the aspects of colour and engagement per influencers. We believe this is a large enough sample to ensure that the results are representative of the population we want to investigate. On an Instagram photo post, what the audience gets to see is 1, or multiple (max 10) photos per post. A possible caption below, a possible location added, and possibly people are tagged. When multiple pictures were grouped into a single post, only the first picture was included in the study sample because the first image users see tends to garner more views than subsequent photos (Yu, 2020). Videos and posts published before 2021 were excluded. Data were collected and compiled in June 2023.

#### Measures

#### Independent variable

The data analysis for this study was based on the LCH colour space, a model designed according to humans' colour perceptions (Hsieh, 2018). LCH refers to luminance (i.e., perceived brightness), chroma (i.e., richness/saturation), and hue (i.e., perceived colour[s]). This corresponds to the three attributes of colour we discussed.

The scale of lightness (L) and chroma (C) ranges from 0 to 100; the measurement of hue (H) ranges from 0 to 360°. For L and C, the higher the number, the brighter/richer the image. Average values for L and C were collected for each image to develop a general perception of the brightness and colourfulness

of each image. We will test the lightness and saturation hypotheses by doing a regression. We expect the variables "saturation" and "lightness" to have a positive relation to "likes".

Johannes Itten's colour wheel (Fig. 1) states that hue is determined by 360-degree measurements at 30-degree intervals, yielding 12 primary colours (McGuire, 1992). H contains 12 categories: the degree range of 0–30 represents orange, 30–60 is orange-yellow, 60–90 is yellow, 90–120 is yellow-green, 120–150 is green, 150–180 is blue-green, 180–210 is blue, 210–240 is blue-violet, 240–270 is violet, 270– 300 is violet-red, 300–330 is red, and 330–360 (0) is red-orange (Fig. 2). We are approaching 180° as the coldest colour and we will approach 0/360° as the warmest colour in our wheel. To broadly demarcate cold from warm colours, we draw a line from 90° to 270°.



*Fig. 1. Hue Colour Wheel the Image Colour Summarizer tool corresponds to.* 

For the image analysis, we are going to use the same tool as (Yu, 2020), the Image Colour Summarizer, an open-source online tool from Canada's Michael Smith Genome Sciences. In most cases, people perceive various colours simultaneously when viewing a picture; a single indicator of average hue is therefore insufficient and may misconstrue the colour composition of an image. Thus, the hues of selected pictures were classified into five groups using k-means clustering via the Image Colour Summarizer. These groups revealed the top five perceived colours when people view a picture. However, the number of hue clusters in a photograph depends on colour diversity: the hue cluster of a picture with a similar colour scheme could fall

within a single hue category, whereas a colourful picture could contain five different hue clusters. We will make a histogram where likes are set out against hues, to display a pattern.

Since influencer posts present a wide variety of posts, the chosen images were classified by 6 categories. Categorizations were adapted to suit almost all the influencer photo posts and included 'Fashion and Style'', 'Travel and Adventure', 'Fitness and Wellness', 'Beauty and Makeup', 'Lifestyle and Personal Branding', and 'Others'.

Fashion and Style: Influencers that primarily showcase their own personal style, fashion trends, fashion collaborations, and designer relationships fall under this category. For those who love fashion, they frequently provide ideas and suggestions.

Travel and Adventure: Influencers in this field provide beautiful travel images from all around the world. They feature stunning scenery, exotic locations, cultural encounters, adventures, and the discovering of new places.

Fitness and Wellness: Influencers that advocate for a fit and active lifestyle may be found in this category. They exchange exercise plans, fitness challenges, dietary advice, and wellness techniques.

Beauty and Makeup: The focus of beauty and makeup influencers is on sharing routines, tutorials, routines, product reviews, and transformations. They frequently work with cosmetic companies to promote their preferred cosmetics and beauty methods.

Lifestyle and Personal Branding: Influencers that fall under this category post a variety of content, including behind-the-scenes photos, encouraging words, daily routines, and personal experiences. They frequently customize their feed to represent their unique brand and establish a more intimate connection with their audience. Images that do not fit within one of the categories, are labelled as "other'.

#### Dependent variable

Our dependent variable is engagement, which will be measured by the number of likes a post single receives. User engagement in Instagram can also be manifested in other forms such as views, comments, or creating user-generated content, but it is not as feasible to measure engagement in such forms (Li, 2020). Since we have chosen to focus exclusively on imageposts, it is impossible to measure views. We do not include comments, as we want to do research on influential power, and thus measure positive engagement. the comment section is a place where people can freely express their opinions, and thus are also able to leave negative messages there. for this reason, we do not include this in our research. The likes, on the other hand, are meant for users to express that they like, enjoy, or support certain content. It is the most common way for users to engage on Instagram (Xie-Carson, 2023).

#### Image-processing

We proceed as follows. We take screenshots of the photo posts on instagram when viewing the photos. We crop these photos perfectly so that the photo file consists of only the image that was posted. We label each phot to the respective influencer, we select the category it belongs to, we record the date it was posted, and we note the number of likes for each photo. Then, we upload the photos into the image processing tool, the Image Color Summarizer which can extract the colour features of the image procession tool, the Image Color Summarizer which can extract the colour

Table 1.	Sampr	C C						
nr	nrpi	Influencer	Date	Likes	Category	L avg	C avg	H dom
1	1	Cristiano Ronaldo	04/06/2023	7.385.179	T&A	60	21	34
2	2	Cristiano Ronaldo	04/06/2023	6.645.882	F&W	39	13	302
3	3	Cristiano Ronaldo	03/06/2023	3.112.239	L&B	45	18	90
4	4	Cristiano Ronaldo	02/06/2023	6.635.128	L&B	45	8	285
5	5	Cristiano Ronaldo	23/05/2023	11.754.388	F&W	48	20	124
6	6	Cristiano Ronaldo	20/05/2023	12.317.085	F&W	69	14	59
7	7	Cristiano Ronaldo	19/05/2023	6.862.612	F&S	23	5	240
8	8	Cristiano Ronaldo	16/05/2023	8.243.041	F&W	42	29	131
9	9	Cristiano Ronaldo	13/05/2023	8.674.028	L&B	57	20	63
10	10	Cristiano Ronaldo	11/05/2023	16.346.396	F&S	52	10	78

Table 1. Sample

Example: Cristiano Ronaldo

Table 2. Frequencies and percentages of hues

	OR	YO	YL	YG	GR	BG	BL	BV	VL	RV	RD	RO
Frequency	21	19	25	35	6	3	2	5	11	38	31	4
Percent	10.5	9.5	12.5	17.5	3	1.5	1	2.5	5.5	19	15.5	2
Note: OR = orange; YO = yellow - orange; YL = yellow; YG = yellow-green; GR = green; BG = blue-green; BL = blue; BV = blue-violet;												
$VI = violet$ : $RV = red_{violet}$ : $RD = red_{violet}$ : $RO = red_{violet}$												

features of the images (Krzywinski, 2006-2023). The output are image statistics which are computed using every single pixel in the image. From this outpot, we process the average L value, the average C value and the dominant H value. We process all of this in SPSS, and this is how we build a complete dataset (Table. 1) that we can eventually use to try to discover correlations so that we can confirm or reject our hypotheses, or perhaps come up with new insights.

### RESULTS

#### Descriptive statistics

Overall, the findings of the revealed that the lightness of images was 44.58 on average (SD = 16.37) and the chroma was 12.86 (SD = 8.08). Regarding hue, red-violet was most often the dominant colour in the chosen images, with a frequency of 38 out of the 200 (19%) pictures. Together with 35 times yellow-green (17.5%) and 31 times red (15.5%) these were the most common colours. (Table. 2) for more details.

**Table 3. Correlations** 

#### Main Analysis

Before regressions were performed, the correlations between the independent variables were examined (Table. 3). Correlation analysis helps identify possible multicollinearity, which indicates a high degree of correlation between independent variables. Multicollinearity can cause problems in regression analysis because it makes it difficult to separate the individual effects of the independent variables. When independent variables are highly correlated, it becomes difficult to determine independent contributions to the dependent variable. As shown in the table, correlations between independent variables have been found in our sample. but we assume there is no multicollinearity since none of the correlations is more than -0.2 of +0.2.

Linear and multiple regression analyses were conducted to examine the effects of lightness, chroma, and hue on post popularity. We started with performing a simple linear regression analysis to investigate the degree to which

		LIKES	Lavg	Lmed	Lmin	Lmax	Cavg	Cmed	Cmin	Cmax	Hdom
LIKES	Pearson Correlation	1	-0,065	-0,037	-0,049	0,002	0,050	0,022	-0,054	0,040	0,006
	Sig. (2-tailed)		0,364	0,599	0,492	0,982	0,479	0,757	0,447	0,577	0,937
Lavg	Pearson Correlation	-0,065	1	.963**	.310**	.393**	0,088	0,113	0,095	-0,072	-0,112
	Sig. (2-tailed)	0,364		0,000	0,000	0,000	0,217	0,110	0,179	0,309	0,113
	Pearson Correlation	-0,037	.963**	1	.247**	.309**	0,092	0,123	0,081	-0,092	-0,119
Lmed	Sig. (2-tailed)	0,599	0,000		0,000	0,000	0,197	0,084	0,255	0,197	0,092
	Pearson Correlation	-0,049	.310**	.247**	1	-0,007	-0,049	-0,003	.191**	194**	0,035
Lmin	Sig. (2-tailed)	0,492	0,000	0,000		0,916	0,492	0,968	0,007	0,006	0,624
_	Pearson Correlation	0,002	.393**	.309**	-0,007	1	.142*	0,118	-0,084	.167*	0,061
Lmax	Sig. (2-tailed)	0,982	0,000	0,000	0,916		0,045	0,095	0,235	0,018	0,389
	Pearson Correlation	0,050	0,088	0,092	-0,049	.142*	1	.957**	.289**	.524**	-0,126
Cavg	Sig. (2-tailed)	0,479	0,217	0,197	0,492	0,045		0,000	0,000	0,000	0,075
	Pearson Correlation	0,022	0,113	0,123	-0,003	0,118	.957**	1	.329**	.394**	146*
Cmed	Sig. (2-tailed)	0,757	0,110	0,084	0,968	0,095	0,000		0,000	0,000	0,039
	Pearson Correlation	-0,054	0,095	0,081	.191**	-0,084	.289**	.329**	1	-0,027	202**
Cmin	Sig. (2-tailed)	0,447	0,179	0,255	0,007	0,235	0,000	0,000		0,700	0,004
	Pearson Correlation	0,040	-0,072	-0,092	194**	.167*	.524**	.394**	-0,027	1	-0,057
Cmax	Sig. (2-tailed)	0,577	0,309	0,197	0,006	0,018	0,000	0,000	0,700		0,426
	Pearson Correlation	0,006	-0,112	-0,119	0,035	0,061	-0,126	146*	202**	-0,057	1
Hdom	Sig. (2-tailed)	0,937	0,113	0,092	0,624	0,389	0,075	0,039	0,004	0,426	

\*\*. Correlation is significant at the 0.01 level (2-tailed).

\*. Correlation is significant at the 0.05 level (2-tailed).

lightness and chroma predicted the number of "likes" on photos. Overall, no significant differences were observed when predicting the number of "likes" based on lightness and chroma, respectively L: F = 0.828, p = 0.364; C: F = 0.503, p = 0.479. This suggests that these variables do not contribute meaningfully to predicting or explaining our dependent variable's variation.

While lightness and chroma alone did not exert remarkable effects on the number of "likes" on big influencer related posts, outcomes diverged when considering the entire LCH colour space. After we labelled all dominant hues to one of the colour spaces' twelve colours, we made a histogram to visualize how each dominant colour performed when set out to the number of "likes" in our sample (Fig. 2). "Yellow" performed best compared to the other colours.



Fig 2. Histogram.

Since the goal of conducting a regression analysis was to understand the relationship dependent between the variable and independent variables, we chose not to include the fourth independent variable- the category each post belongs to- in our analysis, since adding an extra variable to a regression which was already found to have no significant relationship would be useless. Including an extra independent variable adds complexity to the model without providing any benefit. It would be unlikely to improve the model's predictive power and it can lead to overfitting, meaning the model becomes too specific to the training data and performs bad on new data, considering we already have a small sample size.

Based on our regression models, there appear to be no linear relationships. Machine learning allows us to test whether the differences in likes can be explained by more complex patterns in colour use. Machine learning is a field of artificial intelligence that focuses on developing algorithms and models capable of automatically learning and making predictions or decisions from data without being explicitly programmed. The idea behind machine learning is to use algorithms to find patterns, correlations, or structures in data and then use this knowledge to forecast the future or take action. It entails teaching models on historical data, learning from it, and then applying the acquired information to forecast or categorize brand-new, unseen data.

For this reason, we imported our data into the data mining program Orange. In it, we trained a model (Fig. 3). The model is composed of different machine learning algorithms that are commonly used for classification tasks. Ours consist of "naive bayes," "random Forest," "neural Network," and "logistic Regression".



#### Fig 3. Orange Model.

Naive Bayes is a probabilistic algorithm. Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. Neural Network is inspired by the structure and functioning of the human brain, which is using layers. Logistic Regression is a statistical model used for binary classification tasks. Our dependent variable was made binary, dividing "likes" in our sample into "many" and "few" likes. Based on the F1 scores the software gave us, we were able to evaluate whether the model was significant for use. The F1 score is a widely used evaluation metric that assesses both precision and recall to produce a measure of a model's accuracy. Recall (sensitivity) is the percentage that consists of true positive predictions out of all actual positive cases in the dataset, whereas precision is the percentage of true positive predictions out of all positive predictions generated by the model. The F1 score, which runs from 0 to 1, is comprised of the two criteria together.

With F1 scores of 0.86 for Logistic Regression, 0.835 for Neural Network, 0.83 for Naive Bayes and 0.785 for Random Forest we may interpret that the model we trained is significant. Then, we looked at the nomogram to interpret the model results and learn the relative importance of different variables in making predictions (Fig. 4). The nomogram is a visual tool that graphically displays the coefficients or weights of the predictive model. On top, the most predictive independent variable is displayed, and on the bottom, the least predictive. From our nomogram we

Points	-2.5	2.0 -1.5	-1.0	-0.5 0.0	0.5	1.0	1.5	2.0	2.5
INFLUENCER	Nicki Minaj	Kim Kardashi	an Kh	loé Kardashan	`	/irat Kohli		Cristiano	Ronaldo
HIT LOENGER	Dwayne John	ion E	Beyonce	Justin Bie	ber	Aria	ana Gran	de Lionel I	Messi
CATEGORY				F&S B&M	.88	F&W	T&A		
HUE_COLORWH	EEL		viole red_o	torange blue range yellow_c	range	green			
Cmin			0.8	5 - 1.5 1.5 - 2. < 0.5	5 ≥ 2.5				
Lavg			4	45.5 - 55.5 ≥ 55.5	< 33	.5			
Lmed				45.5 - 59.75 ≥ 59.75	< 27.5				
Lmin				≥ 3.5 0.5 - 1.5	7				
Cavg				8.5 - 11.5 11.5 - 16.9	≥ 16.5 				
Lmax				≥ 99.5 <	92.5 J 8.5				
Total	-	2.5 -2.0	-1.5 -1	1.0 -0.5	0.0 0.5	1.0	1.5	2.0	2.5
Probabilities (%		10	20	30 40	50 60	70	80	90	<u> </u>

Fig 4. Nomogram.

learned that the most predictive variable for the number of likes is which influencer does the post. The category the posts belongs to also seems to be a predictor, but since most influencers mainly post under one category, for this variable we cannot independently draw inferences. For hue, green scores best compared to the other colours and thus is predicted to get the most likes.

## **DISCUSSION & CONCLUSION**

Prior research that tried to explain the variances of social media engagement has already emphasized the importance of the effects of colours. Yu (2020), Bakhshi (2015), and Banerjee (2018) demonstrated that photographs that are brighter and more saturated tend to be more likely attract engagement from viewers. Our contribution to this discussion is that our research indicates that for influencers also hue tends to be a significant tool for engagement with users.

The results of our analysis revealed that most photos in our data sample had a relatively low level of lightness, and our sample also mainly exhibited low saturation. Due to the lack of a relationship between lightness and saturation, the effects of chroma and lightness were evaluated independently. No significant relations were found for these variables in relation to "likes" according to our regression. This means that we can reject our hypothesis, neither positive nor negative relationship was found with the number of likes, as the relationship found could not be proved significant. We could not explain the success of influencers based on the colour saturation and lightness. This means that according to our results, influencers can not enhance their engagement by use of high lightness of saturation. These findings emphasize the comprehend how necessity to varving and brightness saturation levels may unintentionally impact users' "liking" habits.

Regarding to hue, our histogram revealed that posts in which "yellow" was the dominant colour, the most engagement was found, followed by "red". These findings allowed us to reject our hypothesis, cold colours are not positively related to the number of likes for SMIs, in fact, warm colours are. Influencers can apply these findings to enhance their content and increase their own engagement. In marketing for example, the colour yellow could be used strategically, use it for thumbnails, cover images, incorporate the colour in their overall branding strategy, and make sure the yellow photo elements catches the viewers' attention.

Because colour is often just a property of a certain object, research on colour is most likely incomplete enough to be of significant value. (Palmer, 2010) have reported results positing that people like colors to the degree that they like correspondingly colored objects. Certain colors have associations with objects in nature. for example, the color blue is frequently associated with a blue sky or fresh water, which

causes blue to have a positive association. (Schloss, 2011).

We must acknowledge, that nowadays, the fourth industrial revolution is paving the way. Artificial Intelligence (AI) is taking over and therefore the use of data mining techniques is growing. During the process of analyzing, we have realized the limitations of our own sample. For the purposes of making inferences about the examined relationship, a larger sample appears to be required. Therefore, we were dissatisfied with the conclusions we had drawn so far. In order to possibly come up with a stronger study, we started to explore what the possibilities might be if we were to use a data mining program such as Orange. Therefore, we applied data mining techniques in the study to examine the colour space of SMI photos on Instagram. The relationship between the three primary colour dimensions (i.e. lightness, saturation, and hue) of the selected images and the engagement of the entry was assessed.

The machine learning model we made in Orange confirmed that the performances of the influencers on our sample differ significantly. If the average post-performances of the influencers had been closer together then we could have better isolated the effects of the other variables. What was interesting to see, however, was that this analysis still shows that hue may be the best predictive variable we have. So, that could possible mean that using certain colours might have a positive effect on the achieved engagement of an Instagram post.

#### Limitations & recommendations

The results of this study require to take limitations into consideration. Along the way, we discovered our sample size is too small to make proper statements about what effect colour has on engagement. A bigger sample size is acquired in order to represent the target population. We recognize that there are most likely other variables- which we cannot measure in the way we did- that are likely to have a larger influence on engagement such as the effects of certain objects and shapes. Also, it is important to emphasize the limitations of using machine learning software such as Orange. It heavily relies on the quality and quantity of the available data, and if there is a predictive value in it, we do not understand how relationships run, we can only recognize patterns in them. It is a 'black box', in which we can see the input and the output, but we do not know what happens in between, its operations are not visible to the user. The machine learning's internal workings and decisionmaking processes are not easily interpretable or explainable by humans. Despite the limitations, we discovered that machine learning could be a very powerful tool. And because the ultimate goal would be the ability to explain engagement via image variables, it would be interesting to examine the possibilities with machine learning, using big data gained through web scraping. We expect that uploading the pictures in Orange could enable us to build an AI predictor for the number of likes. Orange could help us to investigate what all possible variables are and how they are related to each other. For a follow up studies, we can use AI to investigate what certain shapes and objects' contribution to engagement is.

Additionally, our research focusses solely on Instagram and the photo related content on the platform. Conclusions on factors influencing the engagement would still only be applicable to our field of research. Other platforms, other types of content are disregarded.

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