The Effects of Climate on Social Media Engagement

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Işıl Büdeyri Turan
Advisor: Professor Dr. M. Tolga Akçura

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To my beloved ones who have always been there for me…

ABSTRACT

User-generated content drives engagement, crucial for brand performance. Social media engagement is influenced by individual mood, preferences, and environmental cues, including temperature. Despite its impact, the specific influence of temperature on user engagement remains unclear. This thesis investigates temperature's impact on user engagement and its interaction with social media campaigns. The focus is on temperature due to its overwhelming influence on social media engagement compared to other climate variables such as cloudiness, air pressure, wind speed and humidity. Through a controlled experiment and empirical study spanning five and a half years, the research reveals several key findings: extremely high temperatures decrease user engagement by reducing happiness levels; high temperatures have a greater impact than low temperatures. The detrimental impact of high temperatures is significant on post creation, but not on liking, commenting, and sharing behaviors, indicating content creation behavior is more sensitive to high temperatures than content contribution behavior. A specific dataset composed of user-generated content quantifies the negative impact of high temperatures and shows that a social media campaign during extreme heat mitigates its adverse effects by only 36.7%; and campaign effectiveness decreases by 29.2% during extremely hot weather. This study is the first to comprehensively explore the effects of extreme temperatures on user engagement. The implications extend to researchers, social media managers, and campaign planners, providing insights for enhancing engagement strategies in varying temperature conditions.

ÖZET

Kullanıcıların oluşturdukları içerikler sosyal medyaya olan ilgiyi arttırmakta ve marka performansı açısından önemli bir rol oynamaktadır. Bu ilgi, bireylerin duygu durumundan, tercihlerinden ve hava sıcaklığı gibi çevresel faktörlerden etkilenmektedir. Hava sıcaklıklarının bireyler üzerindeki bilinen etkisine rağmen, sosyal medyaya olan ilgi üzerindeki etkisi belirsizliğini korumaktadır. Bu çalışma hava sıcaklıklarının sosyal medyaya olan ilgi üzerindeki etkisini ve gerçekleşen kampanyalar ile etkileşimini araştırmaktadır. Bulut oranı, hava basıncı, rüzgar hızı, nemlilik gibi iklim değişkenlerine göre hava sıcaklıklarının ilgi üzerindeki etkisi daha kuvvetlidir, bu nedenle bu tez hava sıcaklıklarının etkisine odaklanmaktadır. Kontrollü bir deney ve beş buçuk yıllık gerçek veriler üzeriden gerçekleştirilen örgül çalışmanın ana bulguları şunlardır: aşırı sıcaklıklar, kullanıcıların duygu durumunu olumsuz etkileyerek sosyal medyaya olan ilgisini azaltmaktadır; yüksek sıcaklıkların etkisi düşük sıcaklıklara göre daha fazladır. Yüksek sıcaklıkların, kullanıcıların içerik oluşturma davranışı üzerindeki olumsuz etkisi başkalarının oluşturduğu içeriklere katılma davranışı (beğenme, paylaşma, yorum yazma) üzerinde gözlemlenmemiştir; dolayısıyla sonuçlar içerik oluşturmanın hava sıcaklıklarının olumsuz etkisine daha açık olduğunu göstermektedir. Kullanıcıların oluşturduğu içerikleri kapsayan özel bir veri seti üzerinde yapılan analizler bu olumsuz etkiyi nicelleştirmektedir; aşırı sıcak havalarda başlatılan kampanyaların söz konusu negatif etkiyi sadece %36.7 azaltabildiğini ve kampanya etkinliğinin ise %29.2 azaldığını belgelemektedir. Bu çalışma, aşırı sıcaklıkların sosyal medyaya olan ilgi üzerindeki etkisini kapsamlı olarak inceleyen ilk çalışmadır. Sonuçlar, araştırmacılar, sosyal medya yöneticileri, kampanya planlayıcıları ve marka yöneticileri açısından önem atfetmektedir.

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CHAPTER I

INTRODUCTION

In the CMO Survey [1], it was reported that marketers currently allocate 17% of their budget to social media, a figure projected to rise to 26.4% within five years. Social media serves as a pivotal tool for managers aiming to enhance brand awareness, cultivate brand identity, drive sales through promotions, introduce new products, acquire new customers, and retain existing ones [1]. However, achieving these objectives necessitates the development of effective strategies to capture and retain consumer attention on branded accounts, as well as creating compelling campaigns tailored to the appropriate audience, content, and timing. This process presents challenges to managers due to the dynamic nature of social media, which demands ongoing monitoring of marketing metrics, and the presence of numerous uncontrollable variables that can impact user engagement with branded content. One such variable of interest is temperature.

In marketing literature, it is well-documented that temperature, whether measured as ambient temperature or atmospheric conditions, significantly influences individual mood and cognition [2]. This influence extends across various domains, including decision making [3], consumption culture [4], hedonic consumption [5], variety-seeking behavior [6], consumer spending [7], and willingness to pay in auctions and negotiations [8] as well as retail and online sales dynamics ([9]; [10]).

The impact of temperature on mood and behavior exhibits a non-linear pattern ([11]; [12]) leading to adverse effects in both hotter and colder temperatures. Departures from average temperature levels evoke negative emotions (e.g., anger) and diminish positive emotions such as joy and happiness [13]. This negative influence extends to the sentiment expressed in social media comments ([14]; [15]). Given that users facilitate the dissemination of brand-related news on social media [16], and generate contents that drive engagement which enhance brand performance metrics ([17]; [18]), understanding the potential effects of temperature on sentiment and engagement behavior becomes crucial.

This thesis examines how and why temperature influences user engagement, focusing on the impact of extremely hot and cold temperatures compared to season-normal temperatures, using experimental and empirical settings. The study, then, compares the impacts of high and low temperatures on user engagement and seeks to explore how user engagement changes in the presence of a social media campaign at extreme temperatures for managerial purposes regarding the campaign timing and impact. My emphasis on the effects of extreme temperatures is motivated by the increased exposure to weather variability resulting from climate change. During the empirical study period (2014-2019), data on temperature reflect growing disparities in the monthly maximum and minimum temperature values across different seasons. This escalation suggests that temperature effects on mood and consumer behavior may intensify in magnitude and frequency, potentially becoming endogenous to marketing outcomes.

Similar to temperature, mood states which are a set of affective states play a crucial and causal role in shaping consumer behavior [19]. Of these states, happiness carries managerial significance due to its profound impact on human physiology compared to other affect types [20]. Happiness triggers a myriad of positive outcomes, including longevity [21], success [22], increase productivity at work [23], entrepreneurial initiatives [24], abstract construal (high-level thinking) [25], and creative thinking ([26]; [27]).

Happiness has the power to influence decision-making processes ([28]; [29]; [30]), engagement (e.g., livestreaming [31]; internet video advertisements [32], and foster brand loyalty [33]. Consequently, many brands across different industries endeavor to promise happiness to connect with consumers, incorporating happiness into their brand imagery [34]. Examples include Coca Cola “Happy Tears” [35], Amazon “Joy is shared” [36], BMW “Joy Days” [37], LG “Experience Happiness” [38], and IKEA “Happiness Hunter” [39]. Given the pivotal role of happiness in affecting user engagement and its susceptibility to unpleasant temperatures [40], investigating potential causal associations among these three factors becomes imperative.

To explore the potential impact of extreme temperatures on user engagement and the role of happiness in this relationship, I first conducted an experiment. I define user engagement as post creation, commenting, liking, and sharing behavior, and explore the impact of extremely hot and extremely cold temperatures compared to season-normal temperatures on each aspect of user engagement. The experiment results reveal that extremely hot temperatures compared to season-normal temperatures diminish user engagement by reducing happiness levels. Specifically, this impact is significant for post creation, but not for liking, commenting, and sharing intention. I also find that extremely hot temperatures’ negative impact on each user engagement type is at least 1.5 times higher than that of extremely cold temperatures.

Subsequently, I conducted an empirical study using comprehensive real-life data spanning five and a half years to quantify the impact of extreme temperatures on user engagement and explore the campaign effect on user engagement during extreme temperatures. The dataset facilitated the correlation of daily user-generated content across all social media platforms with daily weather patterns. This unique dataset enables linking language-specific social media posts with geography-specific social media content while respecting consumer privacy. Through the empirical study, I quantified the impact of extremely hot temperatures on user engagement and confirmed the disparity between the magnitude of negative impact of hot and cold temperatures. Regarding the campaign effect and timing, I additionally ran an interaction model and found that a social media campaign run during extreme heat can compensate the negative impact of extremely high temperatures on user engagement by only 36.7%. In other words, during extremely hot weather, the presence of a social media campaign does not fully prevent users from being less likely to engage. It helps lessen the negative impact of hot temperatures but cannot eliminate or reverse the negative impact of hot temperatures. Moreover, the positive impact of a campaign on user engagement lessens by 29.2% if run during extremely hot weather.

This thesis offers significant theoretical and managerial contributions. First, it explores the impact of extremely hot and cold temperatures on social media engagement, representing to my knowledge, the first study to address such a broad scope within the domain of weather – social media studies. I examine the effects of both cold and hot weather compared to season-normal temperatures on various engagement metrics including post creation, liking, commenting, and sharing behaviors across all major social media platforms. Second, this research delves into why the effects of extreme temperatures on engagement might occur, employing an experimental approach. This aspect distinguishes the work as pioneering among weather-social media literature, as it stands out as a preliminary effort to understand the causality behind. The findings contribute to the literature by demonstrating the detrimental impact of extremely hot temperatures on social media engagement, specifically on content creation, and identifying weather-induced fluctuations in happiness as the driving factor. This emphasis on causal relationships underscores the significance of integrating temperature data into both social media and sales analytics performed by researchers and managers.

Third, this thesis emphasizes the importance of considering campaign timing in relation to temperature to maximize the effectiveness of social media campaigns in generating high engagement. The research demonstrates that users remain less engaged with social media posting during periods of extremely hot temperatures, even when a social media campaign is active during the same period. Furthermore, I illustrate that the impact of a campaign is relatively diminished during extremely hot weather compared to other times. These findings contribute to the effectiveness of social media campaign studies by informing campaign timing decisions and integrating temperature considerations into measures of campaign effectiveness.

In a managerial context, high user engagement is of paramount importance for social media managers, brand managers, and campaign planners, serving as a vital tool to monitor consumer voice and preferences [41]. Consequently, it facilitates driving sales, and enhancing brand image and salience through branded and consumer-focused social media activities. This research illuminates the reasons behind the potential decrease in user engagement during extremely hot temperatures, providing insights for the development of strategies that prioritize fostering happiness to boost engagement with branded content.

The structure for the rest of this thesis is as follows. First, I review literature on temperature effects in marketing. Next, drawing on the mood and social media literatures I propose the research hypotheses regarding the effect of extreme temperatures on user engagement. Chapter 2 presents the experiment. Following the design and procedure, comes analysis and results of the experimental study. After concluding the study with a discussion, the reader will find Chapter 3, which presents the field work. The thesis ends with a comprehensive discussion of the results, highlighting key findings, implications, and avenues for future research.

1.1 Theoretical Background

1.1.1 Temperature Effects in Marketing

Besides external factors like décor, sounds, aromas, lighting, temperature stands out as a significant situational factor in the physical environment of a consumer [42]. When environmental conditions become abnormal and extreme, they are often referred to as "stressors," which can influence performance, intellectual and physiological outcomes [43]. These influences are also observed for temperature in many contexts, such as decision making [3], purchase behavior [44], willingness to pay in auctions and negotiations [8], and hedonic consumption [5], providing important managerial and policy implications. In warmer temperatures, for instance, people are less likely to gamble, to purchase an innovative product, and more likely to perform poorly in cognitive tasks that require processing resources. These influences primarily stem from the resource-depleting nature of temperature, triggering a shift towards reliance on System-1 processing, which requires fewer resources and is relatively effortless [3]. Sinha and Bagchi [8] find that higher ambient temperatures (vs. normal) elicit higher bids in auctions but lead to lower offers in negotiations, as such temperatures create discomfort in individuals, and trigger hostile aggression. In addition, they explore the impact of lower temperatures (vs. normal) and find similar results. Govind et al. [5] establish the association between weather and consumption of hedonic products, and that such association is mediated by affect (which is measured by the level of happiness and sadness).

Temperature is considered as an influential variable for explaining retail sales of many sectors including textile, clothing, footwear, sporting equipment, alcoholic drinks, and other beverages [45], and for obtaining better sales forecasting results ([9]; [10]). For example, Bertrand and Parnaudeau [45] examine retail sales of all retail categories and find that each sector exhibits different weather sensitivity to the same weather variable such that in autumn a positive deviation of 1°C increases sales of alcoholic drinks by more than 11%, while the same deviation in temperature causes sales of footwear to decrease by about 1%. Murray et al. [7] shows that sales of tea and related accessories of an independent retail store decline when the weather is warmer and more humid. Steinker et al. [10] examining the sales of an online fashion retailer, find that using temperature improves sales forecast accuracy, by lowering forecast error variance. They demonstrate that the retailer can reduce excess costs by 10% to 12% with more efficient capacity planning and scheduling via using weather. Similarly, Verstraete et al. [9] illustrate that using weather as an input in decision making may improve sales forecast accuracy in the context of a swimming pool retailer, preventing unnecessary inventory and transportation costs (see Appendix A for a comprehensive list of studies in marketing on temperature).

1.1.2 Temperature Effects on Mood

Temperature effects on mood are examined extensively using both experimental and empirical approaches. As presented in Table 1, the earlier studies focus more on experimental studies ([43]; [46]; [47]; [48]; [49]; [50]). Griffit and Veitch [43] examine the impact of high effective temperatures (vs. normal) on mood, social and non-social affective experiences, and attraction. They find that in high effective temperatures, aggression, fatigue, and sadness are significantly higher; whereas surgency, elation, concentration, social affection, and vigor are significantly lower compared to their scores in normal effective temperatures. They also observe more negative social affective responses (attraction) and non-social (room and experiment evaluation) affective ratings in higher effective temperature conditions. Baron and Bell [46] focus on the effect of ambient temperatures on aggression under negative and positive affective states; and find that higher ambient temperatures facilitate aggression when other sources of negative affect are available, but inhibited such behavior when sources of negative affect are available. Bell and Baron [47] add that aggression is influenced by exposure to both high and low ambient temperatures. Cunningham [51] examines weather's impact on helping behavior, showing that temperature's impact is non-linear, such that it is negatively related to helping behavior in summer, but positively related in winter. Anderson et al. ([49]; [50]) examines the impact of different ambient temperatures on perceived and physiological arousal, perceived comfort, positive and negative affect, hostility, and aggression. The findings on hostility support previous experimental studies on aggression such that hot temperatures increase hostility and hostile cognition. In addition, they find that hot temperatures decrease perceived arousal, but increase physiological arousal measured by heart rate [49] but find no effect on negative affect which is measured by a combination of different negative affect states. Anderson et al. [50] suggests that there may be more specific types of negative affect that are influenced by temperature. Their finding on temperature-induced discomfort is non-linear in nature, meaning both hotter and colder temperatures cause discomfort.

More recent works on weather-mood relationship shift their focus to empirical studies which entail larger datasets involving different geographic locations, climates, economic and individual factors. For instance, Rehdanz and Maddison [52] analyze panel data of 67 countries to understand the differences in self-reported levels of happiness with reference to temperature and precipitation. They find that higher mean temperatures in the hottest month decrease happiness, while higher mean temperatures in the coldest month increase happiness. Countries' geographic locations matter in temperature's impact on self-reported happiness, such that happiness of countries in high latitudes like Canada, Norway, Finland, Sweden, or Iceland is positively affected by the increases in temperature. However, most countries are expected to be negatively affected from climate change as temperature is expected to increase over time. Levinson [53] analyzes General Social Survey data which is collected annually in the U.S., and merges weather and air quality data with survey data. He finds that temperature has a non-linear impact on happiness, such that average temperatures increase happiness, but quadratic temperatures have negative impact on happiness. He further monetizes this impact and finds that a rise from -1.1^{o}C to 4.4^{o}C makes people happier by an amount equivalent to having an extra $36 per day, while a rise from 26.7^{o}C to 32.2^{o}C makes people less happy by $55. In other words, the loss caused by an increase in hot temperatures is greater than the gain attained by an increase in cold temperatures. Tsutsui [40] finds similar non-linear impact of temperature on happiness; such that average temperatures increase happiness, but as temperature gets hotter this impact becomes negative. Connolly [54] analyzes Princeton Affect and Time Survey data collected in the U.S. and find that women are more responsive to environmental variables emotionally, such that happiness level decreases significantly when temperature is higher than or equal to 32.2^{o}C. Lower temperatures, on the other hand, increase happiness, reduce tiredness, stress, and sadness. Noelke et al. [13] support previous findings indicating that when temperatures exceed average levels, positive emotions such as joy and happiness decrease, while negative emotions such as stress and anger increase along with feelings of fatigue. The authors also note that a lack of consistent evidence suggesting that individuals living in areas with mild and hot summers respond differently to heat exposure, indicating a limited role for heat adaptation in mitigating the impact of heat on well-being.

Several studies explore the potential moderators that would influence weather-mood relationships. Keller et al. [2] examine the role of time spent outdoors, while Kööts et al. [55] investigate the influences of age and personality traits, and Denissen et al. [56] delve into the seasonal dimensions of this relationship. Additionally, numerous studies treat mood as the mediator between weather and consumer behavior. For instance, affect mediates the impact of weather on hedonic consumption [5], and positive mood mediates the impact of pleasant weather on recommending behavior in a restaurant setting [57]. Bujisic et al. [57] demonstrate that pleasant weather elevates mood, leading to positive word-of-mouth (WOM). Their findings underscore how weather can modulate mood, subsequently shaping consumers' affective experiences and resulting in positive recommendations.

Gardner [19] highlights that mood states have direct and indirect effects on behavior, with consumers' mood susceptible to minor alterations in their physical environment. Specifically, happiness, influenced by both higher and lower temperatures, and acting as a mediator in the relationship between weather and behavior, may also mediate how extreme temperatures impact user engagement. In the next section, I will examine the weather – social media literature to elucidate how temperature may affect user engagement and present my hypotheses.

Table 1: Selected Works Examining Weather Impact using Mood as a Dependent Variable or a Mediator (Sorted chronologically)

Study	**Dependent Variable (DV)**	**Temperature Operationalization**	**Field Study**	**Experi-ment**	**Mediator / Moderator**	**Findings**
Govind et al. 2020 **[5]**	Hedonic consumption	-Weather report -Perceived weather pleasantness -Weather forecasts	√	√	Mediator: Affect (happy, sad) Moderator: Gender	- the association between weather and consumption of hedonic products (food and non-food) is mediated by affect. - strength of this mediation differs by gender (stronger among females). -Females (vs. males) experience a stronger negative affective response to unfavorable weather conditions and subsequently consume more hedonic food in response to that negative affect.
Sinha & Bagchi 2019 **[5]**	Willingness to pay in auctions and negotiations	- Ambient temperature (High: 77ºF-82ºF/ 25ºC-27.8ºC, Moderate: 67ºF -70ºF/ 19.4 ºC-21.1ºC, Low: 63ºF/ 17.2ºC)	√	√	Mediator: -Thermal discomfort -Hostile aggression	-higher (vs. moderate) temperatures elicit higher bids in auctions but lead to lower offers in negotiations. -both high and low temperatures have a similar effect on bids (both high and low temperature-induced discomfort incites higher aggression, and thus elicit similar results)
Bujisic et al. 2019 **[57]**	- Comment valence - Comment content - Recommending behavior (WOM)	-Weather report (study1) -Weather perception: Pleasant/ unpleasant; Good/Bad; Worse/Better than usual; Enjoyable/ unenjoyable (study 2) - Weather description (unpleasant weather: cold, raining and snowing) (study 3)	√	-	- Positive/Negative Mood (study 2) - affective experience in restaurant (study 3- serial mediation)	- Study 1: Higher temperature and rain) result in more negative valence -Study 2: Mood mediates the relationship with weather and WOM; no direct effect of pleasant weather on WOM) -Study 3: Weather influences mood and this mood change transfer to consumer's affective experience and behavior. Pleasant weather has positive indirect effect on WOM through escalating mood and mood escalating affective experience (serial mediation).
Noelke et al. 2016 **[13]**	- Well-being (enjoyment, worry, sadness, stress, anger, happiness)	- Ambient temperature	√	-	-	- increasing temperatures significantly reduce well-being. - Compared to average daily temperatures in the 10–16 °C range, temperatures above 21 °C reduce positive emotions (e.g., joy, happiness), increase negative emotions (e.g., stress, anger), and increase fatigue (feeling tired, low energy).

Study	Dependent Variable (DV)	Temperature Operationalization	Field Study	Experi-ment	Mediator / Moderator	Findings
	positive emotions (happiness, enjoyment, smiling/laughter negative emotions (anger, stress, worry, sadness, not treated with respect), fatigue (well-rested, enough energy)					-there is no consistent evidence suggesting that individuals living in areas with mild and hot summers respond differently to heat exposure, suggesting a limited role for heat adaptation to mitigate the impact of heat on well-being in the contemporary U.S.
Bogomolov et al. 2014 **[58]**	-Daily stress	- Weather report	√	-	-	-daily stress is predicted using mobile phone activity, weather conditions and individual traits. -temperature and daily stress are positively associated.
Connolly 2013 **[54]**	-Subjective well-being: -life satisfaction, -affective state (PATS survey: intensity of happiness, tiredness, stress, sadness, interest, pain) (2 indices: Net affect = happy – mean (stressed, sad, pain); U-index-binary, 1 if max (stressed, sad, in pain) > happy)	-Weather Report	√	-	-	- Women are more responsive to environmental variables emotionally (significant impact is observed only for women on affect metrics) -Happiness and net affect decreases significantly when temperature is higher than or equal to 90ºF (32.2ºC) - Low temperatures increase happiness, reduce tiredness, stress, and sadness; thus, increase net affect
Tsutsui 2013 **[40]**	Happiness (scale: "very unhappy" to "very happy")	-Weather report	√	-	-	- Average temperature increases happiness, but quadratic temperature decreases happiness: as temperature gets hotter, its impact on happiness becomes negative. Happiness is maximized at 13.9ºC in a quadratic model.
Levinson 2012 **[53]**	Happiness (General social Survey measure: very happy/ pretty happy/ not too happy)	-Weather report	√	-	-	-Average temperature increases happiness, but when temperature gets higher happiness decreases (quadratic temperature has negative impact on happiness): -a 10ºF rise in temperature from 30 (-1.1ºC) to 40ºF (4.4ºC) makes people happier by an amount equivalent to having an extra $36 per day, while a rise from 80ºF (26.7ºC) to 90ºF (32.2ºC) makes people less happy by $55.

Study	Dependent Variable (DV)	Temperature Operationalization	Field Study	Experi-ment	Mediator / Moderator	Findings
Muller et al. 2011 **[59]**	Mood (POMS scale: vigor, fatigue, depression, confusion, tension, anger)	-Ambient temperature of 5ºC, skin temperature through chest, triceps, thigh, and calf.	-	√	Physical exercise	- Body warming via exercise improves mood in the cold; but does not affect temperature-induced selective attention. -Continuous exercise is more effective than interval exercise.
Klimstra et al. 2011 **[60]**	-happiness -anxiety -anger (intensity of feelings using a scale)	-Weather report	√	-	-	- a typology of individuals based on weather reactivity (summer lovers, summer haters, rain haters, unaffected) was constructed. -there are individual differences in the relationship between weather and mood.
Kööts et al. 2011 **[55]**	-Affective Experience (measured by: -Negative affect (anger, contempt, disappointed, disgust, fear, irritated, sad) -Positive affect (happy, surprised) -Fatigue (sleepy, tired))	-Weather report	√	-	Moderator: - age -personality traits (Neuroticism, Extraversion, Openness, Agreeableness, Conscientiousness)	- In warmer temperatures, individuals' feelings tend to be more intense (increases both in positive and negative affect are observed, small in magnitude). (study location: high northern latitude- 58º23') -Temperature – fatigue relationship is moderated by age, and individual characteristics (openness, agreeableness, conscientiousness). Older people are more affected by temperature than young people in terms of their fatigue level. -Temperature – negative affect relationship is moderated by Neuroticism trait only. People who felt more negative feelings also tended to be more influenced by warmer temperatures. - Being outside strengthens the impact of temperature on negative affect.
Denissen et al. 2008 **[56]**	-Positive and negative affect (PANAS-X scale) -Tiredness	-Weather report -Photoperiod (time of sunset – time of sunrise)	√	-	-Moderator: Personality (Five factor model - BFI) -Season Mediator: Sunlight	-Temperature increases negative affect. -The effects of temperature and other weather variables on all DVs vary significantly among individuals, but this cannot be explained with personality, age, and gender as their interaction effects with weather are not significant.
Nastos et al. 2006 **[61]**	-Mood: depression, sleep disorder, aggressiveness, self-	-Weather report (discomfort index is calculated using	√	-	-	- Discomfort caused by temperature and humidity increases sleep disturbance, anxiety-panic, and depressive mood.

Study	Dependent Variable (DV)	Temperature Operationalization	Field Study	Experi-ment	Mediator / Moderator	Findings
	destructive mood, anxiety (daily number of cases in a psychiatric clinic)	temperature and humidity)				
Rehdanz & Maddison 2005 **[52]**	- happiness (1-not at all happy,2-not very happy, 3-quite happy, 4-very happy)	-Weather report (annually averaged mean temperature, precipitation, mean temperature of coldest/ hottest/ driest/wettest month, number of cold/hot, dry/wet months)	√	-		- Higher mean temperatures in the hottest month decrease happiness, while higher mean temperatures in the coldest month increase it. -Most countries lose from climate change as temperature is expected to increase over time. Only a few, in high latitudes like Canada, Norway, Finland, Sweden or Iceland
Keller et al. 2005 [2]	-Mood valence (PANAS Scale, Affect grid, Implicit Mood, Explicit Mood) -Digital span (working memory capacity: max. number of digits repeated after hearing a digital string) -Cognitive broadening (openness to new information)	-Weather report	√	√	Moderator: -Time spent outside	-Positive impact of temperature on mood valence when time spent outside increases in spring - Exposure to high temperatures has a negative impact on explicit mood in summer as time spent outside increases. -Finds inverted-U temperature-mood relationship among participants who spent more than 45 minutes outside. -being outdoors is a causal factor that changes weather-mood and weather-memory relationships (it strengthens the relationship between weather and mood)
Anderson et al. 2000 (Experiment 1) **[50]**	-Perception of cold and hot effects on anger and hostility, alertness and energy, aggression, and violence	- temperature perception (hot or cold)	-	√	-	- people have social theories of temperature effects on arousal, affect and behavior. - people believe hot temperatures (vs. comfortable) increase feelings of anger & hostility, decrease alertness and energy and increase aggression and violence. -people also believe cold temperatures have exactly the opposite effects. -magnitude of hot effects are higher than magnitude of cold effects.
Anderson et al. 2000	-Physiological arousal (heart rate, blood pressure)	Ambient temperature 12.8ºC (55ºF), 18.3ºC (65ºF), 23.9ºC (75ºF),	-	√	-	- hotter temperatures lead to an increase in heart rate, colder temperatures lead to a decrease (linear)

Study	Dependent Variable (DV)	Temperature Operationalization	Field Study	Experi-ment	Mediator / Moderator	Findings
(Experiment 2) **[50]**	-Perceived arousal (scale) -Perceived comfort (scale) -Positive and negative affect (PANAS scale)	29.4ºC (85ºF), 35ºC (95ºF)				- hotter temperatures lead to a decrease in perceived arousal (linear) - a curvilinear impact of temperature on comfort (non-linear) - there may be more specific types of negative affect that is influenced by temperature (instead of combining all affect types in a scale)
Anderson et al. 1995 **[49]**	-Perceived arousal (scale) -General affect (scale) -Physiological measures -State hostility -Hostile Cognition	Ambient temperature (comfortable: 72-78ºF, warm: 79-86ºF, hot:87-94ºF)	-	√	-	- hot temperatures increase state hostility and hostile cognition. - hot temperatures decrease perceived arousal. - hot temperatures produce increases in heart rate (physiological arousal) - negative affect (as a construct of several negative affect states) is not influenced by temperature.
Howarth & Hoffmann 1984 **[48]**	-Mood (concentration, cooperation, anxiety, potency, aggression, depression, sleepiness, skepticism, control, optimism)	-Weather report (low -28ºC, high 4ºC, average= -8.3ºC)	-	√	-	- Temperature is positively correlated with sleepiness, negatively correlated with anxiety, potency, aggression, skepticism) - increases concentration - Significantly correlated with mood of aggression: aggressive feelings increase at very cold temperatures (-8ºC to -28ºC)
Cunningham 1979 (study 1) **[51]**	-Helping behavior (study 1)	-Weather report	-	√	-	-Temperature is negatively related to helping behavior in summer, positively related in winter. Impact is non-linear.
Bell & Baron 1977 **[47]**	-Aggression (index calculated by shock intensity and duration)	-Ambient temperature: cold (64ºF/17.7ºC), cool (72ºF/22.2ºC), warm (85ºF/29.4ºC), hot (93ºF/33.8ºC)	-	√	- Negative affect (receiving Positive / Negative personal evaluations) (4 temperature conditions x 2 affective states)	-aggression is influenced by exposure to high or low ambient temperatures. This influence may depend on the overall affective states of the individual (moderate vs extreme) -exposure to uncomfortably cold ambient temperatures may have the same effects on aggressive tendencies as does exposure to uncomfortably hot ambient temperatures. - a curvilinear relationship between negative affect and aggression
Baron & Bell 1976 **[46]**	- Aggression (index calculated by shock intensity and duration)	-Ambient temperature cool (22.4-22.8ºC), warm (~29-29.3ºC), hot (33.8ºC-34.9ºC)	-	√	Negative affect	- a curvilinear relationship between negative affect and aggression - Study 1: High ambient temperatures facilitated aggression when other sources of negative affect were

Study	Dependent Variable (DV)	Temperature Operationalization	Field Study	Experi-ment	Mediator / Moderator	Findings
					(3 temperature conditions x 2 affective states)	absent; but inhibited such behavior when sources of negative affect were available. - The combination of oppressive heat and negative evaluations induced higher levels of negative affect. - the influence of high temperatures upon aggression can be reduced by the administration of a cool drink. (Cool drink reduces negative affect)
Griffit & Veitch 1971 **[43]**	- Interpersonal affective behavior (agreement with a stranger in .75 of issues vs .25 of issues; Interpersonal Judgement Scale) - Mood (MACL scale) - Affective feelings (comfortable/uncomfortable, bad/good, high/low, sad/happy, pleasant/unpleasant, negative/positive)	-Effective temperature (index) (normal vs. high- 73.4ºF/23ºC vs 93.5ºF/34ºC) -Population density	-	√	-	- In high temperature condition: - the scores of negative mood items (aggression, fatigue, sadness) were significantly higher (vs. normal). - Surgency, elation, concentration, social affection, and vigor scores were significantly lower (vs. normal). - more negative personal feelings (affective experiences) - more negative social affective responses (attraction) - more negative non-social affective ratings (room and experiment evaluation)
This research	User engagement on social media	- Weather perception - Weather report	√	√	Happiness	- both extremely high and low temperatures induce happiness; but only extremely high temperatures decrease user engagement - happiness mediates the relationship of extremely high temperatures and user engagement

1.1.3 Temperature Effects on Social Media Valence and Behavior

Existing studies indicate three main strands within the weather – social media literature. Table 2 provides a summary. The last row in the table outlines this study's differences. The first strand focuses on using social media content generated specifically on Twitter and other microblogging platforms (e.g., Sina Weibo, also known as Chinese Twitter) to examine public-policy issues. The examples include exploring relationship between mortality and heat-related tweets [62], climate change talks [63], predicting crime [64] or assault behavior [65]. Cecinati et al. [62] finds that the number of Indian tweets about heat waves is strongly correlated with the number of heat-related excess deaths and validate that Twitter data is precise in identifying heat wave events that have an impact on the population. Sisco et al. [63] illustrates that attention to climate change on Twitter increases after events began, and occurrences of excessive heat and extreme cold events escalate the attention to climate change. The authors additionally show that relative temperature (calculated as a z-score using 10-year average temperature) is a strong predictor of attention. They conclude that actual experiences of events are more impactful than purely descriptive information about the events before each event hits. Chen et al. [64] demonstrates that the probability of theft incidence in Chicago, USA can be predicted using Twitter sentiment data and weather variables; and find that in higher temperatures, there is a higher chance of theft crimes. Stevens et al. [65] predict assault behavior using online anger on Twitter data in Australia. The authors additionally examine the relationship of temperature, online anger, and assault behavior, finding a non-linear worsening impact of higher and lower temperatures. All these studies focus on either exploring associative relationships or predicting behaviors using empirical analysis after running sentiment analysis via natural language processing (NLP) models.

Table 2: Weather - Social media studies in literature (Sorted by the year of publishment)

Study	Industry	Dependent Variable	Weather Variable	Online Platform	Location	Empi-rical	Experi-mental	Data Span	Findings on Temperature Effects
Cheng et al. 2023 **[66]**	Generic	- Expressed happiness	Temperature Sea pressure, wind speed, cloud cover, humidity	Sina Weibo	China	√	-	1 Jul.2014 – 31 Aug. 2018 (Only summer)	- non-linear impact of temperature (inverted-U shaped) on happiness (in total sample) (optimal temperature (OT) is ~22.8ºC) - 1 standard deviation increase in summer temperature is associated with a 0.255 standard deviation decrease in happiness index - there is not a significant association between temperature and expressed happiness in below-OT fraction of the sample. Explained as: in outdoor setting people can wear additional clothing to stay warm, whereas the ability to respond to hot temperatures by changing clothing is much more limited.
Brandes & Dover 2022 **[67]**	Tourism (Hotel reviews)	-online review provision (engagement) -online review content (experience rating)	-Bad Weather (=presence of rain and snow)	online travel portal	Germany	√	-	Sep. 2004 – May 2017	- not reported; focus on bad weather
Zor et al. 2022 **(study 3) [68]**	News-paper (articles)	-number of likes (engagement)	-Time of the day -Temperature	Twitter	India	√	-	Apr. 2018 - Nov. 2018	- in high temperatures, the number of likes increases for vice content, but decreases for virtue. - temperature causes a sooner self-control failure. Engagement shifts away from virtues to vices at earlier times when temperature is high.
Steche-messer et al. 2022 **[69]**	Generic	-online hate speech (both in absolute volume and as a proportion of total tweeting activity)	-Temperature	Twitter	USA	√	-	May 2014 – May 2020	- non-linear negative impact (hate tweets increase at temperatures warmer than 27ºC and colder than 6ºC.) - non-linear impact is robust **across all** climate zones and socio-economic subgroups (income, religious and political beliefs).
Stevens et al. 2021 **[65]**	Generic	-online anger -assault (counts - offline)	-Temperature	Twitter	Australia	√	-	Jan. 2015 – Dec. 2017	- online anger in Twitter is a predictor of assault behavior. - impact is non-linear (have a peak at around 30ºC) on both DVs
Wang et al. 2021 **[70]**	Tourism	-expressed sentiment (over 100, the higher, the more positive)	-Temperature -Wind level -Rain	Sina Weibo	China	√	-	Aug. 2015 – Oct. 2019	- non-linear negative impact (inverted-U) effect on tourists' emotional experience

Study	Industry	Dependent Variable	Weather Variable	Online Platform	Location	Empi-rical	Experi-mental	Data Span	Findings on Temperature Effects
	(emotional experience of tourists)		-Cloudiness						
Martin et al. 2021 **[71]**	Public utility	-engagement: (number of reactions, probability of comment, probability of share) -posting design: content (company relevant vs non-relevant), use of picture, number of words	-Temperature -Precipitation -Humidity -B. Pressure -Wind speed -Sunshine -Point-in-time	Facebook	Austria	√	-	Aug 2016 – Feb. 2018	- increase the number of reactions by women. - no impact of temperature on probability of commenting. - higher temperatures decrease: - the probability of shares - the number of words - the probability of using images in a post).
Wang et al. 2020 **[72]**	Generic	Expressed sentiment	-Temperature	Sina Weibo	China	√	-	Jan – Dec 2014	- non-linear negative impact -adaptation to extreme cold by heating works, but adaptation to extreme hot via AC does not work. Comparison of different AC penetration levels shows there is no difference in the negative impact of hot temperatures. Using AC does not mitigate the negative impacts on expressed sentiment.
Baylis 2020 **[14]**	Generic	-Expressed sentiment -Use of profanity -Use of aggressive profanity	-Temperature -Precipitation	Twitter	USA, Australia, Kenya, India, South Africa, Philippines, Uganda	√	-	USA: Jun. 2014 – Oct. 2016 Other: Oct.2015 – Mar. 2019	-USA: low and high temperatures lead to significant declines in expressed sentiment, increases use of profanity and aggressive profanity. - Australia has similar results to USA. - Australia, India, Kenya: evidence of preference for moderate temperatures over very hot or very cold temperatures. -South Africa and the Philippines: evidence of preference for moderate temperatures over hot temperatures.
Zheng et al 2019 **[73]**	Generic	Expressed happiness (median of index: 0-strongly negative mood, 100 strongly positive mood)	-Air quality index (AQI) -$PM_{2.5}$ concentration -Temperature -Wind speed -Cloudiness	Sina Weibo	China	√	-	Mar. – Nov. 2014	- non-linear negative impact (inverted U) on expressed happiness. - 1ºC move away from temperature's turning point (17.5ºC) leads to a decrease in happiness which is equivalent to the effect of 1 μg m^{-3} increase in $PM_{2.5}$ concentration on happiness.

Study	Industry	Dependent Variable	Weather Variable	Online Platform	Location	Empi-rical	Experi-mental	Data Span	Findings on Temperature Effects
			-Rain						
Cecinati et al. 2019 **[62]**	Generic	Mortality	-Heat-related tweets -Temperature and Humidity (for heat index calculation)	Twitter	India	√	-	Jan. 2010 – Dec. 2017	- strong correlation between the number of tweets about heat waves and the number of heat-related excess deaths - Twitter data is precise in identifying heat wave events that have an impact on the population
Baylis et al. 2018 **[15]**	Generic	Expressed positive and negative sentiment	-Temperature -Precipitation -Temp. range -Cloud cover -Humidity	Facebook, Twitter	USA	√	-	Facebook: Jan. 2009 – Mar. 2012 Twitter: Nov. 2013 – Jun. 2016	- non-linear (inverted-U) negative impact on both social platforms. -Positive expressions increase up to maximum temperatures of 20˚C and decline past 30˚C. Opposite pattern is observed for negative expressions, but smaller in magnitude. -When excluded weather-related terms, similar pattern is observed, but effect sizes are smaller compared to all posts.
Sisco et al. 2017 **[63]**	Generic	Attention to climate change. (relative increase in climate change messages directly after each event occurs)	-Temperature -Wind speed -Precipitation -Weather events (floods, drought, strong wind, wildfire, excessive heat, extreme cold, heavy snow)	Twitter	USA	√	-	Dec. 2011 – Nov. 2014	- attention to climate change was higher after events began, compared to directly before. - excessive heat and extreme cold increase the attention to climate change after occurrence. -relative temperature (z-score using 10-year average) is a strong predictor of attention. →**actual experiences** of events **are more impactful** than purely descriptive information about the events before each event hits.
Grasso et al. 2017 **[74]**	Generic	Heat-related online activity	-Temperature	Twitter	Italy	√	-	May – Sep. 2015	Twitter data related to heat conditions correctly identify the peak days of heat wave episodes and allows a geographical identification of high impact situations
Curini et al. 2015 **[75]**	Generic	Happiness (index)	-Temperature -Rain -Snow	Twitter	Italy	√	-	Jan. – Dec. 2012	- temperature increases augment happiness in winter and spring (vs. autumn). - In summer it increases up to 30ºC, then have a negative impact.
Chen et al. 2015 **[64]**	Generic	Theft incidence (binary: crime=1, non-crime=0)	-Temperature -Dew point -Humidity -Pressure -Visibility -Cloud cover	Twitter	Chicago, USA	√	-	Jan. – Dec 2014	- crime incidence can be predicted using crime density and weather variables (AUC 67%). - in higher temperatures, there is a higher chance of theft crimes.

Study	Industry	Dependent Variable	Weather Variable	Online Platform	Location	Empi-rical	Experi-mental	Data Span	Findings on Temperature Effects
			-Wind speed						
Li, Wang, Hovy 2014 **[76]**	Generic	-Positive/ Negative Mood (score: positive counts / (negative + positive counts)) -4 mood dimensions: hostility-anger, depression-dejection, fatigue-inertia, sleepiness-freshness	Temperature, Precipitation, Snow depth, wind speed, total solar energy received, hail-thunder-smoke-fog-frost presence.	Twitter	USA	√	-	Jan. 2010 – Dec. 2011	-positivity of sentiment on Twitter is sensitive to temperature change (vs. previous day). People tend to be happier as the temperature becomes cooler but feel uncomfortable with drastic temperature decrease. People are more negative when small temperature increases occur. - The hotter, the angrier - high temperature (above 30ºC) leads to tiredness - sleepiness is higher in colder (below ~ -5ºC) and hotter temperatures (above 30ºC)
Hannak et al. 2012 **[77]**	Generic	Positive/ Negative aggregate sentiment	Temperature, Cloud cover, Humidity, Precipitation, Wind speed	Twitter	USA	√	-	Jan. - Sep. 2009	- Sentiment score prediction has the highest accuracy when time of day, season, location, and weather variables are included (ROC area= 0.78).
THIS STUDY	**Study 1: Generic** **Study 2: Alcoholic beverages (beer)**	**User engagement (post creation, liking, commenting, sharing)** **Mediator: Happiness**	**Extremely hot and cold temperatures**	**Facebook, Twitter, Instagram, YouTube, blogs**	**Türkiye**	√	√	**Study1: Experiment** **Study2: Jan. 2014 – Jun. 2019**	**- non-linear on happiness (study1)** **- extremely hot temperatures decrease user engagement on social media (both studies).** **- impact of hot temperatures on user engagement is greater than that of cold (both studies)** **- temperature-induced happiness mediates the relationship (study1)**

The second strand focuses solely on how weather and other external variables impact expressed sentiment on social media. This strand finds that extremely high and low temperatures decrease positive sentiment and increase negative sentiment on social media. In these studies, expressed sentiment operationalizations are various among these studies such as positive / negative sentiment ([14]; [15]; [70]; [72]), use of profanity and aggressive profanity [14], online hate speech [69], negative mood [76], and happiness ([73]; [75]). These studies focus on sentiment analysis using NLP models and then assess the association between weather and sentiment through regression models. For example, Baylis et al. [15] examining Facebook and Twitter posts find that cold temperatures (below ~15^{o}C), and hot temperatures (above ~30^{o}C) are associated with worsened expressions of sentiment. Positive expressions increase up to 20^{o}C and decline above 30^{o}C. Baylis [14] identifies significant declines in the expressed sentiment and significant increases in the use of profanity and aggressive profanity for both cold and hot temperatures. Wang et al. [70] using Sina Weibo posts in China, show that temperature has a non-linear (inverted-U) effect on tourists' real-time emotional experience such that positivity of the sentiment decreases in cold and hot temperatures. Wang at et. [72] find similar non-linear results pointing an escalation of negative sentiment in extremely high and low temperatures. The authors further examine the adaptation to extreme cold by heating, and extreme heat by air conditioning (AC) by comparing sentiment at different AC penetration levels; and find that heating mitigates the negative impact of extreme cold, but AC does not mitigate the negative impact of extremely hot temperatures. Stechemesser et al. [69] examine hate speech using Twitter data, and document that a non-linear relationship exists for hate speech, as well. They find that temperatures warmer than 27^{o}C and colder than 6^{o}C increase hate tweets, and this non-linear impact is robust across five climatic zones (cold climate, hot-dry climate, hot-humid climate, marine climate, and mixed-humid climate) in the USA, and across socio-economic subgroups of income (low, medium-low, medium-high, high), religious (catholic, evangelical) and political (democratic, republican) beliefs. Zheng et al. [73] examine the impact of air pollution and weather variables on expressed happiness on Sina Weibo and show that hotter and colder temperatures decrease expressed happiness, confirming the inverted-U impact of temperature on positive sentiment found in previous studies. Curini et al. [75] examine how happiness changes in Italian tweets due to weather and uncover that temperature increases which exceed 30^{o}C have negative impact on happiness level on Twitter.

The last strand of research is limited in terms of the number of papers, and their scope; however, it is the main strand in which this paper's contributions reside. These studies examine the impact of weather on various online engagement contexts, such as online hotel review provision [67], the number of likes newspaper articles receive [68], and number of reactions, and probability of commenting and sharing posts on a public utility [71]. Brandes and Dover [67] focus on bad weather's impact on online review provision and content of hotel reviews collected from a major online travel portal in Germany. The authors conceptualize bad weather as the presence of rain and snow and show that reviews written on a rainy day include lower happiness scores, lower proportion of words related to positive affect, and lower arousal levels. They additionally find that people are more likely to write reviews on a rainy day. I have previously investigated the impact of different weather variables such as cloud cover, air pressure, humidity, wind speed and temperature, and find evidence that temperature has the largest significant impact on user engagement (see Web Appendix B for details). Therefore, I focus on the temperature impact in this research. Zor et al. [68] focus on how the number of likes of vice and virtue contents change by the time of the day and temperatures. The authors define vice contents as the contents that offer immediate pleasure with consumption. Virtue contents are contents that may not be pleasurable during consumption but provide benefits in the long run (p. 474). Examples of vice topics include entertainment, fashion, humor, and sports; and examples of virtue topics include business, environment, politics, science, technology, and local matters (third study, p. 484). The authors find that the time of the day is not effective on the total number of likes, but significantly impacts on the content type: as the day progresses, the engagement (the number of likes) shifts from virtue to vice contents. They further examine the role of temperature on content type engagement and conclude that high temperatures have similar effect; and strengthens vice-virtue asymmetry. Not only in high temperatures, the number of likes increase for vice contents, but also engagement shifts from virtues to vices at earlier times if temperature is high. They propose that temperature causes a sooner self-control failure, which increases engagement to vice contents earlier during the day. Martin et al. [71] conduct a case study analysis focusing on a public utility in Austria, exploring the associations between weather variables, timing, and user engagement using 321 firm-generated posts in the utility's official Facebook account. Maintaining its explorative nature, the findings on temperature and user (stakeholder) engagement indicate that temperature does not have a significant impact on the probability of comments provided by stakeholders to the utility's posts, but a negative impact on the probability of shares made by the same audience. Additionally, the findings suggest that higher temperatures increase the number of reactions per post given by female users, but no significant impact in total. The study also demonstrates that increases in temperature decreases the number of words used, and the probability of using images in a post created by the utility. The authors focus on a limited number of firm-generated posts, and the firm's stakeholders' engagement in terms of the number of reactions, the probability of sharing, and commenting. In this thesis, I explore a larger dataset composed of user-generated contents and users' reaction on social media including their comments, images, memes, emojis, etc. that are created by users in all social media platforms.

To sum up, the existing works on weather and social media establish the non-linear impact of temperature on sentiment such that departure from moderate temperatures to higher (hotter) and lower (colder) temperatures decrease positive sentiment, increase negative sentiment and the use of more aggressive and angry language. These studies are all empirical and conducted using microblogging platforms (e.g., Twitter and Sina Weibo), and a few using Facebook; suggesting there is a need for investigating temperature impact including other platforms to get a holistic view. Studies on engagement also provide evidence that online engagement behavior can be affected by temperature. Unlike the results of online sentiment, though, the findings so far indicate that engagement metrics (including creation of posts with images and with longer texts) are affected by higher temperatures. Overall, these works clearly identify the significant impact of temperature on online sentiment and engagement via empirical methods, but do not explain why such effects might occur in a causal framework. Moreover, the studies on the impact of extreme temperatures on user engagement is limited platform-wise, and in terms of engagement types examined.

1.2 Hypotheses

Although prior research suggests that engagement is significantly affected with hot temperatures, the role of mood and its role on post creation and content contribution behavior such as liking, commenting, and sharing remains unexplored. This represents a significant contribution from this thesis compared to the existing literature. Understanding whether a specific mood is driving the observed effects and exploring strategies to mitigate these negative impacts could have practical implications for social media marketing campaigns. Furthermore, this study offers a broader perspective by generalizing the results across various social media platforms, providing a comprehensive examination of the impact of extreme temperatures on user engagement. I propose the potential mediating role of happiness in the relationship between extreme temperatures and social media user engagement. I therefore hypothesize that:

H1: Extremely hot and cold weather, compared to season-normal conditions, will diminish user engagement on social media.
H2: Temperature-induced happiness will result in decreased user engagement on social media.

Anderson et al. [50] reveal that participants perceive the impact of extremely high temperatures to be significantly greater than that of extremely cold temperatures in terms of the negative emotions they elicited, despite both conditions causing similar discomfort levels. Sinha and Bagchi [8] conduct experiments investigating the effect of higher and lower temperatures on willingness to pay (WTP) in auctions and negotiations. They find that both high and low temperatures, compared to moderate temperatures, increase the amount participants are willing to pay in auctions due to heightened hostile aggression. However, the amount of WTP is higher in high temperatures (82ºF / 27.8ºC) compared to cold temperatures (63ºF/ 17.2ºC), indicating a stronger effect of high temperatures. Furthermore, Anderson et al. [50] suggest that cold effects are less likely to occur in natural environment as individuals can compensate more easily for cold temperatures by adding clothing or by heating compared to heat effects. This suggestion aligns with the findings of Wang et al. [72], who examine adaptation to extreme heat and cold and find that adaptation to extreme cold through heating mitigates the negative impact on expressed sentiment, whereas adaptation to extreme heat via air conditioning does not. Building on these studies, I anticipate a similar negative impact of extremely hot and cold temperatures on happiness, but a larger impact of hot temperatures on user engagement when controlling for happiness. Therefore, I propose a third hypothesis as follows:

H3: The negative impact of hot temperatures on user engagement will be greater than that of cold temperatures.

CHAPTER II

EXPERIMENTAL STUDY

This experimental study aims to explore the potential impact of extreme temperatures on user engagement, including post creation, liking, commenting, and sharing behavior, and to investigate the mediating role of happiness in this relationship, thereby testing H1 and H2. Additionally, the study will examine the comparative effect of extremely hot and cold temperatures on user engagement, exploring H3.

2.1 Participants, Design and Procedure

A one-factor, three-level (weather condition: hot, cold, season-normal) between-subjects design is used. The study is conducted online using Qualtrics, at a European university's research platform where university students participate studies for course credit (N=293, mean age 21.52, 70% female, 30% male). Participants are randomly assigned to one of the weather conditions and completed an online survey in the following order measuring: (1) baseline happiness, (2) weather perception articulation task (weather condition manipulation), (3) user engagement (post creation, liking, commenting, sharing), (4) post-manipulation happiness, (5) demographics and controls.

I adapted the affect measure of Govind et al. [5] to measure baseline happiness asking participants to rate two items, happy and sad: "Please think about how you feel now. For each emotion type below, please select the emotion level that suits your current feeling the best?" (1 = "don't feel at all," 9 = "extremely feel"). To prevent any possible order bias, the item order was randomized. The scores were invariant across the three weather conditions using the analysis of variance (ANOVA) – happiness ($F(2,290) = 1.018$, $p=.362$), and sadness ($F(2,290) = 1.194$, $p = .304$); indicating that there were no a priori differences in the baseline happiness across three different weather conditions.

For the weather manipulation task, I followed the methodology from Govind et al. [5]. Participants were asked what air temperature would be on a day which they experienced one of the three weather situations – extremely cold, extremely hot, or season-normal weather, and they were asked to think about and describe their feelings and thoughts on such a day.

For the measurement of post creation, liking, commenting, and sharing behavior, all respondents read a text describing that they go to a café with friends on a normal/ extremely cold/ extremely hot day. They were told to imagine they were having a good time with their friends in the café, they wanted to create a memory of their time, and that this could be a comment, video, photo, meme, etc. Then they were asked how likely they would share a post about their time in the café on their social media account using a 7-point Likert scale (1 = "extremely unlikely," 7 = "extremely likely"). After post creation measurement, all respondents saw another text describing they are still in the same café environment on the same extremely hot/cold/season-normal day, feeling the impact of weather outside, and a friend of theirs shares a post on social media during their gathering. Participants were, then, asked how likely they would like/ comment/ share this post using the same scale (1 = "extremely unlikely," 7 = "extremely likely"). Three comprehension questions were asked after each text to make sure the participants understood the text scenarios.

I used the same affect measure as baseline happiness [5], adapting the question text using weather manipulation: "Please think about how you would feel when the weather is extremely hot/ cold/ season normal. For each emotion type below, please select the emotion level that would suit your feeling the best in such weather." (1 = "don't feel at all," 9 = "extremely feel"). To prevent any possible order bias, the item order was randomized. The negatively valanced item was reverse coded. Their average (α = .78) is used as a measure of happiness.

Demographic and control variables encompassed gender, individual factors such as sensitivity to weather changes, and preference for hot and cold weather, as well as ambient factors including interior vs. exterior environment, ambience comfort level, and perceived ambience temperature. Additionally, social media usage frequency was assessed to account for its potential influence on user engagement levels (see Web Appendix C for all measures). The control variables are used in all regression equations. To address multicollinearity, hot weather and cold weather preference scores were combined due to their high correlation (r = -.75). This was achieved by first reverse-coding the hot weather preference, and then averaging the two items (α = .86). Importantly, all control variables are invariant across all weather groups (Appendix D).

2.2 Analysis and Results

2.2.1 Comprehension and Manipulation Checks

Initially, responses were collected from 300 participants, and seven responses were excluded due to incorrect answers to two out of the three comprehension questions. Consequently, the final sample consisted of 293 participants. The manipulation check ensured the successful implementation of the weather manipulation, with significant variations observed in the average air temperature mentioned across the three weather conditions

($F(2,290) = 424.06$, $p < .001$), indicating the weather manipulation was successful (M_{normal} = 20.0°C, M_{hot} = 30.6 °C, M_{cold}: 7.0°C).

Baseline happiness scores did not differ significantly among the weather conditions, indicating no pre-existing affect differences across conditions (refer to Figure 1). However, post-manipulation happiness exhibited a notable variation, with significantly lower scores observed in both cold and hot weather conditions ($F(2,290) = 36.366$, $p < .001$), suggesting a robust influence of extreme weather (M_{normal}= 6.60, M_{hot} = 4.91, M_{cold} = 4.95). Notably, both extremely hot and cold temperatures resulted in a similar level of decrease in happiness.

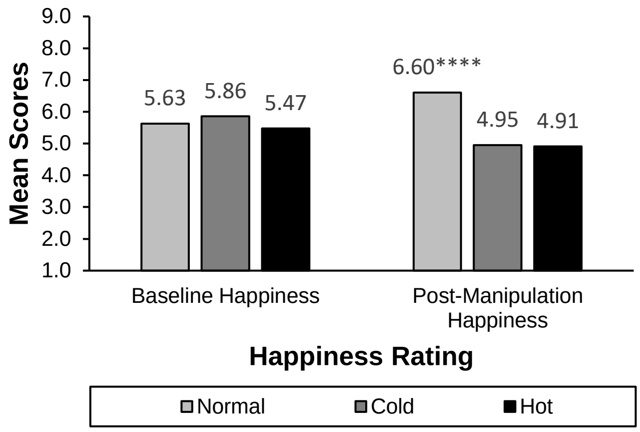


Figure 1: Baseline vs. Post-Manipulation Happiness

*p < .1, **p < .05, ***p < .01, ****p < .001.

Notes: Baseline and post-manipulation happiness scores are calculated by averaging happy and reverse-coded sad ratings ($\alpha_{baseline}$ = .77, $\alpha_{post\text{-}manipulation}$ =.78).

2.2.2 The Effect of Extreme Weather on User Engagement

Initially, I assessed the impact of extreme weather on user engagement metrics (post creation, liking, commenting, and sharing) using linear regression. Equation 1 is applied separately for each user engagement type, resulting in four distinct regression models. To calculate standard errors and confidence intervals, I use bootstrapping with 5,000 iterations.

$$Y_i = \alpha_i + \beta_{ij} T_{ij} + \gamma_{ik} C_{ik} + \varepsilon_i \quad ; \qquad \varepsilon_i \sim N(0, \sigma^2) \qquad (1)$$

where: Y_i is the user engagement for type i, i in {post creation, liking, commenting, sharing} , α_i is the intercept for user engagement type i, T_{ij} is the temperature dummy for engagement type i, extreme temperature j, for j in {extreme hot, extreme cold}, β_{ij} is the coefficient for the associated temperature dummy for engagement type i, C_{ik} is the control variable for user engagement type i and for control variable k, for k in {gender, sensitivity to weather changes, preference for hot and cold weather, interior environment, ambience comfort level, perceived ambience temperature, social media usage frequency}, γ_{ik} is the coefficient for the associated control variable for control variable k, ε_i is the error term for the respective equation for the engagement type i, modeled as independent and identically distributed (i.i.d.) random variables following a normal distribution with zero-mean and constant variance. Season-normal temperature scenario was treated as the reference category for extreme temperature scenario dummies.

Figure 2 indicates the standardized coefficients of extremely hot and cold weather dummies for each of the user engagement types. Standard errors and confidence intervals were calculated using 5000 bootstrap samples. Across all engagement metrics, I observed a consistent negative impact of temperature. However, I found a significant effect of extremely hot weather on post creation exclusively. Additionally, the impact of extremely hot weather surpassed that of cold weather by a minimum factor of 1.5 for all engagement types (ranging from 1.5 to 2.3 times), thereby corroborating the third hypothesis.

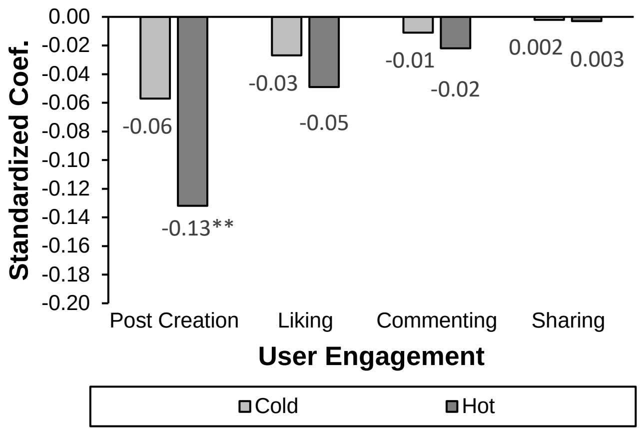


Figure 2: The Effect of Extreme Weather on User Engagement

*p < .1, **p < .05, ***p < .01, ****p < .001.

Among all control variables, females engage with social media significantly more than males in terms of intention to create a post, like, comment, and share other posts ($p < 0.01$ for all usage types). No significant effects were observed for other control variables at $p <= .05$.

2.2.3 Happiness as a Mediator

After establishing the effect of extremely hot weather on post creation, I explored the possible mediation of happiness using Model 4 [78] with bootstrapping (N=10,000). I utilized Process Macro 4.3 via SPSS to execute the mediation model to test H2, employing Equations 2, 3, and 4:

$$H = \alpha_1 + \beta_{i1}T_i + \gamma_{j1}C_j + \varepsilon_1 \tag{2}$$

$$Y = \alpha_2 + \beta_{i2}T_i + \delta H + \gamma_{j2}C_j + \varepsilon_2 \tag{3}$$

$$Y = \alpha_3 + \beta_{i3}T_i + \gamma_{j3}C_j + \varepsilon_3 \tag{4}$$

where: H represents Happiness, Y is the post creation intention, α_n is the intercept for the specific equation n, for n=1..3, T_i is the extreme temperature dummy i, for i in {extreme hot, extreme cold}, β_{in} is the coefficient for the extreme temperature dummy i, for n=1..3, C_j is the control variable j, for j in {gender, sensitivity to weather changes, preference for hot and cold weather, interior environment, ambience comfort level, perceived ambience temperature, social media usage frequency}, γ_{jn} is the coefficient for the associated control variable j and for equation n, and δ is the coefficient for Happiness in Equation 3, ε_n is the i.i.d. error term, with distribution $N(0,\sigma^2)$, for n=1..3. The season-normal temperature scenario dummy was treated as the reference category for extreme temperature scenario dummies.

Table 3 presents the mediation results, displaying unstandardized coefficients. Standard errors are indicated in parentheses and confidence intervals are calculated using bootstrapping (N=10,000). The findings revealed that happiness served as a full mediator in the relationship between extremely high temperatures and post creation on social media. Specifically, extremely hot temperatures diminished happiness, leading to a reduction in post creation intention (β = -.253, SE = .103, 95% CI = [-.466, -.064]). Similarly, for extremely cold temperatures, the indirect pathway was significant (β = -.252, SE = .100, 95% CI = [-.461, -.065]), although no significant total effect was observed. Furthermore, the total effect of hot temperatures on post creation was more than twice (2.3 times) that of cold temperatures, thereby supporting H3.

Table 3: Mediation Model Results

	Total Effect	**Direct Effect**	**Indirect Effect**	**t-stat[a]**	**Conclusions**
Hot temperature→ Happiness→ Post creation intention	-.4752** (.2212)	-.2223 (.2382)	-.2529** (.1026)	-2.4649	Full mediation

Cold temperature→ Happiness→ Post creation intention	-.2037 (.2096)	.0479 (.2225)	-.2517** (.1001)	-2.5144	Indirect route is significant only

*p < .1, **p < .05, ***p < .01.

[a]T-statistics of the indirect effect. T-statistic is |1.645| for p=.10; |1.960| for p=.05; |2.576| for p=.01.

For ensuring the comparability across the Equations 2, 3, and 4, I provide the standardized coefficients of the variables in Table 4. In addition to the impact of extreme weather, participants who are sensitive to weather changes have lower happiness scores. Gender differences do not exist in the impact of extreme temperatures on happiness. In other words, both females and males exhibit significantly lower happiness scores in the extreme temperatures. For post creation, on the other hand, gender matters. Females have significantly higher intention to create and post a content compared to males. These results on post-creation are robust with the previous linear regression results where I establish the association of extremely hot weather with post creation. Females' higher intention to create a post does not dominate the decrease on post-creation scores, as the decrease is observed for both females and males in hot condition (Females: $M_{season\text{-}normal}$ = 4.26, M_{hot} = 3.84; Males: $M_{season\text{-}normal}$ = 2.54, M_{hot} = 2.19). Therefore, these results support that the impact of extremely hot temperatures on happiness and post creation exits for both females and males.

Table 4: Standardized Coefficients and p-values of All Variables

	Equation 2 (Temperature → Happiness)	**Equation 3** (Temperature + happiness → post-creation	**Equation 4** (Temperature → post-creation)
Extremely cold weather	-.9414****	.0283	-.1204
Extremely hot weather	-.9460****	-.1314	-.2809**

	Equation 2 (Temperature → Happiness)	**Equation 3** (Temperature + happiness → post-creation	**Equation 4** (Temperature → post-creation)
Happiness	-	.1580***	-
Gender (female=1, male=0)	.0178	.3597****	.3625****
Cold Weather preference	.0694	-.0518	-.0408
Sensitivity to weather changes	-.1235**	.0717	.0522
Interior-Exterior Environment (indoor=1, outdoor=0)	.0119	.0692	.0711*
Ambience comfort level	.0491	.0789	.0867*
Perceived ambient temperature	-.0338	.0089	.0035
Social media usage frequency	-.0710	.0757	.0645

*$p < .10$, **$p < .05$, ***$p < .01$, ****$p < .001$.

Notes: Standardized coefficients are provided to enable the comparability of the coefficients within and between three regression outputs.

2.3 Discussion

In the experimental study, I discovered that extremely hot weather negatively influences post creation behavior on social media, with temperature-induced happiness mediating this connection. The results did not reveal a primary effect of hot or cold temperatures on liking, commenting, and sharing intention which are amongst content contribution behaviors [79]. Binnewies and Woernlein [80] have shown that positive affect boosts daily creativity; and Isen et al. [81] illustrate how positive affect aids creative problem-solving tasks in experimental settings. Specifically, happiness may enhance creative thinking [27]. Since the creation process is influenced by positive affect and happiness, and these diminish in the face of extreme temperatures, temperature-induced happiness offers an explanation for the decline in post-creation. It is highly likely that extremely hot temperatures hinder creativity by diminishing happiness, leading to decreased levels of post creation.

This study confirms the adverse impact of extremely hot and cold temperatures on happiness, consistent with the findings of Baylis et al. [15] and Baylis [14] where the authors observe that hotter and colder temperatures decrease positive sentiment. As noted by Anderson et al. [50], temperature has a curvilinear impact (inverted-U) such that deviating from optimal temperatures induces discomfort in individuals. This discomfort diminishes positive mood, such as happiness in this study.

In terms of post-creation behavior, I only observed a significant negative impact of hot temperatures, not cold. Despite the substantial decline in happiness observed in both extreme weather conditions, one would expect analogous outcomes in behavior. There are inconsistent and insufficient findings regarding the impact of cold temperatures on behavioral outcomes. For instance, Sinha and Bagchi [8] find significant results for cold temperatures as well. Their study shows that both high and cold temperatures induce discomfort, leading to higher aggression, thus similar effects on willingness to pay (WTP) in auctions; with WTP amounts significantly higher in high temperatures. However, in the context of user engagement, examining a public utility's posts, Martin et al. [71] find that higher temperatures affect posting design components (a part of the post-creation process) such that the number of words used in post and the probability of using images in a post decrease in higher temperatures.

One possible explanation is that cold effects are less likely to occur in a natural environment, as people can compensate relatively easily compared to heat effects by adding clothing or by heating [50]. Wang et al. [72] examine the adaptation to extreme heat and cold and find that adaptation to extreme cold by heating mitigates the negative impact on expressed sentiment, but adaptation to extreme heat via air conditioning does not.

Another explanation could be that people have social theories relating temperature to mood or behavior. Anderson et al. [50] mention that although both extremes create discomfort in lab experiments, when people are asked about their beliefs regarding the effect of temperature on energy level, anger, and aggression, they perceive hot effects to be stronger in magnitude and negative, while cold effects are weaker and in the opposite direction for the mentioned items. In the context of post creation, it is important to note that both extremely cold and hot temperatures can adversely affect the outcome. However, the effect of high temperature is more than doubled compared to cold temperature (see Table 3).

CHAPTER III

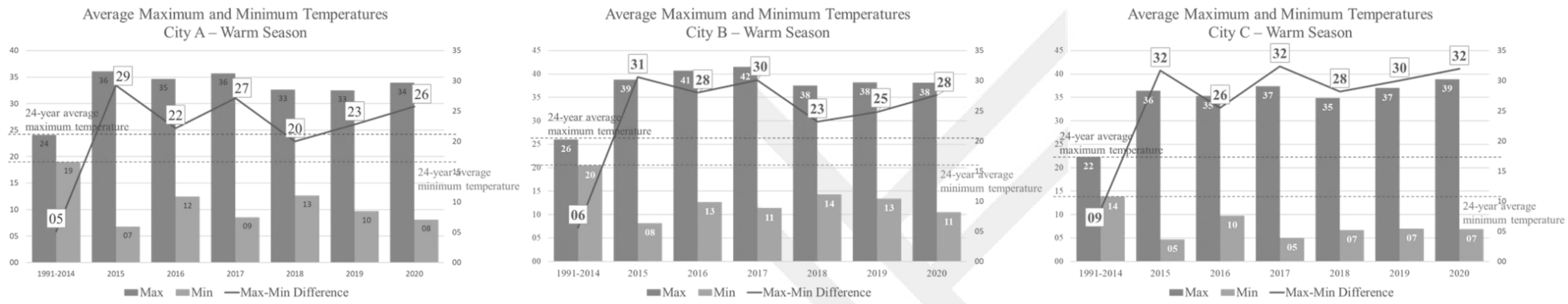
EMPIRICAL STUDY

Having established the influence of extreme temperatures on user engagement through the experimental setup, the objective of this study is to quantify this experimental finding using time-series data. In this context, I aim to investigate how social media users' interactions with temperature correspond to their engagement on social media platforms in Türkiye. With approximately 68.9 million active social media users, constituting roughly 80.8% of the total population [82], Türkiye stands out as a significant hub of social media activity, providing a wealth of user-generated content (UGC).

Temperature fluctuations can offer valuable insights into shifts in social media behavior, especially considering the growing disparities observed over time and across different regions. To illustrate these discrepancies across different regions, my focus is on three major metropolitan areas in Türkiye, collectively representing a substantial portion of social media activity in the country. Figure 3 presents the yearly maximum and minimum temperature levels within the dataset alongside 24-year historic averages for these three cities during both warm and cold seasons. The warm season spans from April to October while the cold season extends from November to March.

The figure underscores a noteworthy increase in the discrepancy between yearly maximum and minimum temperatures, shifting from low single digits during the period of 1991-2014 to well

Warm season (April to October)**:**



Cold season (November to March)**:**

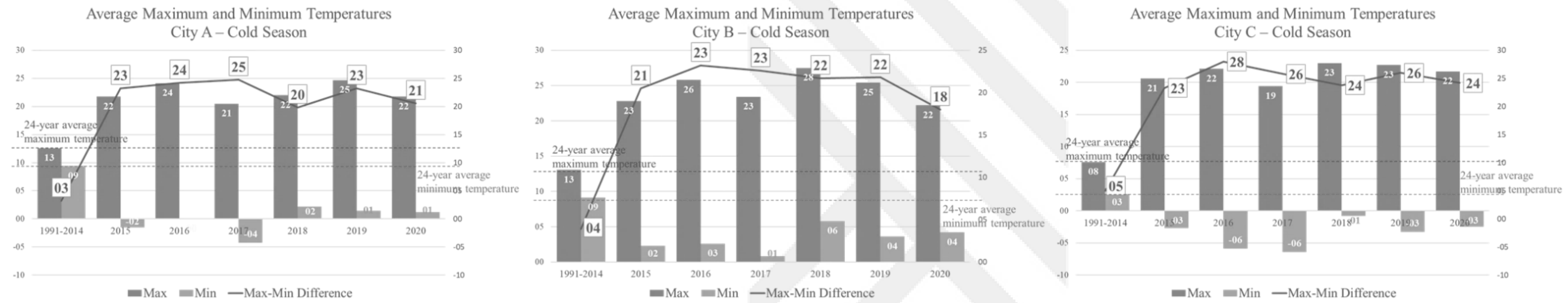


Figure 3: Yearly Average of Maximum and Minimum Temperatures and Variation 2014-2020.

Note: Figure 3 indicates the average maximum and minimum temperatures and variations by year, separately for warm and cold seasons. Average maximum temperature in 1991-2014 is calculated by averaging monthly maximum temperature values of respective years. The same calculation method is followed for average minimum temperature.

above 20 degrees in recent years. This trend suggests the potential for capturing a more pronounced impact of temperature variations on social media behavior at the aggregate level.

3.1 Data

The social media engagement data utilized in this study was obtained from a leading big data social media analytics firm. This dataset includes geography-specific, daily data covering 14,276,981 posts in Turkish. These posts revolve around beer brands and the broader beer category, as indicated by phrases like 'give me a Tuborg' or 'love to drink beer.' The data spans from January 1, 2014, to June 30, 2019.

To streamline the identification of beer-related content, the company utilized computer-aided image recognition technology to detect images associated with beer. Consequently, the dataset on user engagement, quantified as the number of beer-mentions, encompasses mentions extracted from various types of posts (such as comments, pictures, memes, retweets) across multiple social media platforms (including Twitter, Instagram, Facebook, YouTube, and blogs).

For the empirical analysis, I aggregated the data to compute monthly averages of daily beer mentions. Daily data, as I discuss later in the analysis, lacked stationarity due to significant fluctuations and noise from one day to the next. Furthermore, analyzing monthly data is a common approach when examining the effects of weather (as demonstrated by previous studies such as [45]). Monthly aggregation provided 66 months of observations for the daily averages. The aggregated data exhibited a monthly average of 7109 daily mentions with a notable standard deviation (see Table 5).

In the analysis, I include two control variables. The first variable indicates the presence of large-scale social media campaigns, with months featuring such a campaign coded as 1, otherwise coded as 0. Large-scale social media campaigns refer to volume-generating campaigns conducted by beer brands nationwide. The second control variable is an economic indicator, specifically the cost-of-living index for culture, education, and entertainment, downloaded from the data central of the Central Bank of the Republic of Türkiye [83]. I included this measure to control economic influences on beer-related user-generated content, serving as a proxy for economic factors affecting beer consumption. I hereafter denoted this index variable as 'cost of living.'

Table 5: Descriptive Statistics of Daily Average Mentions, Cost of Living for each month and Campaign Presence

	Average Mentions	**Cost of Living**	**Campaign Presence**
Count	66	*66*	*66*
Mean	7,108.704	2,664.584	0.167
Standard Deviation (SD)	5,456.604	617.868	0.376
Minimum value (Min.)	3,103.433	1,968.684	0.000
25%	4,104.050	2,191.786	0.000
50%	4,872.583	2,522.430	0.000
75%	6,209.557	2,959.056	0.000
Maximum value (Max.)	27,851.194	4,080.847	1.000

Meteorological Service and consist of daily temperature recordings (in degrees Celsius) spanning from January 1st, 2014, to June 30th, 2019. These recordings were collected at the city level, from 37 cities, across five major geographical regions within the country. These regions are recognized for generating beer-related social media content and collectively represent 70.4% of the total population [84], capturing 80.4% of the country's GDP [85]. Central weather stations located closest to city centers were selected for each city to ensure accuracy.

To enhance reliability, I aggregated city-level data into country-level metrics. Location-based data can be unreliable due to non-disclosure of location and VPN usage. Initially, I averaged the data at the regional-level and then aggregated the regional data to the country level based on the distribution of social media users across regions. The resulting daily country-level temperature data were further aggregated to the monthly level by averaging. The country-level temperature data consist of 66 months, with an approximate mean temperature of 19.7°C and a standard deviation of around 7.9°C (see Table 6). In total, there are 13 months in which average temperature levels were extremely high or low compared to season-normal levels (see Table 6). To identify extreme values, I utilized the mean absolute deviation of the first-differenced temperature data (see Web Appendix E for details)

Table 6: Descriptive Statistics of Average Monthly Temperatures

	Average Temperature
Count	66
Mean	19.739

	Average Temperature
SD	7.854
Min.	5.099
25%	13.205
50%	20.433
75%	26.966
Max.	31.382
Number of extremely hot months	*9*
Number of extremely cold months	*4*
Total number of months with extreme temperatures	*13*

3.2 Analysis

I analyzed the data for the presence of deterministic and/or stochastic trends by decomposing the variables into trend, seasonal, cyclic, and stochastic components using locally estimated scatterplot smoothing [86]. Visual inspection revealed that the social media data, in its original levels, exhibited a deterministic trend and is non-stationary. This non-stationary nature is further confirmed through Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests [87].

To address the trend and mitigate potential issues with spurious regression results arising from non-stationarity [88], I employed logarithmic transformation followed by first differencing [89]. Subsequently, I applied seasonal differencing to account for fixed effects. This year-on-year differencing methodology enabled to accommodate idiosyncratic shocks associated with specific dates such as New Year, Valentine's Day, and holidays, control for seasonality and seasonal impacts of beer consumption, capture net variation over the years, and render the data stationary (see Figure 4, 5, and 6).

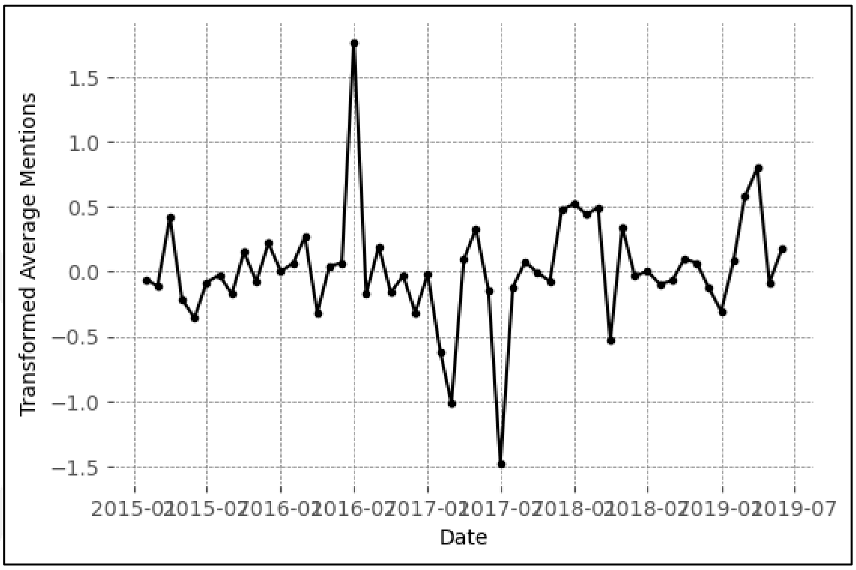


Figure 4: Transformed Monthly Data of Daily Average Mentions

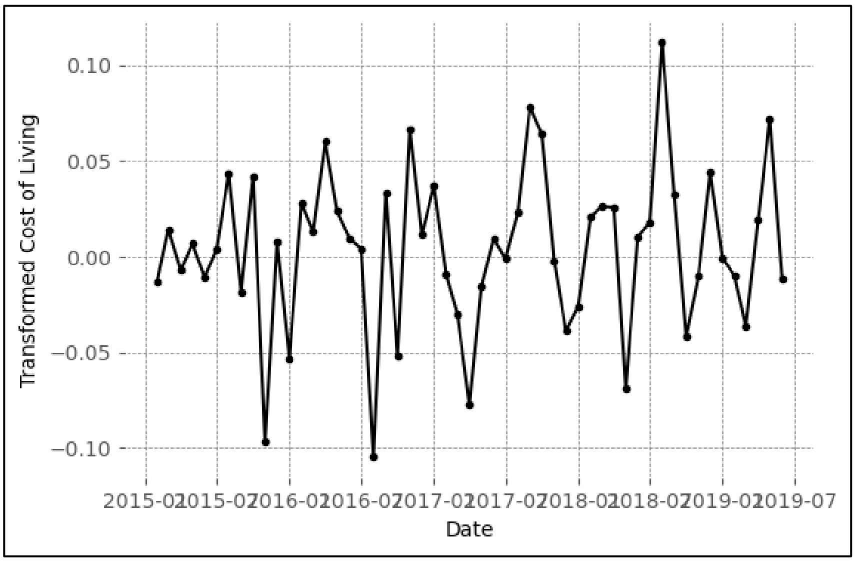


Figure 5: Transformed Monthly Data of Cost of Living

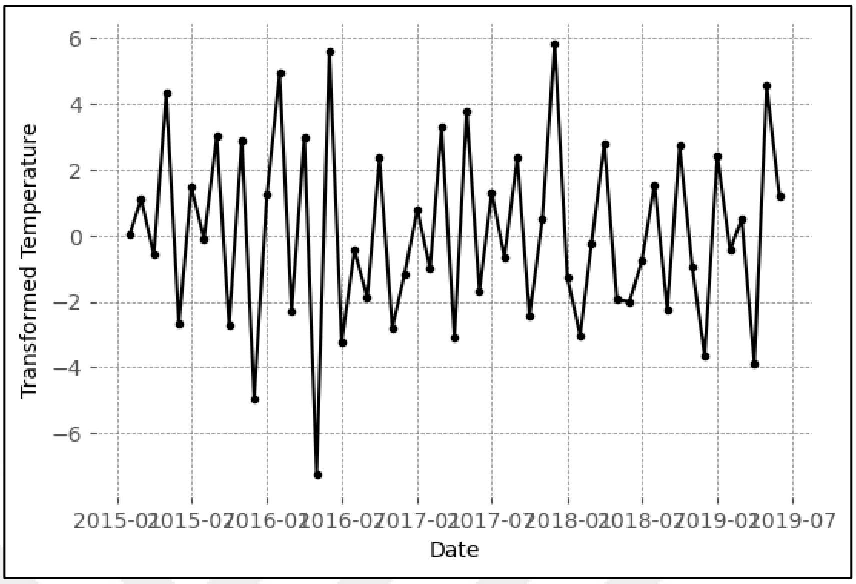


Figure 6: Transformed Monthly Data of Temperature

I confirmed the stationarity of the transformed data by conducting ADF and KPSS tests (refer to Table 7). Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots indicated that lags do not display significant autocorrelation, confirming the absence of a requirement for autoregressive components (see Figure 7). ADF test results indicated that the process did not contain a unit root; and KPSS test results illustrated that the data were level or trend stationary.

Table 7: ADF and KPSS Test Results for Transformed Mentions Data

	Test Results	**With constant**	**With constant and linear time trend**	**With constant and linear & quadratic time trend**
	Test statistic	-6.300	-6.285	-6.312

	Test Results	**With constant**	**With constant and linear time trend**	**With constant and linear & quadratic time trend**
ADF Test Results	p-value	0.000	0.000	0.000
	Number of lags	0	0	0
	Critical values for test statistic	-3.56 (1%), -2.92 (5%), -2.60 (10%)	-4.14 (1%), -3.50 (5%), -3.18 (10%)	-4.61 (1%), -3.95 (5%), -3.63 (10%)
KPSS Test Results	Test statistic	0.109	0.077	-
	p-value	0.1	0.1	-
	Number of lags	1	2	-
	Critical values	0.739 (1%), 0.463 (5%), 0.347 (10%)	0.216 (1%), 0.146 (5%), 0.119 (10%)	-

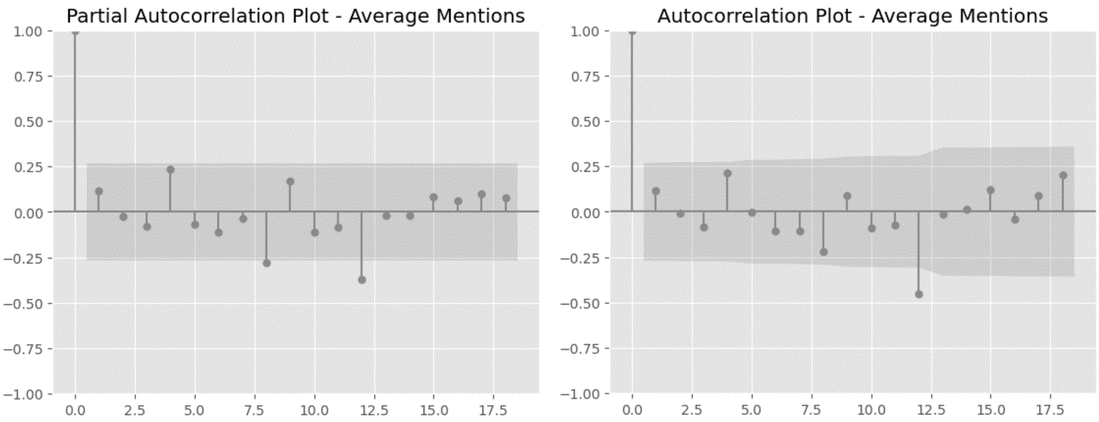


Figure 7: ACF and PACF Plots for Transformed Mentions Data

I operationalized temperature data by generating three dummy variables. The first dummy incorporates all extreme conditions, including both extremely high and extremely low temperatures across warm and cold seasons. The other two dummies capture instances of extremely high and low temperatures (see Web Appendix E for the calculation method). I employed a Generalized Linear Model (GLM), which accommodates dependent variables with non-normal distributions and allows for linear variations with the predictor variables. The model is represented by Equation 5. The cost of living and social media campaign variables are the control variables in Equation 5.

$$\Delta \ln Y_t = \alpha + \beta T_t + \gamma \Delta \ln C_t + \delta D_t + \varepsilon_t \quad ; \quad \varepsilon_t \sim N(0, \sigma^2) \qquad (5)$$

where: Y_t is the number of average daily mentions in month t, Δ is the year on year change operator such that $\Delta Y_t = (Y_t - Y_{t-1}) - (Y_{t-12} - Y_{t-13})$, α is the constant term, T_t is the extreme temperature dummy in month t, β is the coefficient associated with the extreme temperature dummy variable T_t, C_t is the cost of living in month t, γ is the associated coefficient with the cost of living variable C_t, D_t is the campaign dummy in month t, δ is the associated coefficient for D_t, ε_t is the i.i.d. error term, with distribution $N(0,\sigma^2)$.

To distinguish the impact of extremely hot and cold temperatures on user engagement, I employed a second model, using Equation 6, only replacing the extreme temperature dummy in equation 5 with extremely hot and extremely cold temperature dummies. In Equation 6, T_{mt} is the extreme temperature dummy m, for m in {extreme hot, extreme cold}, in month t, β_m is the coefficient associated with the extreme temperature dummy variable T_{mt}.

$$\Delta \ln Y_t = \alpha + \beta_m T_{mt} + \gamma \Delta \ln C_t + \delta D_t + \varepsilon_t \quad ; \quad \varepsilon_t \sim N(0, \sigma^2) \qquad (6)$$

In the next section I provide results for Model 1 using Equation 5, and for Model 2 using Equation 6.

3.3 Results

For both models, the results showed that the resulting errors (ε_t) did not show autocorrelation and heteroskedasticity, in line with the models' original i.i.d. assumptions. For Model 1, the scores for parameter coefficients, standard error (SE), and p-values are provided in Table 6. The results revealed that extreme temperatures led to a significant decline in the number of beer-related mentions ($\beta = -.256$, $p = .032$) compared to season-normal weather conditions.

Table 8: Empirical Model (GLM) Results for Model 1 using Equation 5

Model 1:	**Coefficient:**	**SE:**	**p-value:**
Constant	.052	.065	.424
Extreme temperature	**-.256****	.116	**.032**
Social Media Campaign	.132	.188	.486
Cost of living	.475	.900	.600

$*p < .10$, $**p < .05$, $***p < .01$, $****p < .001$.

I further examined if this negative influence of extreme temperatures persists in both extremely high and low temperatures in Model 2 (see Table 7). The results confirmed that the decline observed in Model 1 is consistent for both extremely high and low temperatures, albeit in a directional manner for extremely low temperatures. Specifically, there was a significant decline in beer-related mentions when temperatures were extremely high (β = -.322, p = .017). These findings underscore the substantial influence of extremely high temperatures on user engagement.

Table 9: Empirical Model (GLM) Results or Model 2 Using Equation 6

Model 2:	**Coefficient:**	**SE:**	**p-value:**
Constant	.054	.064	.409
Extremely high temperature	**-.322****	.131	**.017**
Extremely low temperature	-.100	.114	.385
Social Media Campaign	.122	.189	.521
Cost of living	.360	.857	.676

*$p < .10$, **$p < .05$, ***$p < .01$, ****$p < .001$.

As I transformed all continuous variables in the equation by taking their natural logs, I applied exponential function to the betas of extreme temperature dummies to derive elasticities. Model 2 (Equation 6) results indicated that employing a large-scale social media campaign escalated user engagement by 13.0%. The occurrence of extremely high temperatures, on the contrary, led to a 27.5% decrease in user engagement, whereas in extremely low temperatures this decrease is equivalent to 9.5%. These impacts support the third hypothesis, suggesting that hot temperatures have a greater negative impact on user engagement compared to cold temperatures.

Can running a social media campaign mitigate the negative impact of extreme temperatures? The findings indicate that the existence of a campaign on its own is not sufficient to mitigate the impact of extremely high temperatures, as their impacts on mentions are 13.0% and -27.5% respectively. I illustrate this inadequacy in Figure 8. Using the GLM coefficients of the parameters in Table 9, and Equation 6, I calculated how much user engagement would shift if extreme temperatures occurred in a campaign vs. no-campaign month. In the calculations, in Equation 6, for the cost of living, I inserted a constant value. It is noteworthy that the negative impact of low temperatures is much weaker than that of high temperatures, supporting the third hypothesis, and can be mitigated by a social media campaign.

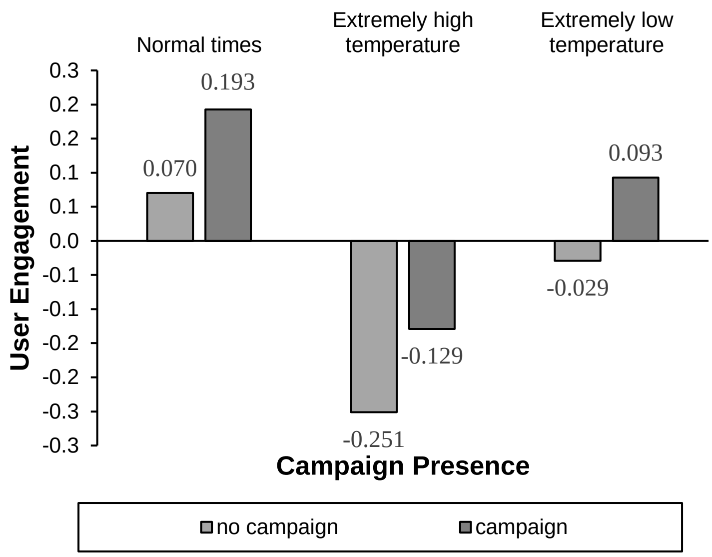


Figure 8: Campaign Effect

As an extension to my empirical model, I further investigated whether social media campaigns exhibit differential effects on engagement during extreme temperatures. I introduced a model incorporating an interaction term between temperature and campaign (Equation 7) and compared it with a baseline model that excludes the interaction term (Equation 8). This comparison allowed to discern how coefficients change with the inclusion of the interaction term. In this analysis, I utilized year-on-year differenced temperature data instead of extreme temperature dummies.

$$\Delta \ln Y_t = \alpha + \beta\, \Delta T_t + \gamma\, \Delta \ln C_t + \delta\, D_t + \omega\, \Delta T_t{}^* D_t + \varepsilon_t \quad ; \quad \varepsilon \sim N(0, \sigma^2) \tag{7}$$

$$\Delta \ln Y_t = \alpha + \beta\, \Delta T_t + \gamma\, \Delta \ln C_t + \delta\, D_t + \varepsilon_t \quad ; \quad \varepsilon \sim N(0, \sigma^2) \tag{8}$$

where: Y_t is the number of average daily mentions in month t, Δ is the year on year change operator such that $\Delta Y_t = (Y_t - Y_{t-1}) - (Y_{t-12} - Y_{t-13})$, α is the constant term, T_t is temperature in month t, β is the coefficient associated with temperature variable T_t, C_t is the cost of living in month t, γ is the associated coefficient with the cost of living variable C_t, D_t is the campaign dummy in month t, δ is the associated coefficient for D_t, ω is the associated coefficient with the interaction term of temperature variable T_t and campaign dummy variable D_t, ε_t is the i.i.d. error term, with distribution $N(0,\sigma^2)$.

The findings revealed a negative interaction component, albeit not significantly affecting engagement. As illustrated in Figure 9, a large-scale campaign during extreme temperatures mitigates the negative impact of temperature by approximately 36.7% (from -0.041 to -0.026). However, I also observed a reduction in the positive effect of the campaign on user engagement by 29.2% (from 0.125 to 0.088).

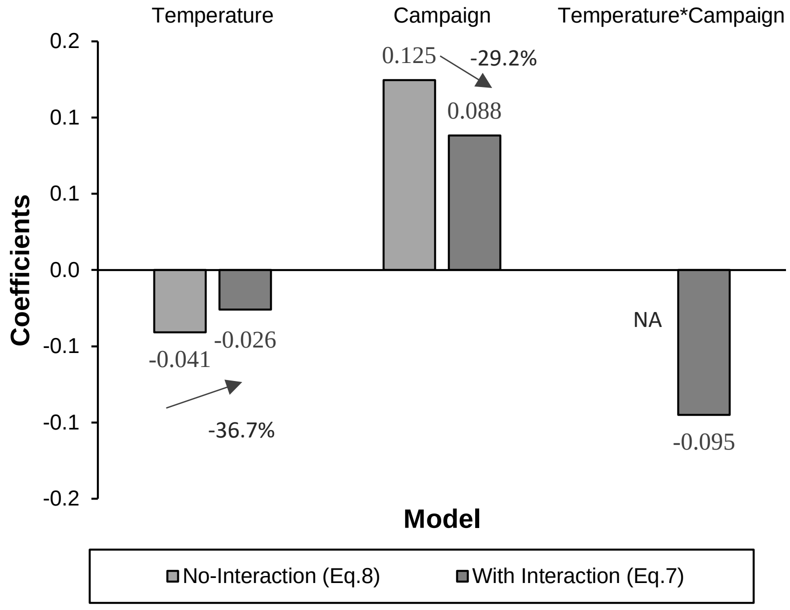


Figure 9: Campaign Interaction Effect

For the robustness of the interaction model results, I executed Equation 6 using Process Macro Model 1 [78] with bootstrapping (N=10,000). Similar coefficients were obtained in terms of magnitude, and the effects remained consistent in terms of direction, with a non-significant interaction term (refer to Web Appendix F). The Process Macro also facilitated visualizing the effect of the interaction using the Johnson-Neyman technique [90], providing conditional effects of the focal predictor, in this case, temperature, at different values of the moderator variable, which is the campaign dummy. As depicted in Figure 10, the engagement level decreases as the temperature increases in the presence of a campaign, aligning with the findings from Equation 6. However, given the non-significance of the interaction term, I cannot conclude that large-scale campaigns are significantly less effective during extremely hot temperatures. While such campaigns provide some assistance, they are unable to fully mitigate the negative impact of high temperatures on user engagement.

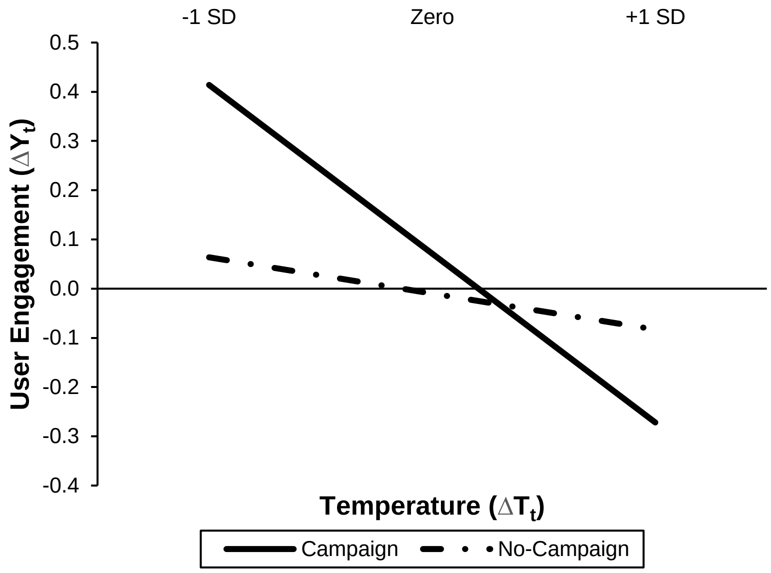


Figure 10: Johnson-Neyman Output

Notes: The figure indicates the estimated user engagement levels (using equation 7 and Process Macro Model 1) in campaign presence and absence, as temperature (ΔT_t in Equation 7) gets values of -1 standard deviation, zero, and +1 standard deviation ($SD_{\Delta Tt}$ = 2.836).

3.4 Discussion

The empirical model results provide quantifiable evidence of the significance of extremely hot temperatures compared to season-normal temperatures in a real-world data setting where users experience temperature. Furthermore, extremely cold temperatures demonstrate a negative directional impact, albeit of lesser magnitude compared to high temperatures. It is thus evident that extreme temperatures affect the creation of beer-related content on social media and hotter temperatures have a larger negative impact on user engagement, compared to colder temperatures, supporting experiment results.

In the empirical study, I investigated the effects of extremely high and low temperatures on beer-related content creation. Beer is a weather-sensitive, seasonal category, and consumed more in warm season in Türkiye. Studies indicate that temperature significantly impacts on seasonal product sales ([91]; [92]) and engaging with product-related content on social media platforms often reflects consumer sentiment, lifestyles, and behaviors [93]. Given these studies, one might anticipate an increase in social media content creation when temperature increases, and a decrease during low temperatures, aligning with beer consumption patterns. However, by employing a rigorous differencing methodology, and addressing any seasonal or fixed effects, the results unveiled a negative influence of both extremely high and low temperatures, contrary to initial expectations. Consequently, I find evidence that when temperatures go extreme, beer-related content creation on social media decreases.

Beer additionally represents a hedonic and psychology-driven product category. Several studies demonstrate that with the negative impact of higher temperatures, hedonic consumption tends to increase ([94]; [5]). However, I did not observe such a tendency extending to creating hedonic product-related content on social media. This result may suggest that product-related content creation may not solely be driven by or done in parallel to product consumption. Alternatively, a non-linearity between temperature increases and consumption, wherein extreme increases may eventually decrease consumption, could be a contributing factor.

Regarding the effectiveness of a social media campaign, the results indicate that managers should not expect higher engagement results for seasonal products during the times temperature goes to extreme levels. This contradicts with the traditional belief that people consume, for example, more ice cream or engage with more ice-cream related communications as the weather gets hotter with an expectation of a linear increase in engagement. Yet, after experiencing heat waves in a higher frequency and impact magnitude, more businesspeople admit that such extreme weather hinders their seasonal business [95]. This study supports that hot temperatures have a strong adverse impact which hinders engaging with social media.

CHAPTER IV

CONCLUSIONS

4.1 Conclusions and Implications

One of the consequences of climate change is the increases in global temperature both in magnitude and variability. The average global temperature has increased by at least 1.1°C since the industrial revolution, with the last nine years recording the warmest years [96]. The impact is expected to continue growing drastically in the near future. Arnell et al. [97] estimates impacts and risks associated with increases in global mean temperature up to 5°C above pre-industrial levels. The authors find that the average chance of a major heatwave at the global level increases from 5% in 1981–2010 to 28% at 1.5°C and 92% at 4°C, underscoring the importance of understanding the scope of temperature effects across all disciplines.

Many business and economic reports highlight the adverse effects of hot temperatures are spreading through different industries ([98]; [99]), even discussing how workers are affected and addressing worker conditions and legal rights ([100]; [101]). This research is the first to document that individuals have a lower willingness to create posts on social media when faced with extremely hot temperatures because extremely hot weather reduces their happiness. Given the positive influence of happiness on the creation process, this study provides preliminary evidence that extremely hot temperatures hinder content creation on social media by diminishing happiness. Utilizing a controlled experiment followed by an empirical study analyzing a comprehensive social media dataset, the current research further quantifies the negative impact of hot temperatures on post creation, which is stronger than that of cold temperatures.

Studies have indicated that product-related online content can influence consumer purchasing behavior ([102]; [103]). As the user base of social media platforms expands and usage frequencies increase, coupled with a rise in digital spending budgets, firms are directing more resources towards content creation and distribution within the social media landscape ([104]). Consequently, the challenges posed by extreme weather present serious obstacles for all content creators, encompassing consumers, influencers, and managers alike. There are several managerial implications for businesses and social media marketers concerning the timing of posting contents and initiating campaigns, content themes, and social media analytics.

In determining the timing for new product launches, or major initiatives through social media campaigns, consideration of more moderate (season – normal) weather is recommended when individuals tend to be more receptive to active engagement. Cheema and Patrick [3], for instance, indicate that warmer temperatures compared to cooler temperatures may hinder new product purchases. Extremely hot weather could exacerbate this impact, potentially leading to a setback or failure in the promotion or launch of new product ideas through social media. In a broader context, the consumer buying process may also be influenced by social media activities [105]; therefore, lower levels of engagement with such activities could impact consumer buying.

As happiness level decreases during extreme weather, managers and social media marketers can contemplate the adoption of more uplifting and positive campaigns to counteract the negative emotional impact caused by extreme weather. Although the role of positive content is not tested in this study as a moderating variable of temperature-induced happiness and post-creation relationship, Berger et al. [106] show that emotionally arousing content encourages content engagement, and that content evoking sadness or contentment is not helpful. Therefore, happiness-generating content holds the potential to encourage users to actively engage with social media.

4.2 Limitations and Avenues for Future Research

In this thesis, I investigated the impact of extreme weather conditions within a social context by examining the intention of post creation, and liking, commenting on, and sharing a friend's post. Subsequently, I analyzed real-world data, which mirrors social dynamics, and focuses on beer-related mentions created on social media platforms. These mentions mostly occur during or after consumption, suggesting the presence of social interactions. In other words, the study reflects how extreme temperatures may affect post creation in a social environment. Phithakkitnukoon et al. [107] examine how weather affects mobile social interactions and finds that people tend to be less connected with their social ties during extreme temperatures (either very cold or very warm temperatures). Exploring user engagement within non-social contexts, such as individuals opting to remain indoors to mitigate discomfort induced by extreme weather, presents an intriguing avenue for investigating the broader impacts of extreme weather and enhancing the generalizability of findings.

This thesis also focuses on the cumulative effect of all social media platforms, reflecting real-world dynamics more closely. To develop tailored strategies for each platform, a platform-specific comparative perspective can be adopted in future studies to examine the effects of extreme weather. It is plausible that the intention to create posts on an image-sharing platform may differ from that on a microblogging platform as they differ by engagement motivations. For example, Pelletier et al. [108] show that consumers engage with Twitter for informational and social purposes, whereas Instagram is the primary platform for entertainment motivation and for co-creating with brands via social media [108].

Additionally, exploring how extreme weather influences specific elements or features within posts that contribute to higher engagement would be another avenue for research. Martin et al. [71] show that extremely high temperatures affect a utility's posting design by reducing the use of images and number of words. Further research can investigate the impact of extreme temperatures on the use of various types of posts such as images, memes, videos, etc., or on the creation of more individualistic images versus product-related images from the users' perspective, which could yield valuable insights.

In this thesis, I also observe a pronounced impact of hot temperatures on behavior compared to cold temperatures. However, this does not imply that cold temperatures do not have influence at all (see Singha and Bagchi [8] for a review on cold temperature impact on willingness to pay). Existing literature (e.g., [14]; [15]; [72]; [73]) and findings from this research confirm that cold temperatures can indeed affect mood negatively (specifically happiness), like hot temperatures. The distinction possibly lies in how cold and hot temperatures impact our physiology, how we react and behave in turn, and the degree of compensation of adverse effects as discussed in Wang et al. [72]. Subsequent studies could explore the potential impacts of such differences on consumer decision making and behavior.

In the experimental design, I measured the temperature impact using an online experiment, which could potentially lead to demand effects [109]. However, I observed an asymmetry between the impact of hot and cold temperatures on user engagement, suggesting the results may not be solely attributable to demand effects. Furthermore, I found similar results when analyzing time-series data that reflect users' experiences of actual temperature, reinforcing my research claims. In future studies, real experiments could be conducted in a laboratory setting with varying temperature levels to explore user engagement across different tasks.

In this study I focused on the mediation impact of happiness. One could argue that there are different mood states playing different roles in user engagement. The literature suggests happiness as the strongest emotion; however, there can be other mood states that may be effective on different types of user engagement. Although I did not find significant impact on liking, sharing, and commenting intentions, specific mood states may play different roles on contribution to an existing post.

This work demonstrates that it is important to include temperature in all social media performance measurements due to its significant impact on post creation behavior. A regular and active listening to user sentiment on social media is essential as well. Such monitoring would help understand weather-related fluctuations in user engagement, allowing managers to refine content strategies, and content posting schedules accordingly. Given the challenges posed by climate change, it is essential for social media strategies to be flexible and responsive to changes in user emotions and behaviors, incorporating a weather-inclusive perspective. As Burke et al. [110] puts it: *"if hot temperatures increase the likelihood of riots in a city – even if extreme temperatures are experienced only for a few hours – then this is important for understanding climate impacts because the frequency of these momentary events may change if the distribution of daily temperatures changes"* (p.579). This is what we are facing today and will be facing tomorrow.

APPENDIX A

Table 10: Selected Works on Weather and Ambient Temperature in Marketing Literature 2000-2023 (Sorted by Category)

Study	**Field / Category**
Busse et al. 2015 **[111]**	Car purchases (Vehicle sales), Used and new vehicle prices
Conlin et al. 2007 **[112]**	Catalogue orders and returns
Cen et al. 2023 **[113]**	Cognitive performance
Gaoua et al. 2012 **[114]**	Cognitive performance
Mäkinen et al. 2006 **[115]**	Cognitive performance
Tham et al. 2010 **[116]**	Cognitive performance (mental alertness)
Carlsmith & Anderson 1979 **[117]**	Collective violence
Tong et al. 2018 **[118]**	Complex choices - Decision making
Joslyn & Grounds 2015 **[119]**	Complex Decision Making
Hadi & Block 2019 **[120]**	Complex decision tasks
Murray et al. 2010 **[7]**	Consumer behavior
Parker & Tavassoli 2000 **[4]**	Consumer behavior
Kolb et al. 2012 **[121]**	Customer-oriented helping behavior
Cheema & Patrick 2012 [3]	Decision Making
Simonsohn 2007 **[122]**	Decision making
Watkins et al 2014 **[123]**	Decision Making performance
Federspiel et al 2004 **[124]**	Employee performance
Lan et al 2010 **[125]**	Employee productivity
Huang et al. 2014 **[126]**	Financial Decision Making
Bao & Fan 2018 **[127]**	Gaming productivity
Hu & Lee 2020 **[128]**	Housing market
Hsiang et al. 2013 **[129]**	Human conflict
Mittal et al. 2004 **[130]**	Importance perception of quality and dealership service

Study	**Field / Category**
Tellis et al. 2003 **[131]**	Innovative product adoption (climate measure is temperature, used as a proxy for industriousness)
Schmittmann et al. 2015 **[132]**	Investor behavior
Khanthavit 2018 **[133]**	Investor mood
Yap et al. 2017 **[134]**	Life satisfaction
Berry et al. 2010 **[135]**	Mental health
Li et al. 2017 **[136]**	Mobile promotion effectiveness
Phithakkitnukoon et al. 2012 **[107]**	Mobile social interactions
Sudo et al. 2021 **[137]**	Moral Decision Making
Steinker et al. 2017 **[10]**	Online retail
Wei et al. 2023 **[138]**	Outdoor Productivity & Performance - soccer
Govind et al. 2014 **[139]**	Product Consumption
Govind et al. 2020 **[5]**	Product Consumption
Zhang et al. 2021 **[140]**	Product Consumption – food intake
Zwebner et al. 2014 **[11]**	Product valuation
Niemelä et al. 2012 **[141]**	Productivity & Performance
Pilcher et al 2002 **[142]**	Productivity & Performance
Buchheim & Kolaska 2017 **[44]**	Purchase behavior
Steinmetz & Posten 2017 **[143]**	Response Behavior
Bujisic et al. 2017 **[144]**	Restaurant Sales
Rind et al. 2001 **[145]**	Restaurant tipping
Arunraj & Ahrens 2015 **[146]**	Retail sales
Bahng & Kincade 2012 **[92]**	Retail sales
Bertrand & Parnaudeau 2019 **[45]**	Retail sales
Bertrand, Brusset & Fortin 2015 **[147]**	Retail sales
Star-McCluer 2000 **[148]**	Retail sales
Badorf & Hoberg 2020 **[149]**	Retail sales – brick and mortar
Verstraete et al. 2019 **[9]**	Retail sales / Sales forecasting
Keleş et al. 2018 **[150]**	Shopping behavior
Moon et al. 2018 **[151]**	Shopping behavior

Study	**Field / Category**
Parsons, 2001 **[152]**	Shopping behavior
Tian et al. 2018 **[6]**	Shopping behavior: consumers’ variety-seeking
Cao & Wei 2005 **[153]**	Stock market returns
Kang et al 2010 **[154]**	Stock returns
Feddersen et al. 2016 **[155]**	Subjective well-being
Agnew & Pautikof 2006 **[156]**	Tourism
Toeglhofer et al. 2012 **[157]**	Tourism
Aaheim & Hauge 2005 **[158]**	Travel Behavior
Horanont et al. 2013 **[159]**	Travel behavior
Liu et al. 2014 **[160]**	Travel Behavior
Liu et al. 2016 **[161]**	Travel Behavior
An et al 2019 **[162]**	Travel Behavior
Chen & Mahmassani 2015 **[163]**	Travel behavior – activity stress
Bujisic et al. 2019 **[57]**	Valence of Consumer Comments & WOM (restaurant setting)
Sinha & Bagchi 2019 **[8]**	Willingness to pay in auctions, negotiations

APPENDIX B

Impact of Climate Variables on User Engagement

Using the same dataset analyzed in the empirical section of this thesis, I previously explored the potential impact of several climate variables on user engagement and compared their relative impacts using Equation 8 for each weather variable. In total I executed five different models.

$$\Delta \ln Y_t = \alpha + \beta_m \Delta W_{mt} + \gamma \Delta \ln C_t + \delta D_t + \varepsilon_t \quad ; \quad \varepsilon \sim N(0, \sigma^2)$$

(8)

where: Y_t is the number of average daily mentions in month t, Δ is the year on year change operator such that $\Delta Y_t = (Y_t - Y_{t-1}) - (Y_{t-12} - Y_{t-13})$, α is the constant term, W_{mt} is the weather variable m, for m in {temperature, cloudiness, humidity, air pressure, wind speed}, in month t, β_m is the coefficient associated with weather variable W_{mt}, C_t is the cost of living in month t, γ is the associated coefficient with the cost of living variable C_t, D_t is the campaign dummy in month t, δ is the associated coefficient for D_t, ω is the associated coefficient with the interaction term of temperature variable T_t and campaign dummy variable D_t, ε_t is the i.i.d. error term, with distribution $N(0,\sigma^2)$.

Table 11 provides the coefficients, standard errors, p-values, and model fits using Akaike Information Criterion (AIC) for each weather variable. The results indicate that temperature is the only significant variable at $p <= .05$ and offers the best model fit compared to other variables.

Table 11: GLM Model Results for Each Climate Variable

Model / Climate Variable	**Coefficient**	**SE**	**p-value**	**AIC**
Model 1 / temperature	-.041	.019	.038	66.161
Model 2 / cloudiness	.006	.003	.062	67.371
Model 3 / humidity	.010	.009	.282	68.840
Model 4 / air pressure	.000	.015	.980	69.937
Model 5 / wind speed	.050	.124	.686	69.823

APPENDIX C

Table 12: Operationalization of the Variables in the Experimental Study

Purpose:	Variables:	Question & Item:	Scale & Coding:
Dependent Variable	Post Creation	*Q: How likely would you share a post about your time in this café on your social media account?*	7-point Likert scale: 1 = Extremely unlikely 2 = Moderately unlikely 3 = Slightly unlikely 4 = Neither likely nor unlikely 5 = Slightly likely 6 = Moderately likely 7 = Extremely likely
Dependent Variable	Liking	*Q: How likely would you like your friend's post by hitting the like button?*	
Dependent Variable	Commenting	*Q: How likely would you add a comment to this (your friend's) post?*	
Dependent Variable	Sharing	*Q: How likely would you share this (your friend's) post with others in your own social media account?*	
Baseline Affect Mediator	Baseline Happiness Post-Manipulation Happiness	*Q: For each emotion type below, please select the emotion level that would suit your feeling the best* ***now/ in such weather*** [a]*:* Happy / Sad	9-point Likert scale: 1 = do not feel at all 5 = neither feel nor not feel 9 = extremely feel
Control Variables	 Weather sensitivity Hot Weather Preference Cold Weather Preference	*Q: To what degree, do you agree with the following statements?* [b] I am sensitive to weather changes. I usually prefer hot weather. I usually prefer cold weather.	7-point Likert scale: 1 = Strongly disagree 2 = Disagree 3 = Somewhat disagree 4 = Neither agree nor disagree 5 = Somewhat agree 6 = Agree 7 = Strongly agree
Control Variable	Interior/ Exterior environment	*Q: Are you currently in an interior or exterior environment?*	Nominal

Purpose:	**Variables:**	**Question & Item:**	**Scale & Coding:**
		Indoor (a study room, class, home, interior part of a café, etc.) / Outdoor	(Recoded as binary variable: indoor = 1, outdoor = 0)
Control Variable	Ambience comfort level	*Q: How comfortable do you feel in the environment you are in now?*	7-point Likert scale: 1 = Extremely uncomfortable 2 = Moderately uncomfortable 3 = Somewhat uncomfortable 4 = Neither comfortable nor uncomfortable 5 = Somewhat comfortable 6 = Moderately comfortable 7 = Extremely comfortable
Control Variable	Perceived Ambient Temperature	*Q: How the ambient temperature is like in the environment you are in now?*	7-point Likert scale: 1 = Too cold 2 = Moderately cold 3 = Slightly cold 4 = Neither cold nor hot 5 = Slightly hot 6 = Moderately hot 7 = Too hot
Control Variable	Social Media Usage Frequency	*Q: How frequently do you scroll through the social media?*	10-point scale: 1 = Less often 2 = Once a week 3 = Once in 2-3days 4 = Once a day 5 = Twice a day 6 = Every 4-5 hours 7 = Every 2-3 hours 8 = Every hour 9 = Every half an hour 10 = Constantly

[ab] The order of the items is randomized.

APPENDIX D

Table 13: One-way Analysis of Variance (ANOVA) Results for Baseline Happiness and Control Variables

	$F^a(2^b,290^c)$	**p-value**	**Welch Test[d] p-value**	**Brown-Forsythe Test[d] p-value**
Baseline Happiness - Happy	1.018	.362	.361	.362
Baseline Happiness - Sad	1.194	.304	.317	.305
Baseline Happiness – Latent construct	1.226	.295	.312	.295
Ambience comfort level	.476	.622	.632	.623
Weather sensitivity	1.540	.216	.223	.217
Hot Weather Preference	1.493	.226	.253	.225
Cold Weather Preference	.696	.500	.500	.499
Cold Weather Preference – Latent construct	1.493	.226	.253	.225
Social Media Usage Frequency	1.030	.358	.361	.360

[a] F-statistic [b] degree of freedom between groups [c] degree of freedom within groups [d] Robust Tests of Equality of Means.

Notes: Table 13 results demonstrate that for baseline happiness and control variables there are no a priori differences across three different weather conditions. Robustness tests of equality of means confirm ANOVA results.

APPENDIX E

Calculation of Extreme Temperature Variables

The extreme values are based on the mean absolute deviation (MAD) of the first differenced monthly data in warm and cold seasons separately. If above MAD, data were referred to as extremely high, and if below MAD, data were referred to as extremely low. Then seasonal differencing is applied to determine net extremes from one year to another.

Table 14: Year on Year Calculation of Extreme Temperature Variables

Variable	Calculation Method	Definition
temp_warm_high = Extreme increases in temperature in warm season	1) On the first differenced monthly data, mean absolute deviation of temperature is calculated for warm season and cold season separately. 2) if monthly deviation in temperature is greater than mean absolute deviation, coded as one; else	Indicators of Monthly variation: If high/low, there is an extreme increase/ decrease in monthly temperatures compared to previous year's monthly changes.
temp_warm_low = Extreme decreases in temperature in warm season		

Variable	Calculation Method	Definition
temp_cold_high = Extreme increases in temperature in cold season	zero. (Two dummies are obtained at the end: temp_warm_high, temp_cold_high) 3) if monthly deviation in temperature is less than mean absolute deviation, coded as one; else zero. (Two dummies are obtained at the end: temp_warm_low, temp_cold_low) 4) After dummy creation, second-order differencing (seasonal differencing) is applied. 5) Values of -1 are coded as zero.	Ex: If 2014 month 2 – month 1 is coded as 1, and 2015 month 2 – month 1 is also coded as 1, then with seasonal differencing (1-1=0), there is no extreme increase or decrease (variation) in temperature from one year to another.
temp_cold_low = Extreme decreases in temperature in cold season		

APPENDIX F

Moderation Model Results

Table 15: Moderation Model Results Using Process Macro Model 1

	Coefficient:	**SE:**	**p-value:**	**Bootstrap Confidence Intervals**
Constant	-.008	.056	.895	[-0.133, 0.098]
Temperature	-.026	.017	.134	[-0.069, 0.003]
Social Media Campaign	-.081	.154	.602	[-0.411, 0.405]
Temperature * Social Media Campaign	-.095	. 069	. 177	[-0.344, 0.075]
Cost of living in culture and entertainment	-. 511	. 874	.561	[-2.961, 1.238]

*p < .10, **p < .05, ***p < .01, ****p < .001.

Notes: The table indicates the scores for parameter coefficients, standard error (SE), and p-values. The moderation model (Equation 6) is run using Process Macro 4.3 via SPSS with bootstrapping (N=10,000).

BIBLIOGRAPHY

[1] The CMO Survey, "Managing brand, growth and metrics: The highlights and insights report," 2023. [Online]. Available: https://cmosurvey.org/wp-content/uploads/2023/03/The_CMO_Survey-Highlights_and_Insights_Report-March_2023.pdf [Accessed April 4, 2024]

[2] M. C. Keller, B. L. Fredrickson, O. Ybarra, S. Côté, K. Johnson, J. Mikels, A. Conway, and T. Wager, "A warm heart and a clear head: The contingent effects of weather on mood and cognition," *Psychological Science*, vol. 16(9), pp. 724-731, 2005.

[3] A. Cheema and V. M. Patrick, "Influence of warm versus cool temperatures on consumer choice: A resource depletion account," *Journal of Marketing Research*, vol. 49(6), pp. 984-995, 2012.

[4] P. M. Parker and N. T. Tavassoli, "Homeostasis and consumer behavior across cultures," *International Journal of Research in Marketing*, vol. 17(1), pp. 33-53, 2000.

[5] R. Govind, N. Garg, and V. Mittal, "Weather, affect, and preference for hedonic products: The moderating role of gender," *Journal of Marketing Research*, vol. 57(4), pp. 717-738, 2020.

[6] J. Tian, Y. Zhang, and C. Zhang, "Predicting consumer variety-seeking through weather data analytics," *Electronic Commerce Research and Applications*, vol. 28, pp. 194-207, 2018.

[7] K. B. Murray, F. Di Muro, A. Finn, and P. P. Leszczyc, "The effect of weather on consumer spending," *Journal of Retailing and Consumer Services*, vol. 17(6), pp. 512-520, 2010.

[8] J. Sinha and R. Bagchi, "Role of ambient temperature in influencing willingness to pay in auctions and negotiations," *Journal of Marketing*, vol. 83(4), pp. 121–138, 2019.

[9] G. Verstraete, E.-H. Aghezzaf, and B. Desmet, "A data-driven framework for predicting weather impact on high-volume low-margin retail products," *Journal of Retailing and Consumer Services*, vol. 48, pp. 169-177, 2019.

[10] S. Steinker, K. Hoberg, and U. W. Thonemann, "The value of weather information for e-commerce operations," *Production and Operations Management*, vol. 26(10), pp. 1854-1874, 2017.

[11] Y. Zwebner, L. Lee, and J. Goldenberg, "The temperature premium: Warm temperatures increase product valuation," *Journal of Consumer Psychology*, vol. 24(2), pp. 251-259, 2014.

[12] P. Bruno, V. Melnyk, and F. Völckner, "Temperature and emotions: Effects of physical temperature on responses to emotional advertising," *International Journal of Research in Marketing*, vol. 34(1), pp. 302-320, 2017.

[13] C. Noelke, M. McGovern, D. J. Corsi, M. P. Jimenez, A. Stern, I. S. Wing, and L. Berkman, "Increasing ambient temperature reduces emotional well-being," *Environmental Research*, vol. 151, pp. 124-129, 2016.

[14] P. Baylis, "Temperature and temperament: Evidence from twitter," *Journal of Public Economics*, vol. 184, pp. 15, 2020.

[15] P. Baylis, N. Obradovich, Y. Kryvasheyeu, H. H. Chen, L. Coviello, E. Moro, M. Cebrian, and J. H. Fowler, "Weather impacts expressed sentiment," *Plos One*, vol. 13(4), pp. 11, 2018.
[16] T. Akcura, K. Altinkemer, and H. Chen, "Noninfluentials and information dissemination in the microblogging community," *Information Technology and Management*, vol. 19, pp. 89-106, 2018.
[17] A. Castillo, J. Benitez, J. Llorens, and X. R. Luo, "Social media-driven customer engagement and movie performance: Theory and empirical evidence," *Decision Support Systems*, vol. 145, pp. 113516, 2021.
[18] L. Dessart, "Social media engagement: A model of antecedents and relational outcomes," *Journal of Marketing Management*, vol. 33(5-6), pp. 375-399, 2017.
[19] M. P. Gardner, "Mood states and consumer behavior: A critical review," *Journal of Consumer Research*, vol. 12(3), pp. 281-300, 1985.
[20] L. Nummenmaa, E. Glerean, R. Hari, and J. K. Hietanen, "Bodily maps of emotions," *Proceedings of the National Academy of Sciences*, vol. 111(2), pp. 646-651, 2014.
[21] R. Veenhoven, "Healthy happiness: Effects of happiness on physical health and the consequences for preventive health care," *Journal of Happiness Studies*, vol. 9, pp. 449-469, 2008.
[22] S. Lyubomirsky, L. King, and E. Diener, "The benefits of frequent positive affect: Does happiness lead to success?," *Psychological Bulletin*, vol. 131(6), pp. 803-855, 2005.
[23] A. J. Oswald, E. Proto, and D. Sgroi, "Happiness and productivity," *Journal of labor economics*, vol. 33(4), pp. 789-822, 2015.
[24] A. Usai, B. Orlando, and A. Mazzoleni, "Happiness as a driver of entrepreneurial initiative and innovation capital," *Journal of Intellectual Capital*, vol. 21(6), pp. 1229-1255, 2020.
[25] A. A. Labroo and V. M. Patrick, "Psychological distancing: Why happiness helps you see the big picture," *Journal of Consumer Research*, vol. 35(5), pp. 800-809, 2009.
[26] E. G. Fernández-Abascal and M. D. M. Díaz, "Affective induction and creative thinking," *Creativity Research Journal*, vol. 25(2), pp. 213-221, 2013.
[27] C. K. De Dreu, M. Baas, and B. A. Nijstad, "Hedonic tone and activation level in the mood-creativity link: Toward a dual pathway to creativity model," *Journal of Personality and Social Psychology*, vol. 94(5), pp. 739, 2008.
[28] C. Mogilner, J. Aaker, and S. D. Kamvar, "How happiness affects choice," *Journal of Consumer Research*, vol. 39(2), pp. 429-443, 2012.
[29] D. J. Howard and C. Gengler, "Emotional contagion effects on product attitudes," *Journal of Consumer Research*, vol. 28(2), pp. 189-201, 2001.
[30] D. Bettiga and L. Lamberti, "Future-oriented happiness: Its nature and role in consumer decision-making for new products," *Frontiers in Psychology*, vol. 11, pp. 528506, 2020.
[31] Y. Lin, D. Yao, and X. Chen, "Happiness begets money: Emotion and engagement in live streaming," *Journal of Marketing Research*, vol. 58(3), pp. 417-438, 2021.
[32] T. Teixeira, M. Wedel, and R. Pieters, "Emotion-induced engagement in internet video advertisements," *Journal of Marketing Research*, vol. 49(2), pp. 144-159, 2012.
[33] P. Cuesta-Valiño, P. Gutiérrez-Rodríguez, and E. Núnez-Barriopedro, "The role of consumer happiness in brand loyalty: A model of the satisfaction and brand

image in fashion," *Corporate Governance: The International Journal of Business in Society*, vol. 22(3), pp. 458-473, 2022.
[34] L. Handley, "The secrets of being a happy brand," *MarketingWeek*, February 5, 2014. [Online]. Available: https://www.marketingweek.com/the-secrets-of-being-a-happy-brand/ [Accessed: April 3, 2024].
[35] L. Dominguez, "Coca-cola launches tiktok-exclusive beverage in latest marketing push," *Consumer Goods Technology*, February 23, 2024. [Online]. Available: https://consumergoods.com/coca-cola-launches-tiktok-exclusive-beverage-latest-marketing-push [Accessed: April 3, 2024].
[36] J. Deyo, "Amazon embraces the joy of friendship for global holiday campaign," *Marketing Dive*, November 7, 2023. [Online]. Available: https://www.marketingdive.com/news/amazon-global-holiday-marketing-campaign-the-beatles/698950/ [Accessed: April 4, 2024].
[37] A. Dange, "BMW Joy Days: Bring home sheer driving pleasure with ease," BMW Group, February 26, 2021. [Press Release]. [Online]. Available: https://www.press.bmwgroup.com/india/article/detail/T0326751EN/bmw-joy-days:-bring-home-sheer-driving-pleasure-with-ease?language=en [Accessed: April 4, 2024].
[38] J. Pijak, "Tech brand happiness initiatives: Lg's 'experience happiness' campaign aims to help youth de-stress," *Trendhunter*, August 27, 2019. [Online]. Available: https://www.trendhunter.com/trends/experience-happiness [Accessed: April 2, 2024].
[39] K. Pendrill, "Furniture brand happiness experiments: Ikea wants to send a 'happiness hunter' to denmark," *Trendhunter*, June 14, 2019. [Online]. Available: https://www.trendhunter.com/trends/happiness-hunter [Accessed: April 4, 2024].
[40] Y. Tsutsui, "Weather and individual happiness," *Weather Climate and Society*, vol. 5(1), pp. 70-82, 2013.
[41] E. C. Malthouse, B. J. Calder, S. J. Kim, and M. Vandenbosch, "Evidence that user-generated content that produces engagement increases purchase behaviours," *Journal of Marketing Management*, vol. 32(5-6), pp. 427-444, 2016.
[42] R. W. Belk, "Situational variables and consumer behavior," *Journal of Consumer Research*, vol. 2(3), pp. 157-164, 1975.
[43] W. Griffit and R. Veitch, "Hot and crowded: Influence of population density and temperature on interpersonal affective behavior," *Journal of Personality and Social Psychology*, vol. 17(1), pp. 92, 1971.
[44] L. Buchheim and T. Kolaska, "Weather and the psychology of purchasing outdoor movie tickets," *Management Science*, vol. 63(11), pp. 3718-3738, 2017.
[45] J.-L. Bertrand and M. Parnaudeau, "Understanding the economic effects of abnormal weather to mitigate the risk of business failures," *Journal of Business Research*, vol. 98, pp. 391-402, 2019.
[46] R. A. Baron and P. A. Bell, "Aggression and heat: The influence of ambient temperature, negative affect, and a cooling drink on physical aggression," *Journal of Personality and Social Psychology*, vol. 33(3), pp. 245-255, 1976.
[47] P. A. Bell and R. A. Baron, "Aggression and ambient temperature: The facilitating and inhibiting effects of hot and cold environments," *Bulletin of the Psychonomic Society*, vol. 9(6), pp. 443-445, 1977.
[48] E. Howarth and M. S. Hoffman, "A multidimensional approach to the relationship between mood and weather," *British Journal of Psychology*, vol. 75(1), pp. 15-23, 1984.

[49] C. A. Anderson, W. E. Deuser, and K. M. DeNeve, "Hot temperatures, hostile affect, hostile cognition, and arousal: Tests of a general model of affective aggression," *Personality and social psychology bulletin*, vol. 21(5), pp. 434-448, 1995.

[50] C. A. Anderson, K. B. Anderson, N. Dorr, K. M. DeNeve, and M. Flanagan, *Temperature and aggression*, in *Advances in experimental social psychology*. 2000, Elsevier. p. 63-133.

[51] M. R. Cunningham, "Weather, mood, and helping behavior: Quasi experiments with the sunshine samaritan," *Journal of Personality and Social Psychology*, vol. 37(11), pp. 1947, 1979.

[52] K. Rehdanz and D. Maddison, "Climate and happiness," *Ecological Economics*, vol. 52(1), pp. 111-125, 2005.

[53] A. Levinson, "Valuing public goods using happiness data: The case of air quality," *Journal of Public Economics*, vol. 96(9-10), pp. 869-880, 2012.

[54] M. Connolly, "Some like it mild and not too wet: The influence of weather on subjective well-being," *Journal of Happiness Studies*, vol. 14(2), pp. 457-473, 2013.

[55] L. Kööts, A. Realo, and J. Allik, "The influence of the weather on affective experience," *Journal of Individual Differences*, vol. 32(2), pp. 74-84, 2011.

[56] J. J. A. Denissen, L. Butalid, L. Penke, and M. A. G. van Aken, "The effects of weather on daily mood: A multilevel approach," *Emotion*, vol. 8(5), pp. 662-667, 2008.

[57] B. V. Bujisic M., Parsa H. G., Jovanovic V., Sukhu A. , "It’s raining complaints! How weather factors drive consumer comments and word-of-mouth," *Journal of Hospitality and Tourism Research*, vol. 43(5), pp. 656-681, 2019.

[58] L. B. Bogomolov A., Ferron M., Pianesi F., Pentland A. *Daily stress recognition from mobile phone data, weather conditions and individual traits*. in *22nd ACM international conference on Multimedia*. 2014.

[59] M. D. Muller, S. M. Muller, C. H. Kim, E. J. Ryan, J. Gunstad, and E. L. Glickman, "Mood and selective attention in the cold: The effect of interval versus continuous exercise," *European Journal of Applied Physiology*, vol. 111(7), pp. 1321-1328, 2011.

[60] T. A. Klimstra, T. Frijns, L. Keijsers, J. J. Denissen, Q. A. Raaijmakers, M. A. Van Aken, H. M. Koot, P. A.C. Van Lier, and W. H. Meeus, "Come rain or come shine: Individual differences in how weather affects mood," *Emotion*, vol. 11(6), pp. 1495, 2011.

[61] P. Nastos, A. Paliatsos, V. Tritakis, and A. Bergiannaki, "Environmental discomfort and geomagnetic field influence on psychological mood in athens, greece," *Indoor and Built Environment*, vol. 15(4), pp. 365-372, 2006.

[62] F. Cecinati, T. Matthews, S. Natarajan, N. McCullen, and D. Coley, "Mining social media to identify heat waves," *International Journal of Environmental Research and Public Health*, vol. 16(5), pp. 19, 2019.

[63] M. R. Sisco, V. Bosetti, and E. U. Weber, "When do extreme weather events generate attention to climate change?," *Climatic Change*, vol. 143(1-2), pp. 227-241, 2017.

[64] X. Chen, Y. Cho, and S. Y. Jang, "Crime prediction using twitter sentiment and weather," in *Proceedings of 2015 Systems and Information Engineering Design Symposium*, IEEE, pp. 63-68, 2015.

[65] H. R. Stevens, P. L. Graham, P. J. Beggs, and I. C. Hanigan, "In cold weather we bark, but in hot weather we bite: Patterns in social media anger, aggressive

behavior, and temperature," *Environment and Behavior*, vol. 53(7), pp. 787-805, 2021.
[66] Y. Cheng, Z. Yu, C. Xu, G. Manoli, X. Ren, J. Zhang, . . . H. Vejre, "Climatic and economic background determine the disparities in urbanites' expressed happiness during the summer heat," *Environmental Science & Technology*, vol. 57(30), pp. 10951-10961, 2023.
[67] L. Brandes and Y. Dover, "Offline context affects online reviews: The effect of post-consumption weather," *Journal of Consumer Research*, vol. 49(4), pp. 595-615, 2022.
[68] O. Zor, K. H. Kim, and A. Monga, "Tweets we like aren't alike: Time of day affects engagement with vice and virtue tweets," *Journal of Consumer Research*, vol. 49(3), pp. 473-495, 2022.
[69] A. Stechemesser, A. Levermann, and L. Wenz, "Temperature impacts on hate speech online: Evidence from 4 billion geolocated tweets from the USA," *Lancet Planetary Health*, vol. 6(9), pp. E714-E725, 2022.
[70] Y. Wang, Y. Yang, S. Huang, L. Huang, and W. J. Sun, "Effects of air quality and weather conditions on chinese tourists' emotional experience," *Journal of Hospitality and Tourism Management*, vol. 48, pp. 1-9, 2021.
[71] S. Martin, D. Wetzelhütter, and B. Grüb, "Do you like me when the sun is shining? The influence of weather and point-in-time on the stakeholder-dialogue in facebook," *International Journal of Energy Sector Management*, vol. 15(3), pp. 578-599, 2021.
[72] J. H. Wang, N. Obradovich, and S. Q. Zheng, "A 43-million-person investigation into weather and expressed sentiment in a changing climate," *One Earth*, vol. 2(6), pp. 568-577, 2020.
[73] S. Zheng, J. Wang, C. Sun, X. Zhang, and M. E. Kahn, "Air pollution lowers chinese urbanites' expressed happiness on social media," *Nature human behaviour*, vol. 3(3), pp. 237-243, 2019.
[74] V. Grasso, A. Crisci, M. Morabito, P. Nesi, and G. Pantaleo, "Public crowdsensing of heat waves by social media data," *Advances in Science and Research*, vol. 14, pp. 217-226, 2017.
[75] L. Curini, S. Iacus, and L. Canova, "Measuring idiosyncratic happiness through the analysis of twitter: An application to the italian case," *Social Indicators Research*, vol. 121, pp. 525-542, 2015.
[76] J. Li, X. Wang, and E. Hovy, "What a nasty day: Exploring mood-weather relationship from Twitter," in *proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management*. 2014.
[77] A. Hannak, E. Anderson, L. F. Barrett, S. Lehmann, A. Mislove, and M. Riedewald, "Tweetin'in the rain: Exploring societal-scale effects of weather on mood," in *Proceedings of the International AAAI Conference on Web and Social Media*. 2012.
[78] K. J. Preacher and A. F. Hayes, "Spss and sas procedures for estimating indirect effects in simple mediation models," *Behavior research methods, instruments, & computers*, vol. 36, pp. 717-731, 2004.
[79] D. G. Muntinga, M. Moorman, and E. G. Smit, "Introducing cobras: Exploring motivations for brand-related social media use," *International Journal of advertising*, vol. 30(1), pp. 13-46, 2011.
[80] C. Binnewies and S. C. Wörnlein, "What makes a creative day? A diary study on the interplay between affect, job stressors, and job control," *Journal of Organizational Behavior*, vol. 32(4), pp. 589-607, 2011.

[81] A. M. Isen, K. A. Daubman, and G. P. Nowicki, "Positive affect facilitates creative problem-solving," *Journal of Personality and Social Psychology*, vol. 52(6), pp. 1122-1131, 1987.
[82] S. Kemp, "Digital 2022: Turkey," *DataReportal*, February 15, 2022. [Online]. Available: https://datareportal.com/reports/digital-2022-turkey?rq=digital%202022%20turkey [Accessed: April 11, 2024].
[83] EVDS Data Central, "Cost of living indices for wage earners-istanbul (1985=100) – cultural, educational and entertainment expenses," Central Bank of the Republic of Türkiye, 2024. [Online]. Available: https://evds2.tcmb.gov.tr/index.php?/evds/searchEvdsValue/QFRQLkZHLkk4QA== [Accessed: April 26, 2024].
[84] TUIK (Turkish Statistical Institute), "Population by province, age group and sex, 2007-2023," 2023. [Online]. Available: https://data.tuik.gov.tr/Bulten/Index?p=Adrese-Dayali-Nufus-Kayit-Sistemi-Sonuclari-2023-49684 [Accessed: April 3, 2024].
[85] TUIK (Turkish Statistical Institute), "*Gross domestic product per capita by provinces, 2004-2022*," 2022. [Online]. Available: https://data.tuik.gov.tr/Bulten/Index?p=Il-Bazinda-Gayrisafi-Yurt-Ici-Hasila-2022-45867 [Accessed: April 3, 2024].
[86] R. B. Cleveland, W. S. Cleveland, J. E. McRae, and I. Terpenning, "STL: A seasonal-trend decomposition procedure based on loess," *Journal of Official Statistics*, vol. 6, pp. 3-73, 1990.
[87] R. J. Slotegraaf and K. Pauwels, "The impact of brand equity and innovation on the long-term effectiveness of promotions," *Journal of Marketing Research*, vol. 45(3), pp. 293-306, 2008.
[88] F. J. Fabozzi, S. M. Focardi, S. T. Rachev, and B. G. Arshanapalli, *The Basics of financial Econometrics: Tools, Concepts, and Asset Management Applications*. John Wiley & Sons, 2014.
[89] R. S. Tsay, *Analysis of Financial Time Series*. John Wiley & Sons, 2005.
[90] A. F. Hayes, *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. Second Edition. New York: The Guilford Press, 2018.
[91] M. B. Ataman, H. J. Van Heerde, and C. F. Mela, "The long-term effect of marketing strategy on brand sales," *Journal of Marketing Research*, vol. 47(5), pp. 866-882, 2010.
[92] Y. Bahng and D. H. Kincade, "The relationship between temperature and sales: Sales data analysis of a retailer of branded women's business wear," *International Journal of Retail & Distribution Management*, vol. 40(6), pp. 410-426, 2012.
[93] B. Schivinski, G. Christodoulides, and D. Dabrowski, "Measuring consumers' engagement with brand-related social-media content: Development and validation of a scale that identifies levels of social-media engagement with brands," *Journal of advertising research*, vol. 56(1), pp. 64-80, 2016.
[94] S. Bruyneel, S. Dewitte, P. H. Franses, and M. G. Dekimpe, "Why consumers buy lottery tickets when the sun goes down on them. The depleting nature of weather-induced bad moods," *ERIM Report Series*, Reference No. ERS-2005-045-MKT. SSRN, December 15, 2005. Available: https://ssrn.com/ abstract=870245.
[95] N. Clemmons, "It's crazy hot': South florida business owners weather the impacts of extreme heat," *NBC 6 South Florida*, August 9, 2023. [Online]. Available: https://www.nbcmiami.com/news/local/its-crazy-hot-south-florida-business-

owners-weather-the-impacts-of-extreme-heat/3088295/ [Accessed: April 3, 2024].
[96] NASA Earth Observatory, "World of change: Global temperatures", 2024. [Online]. Available: https://earthobservatory.nasa.gov/world-of-change/global-temperatures [Accessed: March 11, 2024].
[97] N. W. Arnell, J. A. Lowe, A. J. Challinor, and T. J. Osborn, "Global and regional impacts of climate change at different levels of global temperature increase," *Climatic Change*, vol. 155, pp. 377-391, 2019.
[98] P. Cohen, "The economic fallout from extreme heat will rise over time," *The New York Times*, July 18, 2023. [Online]. Available: https://www.nytimes.com/2023/07/18/business/extreme-heat-economy.html#:~:text=Among%20the%20costs%20of%20very,trade%%2020disruption%20and%20dampened%20investment [Accessed: April 4, 2024].
[99] J. Worland, "Extreme heat is hitting companies where it hurts," *TIME*, July 13, 2023. [Online]. Available: https://time.com/6294411/extreme-heat-impacting-companies-economy/ [Accessed: April 3, 2024].
[100] J. Bogage and E. Tan, "Forcing people to work in deadly heat is mostly legal in the U.S.," *The Washington Post*, July 14, 2023. [Online]. Available: https://www.washingtonpost.com/business/2023/07/14/heat-workers-osha-protections/ [Accessed: April 5, 2024].
[101] J. Heniff, "Extreme heat affects workers in many ways, both long- and short-term," *Industrial Safety & Gygiene News*, April 14, 2022. [Online]. Available: https://www.ishn.com/articles/113306-extreme-heat-affects-workers-in-many-ways-both-long--and-short-term#:~:text=Workplace%20%20Training%20Strategies-,Extreme%20heat%20affects%20workers%20in%20many,both%20%20long%2D%20and%20short%2Dterm&text=Dripping%20beads%20of%20sweat%20and,body%20systems%20than%20we%20realized [Accessed: April 5, 2024].
[102] K.-Y. Goh, C.-S. Heng, and Z. Lin, "Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content," *Information systems research*, vol. 24(1), pp. 88-107, 2013.
[103] A. Kumar, R. Bezawada, R. Rishika, R. Janakiraman, and P. Kannan, "From social to sale: The effects of firm-generated content in social media on customer behavior," *Journal of Marketing*, vol. 80(1), pp. 7-25, 2016.
[104] H. Shahbaznezhad, R. Dolan, and M. Rashidirad, "The role of social media content format and platform in users' engagement behavior," *Journal of Interactive Marketing*, vol. 53(1), pp. 47-65, 2021.
[105] A. R. Saboo, V. Kumar, and G. Ramani, "Evaluating the impact of social media activities on human brand sales," *International Journal of Research in Marketing*, vol. 33(3), pp. 524-541, 2016.
[106] J. Berger, W. W. Moe, and D. A. Schweidel, "What holds attention? Linguistic drivers of engagement," *Journal of Marketing*, vol. 87(5), pp. 793–809, 2023.
[107] S. Phithakkitnukoon, T. W. Leong, Z. Smoreda, and P. Olivier, "Weather effects on mobile social interactions: A case study of mobile phone users in lisbon, portugal," *PLoS ONE*, 7 (10), e45745, 2012.
[108] M. J. Pelletier, A. Krallman, F. G. Adams, and T. Hancock, "One size doesn't fit all: A uses and gratifications analysis of social media platforms," *Journal of Research in Interactive Marketing*, vol. 14(2), pp. 269-284, 2020.
[109] P. C. Verhoef, K. H. Pauwels, and M. A. Tuk, "Assessing consequences of component sharing across brands in the vertical product line in the automotive

market," *Journal of Product Innovation Management*, vol. 29(4), pp. 559-572, 2012.

[110] M. Burke, S. M. Hsiang, and E. Miguel, "Climate and conflict," *Annual Review of Economics*, vol. 7(1), pp. 577-617, 2015.

[111] M. R. Busse, D. G. Pope, J. C. Pope, and J. Silva-Risso, "The psychological effect of weather on car purchases," *The Quarterly Journal of Economics*, vol. 130(1), pp. 371-414, 2015.

[112] M. Conlin, T. O'Donoghue, and N. J. Vogelsang, "Projection bias in catalog orders," *American Economic Review*, vol. 97(4), pp. 1217-1249, 2007.

[113] C. Cen, S. Cheng, and N. H. Wong, "Effect of elevated air temperature and air velocity on thermal comfort and cognitive performance in the tropics," *Building and Environment*, vol. 234, pp. 110203, 2023.

[114] N. Gaoua, J. Grantham, S. Racinais, and F. El Massioui, "Sensory displeasure reduces complex cognitive performance in the heat," *Journal of Environmental Psychology*, vol. 32(2), pp. 158-163, 2012.

[115] T. M. Mäkinen, L. A. Palinkas, D. L. Reeves, T. Pääkkönen, H. Rintamäki, J. Leppäluoto, and J. Hassi, "Effect of repeated exposures to cold on cognitive performance in humans," *Physiology & Behavior*, vol. 87(1), pp. 166-176, 2006.

[116] K. W. Tham and H. C. Willem, "Room air temperature affects occupants' physiology, perceptions and mental alertness," *Building and Environment*, vol. 45(1), pp. 40-44, 2010.

[117] J. M. Carlsmith and C. A. Anderson, "Ambient temperature and the occurrence of collective violence: A new analysis," *Journal of Personality and Social Psychology*, vol. 37(3), pp. 337-344, 1979.

[118] L. Tong, R. Zhu, Y. Zheng, and P. Zhao, "Warmer or cooler: The influence of ambient temperature on complex choices," *Marketing Letters*, vol. 29, pp. 337-350, 2018.

[119] S. L. Joslyn and M. A. Grounds, "The use of uncertainty forecasts in complex decision tasks and various weather conditions," *Journal of Experimental Psychology: Applied*, vol. 21(4), pp. 407-417, 2015.

[120] R. Hadi and L. Block, "Warm hearts and cool heads: Uncomfortable temperature influences reliance on affect in decision-making," *Journal of the Association for Consumer Research*, vol. 4(2), pp. 102-114, 2019.

[121] P. Kolb, C. Gockel, and L. Werth, "The effects of temperature on service employees' customer orientation: An experimental approach," *Ergonomics*, vol. 55(6), pp. 621-635, 2012.

[122] U. Simonsohn, "Clouds make nerds look good: Field evidence of the impact of incidental factors on decision making," *Journal of Behavioral Decision Making*, vol. 20(2), pp. 143-152, 2007.

[123] S. L. Watkins, P. Castle, A. R. Mauger, N. Sculthorpe, N. Fitch, J. Aldous, . . . L. Taylor, "The effect of different environmental conditions on the decision-making performance of soccer goal line officials," *Research in Sports Medicine*, vol. 22(4), pp. 425-437, 2014.

[124] C. Federspiel, W. Fisk, P. Price, G. Liu, D. Faulkner, D. Dibartolomeo, D. P. Sullivan, and M. Lahiff, "Worker performance and ventilation in a call center: Analyses of work performance data for registered nurses," 2004. [Online]. Available: https://escholarship.org/uc/item/8rn715gj [Last accessed: May 5, 2024].

[125] L. Lan, Z. W. Lian, and L. Pan, "The effects of air temperature on office workers' well-being, workload and productivity-evaluated with subjective ratings," *Applied Ergonomics*, vol. 42(1), pp. 29-36, 2010.

[126] X. Huang, M. Zhang, M. K. Hui, and R. S. Wyer, "Warmth and conformity: The effects of ambient temperature on product preferences and financial decisions," *Journal of Consumer Psychology*, vol. 24(2), pp. 241-250, 2014.

[127] X. J. Bao and Q. L. Fan, "The impact of temperature on gaming productivity: Evidence from online games," *Empirical Economics*, vol. 58(2), pp. 835-867, 2020.

[128] M. R. Hu and A. D. Lee, "Outshine to outbid: Weather-induced sentiment and the housing market," *Management Science*, vol. 66(3), pp. 1440-1472, 2020.

[129] S. M. Hsiang, M. Burke, and E. Miguel, "Quantifying the influence of climate on human conflict," *Science*, vol. 341(6151), pp. 1235367, 2013.

[130] V. Mittal, W. A. Kamakura, and R. Govind, "Geographic patterns in customer service and satisfaction: An empirical investigation," *Journal of Marketing*, vol. 68(3), pp. 48–62, 2004.

[131] G. J. Tellis, S. Stremersch, and E. Yin, "The international takeoff of new products: The role of economics, culture, and country innovativeness," *Marketing Science*, vol. 22(2), pp. 188-208, 2003.

[132] J. M. Schmittmann, J. Pirschel, S. Meyer, and A. Hackethal, "The impact of weather on german retail investors," *Review of Finance*, vol. 19(3), pp. 1143-1183, 2015.

[133] A. Khanthavit, "Investors' weather-related moods and the stock market," *Human Behavior, Development and Society*, vol. 19, pp. 7-15, 2018.

[134] S. C. Yap, J. Wortman, I. Anusic, S. G. Baker, L. D. Scherer, M. B. Donnellan, and R. E. Lucas, "The effect of mood on judgments of subjective well-being: Nine tests of the judgment model," *Journal of Personality and Social Psychology*, vol. 113(6), pp. 939, 2017.

[135] H. L. Berry, K. Bowen, and T. Kjellstrom, "Climate change and mental health: A causal pathways framework," *International journal of public health*, vol. 55, pp. 123-132, 2010.

[136] C. Li, X. Luo, C. Zhang, and X. Wang, "Sunny, rainy, and cloudy with a chance of mobile promotion effectiveness," *Marketing Science*, vol. 36(5), pp. 762-779, 2017.

[137] R. Sudo, S. F. Nakashima, M. Ukezono, Y. Takano, and J. Lauwereyns, "The role of temperature in moral decision-making: Limited reproducibility," *Frontiers in Psychology*, vol. 12, pp. 681527, 2021.

[138] X. Wei, J. Li, H. Liu, and J. Wan, "Temperature and outdoor productivity: Evidence from professional soccer players," *Journal of Asian Economics*, vol. 87, pp. 101622, 2023.

[139] R. Govind, N. Garg, and W. Sun, "Geographically varying effects of weather on tobacco consumption: Implications for health marketing initiatives," *Health Marketing Quarterly*, vol. 31(1), pp. 46-64, 2014.

[140] C. Zhang, H. Liao, F.-Z. Wang, and R. Li, "Ambient temperature and food behavior of consumer: A case study of china," *Weather, Climate, and Society*, vol. 13(4), pp. 813-822, 2021.

[141] R. Niemelä, M. Hannula, S. Rautio, K. Reijula, and J. Railio, "The effect of air temperature on labour productivity in call centres—a case study," *Energy and buildings*, vol. 34(8), pp. 759-764, 2002.

[142] J. J. Pilcher, E. Nadler, and C. Busch, "Effects of hot and cold temperature exposure on performance: A meta-analytic review," *Ergonomics*, vol. 45(10), pp. 682-698, 2002.
[143] J. Steinmetz and A.-C. Posten, "Physical temperature affects response behavior," *Journal of Experimental Social Psychology*, vol. 70, pp. 294-300, 2017.
[144] M. Bujisic, V. Bogicevic, and H. Parsa, "The effect of weather factors on restaurant sales," *Journal of Foodservice Business Research*, vol. 20(3), pp. 350-370, 2017.
[145] B. Rind and D. Strohmetz, "Effect of beliefs about future weather conditions on restaurant tipping," *Journal of Applied Social Psychology*, vol. 31(10), pp. 2160-2164, 2001.
[146] N. S. Arunraj and D. Ahrens, "A hybrid seasonal autoregressive integrated moving average and quantile regression for daily food sales forecasting," *International Journal of Production Economics*, vol. 170, pp. 321-335, 2015.
[147] J.-L. Bertrand, X. Brusset, and M. Fortin, "Assessing and hedging the cost of unseasonal weather: Case of the apparel sector," *European Journal of Operational Research*, vol. 244(1), pp. 261-276, 2015.
[148] M. Starr, "The effects of weather on retail sales," *SSRN*, January 12, 2000. [Online]. Available: http://dx.doi.org/10.2139/ssrn.221728 [Last accessed: May 5, 2024].
[149] F. Badorf and K. Hoberg, "The impact of daily weather on retail sales: An empirical study in brick-and-mortar stores," *Journal of Retailing and Consumer Services*, vol. 52, pp. 101921, 2020.
[150] B. Keleş, P. Gómez-Acevedo, and N. I. Shaikh, "The impact of systematic changes in weather on the supply and demand of beverages," *International Journal of Production Economics*, vol. 195, pp. 186-197, 2018.
[151] S. Moon, J. Kwon, S.-U. Jung, and Y. H. Bae, "The impact of individual differences in weather sensitivity on weather-related purchase intentions," *International Journal of Market Research*, vol. 60(1), pp. 104-117, 2018.
[152] A. G. Parsons, "The association between daily weather and daily shopping patterns," *Australasian Marketing Journal (AMJ)*, vol. 9(2), pp. 78-84, 2001.
[153] M. Cao and J. Wei, "Stock market returns: A note on temperature anomaly," *Journal of Banking & Finance*, vol. 29(6), pp. 1559-1573, 2005.
[154] S. H. Kang, Z. Jiang, Y. Lee, and S.-M. Yoon, "Weather effects on the returns and volatility of the shanghai stock market," *Physica A: Statistical Mechanics and its Applications*, vol. 389(1), pp. 91-99, 2010.
[155] J. Feddersen, R. Metcalfe, and M. Wooden, "Subjective wellbeing: Why weather matters," *Journal of the Royal Statistical Society Series A: Statistics in Society*, vol. 179(1), pp. 203-228, 2016.
[156] M. Agnew and J. P. Palutikof, "Impacts of short-term climate variability in the uk on demand for domestic and international tourism," *Climate Research*, vol. 31(1), pp. 109-120, 2006.
[157] C. Toeglhofer, R. Mestel, and F. Prettenthaler, "Weather value at risk: On the measurement of noncatastrophic weather risk," *Weather, Climate, and Society*, vol. 4(3), pp. 190-199, 2012.
[158] H. A. Aaheim and K. E. Hauge, "Impacts of climate change on travel habits," *CICERO Center for International Climate and Environmental Research*, vol. 7, 2005. Available: http://hdl.handle.net/11250/191992.

[159] T. Horanont, S. Phithakkitnukoon, T. W. Leong, Y. Sekimoto, and R. Shibasaki, "Weather effects on the patterns of people's everyday activities: A study using gps traces of mobile phone users," *Plos One*, vol. 8(12), pp. e81153, 2013.
[160] C. Liu, Y. O. Susilo, and A. Karlström, "Examining the impact of weather variability on non-commuters' daily activity–travel patterns in different regions of sweden," *Journal of Transport Geography*, vol. 39, pp. 36-48, 2014.
[161] C. Liu, Y. O. Susilo, and A. Karlström, "Measuring the impacts of weather variability on home-based trip chaining behaviour: A focus on spatial heterogeneity," *Transportation*, vol. 43, pp. 843-867, 2016.
[162] R. An, R. Zahnow, D. Pojani, and J. Corcoran, "Weather and cycling in new york: The case of citibike," *Journal of Transport Geography*, vol. 77, pp. 97-112, 2019.
[163] R. B. Chen and H. S. Mahmassani, "Let it rain: Weather effects on activity stress and scheduling behavior," *Travel behaviour and society*, vol. 2(1), pp. 55-64, 2015.

VITA

Işıl Büdeyri Turan is a graduate of American Robert College and received her Bachelor of Arts (BA) degree in International Relations from Istanbul University, Istanbul, Türkiye, in 2003. She completed her first Master of Arts (MA) degree in European Integration from the University of Essex, Colchester, United Kingdom, in 2005, attaining Jean Monnet Scholarship. She received her second MA degree in Production Management and Marketing from Marmara University, Istanbul, Türkiye, in 2011. She has worked in leading marketing research agencies in Türkiye. Throughout her employment, she has held executive roles involving account management, team management, project management, and sales. She possesses experience in utilizing brand tracking and health, advertising research (including advertising effectiveness and pre-posttests), A/B testing involving product, concept, and packaging tests, claim tests, usage and attitude surveys, in-store excellence research, and customer and employee satisfaction research. With over 10 years of expertise in account management, she has worked across various sectors including fast-moving consumer goods (FMCG), telecommunications, white goods, small home appliances, and banking and finance sectors. She started her Ph.D. education at Özyeğin University Graduate School of Business, in 2018, with a specialization in Quantitative Marketing and Modeling under the supervision of Prof. Dr. M. Tolga Akçura. During her Ph.D. study, she has been teaching assistant to undergraduate courses such as Marketing, Consumer Behavior, Consumption in the Digital Age, Brand Management, Fundamentals of Business, Introduction to Business II-Entrepreneurship, Organizations, and Strategic Management. She is also a certified

Business Management teacher in the International Baccalaureate Diploma Program. She has represented Özyeğin University in distinguished marketing conferences such as ISMS Marketing Science Conference (2021, 2022, 2023), European Marketing Academy Conferences (EMAC; Regional 2019, Annual 2022), and Marketing Dynamics conference (2022), presenting her academic work. She possesses Doctoral Consortium Honors attained in 2022 and 2023 ISMS Marketing Science Conferences. She has two publications, and research interests in social media engagement, branding, advertising, and artificial intelligence, and employs an extensive range of methodologies involving time-series analysis, vector autoregression models, machine learning, experimental and qualitative research.