THESIS

SWEET PERSUASION: DECODING CGM APPS' STRATEGIES ON INSTAGRAM IN THE AGE OF HEALTH AND WELLNESS

Submitted by

Vybhavi Krishna Gopalakrishna Anuradha

Department of Journalism and Media Communication

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Summer 2024

Master's Committee:

Advisor: Gayathri Sivakumar

Samuel Tham
David Most

ABSTRACT

SWEET PERSUASION: DECODING CGM APPS' STRATEGIES ON INSTAGRAM IN THE AGE OF HEALTH AND WELLNESS

The study investigates how Continuous Glucose Monitor (CGM) companies are now expanding beyond diabetes management. They are expanding their horizons to include non-diabetes individuals who are struggling with weight management, and this new development is reflected in their Instagram messaging strategies. Psychological phenomena derived from social cognitive theory, such as observational learning, forethought, self-efficacy, and other content strategies suggested from Hubspot reports, like the format of the post, caption length, and the time of the post, are used to engage the audience on the platform. Nutrisensio, Levels, and January AI's Instagram posts and their engagement rates are used to conduct a quantitative content analysis. The findings prove the presence of these strategies and suggest techniques that can be used in health tech Instagram accounts to make better connections with the audience.

TABLE OF CONTENTS

LIST OF TABLES

INTRODUCTION

1.1 Overviews and Rationales

Instagram has gradually become a powerful tool for health communication and influencing lifestyle behaviors. The research focuses on the Instagram accounts of apps that sync with continuous glucose monitors (CGM), which are traditionally used in diabetes care. A continuous glucose monitor (CGM) is a wearable device that measures the blood sugar level in the body over 24 hours a day (*Continuous Glucose Monitoring - NIDDK*, n.d.). With the advancement of technology and pharmaceuticals, diabetes is more of a metabolic disease you can manage by lifestyle modification than an irreversible chronic condition; this notion and perspective contribute to how non-diabetes people adopt diabetes care to manage their lifestyle problems involving food and nutrition, weight management issues, and hormonal balance (White et al., 2018). People without diabetes are now trying or planning on adopting a healthy lifestyle using CGM to monitor their sugar levels constantly (Klonoff et al., 2022). This trend, which started with the diabetes drug Ozempic, encouraged other diabetes management players to expand.

This phenomenon is analyzed by applying social cognitive theory (SCT) to those Instagram messages, especially using concepts like observational learning, where people learn skills by observing others using CGM self-efficacy, which promotes people's belief that they are capable of taking charge of their health using CGM and forethought, which taps into the expected outcome of using CGM. These concepts are also studied further to see whether they create enough engagement, meaning the content resonates with the audience. It also analyzes digital content strategies like the type of post format, length of the caption, and post time associated with a higher engagement rate. All these analyses give us insights into how people react and behave toward the CGM app's intentions to develop broader content that talks to diabetes and non-diabetes individuals.

By studying messaging strategies, this research contributes to the broader understanding of how health-based information is promoted on social media platforms; this helps other researchers study digital communication. Discovering the impacts of SCT's concepts and content strategy on user engagement in the platform helps develop effective health communication campaigns by collecting user behavior data to better understand what content works for what type of audience. Any health professionals and social media marketers could use these insights. The academic significance of this research is also achieved since the study is the intersection of social cognitive theory and user engagement on social media, especially from a health perspective, which is a fresh and unique study, and other researchers could use this as a point of reference for further studies involving these concepts.

Limited research discusses the messaging strategies on Instagram utilized by CGM apps to position themselves as health and wellness management. There is also a need for more insights into whether those messaging strategies engage the users. This research seeks to bridge these two gaps. The study contributes to understanding social media's effects on behavioral change and recognizing how users engage with the health and lifestyle information on the platform.

1.2 Goal and Research Questions

The research aims to establish the foundation for creating communication models for digital health promotion. It also proves the applicability of social cognitive theory in health campaigns to find better and more effective strategies to communicate fact-based health information to engage the users. Another goal of this research is to uncover the techniques that are used by CGM apps to expand their horizons for non-diabetic individuals.

The following research questions and hypotheses guide the present research:

RQ1: What messaging strategies are often used by CGM apps on Instagram?

RQ2: Which of the messaging strategies creates significant user engagement?

H1. Video posts have a higher engagement rate compared to carousel posts.

H2. Posts with captions length of less than 20 characters have a higher engagement rate than posts with more than 20 characters.

H3. The engagement rate is higher in the content that is posted after 8 p.m. compared to posts before 8 p.m.

H4: Instagram posts with one or more elements, including observational learning, forethought, and self-efficacy, drive significant user engagement on the platform compared to posts without any of those elements.

A quantitative content analysis method is used to examine this. A sample of Instagram posts with the caption are studied.

1.3 Organization of the Thesis

The flow of the thesis is in this order: Chapter 2 is the literature review that explains what a continuous glucose monitor and its history and technology, the current market for the device, the trend of non-diabetes people using CGM, and the new expansion of CGM industry then it also explains health messaging strategies on Instagram and why do we need engagement metrics and the factors that influence the engagement then finally it describes how we are looking at all these from social cognitive theory perspective and the concepts and variables that are derived from that theory. Chapter 3 is the methods section, which discusses the quantitative content analysis, the nominal scales and samples, the scrapping method to collect the data, and the measures used to establish the reliability and validity of this study. Chapter 4 explains the data analysis that was conducted and what were their results. Chapter 5 provides a detailed discussion of the results and which mention the overall limitation of this project, the inferences that can be made using the results, and the recommendations for future research in this background.

LITERATURE REVIEW

2.1 CGM History

Diabetes can be defined as a chronic illness caused by an unusual increase in the body's sugar level, which can damage the heart, eyes, kidneys, and blood vessels (Zafar et al., 2022). Diabetes can sometimes be life-threatening if you do not monitor your blood sugar level properly. CGM are the devices that measure the blood glucose level every few minutes day and night (*Continuous Glucose Monitoring - NIDDK*, n.d.) Painless self-monitoring of the glucose levels for individuals affected by diabetes has given a sense of control over the disease and life, Thanks to the invention of CGM systems.

The earliest method to study diabetes is through urine examination, but most of the time, the examination only occurs when the diabetes patient is near death (Olczuk & Priefer, 2018). In the 1920s, insulin became a widely popular method, injecting pancreas extract into diabetes patients, but there was no standard way to measure a patient’s blood glucose levels before injecting (Olczuk & Priefer, 2018). In 1925, home testing for sugar in urine was introduced, followed by the 1940s “dip-and-read” urine test and then the Combur Test in 1964 (Olczuk & Priefer, 2018).

The main limitation of these methods was that they were inconvenient to use regularly. It was very challenging to read the blood sugar levels and make conclusions from them because the levels were what was being excreted versus the level of the blood sugar present in the blood (Olczuk & Priefer, 2018). All these methods showed patients many benefits in measuring the blood sugars in their bodies, and this information started to spread worldwide, eventually increasing the demand for those devices in the diabetes market (Olczuk & Priefer, 2018).

Dextrostix became the first blood sugar test strip that laid the foundations for diabetes treatment through blood glucose meters (Olczuk & Priefer, 2018). This led to the beginning of the blood glucose biosensor system(Olczuk & Priefer, 2018), where blood glucose is administered through self-monitoring systems for diabetes management. In 1999, the first-ever CGM was approved by the FDA for people diagnosed with diabetes (Innovation Milestones, 2012).

With the new popularity of CGM technologies, diabetes care looks promising for patients. Various technologies, from urine tests to CGM systems, have been invented to assist patients suffering from diabetes. To help them test the blood sugar levels in their body and make necessary changes to control chronic illness.

2.2 CGM Technology

As mentioned before, regular glucose monitoring is critical for diabetes 1 and 2 management. There are three techniques for monitoring and measuring the blood sugar in the body, i.e., invasive, minimally invasive, and non-invasive techniques. Finger-prick is the standard invasive method using test strips and a glucometer. Minimally invasive and non-invasive methods extract biological fluids from the body, like interstitial fluids, tears, and saliva, and measure the glucose concentration (Zafar et al., 2022). Continuous glucose monitors (CGM) measure blood sugars minimally and non-invasively.

Interstitial fluid monitors evaluate the interstitial glucose for 24 hours, provide real-time data, and have shown benefits in managing diabetes (Mian et al., 2019). This type of CGM contains three parts: sensors, which stick to your skin; transmitter, and the app in your phone acts as a receiver; the tiny sensor which is attached to the skin has a sticky patch to stay there for a few weeks that estimates the glucose level in the fluid then the transmitter in the device sends that information to the app in your phone (*Continuous Glucose Monitoring - NIDDK*, n.d.).

In 2015, secondary transmitters like Dexcom Share and MiniMed Connect were released, which were essential compatibility features of CGM with mobile devices (Didyuk et al., 2021). These accessories work with the company-released mobile app, which lets users see their glucose levels without carrying a separate receiver (Didyuk et al., 2021). Future research technology for CGM systems includes artificial pancreas by linking CGM devices with automated insulin dosing systems, and these new developments can lead to less expensive CGM gadgets (Didyuk et al., 2021).

According to NIH (*Continuous Glucose Monitoring - NIDDK*, n.d.), Some of the unique features of these monitors are that they track the physical activity and food, beverages, and medicine that you consume; you can see all the data trends directly in your phone, and there is an alarm that goes off to indicate the high and low blood sugar levels. Due to CGM, medical providers and patients have up-to-date information about blood sugar fluctuations, which is monitored every 5 minutes; this gives an in-depth knowledge of any unique individual's glucose levels (Olczuk & Priefer, 2018). CGM can improve the quality of life of patients by preventing any complications of diabetes before its occurrence and also reducing the cost burden of diabetes management in the US healthcare system (Olczuk & Priefer, 2018).

CGM devices have transformed the lives of diabetes patients. It has led to the empowerment of patients who are struggling with diabetes management. Awareness about glucose levels impacts lifestyle choices. Immediate sensor feedback can allow patients to alter their diet and activity in real-time. Making informed decisions through CGM data reduces stress and pressure by knowing they will get prompt alerts from the sensors when necessary.

2.3 The CGM Market

Numerous companies manufacture these monitors and sell them to third-party apps to sync with their applications. The global CGM market is estimated to be valued at US$ 8,865.65 million in 2022 (Coherent Market Insights, 2023). Currently available CGM are manufactured by Medtronic, Dexcom, Abbott diabetes care, Senseonics, Tandem (Didyuk et al., 2020). Some companies directly sell to patients, and others to third-party apps. The CGM apps provide an online platform where individuals can connect the sensors and get real-time data. Interested patients can directly access these CGM apps. They fill out a form with or without a prescription for CGM, and the physician at these apps further decides if an individual needs a CGM. Third-party apps do not manufacture their sensors but adapt them from big players like Dexcom or Abbott.

A research study conducted in 2004 discusses the marketplace of the 40 blood glucose meters available back then (Newman & Turner, 2005). It said the companies were trying to accomplish two objectives: maintaining the current market share and expanding themselves to include the new users. The large companies went with acquisition rather than innovation to satisfy these objectives, where the technology was sold with a new outer package with aggressive marketing campaigns (Newman & Turner, 2005). Introducing the electrochemical biosensors increased the campaign and the market share of LifeScan and Roche Diagnostics, which led to other players offering glucose monitoring (Newman & Turner, 2005). Another study conducted in 2017 performed a SWOT analysis of the wearable devices market in the health industry (Casselman et al., 2017). The study results indicated that CGM systems have a tremendous opportunity for health monitoring for individuals suffering from chronic illness.

2.4 CGM for People without diabetes

A new trend is emerging that people without diabetes are using the CGM to track their glucose concentration (Klonoff et al., 2022). Individuals who want better health by increasing activity, changing their nutrition intake and sleep patterns, and motivating themselves for sustained healthy behavioral change can achieve these goals through constant monitoring and adapting healthy measures during high and low blood sugar levels (Klonoff et al., 2022). CGM provides instant feedback on their overall behaviors.

According to (Klonoff et al., 2022), the applications of CGM beyond diabetes can be divided into four sections, i.e., metabolic diseases, non-metabolic diseases, health and well-being, and elite athletics. Metabolic diseases, such as obesity, are primarily dysregulated of the insulin glucose axis. CGM monitors can help support people who have obesity with portion control, timing, and food quality (Klonoff et al., 2022). Health and well-being talk about healthy behaviors by avoiding emotional eating and processed foods, and the app can act as a cue and impulse control by giving constant feedback (Klonoff et al., 2022). Other benefits include food timing, sequencing, and knowing what triggers the blood glucose to shoot up. Research has provided data to characterize the effects of exercise and meals on glucose by using CGM on healthy individuals without diabetes (Dubose, 2021). Over time, this approach can support the weight management goals that the individuals have by decreasing their constant stress, tailoring their dietary choices, and empowering them to make informed decisions.

Doctors are awaiting research and data to recommend these CGM, but still, this equipment can appeal to those relying on self-managing healthy behaviors (Klonoff et al., 2022). The potential drawbacks of using CGM for people without diabetes are the cost, skin trauma, absence of standards for defining abnormal values, and absence of standards for responding to that abnormal value (Klonoff et al., 2022). There is also limited research on people with eating disorders using CGM (Presseller et al., 2020). The US Food and Drug Administration (FDA) regulates these devices. FDA has recognized the use of these devices for promoting a healthy lifestyle and concluded that they are of low risk and hence, it is not worth spending the FDA's limited resources on regulating such devices (Klonoff et al., 2022).

Given numerous motivations to adopt healthy habits, individuals constantly search for new means to help them achieve their health goals in one way or another. By adapting CGM devices, people without diabetes can enjoy the benefits the systems offer without much to lose. Even though it is new, this trend is here to stay.

2.5 Expanding Horizons

Since the start of the pandemic in 2019, people have been trying new and different ways to stay healthy, and the most significant trend was using diabetes care medicines, which had the effects of weight loss. Moreover, this phenomenon is referred to as Hollywood's expensive, slim, fast diet (Archive & feed, 2022). Elon Musk publicly proclaimed that the secret to his weight loss was the diabetes drug Wegovy, which is used for chronic weight management in adults with type 2 diabetes (Archive & feed, 2022). After the speculations that the same drug was also used by Kim Kardashian and a few of the TikTok influencers sharing the benefits of the diabetes drug, it went viral (Archive & feed, 2022).

Ozempic is a diabetes drug approved by the FDA in 2017 (MD, 2023). One side effect of the drug shown in the clinical tests was that people nearly lost 10 pounds over 30 weeks (MD, 2023). These unintended side effects turned into a selling point for Ozempic (MD, 2023). The Ads of Ozempic did not call it a side effect but lists it under the benefits column along with blood sugar control and lower cardiovascular risk (MD, 2023). In 2021, they renamed the drug Wegovy and received FDA approval for people with obesity and medical problems with excess weight (MD, 2023). The only difference between Wegovy and Ozempic is that Wegovy has a higher dose of semaglutide (MD, 2023). The medicines approved in the US for specific uses can also be used as off-label prescriptions (Bodie, 2021), meaning people without medical reasons can also use the drug to lose weight.

With the increased demand for diabetes drugs for their newfound benefit, people seek physicians to prescribe them off-label or buy them online (Blum, 2022). This led to a 29% increase in sales in the first six months of 2023 for Novo Nordisk, which produces both Ozempic and Wegovy (Bushard, 2023). It is also expected that sales will go up 33% in the next year (Bushard, 2023).

The increased demand for diabetes medicines has caused a massive problem for diabetes people to receive the medicine. Novo Nordisk said in a statement that the sudden surge has created a massive shortage of drug production, and it may continue shortly (Goodman, 2022). Another challenge is the side effects of using diabetes medicine as a weight loss technique. The side effects include and are not limited to malnutrition, aging of the face, diarrhea, fatigue, and severe vomiting (Blum, 2022).

All these new developments involving diabetes care used widely beyond the disease have allowed other players in the diabetes industry to expand, including CGM apps. These apps have publicly written instructions and articles on their website on how people without diabetes can use CGM. The bio in the Instagram accounts of a few apps is labeled as “Health and Wellness,” which does not have to be the products for just diabetes patients trying to monitor their glucose levels. However, any individual who wants to get healthier or know more about their blood sugar level fluctuation, which directly affects their mood and overall health, can use the monitors.

The diabetes industry has expanded its horizons into not just diabetes care but also positioning itself as a Health and Wellness industry. Multiple factors have driven this transformation, which started with Ozempic and Wegovy. The increased demand and new technological innovations have been reflected in some of the CGM app's strategic branding. This significant shift in the healthcare sector ensures leverage for CGM apps beyond diabetes management.

2.6 Health Messaging Strategies on Instagram

Starting during covid 19, social media has become an essential tool for sharing health information (Malik et al., 2021). People with or without diabetes who are interested in CGM are health consumers. Understanding health consumers' behavior is one of the biggest challenges and requires ongoing monitoring of strategies for any social media platforms (Cordoş et al., 2017). As an image-based platform, Instagram is well-suited for sharing images, infographics, and videos regarding public health (Malik et al., 2021). Messaging strategy in Instagram can be defined as how the creators visually and verbally present their information to their social media audience who follow, see, and visit their Instagram account.

Crafting messages that resonate with the target users on the platform is essential because this is the information the users will get exposed to when they intentionally or unintentionally search for lifestyle or health information. Research shows how CDC and WHO's Instagram accounts were active, engaging, and effective during the pandemic (Malik et al., 2021). Instagram has enormous potential to help health professionals share and reach users to disseminate evidence-based health and nutrition information (Hoare et al., 2022).

Through Instagram affordances, you can holistically share your story, insight, and experience with millions of users on any lifestyle topic or issues like exercise, nutrition, obesity, sleep, etc.

Instagram is a powerful space for disseminating weight loss information (S. E. Velasquez, 2021). Sharing pictures of your food can help build a community and support from people on the same journey. Posting images of what they eat can have accountability and lead to higher adherence (S. E. Velasquez, 2021). The diet culture that the users get exposed to on Instagram by numerous nutritionists, influencers, and trainers can have positive, valuable information but also lead to extreme dieting and unrealistic expectations. Those positive or adverse effects can be seen in all genders and age limits. All the curated images of beauty and physique influence how we look at our bodies. Since beauty equals likeability in social media, users are made to think like, and heart buttons tell how attractive an individual is (Stein et al., 2021).

From promoting healthy lifestyles to sharing urgent COVID-19 information, Instagram is a hub for any health and lifestyle topic. Recognizing its unique affordances, it is essential to note that Instagram shapes societal health narratives.

2.7 User Engagement on Instagram

When studying Instagram and messaging techniques, user engagement plays a severe role. It is crucial to any brand's Instagram account that is trying to grow. User engagement in social media can be defined as the extent to which users present across cognitive, emotional, and behavioral while interacting with the content on social network platforms (Xie-Carson et al., 2023). It can be likes, comments, saves, shares, etc. To make a data-driven decision on the content and its strategies, you need in-depth knowledge of Instagram analytics, like engagement rate, performance, reach, etc. (Adobe Express, 2023b).

2.8 Engagement Rate

Engagement rate is the number of unique accounts interacting with the particular content, including likes, comments, shares, and saves (Adobe Express, 2023b).The Engagement rate tells how engaged your followers are with the content being shared on the account (Adobe Express, 2023c). The engagement rate is considered a benchmark for how optimized one Instagram account is and tells us how much influence it has on its followers (Putranto et al., 2022). When there is excellent and robust engagement, the users feel enough connection with your brand, which can sometimes lead to purchase (Adobe Express, 2023) and, in this case, buying the CGM product. It talks about the level of engagement relative to the size of the audience of that account. The data lets you understand which type of content strategies drive the engagement with the users or audience(Adobe Express, 2023b). The point of the engagement rate is to clearly understand the flaws of the content in order to improve the quality of the account (Arman & Pahrul Sidik, 2019).

To calculate the Engagement rate by posts, take the total engagement per post (likes + comments + saves + shares), divide it by the total number of account followers, and multiply by 100 to get the percentage (Adobe Express, 2023). Due to the platform restrictions of Instagram (Instagram, 2023), the insights showing the number of saves and shares per post can only be accessed by the account creator and not anyone else. Hence, to calculate the engagement rates of the posts in this research, only the number of likes and comments are used.

Engagement rate = Like of the post + Comments of the post /followers of the account *100

The limitations of using this formula are: 1. It only considers followers when measuring against the interactions, implying that people who do not follow the account and reacted to the post are skipped. 2. As explained, we skip the number of saves and shares from the equation to get the whole picture.

Once you determine the engagement rate, you must understand whether that is good. Reasonable engagement rates keep changing because Instagram keeps updating its algorithm (Adobe Express, 2023). In any social media platform's 1% to 5% engagement rate is considered good (Sehl, 2023). Notably, Instagram has higher engagement rates due to its one-post format per screen, which requires users to focus their complete attention either on the post content or scrolling it (Adobe Express, 2023c). Anything 3% or more is considered a great engagement rate on Instagram (Adobe Express, 2023c). A higher engagement rate says that you successfully gained the user's attention and proved that they are reacting to the post's content (Adobe Express, 2023c). Higher engagement also increases the visibility of the post on the platform. It also tells how favorably the algorithms treat the content (Adobe Express, 2023). If the engagement fails, that indicates that many followers are inactive, not responding to the content or even fake users who do not care about the company(Hubspot, 2022).

Engagement rates demonstrate the success of Instagram's content strategies. By identifying successful and highly engaging posts and campaigns, brands can adjust their strategies for better results.

2.9 Factors Influencing Engagement

Many factors influence this engagement rate. According to Hubspot and Mention's 2022 report on Instagram Engagement (Hubspot, 2022), reaching average engagement heavily depends on the number of followers that the account has, which means, with an account of 1000 followers, the average would be 50 users engaging with the new post. The other factors that play a role in engaging the users are the type of content (image, carousel, video), emojis, hashtags, length of the caption, tagging, timing of the post, regionality of the post, and geotag, which are suggested in Hubspot and Mention's 2023 report (Hubspot, 2023). The highlights from the report include: 1. Video format is the most engaging type of content because users enjoy it, followed by carousel posts, which are the stream of images in one single post. 2. Caption lengths between 1 and 20 are the best. The longer the caption, the more engagement worsens, but the super-long captions also create more engagement. 3. Posts with more than 11 emojis drop the engagement rate. 4. Posts with more than 11 hashtags are the optimal amount for engagement. 5. Tagging more relevant people will get more engagement 6. Engagement spikes if posted after 8 p.m.

Based on the HubSpot report (Hubspot, 2023) I hypothesize:

H1. Video posts have a higher engagement rate compared to carousel posts.

H2. Posts with captions length of less than 20 characters have a higher engagement rate than posts with more than 20 characters.

H3. The engagement rate is higher in the content that is posted after 8 p.m. compared to posts before 8 p.m.

All the factors explained directly relate to user behaviors with the content. These trends in engagement decide the strategies that the creator wants to use. Understanding these factors that affect the engagement rate will help determine whether the account's messaging is working and whether the factors' presence has made a difference in our data analysis.

2.10 Social Cognitive Theory

The Theory of social cognition is a possible fit for this research to understand the Instagram messaging strategies employed by the CGM apps and users' behavior in the form of engagement towards that content. Social Cognitive theory provides a framework for understanding the determinants and psychological mechanisms through which communication influences human thought, action, and affect (Bandura, 2001). The theory is based on an agentic perspective (Bandura, 1986). The social cognitive theory was introduced by Albert Bandura in 1986. He explains that external stimuli do not just drive humans; somewhat, human function through the dynamic and reciprocal interaction of behavioral, cognitive/ personal, and environmental factors, which means humans do not observe and react to environmental developments, but we process and behave in a way which is equally and simultaneously influenced by all the behavioral, cognitive and environmental factors acting together(Bandura, 1986). People are not just reactive organisms shaped by inner and environmental forces but proactive, self-reflecting, self-organizing, and self-regulating; hence, they are both producers and products of the social systems(Bandura, 2001).

Social cognitive theory is preferred over Social learning theory because SCT involves self-efficacy as one of its core concepts (Tadayon Nabavi & Bijandi, 2023) and that is one of the elements that is being tested in the hypothesis. This theory is well suited to advance understanding and integrated natures of humans and their agentic capability of shaping the world around them (Bandura et al., 2023); it helps us understand how humans function around the information they are exposed to in their environment. In today's world, individual and collective agency influences our virtual life; hence, we need a mechanism to understand the psychology of human agency and basic scientific knowledge of action, which can be explained through this theory (Bandura et al., 2023). With the powerful influence of media, Social cognitive theory has been widely used to explain the media's unintentional effects and to understand how to design the message to maximize its positive impact (Nabi & Oliver, 2009).

Different principles derived from social cognitive theory are continuously applied worldwide as health promotion techniques that assist in promoting change in lifestyle and behavior, which can better the quality of an individual's overall life. The health perspective is changing from a disease model to a health model because it is more proactive than waiting for the disease to occur and emphasizes health promotion (Bandura et al., 2023). Health status affects an individual's entire lifestyle, and Diseases and chronic disabilities compromise that quality of life (Bandura et al., 2023). When good lifestyle habits influence our health, people can control their health through self-management; there can never be better medicine (Bandura et al., 2023). SCT highly focuses on the demand side of health promotion (Bandura et al., 2023). It says that people can take action, and whatever the outside motivations are if an individual does not want to put forth their control over health-promoting behavioral changes, the change will not last. SCT as a Health promotion system explains that when people engage in self-regulatory mode, they can monitor their unhealthy behavior, set health goals to achieve, and trigger self-evaluation reactions (Bandura et al., 2023).

From the above rationale, some SCT components have been significant predictors of short-term behaviors like reactions and engagement on social media platforms. A study examined social media usage using different SCT principles (Khang et al., 2014). The social cognitive determinants of behaviors they looked at include perceived self-efficacy and expected outcomes. It stated that people habitually use social media and engage in making a choice, asses the expected outcome, and trace their activity which is eventually reflected in their media usage

(Khang et al., 2014). It also found that individuals who think they are highly efficacious look for positive outcomes from social media use, and it further acts as an incentive to take action for anticipated outcomes (Khang et al., 2014). Another study examined the effects of Instagram images on male viewer’s workout intention (Peng et al., 2019). It highlighted that self-efficacy motives predict the outcome (Peng et al., 2019). SCT confirms that any information and behavior can be retrieved from the modeling content in the media (Simpson & Mazzeo, 2017). Through modeling/observational learning, people learn the rules and standards for societal behavior portrayed in the media; therefore, such behaviors influence self-regulation (Simpson & Mazzeo, 2017). People also imitate the behavior when it is socially rewarded, like engagement in social media (Simpson & Mazzeo, 2017).

Hence, Observational learning, forethought, and self-efficacy are the most significant and commonly used techniques for behavior change regarding healthy habits (Huang & Zhou, 2019), and Instagram facilitates that health behavior change through the dynamic interactions between the elements of SCT (Razak et al., 2020). Hence, I hypothesize that these elements alone or together can predict significant user engagement on Instagram.

Expected outcome/forethought can be defined as one’s expectations of the outcome. Bandura said the future state of affairs cannot be a cause of current behavior. However, cognitive visualizations and representations of the future can be brought into the present and serve as guidelines and motivators for current behavior (Bandura et al., 2023). People’s intentions of action plans and strategies set the goals for personal achievements and visualize the outcomes of the goal-directed actions (Bandura et al., 2023). This is a form of anticipatory self-guidance that visualizes the goals and anticipates the outcome rather than being in an unrealized future state (Bandura et al., 2023). Hence, when it is projected for the long term, forethought gives coherence, direction, and meaning to one’s life and can incentivize motivation (Bandura et al., 2023).

Research proves that people expect to learn new information through social media platforms when engaging with the content (Velasquez & Rojas, 2017). Every social media app meets the user's expectations differently depending on its features, and it also motivates them to participate more on the platform depending on the outcome they expect interacting and consuming other’s content will bring them (Velasquez & Rojas, 2017).

Another essential element of SCT that can predict engagement is self-efficacy. Self-efficacy is central to multiple psychological mechanisms working in concert to help people act as agents (Bandura et al., 2023). Self-efficacy is people’s beliefs about their ability to control challenges (Bandura et al., 2023). According to (Bandura et al., 2023), Self-efficacy beliefs are important because, when people engage in activities, they directly influence their thoughts, actions, and emotions. Reflections on self-efficacy influence self-regulated behavior like goals, aspirations, expectations, perceptions of opportunity, and affective proclivities.

Self-efficacy takes many forms on social media, notably social persuasion (Kashian & Liu, 2020). Social persuasion is when people are convinced by others that they are capable of a behavior(Kashian & Liu, 2020). It unfolds on the platform as a form of positive reaction, supportive comments, approval, social support, and feedback on behavior (Cavallo et al., 2014; Yang et al., 2015). Through supportive and motivating feedback in the posts, it can inspire the users to think that they are capable of that behavior and hence engage with the content and the depicted behavior.

Observational learning is also a core element in predicting engagement. Observers learn behavior, the standards to evaluate them, the outcome that follows the behavior, and the emotional reactions to them by observing the social world (Bandura et al., 2023). Observational learning in SCT discusses that Humans have the cognitive capacity to represent the information and then draw guidance for future actions from the information provided through modeled action (Bandura et al., 2023). People can acquire vast amounts of knowledge and behavioral skills just by observing the behaviors of others, and then they draw information from those inputs for their future challenges (Bandura et al., 2023).

Observational learning elements on social media are the content depicting instructions and demonstrations, which allows users to learn similar skills (Huang & Zhou, 2019). Research proves that users can learn various skills just by observing the content on social media platforms (Rozaq et al., 2020). It also explains how the actions of others serve as a social prompt for a behavior that you previously learned but not yet performed because of insufficient inducements (Bandura, 2001). It suggests that through exemplification, you can get people to converse on a topic you want, choose a particular food or drink, behave differently, show emotion, be passive or engaging, think creatively or conventionally, and engage in any other course of action (Bandura, 2001). Through this type of content, you can predict that the users will eventually follow the behaviors showcased in the post (Cheung et al., 2014).

Based on the early and existing literature, the following hypothesis is proposed:

H4: Instagram posts with one or more elements, including observational learning, forethought, and self-efficacy, drive significant user engagement on the platform compared to posts without any of those elements.

In conclusion, social cognitive theory emerges as a suitable framework for this research because of its ability to explain and explore the dynamics of health-related content on the Instagram platform. The fundamentals of social cognitive theory explain how an individual's thoughts, actions, and affects determine the communication process of any kind. Supported by previous studies, SCT components used for health promotions provide a framework for predicting user engagement in the forms of likes and comments on Instagram.

2.11 Research Questions and Hypothesis

This review unfolded across many distinct sections. The explanation started with an overview of CGM sensors and their evolution from diabetes-specific technology to referring themselves to health and wellness management, with details on the technology and its benefits to both diabetes and non-diabetes people and how the industry is catering to the new demand and then, it transits to the Instagram platform's role in health communication, focusing on persuasive techniques through messaging strategies. The applicability of the engagement rate formula was also discussed, and metadata in the health context, and then decoded the factors that directly or indirectly influenced the engagement rate. Also concluded by explaining what elements of social cognitive theory are relevant to Instagram in predicting user engagement and how previous studies have used those components in studying social media behaviors.

Research suggests in their future research section the need to study the distinct concepts of social cognitive theory applied to health communication on online media (Schunk & DiBenedetto, 2020). Even though there is much literature on how social media apps like Facebook, Twitter, and TikTok can influence health information seeking and behavioral change, surprisingly, not many talk about how Instagram affects or plays a role in our health behaviors. With the growing interest in adapting CGM for lifestyle modification, there is an insufficiency of research data on people without diabetes using CGM (Klonoff et al., 2022). Hence, it is utterly essential to critically study its applications in this new shift of CGM apps on the Instagram platform.

This study fills that gap by examining how CGM apps utilize various elements on Instagram to convey information and gain engagement. It also analyzes the techniques employed by those apps to see if it is possible to develop more engaging persuasion strategies that health-based companies can adapt to their social media platform. The present research is using the following research questions and hypotheses:

RQ1: What messaging strategies are often used by CGM apps on Instagram?

RQ2: Which of the messaging strategies creates significant user engagement?

H1. Video posts have a higher engagement rate compared to carousel posts.

H2. Posts with captions length of less than 20 characters have a higher engagement rate than posts with more than 20 characters.

H3. The engagement rate is higher in the content that is posted after 8 p.m. compared to posts before 8 p.m.

H4: Instagram posts with one or more elements, including observational learning, forethought, and self-efficacy, drive significant user engagement on the platform compared to posts without any of those elements.

METHOD

In the following section, the methodological framework of the research is explained, which is used to study the messaging strategies employed by the CGM apps in their Instagram account and their effects on the user's engagement. The visual posts and their captions are studied through quantitative content analysis to examine variables like observational learning, forethought, self-efficacy, engagement rates, type of post, different caption lengths, and time of the posts. With the help of Apify, the sample was scraped from three Instagram profiles, and a nominal scale was used in the codebook to study.

3.1 Research Objectives

The research objectives for this thesis are:

I. To analyze the complex messaging strategies on Instagram by CGM apps. To get a comprehensive look by identifying its themes and techniques through visual posts and captions.
   a. To examine the principles of social cognitive theory on the Instagram platform. This theoretical framework can help pin the nuanced Instagram behaviors of the target users.

II. To explore the impact of messaging strategies on user engagement. It helps us understand the user's attitude toward the content.

III. To develop recommendations for effective health communication strategies by synthesizing the research findings into practical guidelines for marketing health products.

Table 1 shows the relationship between the objectives and the method used to achieve them.

Table 1. *Relationship Between Objectives and the Methods*

Objective	Source Data	Method	Outcome data
1) Analyze messaging strategies of CGM apps	Posts and captions	Content analysis	List of messaging strategies
a. Examine SCT principles on Instagram	Posts and captions	Content analysis	List of principles
2) Explore impact of messaging strategies on user engagement	Metadata of the Instagram post	Descriptive statistics	Engagement rate of the posts
3) Develop recommendations for effective health communication	Posts, captions and metadata	Content analysis	List of recommendations

3.2 Theoretical framework of the method

To study the topic of the expansion of CGM apps in the Instagram platform, the method used is quantitative content analysis. Content analysis is a process of systematically and reproducibly examining the communication symbols that have been given a numeric value based on the measurement guidelines, which is followed by the statistical analysis of the relationship of those values in order to explain the communication, to draw conclusions about its meaning or deduce it to production and consumption contexts (Riffe et al., 2019).

The rationale for choosing content analysis is due to its numerous strengths, which can be applied to the research context. Content analysis has a measurement technique that is unobtrusive and non-reactive (Riffe et al., 2019); hence, with the help of this method and SCT framework, It can draw conclusions just by using content evidence and without the help of content creators or users. The content which is used in the study has a life beyond its production and consumption; with content analysis, it is possible to study the archival materials, which may outlive the content creators and users (Riffe et al., 2019). Content analysis is a powerful tool for studying large amounts of social media data. A well-developed coding protocol can operationalize and measure any data for meaningful distinctions (Riffe et al., 2019). Content analysis can be applied to any discipline, including online health communication, focusing on communication in human affairs (Riffe et al., 2019). The trustworthiness of content analysis data depends on the protocol and not the coders; hence, it has increased reliability and validity since it can be applied outside of this research by mimicking its protocol (Riffe et al., 2019). Content analysis is even necessary for this research because the volume of the social media data of the study exceeds individual capacity to examine, and there is a limited data accessibility problem (Riffe et al., 2019).

To study continuous glucose monitors and diabetes, qualitative and quantitative methods have been equally used in the literature. Qualitative interviews have been conducted to analyze the peer support element through a social media community for diabetes (Gavrila et al., 2019). The survey method has also been used to describe the motivations of the online social media community involving CGM (White et al., 2018). You can find much research that has adopted the literature search methods to find relevant articles and evidence for their analysis on CGM (Elnaggar et al., 2020; Klonoff et al., 2022). Similar to content analysis, there is evidence that quantitative researchers are using text-mining methods to study the content on CGM on online platforms (Heitkemper et al., 2023). The huge benefits of using qualitative interviews and surveys are that researchers can offer rich insights into the user's behavior in the online CGM community and explore in-depth narratives and experiences involving the community.

There is less research exploring the topic using quantitative content analysis. Given that the literature supports the application of qualitative methods in this context, It's not convincing to choose any method other than content analysis. The study is also interested in answering the numerical perspective of the research questions and wants to understand the quantity of the data used to study and count instances; hence, qualitative thematic analysis can't be applied, which rather focuses on the overarching themes. Because of the above explanation, quantitative content analysis is very appropriate for the topic of study.

3.3 Instruments and Variables

For studying research questions, specific content themes (self-efficacy, forethought, observational learning, type of post, time of post, and different caption length) within the messaging strategies are the independent variables. As explained, messaging strategy in Instagram can be defined as how the creators visually and verbally present their information through posts to their social media audience who follow, see, and visit their Instagram account. The dependent variable is the user engagement of the Instagram post. As explained, user engagement in Instagram can be defined as the ways, including likes and comments, in which the users interact with the content they are exposed to on the platform.

H1 compares the engagement rate (dependent variable) between the type of post (Video or carousel) (independent variables) and predicts that video posts have higher engagement rates than carousel posts. Video posts can be defined as posts whose format is in a video, and the carousel posts are the two or more static images in the same post.

H2 compares the engagement rate (dependent variable) between the different caption lengths (less than 20 and more than 20) (independent variable) and predicts that posts with less than 20 characters in the caption have a higher engagement rate than posts with more than 20 characters caption. Hashtags and emojis won't be considered as a character.

H3 compares the engagement rate (dependent variable) between the time of the post (before 8 p.m. and after 8 p.m.) (independent variable) and predicts that posting after 8 p.m. has a higher engagement rate compared to posting before 8 p.m.

H4 tests the positive relationship between observational learning, forethought, and self-efficacy (Independent variables) and user engagement of the Instagram post (dependent variable).

The theoretical definition of variable observational learning is when people acquire knowledge and skills just by observing others. Forethought can be defined as one's expectations of the outcome, and self-efficacy is people's beliefs about their capabilities to exert control over challenges. In summary, the research questions and hypotheses try to understand how specific content themes and strategies influence the user engagement of that post.

3.3.1 Scales

Scales and items to test the variables are borrowed from previous research on the same topic. Below is the list of techniques to measure the variables:

I. User engagement – To calculate the post's engagement, you do not require a scale but, as explained before, the list of post metadata to apply the engagement rate formula to that data (Peruta & Shields, 2018).The codebook measures the variable using the post ID, Post URL, Username of the post, Number of likes, comments, followers of that account, and Engagement formula items.

II. Type of the post – In the codebook, a nominal scale is used to identify the type of post by observing the visual post and coding it as 0= carousel post, 1= video post and 2= others. Video posts can be defined as posts whose format is in a video, and the carousel posts are the two or more static images in the same post. Others are the posts with one still image. Example: Under the column "Type of post," a video post are be coded as 1.

III. Different caption length—In the codebook, a nominal scale is used to identify different caption lengths by observing the caption of the post and coding it as 0 = post with caption length more than 20 characters and 1 = post with caption length less than 20 characters. Hashtags and emojis are not considered characters.

Example: Under column “Different caption length,” a caption with less than 20 characters is coded as 1.

IV. Time of the post – In the codebook, a nominal scale is used to identify the time of the post by observing the caption section and coding it as 0= posted before 8 p.m. and 1=posted after 8 p.m.

Example: Under the column “Time of the post,” the caption section that says that posted at 10:00 p.m. is coded as 1.

V. Observational Learning – In the codebook, a nominal scale is used to test the observational learning element in the visual post and its caption by coding it as 1=present and 0=absent (Huang & Zhou, 2019). An item of observational learning is explained as when a post creator explains and demonstrates the use of the CGM device in any form, including guides and tutorials, which allows observers to watch others’ experiences and behaviors regarding CGM.

The item is measured using four columns, which are all independent of each other. The first column is coded for the posts which only contain observational learning and not any other SCT elements. The second column is coded for the posts which have both observational learning and forethought elements. The third column is coded for the posts that contain elements of observational learning and self-efficacy. The fourth column is coded for the posts, which contain observational learning with forethought and self-efficacy elements.

Example: Under the column “Observational learning,” the post where the doctor is explaining how to wear the sensors on your hand is coded 1.

VI. Forethought – A nominal scale is to measure the forethought element (Fulton et al., 2012) in the visual post and its caption by coding it as 1=present and 0=absent in the codebook. An item forethought is explained as content that discusses long-term behavioral strategies and expected outcomes associated with CGM. Also, any aspirations and intentions regarding health management through CGM.

The item is measured using four columns, which are all independent of each other. The first column is coded for the posts which only contain forethought and not any other SCT elements. The second column is coded for the posts which have both forethought and observational learning elements. The third column is coded for the posts, which will contain elements of forethought and self-efficacy. The fourth column is coded for the posts, which contain forethought with observational learning and self-efficacy elements.

Example: Under the column “Forethought,” the post where the influencer is talking about the benefits of prolonged use of CGM is coded as 1.

VII. Self-efficacy – The nominal scale is used for the self-efficacy element of the visual post and its caption by coding it as 1=present and 0=absent in the codebook (Jiang & Beaudoin, 2016). An item self-efficacy is explained as content suggesting that users can take charge of their health through CGM, mastery in handling and understanding the device, and self-assurance that life will change for the better with CGM.

The item is measured using four columns, which are all independent of each other. The first column is coded for the posts which only contain self-efficacy and not any other SCT elements. The second column is coded for the posts which have both self-efficacy and forethought elements. The third column is coded for the posts which contain self-efficacy and observational learning elements. The fourth column is coded for the posts, which contain self-efficacy with forethought and observational learning elements. Example: Under the column "Self-efficacy," the post where the caption says don't be scared of diabetes, you can control it by using the CGM is coded as 1.

A nominal scale has been used for most variables. Nominal scales have numbers assigned to the categories of content, but those numbers are arbitrary and carry no meaning except connecting the content with the category (Riffe et al., 2019). The Study is adopting the multivariable approach, where each category becomes a variable with one number for the presence of variable characteristics and another number for the absence of that variable characteristics; this will allow the same post to be characterized into more than one classification (Krippendorff & Craggs, 2016).

In summary, here is the table with the key variables of the content analysis and the instrument used to measure them:

Table 2. *Variables*

Variable	Data measurement instrument
The specific content theme within messaging strategy (I)	Codebook
User engagement (D)	Codebook
Type of post (I)	Codebook
Different caption length (I)	Codebook
Time of post (I)	Codebook
Observational learning (I)	Codebook
Forethought (I)	Codebook
Self-efficacy (I)	Codebook

3.4 Data Collection

The unit of analysis of this study is Instagram post. All the Posts on the Instagram profiles of all the CGM apps are the population, and the posts from three profiles are the sample. Posts are collected from @levels, @hellojanuaryai, and @nutrisenseio using purposive sampling techniques. Those posts are collected from Instagram through third-party API, Apify (*Apify Instagram Post Scrapper*, n.d.). All the posts are saved in an Excel file and stored safely. The posts posted between the accounts' creation date and October 31, 2023, is studied.

3.4.1 Sample

Based on the list provided by previous research (Klonoff et al., 2022) with all companies that market CGMs for health and wellness applications, It’s filtered to 3 companies that provide CGM applications that are available in the US, namely @levels, @hellojanuaryai, and @nutrisenseio. There is no public record for the total number of third-party apps that exist and are approved by the government to sync with the CGM sensors because the FDA approves the sensors and not the apps; hence, the sampling method is purposive sampling, in which samples are chosen based on the researcher’s logical decision that those sample reflect the characteristics that form the research foundation (Scharrer & Ramasubramanian, 2021). The reasons that led to choose this sample are as follows:

- All three Instagram accounts were created around the same time in 2019.
- All three apps have published articles supporting the use of CGM by non-diabetes people on their websites.
- You do not need a prior prescription to access these apps.
- All three apps provide the same CGM product, Freestyle Libre.
- All three apps are marketed directly to the customers.

- These accounts have different ranges of followers, from 5K to 171K, which will help represent the diversity of the population that's being studied.

The parameter for the posts to be considered in the sample is only the timeline that they are posted under, which is from the date the account was created till the 31st of October, 2023. Any posts, including reels, videos, images, and carousels posted between these dates, are considered in the sample. In Total, these profiles have 1577 posts, 506 from @levels (32%), 725 from @nutrisensio (46%), and 346 from @hellojanuaryai (22%) for the sample. All posts are scrapped using a paid third-party API known as Apify. Apify has a specific Instagram post scraper feature, which can scrape all the details of the post, including post content, URL, date and time of the post, number of likes, number of comments, number of views, caption, etc. and exported this data into the excel sheet for the analysis.

3.4.2 Data Collection Procedure

Here is the step-by-step process of the data collection procedure:

I. Save the username of the three Instagram profiles that is being analyzed.

II. In Apify, copy-paste those usernames, select the option for all posts to scrape all the posts, and hit enter.

III. It takes two hours to scrape all the posts, then hit export and select Excel format.

IV. You now have the downloaded Excel file with all the posts and the required information for those posts.

V. Posts posted after the 31st of October, 2023, are used for training the coders.

VI. Then the data is saved in the password-protected hard drive

3.4.3 Procedure to develop the coding scheme

The codebook contain the following sheets:

I. Post Details: Columns containing Post ID, Post URL, Post Caption, Post Type, Post Time and Date, Number of Likes, Number of Comments, Profile username, Number of followers, and Total number of the posts of that profile.

II. Definitions: Columns containing Code type(deductive code or inductive code), Codes (All Independent variables), Theoretical Definition of those codes, Methodological Definition of the Codes, and Scale/Coding.

III. Deductive Coding: Post ID, Observational Learning item, Forethought item, Self-efficacy Item, Combination of observational learning and forethought item, Combination of observational learning and self-efficacy item, Combination of forethought and self-efficacy item, Combination of observational learning, forethought and self-efficacy item, Others item, SUM(all the eight categories merged into one)and Extra Notes.

IV. Engagement Rate: Post ID, Number of likes, Number of comments, Number of followers of that account, Type of the post, Different Caption Length, Time of the Post, and Engagement formula.

3.5 Validity and Reliability of the Proposed Study

Many reliability and validity measures is taken to maintain the trustworthiness and robustness of this study's findings. To consistently and accurately interpret the data’s meaning, strict and systematic measures is taken to genuinely reflect the nuances of the content that is being studied; the sections below will delve more into the details.

3.5.1 Reliability

Reliability in content analysis is consistency across coders in using the protocol to categorize content (Riffe et al., 2019). To ensure the research's high integrity and reduce bias, various measures, including variable and category definitions, coder training, reliability tests, and reliability coefficients (Riffe et al., 2019) are handled.

Throughout the literature review and method section, all the variables are explained multiple times. Also, in the codebook is an entire sheet dedicated to terms and definitions. It's acknowledged that the study has three variables with some proportion of latent content. Latent content is those variables that require the coders to infer meaning and demand them to make an informed leap from what they are observing to a relative judgment (Scharrer & Ramasubramanian, 2021). This was tackled by intense instructions before every coding session (Riffe et al., 2019).

Systematic coder training was provided to the two other coders (Riffe et al., 2019), who was coding for the pilot study and actual coding. They were provided instructions until they grew comfortable and familiar with the definitions of all the variables and also specified all the coding sessions (Riffe et al., 2019). Enough time was provided for them until they found their rhythm with the coding.

The reliability of this study is about stability, reproducibility, and accuracy (Krippendorff, 2003). Stability is when, at two points in time, a coder consistently applies the protocol to the same set of content (Riffe et al., 2019). Reproducibility is when two or more coders apply the protocol to the same content (Riffe et al., 2019). Accuracy is when coding is consistent with other external standards for the content (Riffe et al., 2019). A reliability test ensures that the coding scheme has achieved these characteristics. This test decides the intercoder reliability. It is an extent to which the different coders have been using the coding system to agree on how to code a particular variable (Scharrer & Ramasubramanian, 2021). For the ICR test, a different sample was used through random sampling (Riffe et al., 2019).

Based on the coders' decisions, many examples and explanations for the variables were renewed during training sessions. Of the posts posted after 31st October, 56 were used to code during training sessions. A new set of 100 posts was given to the three coders to code independently.

The reliability coefficient is a statistics summary of how often the two coders agreed on classifying the content from the protocol (Riffe et al., 2019). Cronbach's alpha is used to report the ICR test score since it is the most versatile ICR test for chance agreement; also, as suggested by content analysis experts, the goal was to achieve 0.60 or above on the ICR for all variables, which is the usual acceptable result (Scharrer & Ramasubramanian, 2021).

Using SPSS, 100 coded posts were analyzed for Cronbach's alpha. The observational learning variable achieved 0.913, the forethought variable had 0.755, and the self-efficacy variable had 0.831. The reliability for coding SCT elements for the H4 hypothesis was achieved.

Since the H1, H2, and H3 hypotheses are automated programming calculated using formulas in an Excel sheet, they were not tested for inter-coder reliability.

3.5.2 Internal Validity

Internal validity can be explained as the extent to which the research questions can be answered trustworthily from the study design and execution without any systematic errors (Andrade, 2018). Content analysis cannot alone possess internal validity by itself without the help of other methods (Riffe et al., 2019). However, the issues of control are addressed. Content analysis designs that explain the content pattern must look outside the content of interest (Riffe et al., 2019). Its being addressed by looking beyond the content on the Instagram platform, as It's explained in the literature review, and how the trend started from different diabetes drugs sold by companies other than CGM apps.

Since the study is trying to analyze the causal relationship in the RQ2, It's acknowledged that the confounding variables like date and time of the post, day of the post, and type of the post have effects on the dependent variable, which is something that cannot be controled; hence it is discussed in the limitations section of the study.

3.5.3 External Validity

External validity is when a study's result can be applied to the outside world and generalized to other populations (Andrade, 2018). The external validity of the content analysis can be increased by two measures (Riffe et al., 2019)Firstly, the nature of the content, which is the content topic, should be important; the more persuasive the content is to the users, the more important it gets. Since the study is on the persuasive strategies of the CGM apps, it is automatically an essential concept for the research and users. Second, the Nature of the categories, meaning the variable definitions and their latent meaning (Riffe et al., 2019). It is addressed by providing a clear set of instructions for the coders to help them understand the definition, context, and purpose of those variables.

Also, the external validity of the research is improved by making a systemic decision to select the three CGM apps as the sample from the list of companies the previous researchers provided; this reduces any sampling bias in the study.

3.5.4 Ecological Validity

Ecological validity discusses the result's application to real-world settings (Andrade, 2018). Since the study is considering the sample of posts from the real world shown to the population of people who are trying to get healthy, the target population, there is no compromise in there. Also, any artificial stimuli is not being used and studying the actual posts that have been posted since the beginning of the accounts, making it more longitudinal data to draw the patterns accurately. In summary, It's ensured a greater ecological validity of the study by keeping a naturalistic setting throughout the data collection and coding process.

3.6 Concluding Summary

In conclusion, this section discusses all the methodological decisions that are pursued to study the research questions and hypotheses. By trying to build a systematic way to understand the nuances of those messaging strategies on the platform by studying all the posts of the three profiles and how that can be generalized to the population of all CGM companies. With a transparent coding system coupled with the two trained coders, efforts are put into achieving an acceptable reliability score to continue studying the sample and draw patterns and themes from the variables. This section is a roadmap for understanding the shift in CGM app strategies.

RESULTS AND ANALYSIS

4.1 Results

Once the coding process was completed for all the variables in the sample, to analyze the sample data, the assumption of normality was assessed using the Shapiro-Wilk test for all the hypotheses based on their sample size, which assumes that the data was drawn from the normally distributed population (*Laerd Statictics - Testing for Normality Using SPSS Statistics*, n.d.). In addition, non-parametric tests have been conducted, including the Kruskal-Wallis Test for H1 and H4, Logistic regression for H2, and the Mann-Whitney Test for H3. These tests don't make any assumptions about the distribution of the data, which can help provide a complete picture of all the relationships between the variables. Descriptive statistics are also applied to all hypotheses to understand the mean engagement rate. Below are the hypotheses:

Table 3. *Relationship between hypotheses, data, and analysis*

Hypothesis	Data Source	Variables
Hypothesis 1: Video posts have a higher engagement rate compared to the carousel posts.	▪ Instagram post and caption	▪ Engagement rate ▪ Type of Post
Hypothesis 2: Posts with the captions length of less than 20 characters have a higher engagement rate than posts with more than 20 characters.	▪ Instagram post and caption	▪ Engagement rate ▪ Different caption length
Hypothesis 3: Engagement rate is higher in the content that is posted after 8 p.m. compared to posts before 8 p.m.	▪ Instagram post and caption	▪ Engagement rate ▪ Time of the post
Hypothesis 4: Instagram posts with one or more elements, including observational learning, forethought, and self-efficacy, drive significant user engagement on the platform compared to posts without any of those elements.	▪ Instagram post and caption	▪ Observational learning ▪ Forethought ▪ Self-efficacy ▪ User engagement

Hypothesis 1 of the project compares the engagement rate, which is a dependent variable, between the type of post (Independent variable) and states that video format posts ($N = 701$) have a higher engagement rate than carousel format posts ($N = 321$). The mean engagement rate for video posts was 0.402 ($SD = 0.767$), and for carousel posts, $M = 0.376$ ($SD = 0.483$). Further, the Shapiro-Wilk test of Normality was conducted on the type of post variable which has the video ($W = 0.382$, $p < 0.001$), carousel ($W = 0.645$, $p < 0.001$), and image categories ($N = 555$, $W = 0.405$, $p < 0.001$), that revealed the data significantly deviates from the normal distribution; based on this outcome, a non-parametric test of Kruskal-Wallis was conducted further to determine the differences in engagement rate across the categories of type of post. It revealed a statistically significant difference($H(2) = 13.107$, $p = 0.001$). Post hoc pairwise comparisons using the Bonferroni correction were also applied to explore the differences further. There was no statistically significant difference between video and carousel posts(test statistic = 519, $p = 0.986$, adjusted $p = 1.000$); however, there was a statistically significant difference between image and carousel (test statistic = 86.572, $p = 0.007$, adjusted $p = 0.020$) and also image and video (test statistic = 87.091, $p = 0.001$, adjusted $p = 0.002$). Based on this statistical analysis, the alternate hypothesis was not supported.

Hypothesis 2 of the project compares the engagement rate (dependent variable) between the different caption lengths (independent variable), posts with less than 20 characters, and posts with more than 20 characters. The Shapiro-Wilk test of Normality was conducted on the different caption length variable ($W = 0.875$, $p < 0.001$), which revealed that the data significantly deviates from the normal distribution; based on this outcome, a non-parametric test of logistic regression was conducted further. The engagement rate was divided into two categories: one with less than or equal to the median value of 0.178 and the second one with anything more than the median value of 0.178. The three missing cases (0.2%) are also noted. The logistic regression model was statistically significant ($X^2(1) = 12.218$, $p < 0.001$), indicating that this model with different caption length as a predictor variable is better fit to the data compared without the predictor. Also, different caption length was a statistically significant predictor of engagement rate ($X^2 = 12.009$, $df = 1$, $p = 0.001$). Meanwhile, it's important to note that the mean post-caption length was 536 characters, which is substantially higher than the defined categories of less or more than 20 characters. Still, the hypothesis was supported by the higher the character in the caption, the lower the post engagement rate. Based on this analysis, the alternate hypothesis was supported.

Hypothesis 3 of the project compares the engagement rate, which is a dependent variable between the time of the post, before 8 p.m., and after 8 p.m. The Shapiro-Wilk test of Normality was conducted on the time of post variable, where before 8 p.m ($W = 0.395$, $p < 0.001$) and after 8 p.m. ($W = 0.540$, $p < 0.001$) revealed that the data significantly deviates from the normal distribution; based on this outcome, a non-parametric test of Mann-Whitney test was conducted further to compare the distribution of engagement rate across categories of time of post which revealed a significant difference ($U = 152145.000$, $Z = -5.736$, $p < 0.001$). Specifically, posts made after 8 pm have a higher engagement rate ($M = 0.477$, $SD = 0.692$) than those made before 8 pm ($M = 0.368$, $SD = 0.744$). Furthermore, looking at the sample number, posting after 8 pm generates a higher engagement rate, but the companies do not follow that strategy. Based on this statistical analysis, the alternate hypothesis was supported.

Hypothesis 4 of this project tests the positive relationship between independent variables of SCT elements like observational learning, forethought, and self-efficacy and how they drive user engagement in the post. Specifically, it aims to determine whether the presence of any of these elements in a post has a higher engagement rate compared to posts that don't have any of the elements. To check the individual and combinational effects of each element, they have been divided into eight categories which are independent of each other, including Observational learning, Forethought, Self-efficacy, Combination Observational learning + Forethought, Combination Observational learning + Self-efficacy, Combination Forethought + Self-efficacy, Combination Observational learning + Forethought + Self-efficacy and Other (None of the SCT elements). Below is the table with descriptive statistics of these categories.

Table 4. *Descriptive statistics for eight categories of SCT elements.*

Categories	N	*M*	*SD*
Observational Learning	388	.44	.62
Forethought	79	.51	.86
Self-efficacy	115	.30	.34
Combination Observation + forethought	675	.35	.78
Combination Observation + self-efficacy	39	.24	.24
Combination forethought + self-efficacy	31	.49	1.52
Combination Observation + Forethought + Self-efficacy	47	.25	.38
Others (None of SCT Elements)	203	.46	.81
Total	1577	.39	.74

The Shapiro-Wilk test of Normality was conducted on the SCT elements variable ($W = 0.850$, $p < 0.001$), which revealed that the data significantly deviates from the normal distribution; based on this outcome, a non-parametric test of Kruskal-Wallis test was conducted further. It revealed a statistically significant difference($H(7) = 39.470$, $p < 0.001$). Based on this statistical analysis, the alternative hypothesis was supported.

Post hoc pairwise comparisons using the Bonferroni correction were also applied to explore the differences further. 11 comparisons were found to have statistically significant differences, including:

1. Combination (Observational learning + Forethought + Self-efficacy) and Self-efficacy (test statistic = 200.755, $p = 0.017$, adjusted $p = 0.468$)
2. Combination (Observational learning + Forethought + Self-efficacy) and Other (None of the SCT elements) (test statistic = -240.728, $p = 0.001$, adjusted $p = 0.031$)
3. Combination (Observational learning + Forethought + Self-efficacy) and Observational learning (test statistic = 247.080, $p < 0.001$, adjusted $p = 0.012$)
4. Combination (Forethought + Self-efficacy) and Other (None of the SCT elements) (test statistic = -208.771, $p = 0.017$, adjusted $p = 0.488$)
5. Combination (Forethought + Self-efficacy) and Observational learning (test statistic = 215.122, $p = 0.011$, adjusted $p = 0.318$)
6. Combination (Observational learning + Self-efficacy) and Other (None of the SCT elements) (test statistic = -160.008, $p = 0.044$, adjusted $p = 1.000$)
7. Combination (Observational learning + Self-efficacy) and Observational learning (test statistic = 166.359, $p = 0.030$, adjusted $p = 0.830$)
8. Combination (Observational learning + Forethought) and Other (None of the SCT elements) (test statistic = -129.274, $p < 0.001$, adjusted $p = 0.011$)
9. Combination (Observational learning + Forethought) and Observational learning (test statistic = 135.625, $p < 0.001$, adjusted $p < 0.001$)

10. Self-efficacy and Other (None of the SCT elements) (test statistic = -126.582, $p = 0.017$, adjusted $p = 0.483$)
11. Self-efficacy and Observational learning (test statistic = 132.934, $p = 0.006$, adjusted $p = 0.169$)

DISCUSSION

The research explores the impact of messaging strategies that are employed by CGM apps on their Instagram account to engage the users towards their content in order to expand themselves as health management companies, and that anyone can use their products if they intend to try and adapt a healthier lifestyle through monitoring their physical activities and food. The research explicitly investigates the elements of social cognitive theory, like observational learning, self-efficacy, and forethought, as well as content strategies, such as the type of post, caption length, and time of the post. It tries to contribute to understanding user behavior when exposed to those psychological and content phenomena on Instagram and uncover better strategies to communicate health products.

The study's first research question was: What messaging strategies were often used by CGM apps on Instagram, mainly focusing on the application of Social cognitive elements? The findings suggest that CGM apps utilize observational learning (N = 388) as their main tactic, where the audience can acquire knowledge and skills by observing the posts. It can have information on various topics like demonstrating the use of CGM, insulin resistance in the body, patterns of sleep affecting insulin, the relationship between various foods, calorie counting, micro and macronutrients, emotional effects of glucose, etc. Self-efficacy is also another major SCT component used on Instagram (N = 115). These posts positively discuss people's beliefs about their capabilities to exert control over challenges regarding their health, struggle with weight management, and glucose management, for example, using words like, "You can," "Trust yourself," and "Take charge." Forethought was less used compared to other elements (N = 79), where posts mainly discussed one's expectations of the outcome and expectations associated with diabetes. However, we also tested the presence of different combinations of these SCT elements in the posts. The combination of observational learning and forethought components was the majority compared to the rest of the combinations (N = 675), which were 42.8% of the sample posts. This means companies favor the implications of results-based demonstrations, including how to use CGM in the long term and their results on the person's health goals and real-life testimonials. By strategically planning their content to motivate people, increase their confidence, and make it socially agreeable since they are observing a lot of people adopting these measures, these companies are able to form a sense of community that doesn't differentiate diabetes and non-diabetes people but individuals who are working towards a long-term goal of a healthy lifestyle.

Another research question tests which of these messaging strategies creates significant user engagement. As the literature review suggests, anything between 1% and 3% of Instagram's engagement rate is considered good engagement (Sehl, 2023), but none of the strategies were able to achieve that range of engagement. We need to keep in mind that we had a compromised engagement rate since we didn't have complete access to the Instagram accounts. Also, those good engagement rate suggestions are generic to any and all types of Instagram accounts, meaning we need to note that those rates will be hard to achieve for scientific Instagram accounts, especially those made for medical devices. Interestingly enough, forethought, which wasn't often used in the posts, creates the highest engagement at 0.51%. This reveals that people respond more to posts that discuss results, meaning the audience strategically interacts with the platform and their majority needs regarding these medical devices. They are seeking out content that reflects their goals surrounding CGM. Another strategy that wasn't majorly used, the combination of forethought and self-efficacy, creates a higher engagement rate of 0.48%. Again, this points out the audience's preference for goal-oriented content and the content that provides them the emotional support they need to achieve that goal. This means they want to feel empowered to achieve the goal that the post is talking about. They believe or want to believe in their ability to reach those goals successfully, meaning the audience within these accounts are highly motivated individuals who pursue achieving a healthy lifestyle as a goal and like to surround themselves with positivity and possibilities. This also signifies that the users could stick to this behavior for the long term due to their resilience when faced with challenges. Others (none of the SCT elements) also created higher engagement at 0.45%, indicating that there are other major components that create a higher engagement rate that aren't tested within the boundaries of this research project. This identifies the remaining huge potential in this field to test underlying strategies that could work for the benefit of the companies.

The main hypothesis, which tests the components of Social cognitive theory, has revealed valuable insights. As Hypothesis 4 states, Instagram posts with one or more elements, including observational learning, forethought, and self-efficacy, drive significant user engagement on the platform compared to posts without any of those elements. As we have already discussed the components that are most often used, it is interesting to note that from the sample of 1577, SCT components were present in the majority of the data (N = 1374); hence, it successfully establishes that the creators are incorporating these psychological phenomena in order to engage the audience. As there was a huge difference between the number of posts with SCT elements and posts without any SCT elements(N = 203), it was not reasonable to compare their engagement rates. Hence, we further tested the individual and combination effects of these elements on the engagement rate. As the Shapiro-Wilk test proved the skewness of the data ($W = 0.850$, $p < 0.001$), the non-parametric test of Kruskal-Wallis proves the statistically significant differences among the groups ($H(7) = 39.470$, $p < 0.001$). As Bonferroni's correction further identified the 11 groups that have statistically significant differences, we need further exploration to understand the meaning behind it. The research requires more comprehensive data to understand in-depth, and it is not just the presence or absence of the component but also the other variables corresponding with it, for example, other persuasion factors, communication channels, etc. Given the nature of the account, it is important to acknowledge the complexities to understand the impact of these elements and strategies on user behavior. Although the hypotheses' findings were found to be statistically significant, further exploration is needed to understand the finer differences between these strategies.

Hypothesis 1 states that video posts have a higher engagement rate compared to carousel posts. The video posts do have a slightly higher engagement rate of 0.40 than the carousel posts (0.38). As the Shapiro-Wilk test of normality revealed that the data is skewed ($p < 0.001$) and that it requires a non-parametric test to determine the differences between those categories, we did find statistically significant differences through Kruskal-Wallis ($H(2) = 13.107$, $p = 0.001$). But, the Bonferroni corrections identified that those differences exist between image post and carousal post (test statistic = 86.572, $p = 0.007$, adjusted $p = 0.020$) and also between image post and video post (test statistic = 87.091, $p = 0.001$, adjusted $p = 0.002$) but not enough proof to differentiate engagement rate between video posts and carousel posts (test statistic = 519, $p = 0.986$, adjusted $p = 1.000$). We require further information on the content, like the type of video, length of the video, the attractiveness of the video, individuals appearing on the video, etc, to analyze in depth to differentiate its engagement rate from the carousel posts. There were notable differences when comparing formats with image posts, which indicates that audiences do respond differently to different formats of the post. Hence, it is important to make this decision while understanding the audience's history, preferences, and type of content that is better suited for the format of the post. However, as these companies most often use video posts, it suggests the potential of using the dynamic nature of the video and storytelling that is possible through this format; there is still a lot of space to optimize these video posts to perform their maximum impact.

Another content strategy tested through hypothesis 2 was that posts with caption lengths of less than 20 characters have a higher engagement rate than posts with more than 20 characters. The Shapiro-Wilk test revealed that the data is skewed(W = 0.875, $p < 0.001$) and requires a non-parametric test of Logistic regression. The results ($X^2 = 12.009$, $df = 1$, $p = 0.001$) signify that different post-caption length is a better fit to predict the engagement rate. This means every character used in the caption has a divided power to engage the audience, and this power is not to be taken lightly. However, the threshold of 20 characters to what is considered a lesser caption where the engagement drops after was suggested by The HubSpot report (Hubspot, 2023). The data didn't support this. The actual threshold for the engagement rate to drop after was 536 characters in the caption, including emojis, hashtags, etc. This highlights the importance of creating a personalized content strategy that is better suited for a medical device's Instagram account, targeting their health-oriented audience and not blindly following generic reports. 536 characters signify that there is a scope for more sentences that go in-depth to explain the concepts. It is important to write a concise caption to grab the short-lived attention span of the users; it is also important to provide a clear context and tell a story that provides detailed information; the balance comes from knowing your audience's history and utilizing other metrics to optimize the post.

After the format type and length of the caption, another crucial content strategy is when to post the content. Hypothesis 3 tests that posting after 8 p.m. has a higher engagement rate compared to before 8 p.m. We also need to note the multiple time differences in the United States. The Shapiro-Wilk test confirmed the skewness of the data ($p < 0.001$) and suggested a non-parametric test of Mann-Whitney, which proved the differences in engagement rate (U = 152145.000, $Z = -5.736$, $p < 0.001$), meaning posting after 8 p.m. is more helpful in creating a higher engagement rate of 0.48 than before 8 pm. (0.37). This delves into how time plays a role in understanding the audience's behavior. After 8 pm till midnight, users are more active, free, reactive, and receptive. This means most of the users prefer to either complete their daily responsibilities and want to spend their free time on the Instagram account, or they are exhausted from their daily responsibilities and they want to take a break by opening their Instagram account. This is their prime leisure hours, and as they are in a relaxed state of mind, they are ready to react to your content. However, looking at the sample size, you can conclude that these companies are not utilizing this strategy (before 8 pm $N = 1274$ and after 8 pm $N = 303$). These creators are not maximizing the engagement opportunities. By timing the post properly, they could easily increase the post's visibility. By understanding your user's trends, behavior patterns, and leisure hours, there is a huge potential for CGM companies to capture the right audience at the right time.

5.1 Theoretical Implications

The research aims to prove the applicability of SCT concepts on Instagram and their worth in creating significant user engagement from the health product audience.

This implies that the social cognitive theory can be applied successfully to social media platforms to communicate information on health products. As the literature review explains, the theory has been traditionally used in psychological, behavioral, and educational frameworks. However, the results of this research validate the SCT's adaptability to the digital landscape, mainly social media platforms like Instagram. People can effectively communicate fact-based information regarding health products by taking advantage of the platform's affordances and using concepts like observational learning, forethought, and self-efficacy.

The results imply the level of psychological mechanisms infused in the Instagram posts and the type of triggers to instigate user engagement. It can't be proved that the post creators purposefully use the SCT concepts to trigger the users' reactions on Instagram. However, the study has successfully detected the presence of complex psychological concepts like self-efficacy, which are traditionally used in advertising to persuade users. These concepts drive the users towards engagement without the users realizing it.

5.2 Practical Implications

The study has many practical implications for the field of continuous glucose management from a social media perspective. The results show how the CGM apps have been adapting various techniques on their social media accounts to establish themselves beyond diabetes care and as health and wellness management by encouraging non-diabetes people struggling to adopt a healthy lifestyle to use CGM devices. CGM apps have been informing and educating non-diabetic people about using CGM devices through their websites. The analysis shows their efforts and methods in doing so on their Instagram account. This approach establishes CGM apps not as a diabetes treatment but as a health gadget that can be used by anyone who is trying to gain or lose weight or wants to track their body activities and meals and their effects on their body. By encouraging the users through different SCT concepts, they establish themselves as health management companies.

This also means the results can be used to understand and analyze the behavioral insights of the users during health campaigns. The results showed us the behavioral patterns of the users through their engagement reactions towards the content they are exposed to, including if they like the content or would be willing to comment on the content or if sharing the content on specific days or times would make any difference in their engagement. Using this data on patterns and trends, we can make informed decisions in understanding and predicting user behaviors when running a health campaign on social media platforms.

By observing the engagement rate of the posts, the content creators can understand what resonates more with the audience to engage them, eventually leading to buying the product.

The current generic advice provided by the Hubspot report has limited applicability to health tech social media like levels, nutrisensio, and hellojanuaryai since the 20-character caption length was not sufficient or the video format engagement rate was not higher than the carousel format. The results show the importance of understanding the format type, caption length, and time of the post, which are better suited for a medical device Instagram account. These strategies should be experimented with various types of content for maximum optimization. Content creators and health professionals can adopt this data-driven approach to build meaningful connections with their audience.

5.3 Limitations

The main goal of this project is to apply the findings in developing strategies for digital health promotion models. During this process, it is also essential to be transparent regarding the limitations and the boundaries with which the research explores. This section acknowledges the constraints, their effects, and the measures are taken to avoid the limitations as much as possible.

Through quantitative content analysis, The deductive themes are coded and analyzed for their engagement rates using a codebook. This process of analyzing the engagement rate has a few limitations that could affect the results. First, the engagement rate formula does not count for the number of saves and reposts, which is traditionally included. At the same time, when calculating the metrics, There is no access to those numbers from the profile, which can limit our overall understanding of how the users engage with the content. Second, need to consider Instagram's ever-changing platform algorithms, which affect what the users see. Even though they are following those three sample profiles, based on their usage, there might be a chance that the post will not appear on their home screen for the users to engage with the content. Third, the limitation caused by the method of choice, content analysis. It is given that analyzing the content without talking to creators limits the contextual understanding of the content and the intentions behind those posts. Fourth, since this is a quantitative study, the qualitative understanding of engagement, like analyzing the comments, is not the main focus, and this could limit the nature of engagement that the study is talking about.

The sampling and analysis techniques could also cause limitations. The sample posts from three Instagram profiles are selected through purposive sampling with the help of the companies list provided by previous researchers. It's acknowledged that those three profiles might not represent each and every characteristic of the population that the study is focused on. However, these samples satisfactorily represent the diversity of the population to the researcher's knowledge.

Some of the coding process involved understanding the latent meaning of the posts. As explained in the method section, due to individual differences, latent meaning is complex in establishing the reliability of those codes. Hence, multiple introductory sessions have been conducted to ensure all the coders know the latent meaning of all the variables they are coding for.

The result of this research is intended to be applied in the strategic health communication sector and could be used by any health professionals, social media managers, and researchers. Few constraints can limit the generalizability of this research. We must remember that this is a single-platform study, and not all social platforms function similarly. Hence, the suggested strategies are to focus solely on Instagram.

Since the trend of non-diabetic people trying diabetes care started from COVID-19, there could be a temporal limitation caused by this pandemic and could limit its applicability for a limited time, given a few years.

Also, this research could not account for external variables affecting user engagement other than the dependent variables. Hence, it's only possible establish the correlation between user engagement with SCT concepts and content strategy but not the causation.

5.4 Future Research

By using the results of this project, future research can try and establish the causation between the independent variable, SCT concept, and dependent variable, user engagement, through an experiment and not just focus on Instagram but a cross-platform study using different CGM app profiles. This could bring more weight and proof of the applicability of social cognitive theory in social media platforms, as well as concrete proof that CGM apps are expanding on all their socials using these psychological concepts to engage users.

Another recommendation for future research would be to bring the cognitive process into understanding these phenomena. Using the Elaboration likelihood model, we could also analyze how people are processing this information given by CGM apps. Is it heuristically or central processing, and would that lead directly to them pursuing the CGM? Answering these questions would give more comprehensive and long-term perspectives to develop better health communication strategies.

REFERENCES

Adobe Express. (2023a). *9 tested tips to boost your Instagram engagement*. https://www.adobe.com/express/learn/blog/instagram-engagement

Adobe Express. (2023b). *Instagram Analytics: What are they and why do they matter?* https://www.adobe.com/express/learn/blog/instagram-analytics

Adobe Express. (2023c). *Your guide to social media engagement rates. | Adobe Express*. https://www.adobe.com/express/learn/blog/what-is-a-good-social-media-engagement-rate

Andrade, C. (2018). Internal, External, and Ecological Validity in Research Design, Conduct, and Evaluation. *Indian Journal of Psychological Medicine*, *40*(5), 498–499. https://doi.org/10.4103/IJPSYM.IJPSYM_334_18

Apify Instagram Post Scrapper. (n.d.). Apify. Retrieved November 7, 2023, from https://apify.com/apify/instagram-post-scraper

Archive, V. A., & feed, G. author R. (2022, October 11). *Hollywood's new secret to losing weight is a diabetes injection*. https://nypost.com/2022/10/11/hollywoods-new-secret-to-losing-weight-is-a-diabetes-injection/

Arman, A. A., & Pahrul Sidik, A. (2019). Measurement of Engagement Rate in Instagram (Case Study: Instagram Indonesian Government Ministry and Institutions). *2019 International Conference on ICT for Smart Society (ICISS)*, *7*, 1–6. https://doi.org/10.1109/ICISS48059.2019.8969826

Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*. Prentice-Hall.

Bandura, A. (2001). Social Cognitive Theory of Mass Communication. *Media Psychology*, *3*(3), 265–299. https://doi.org/10.1207/S1532785XMEP0303_03

Bandura, A., Cervone, D., & Cervone, D. (2023). *Social Cognitive Theory: An Agentic Perspective on Human Nature* (1st ed.). Wiley. https://www.perlego.com/book/3866873/social-cognitive-theory-an-agentic-perspective-on-human-nature-pdf

Blum, D. (2022, November 22). What Is Ozempic and Why Is It Getting So Much Attention? *The New York Times*. https://www.nytimes.com/2022/11/22/well/ozempic-diabetes-weight-loss.html

Bushard, B. (2023). *Shortage Of Weight-Loss Drugs Like Wegovy And Ozempic Persist—And Could For 'Some Years.'* Forbes. https://www.forbes.com/sites/brianbushard/2023/09/16/shortage-of-weight-loss-drugs-like-wegovy-and-ozempic-persist-and-could-for-some-years/

Casselman, J., Onopa, N., & Khansa, L. (2017). Wearable healthcare: Lessons from the past and a peek into the future. *Telematics and Informatics*, *34*(7), 1011–1023. https://doi.org/10.1016/j.tele.2017.04.011

Cavallo, D. N., Tate, D. F., Ward, D. S., DeVellis, R. F., Thayer, L. M., & Ammerman, A. S. (2014). Social support for physical activity—Role of Facebook with and without structured intervention. *Translational Behavioral Medicine*, *4*(4), 346–354. https://doi.org/10.1007/s13142-014-0269-9

Cheung, C. M. K., Xiao, B. S., & Liu, I. L. B. (2014). Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. *Decision Support Systems*, *65*, 50–58. https://doi.org/10.1016/j.dss.2014.05.002

Coherent Market Insights. (2023). *Top Companies—Continuous Glucose Monitoring (CGM) Devices Industry*. https://www.coherentmarketinsights.com/blog/insights/top-companies-continuous-glucose-monitoring-devices-industry-252

Continuous Glucose Monitoring—NIDDK. (n.d.a). National Institute of Diabetes and Digestive and Kidney Diseases. Retrieved November 5, 2023, from https://www.niddk.nih.gov/health-information/diabetes/overview/managing-diabetes/continuous-glucose-monitoring

Continuous Glucose Monitoring—NIDDK. (n.d.b). National Institute of Diabetes and Digestive and Kidney Diseases. Retrieved September 19, 2023, from https://www.niddk.nih.gov/health-information/diabetes/overview/managing-diabetes/continuous-glucose-monitoring

Cordoş, A.-A., Bolboacă, S. D., & Drugan, C. (2017). Social Media Usage for Patients and Healthcare Consumers: A Literature Review. *Publications*, *5*(2), Article 2. https://doi.org/10.3390/publications5020009

Didyuk, O., Econom, N., Guardia, A., Livingston, K., & Klueh, U. (2020). Continuous Glucose Monitoring Devices: Past, Present, and Future Focus on the History and Evolution of Technological Innovation. *Journal of Diabetes Science and Technology*, *15*(3), 676–683. https://doi.org/10.1177/1932296819899394

Didyuk, O., Econom, N., Guardia, A., Livingston, K., & Klueh, U. (2021). Continuous Glucose Monitoring Devices: Past, Present, and Future Focus on the History and Evolution of Technological Innovation. *Journal of Diabetes Science and Technology*, *15*(3), 676–683. https://doi.org/10.1177/1932296819899394

Dubose, S. N. (2021). *Effect of Exercise and Meals on Continuous Glucose Monitor Data in Healthy Individuals Without Diabetes*. https://journals.sagepub.com/doi/10.1177/1932296820905904

Elnaggar, A., Park, V. T., Lee, S. J., Bender, M., Siegmund, L. A., & Park, L. G. (2020). Patients' Use of Social Media for Diabetes Self-Care: Systematic Review. *Journal of Medical Internet Research*, *22*(4), e14209. https://doi.org/10.2196/14209

Fulton, H. G., Krank, M. D., & Stewart, S. H. (2012). Outcome expectancy liking: A self-generated, self-coded measure predicts adolescent substance use trajectories. *Psychology of Addictive Behaviors*, *26*(4), 870–879. https://doi.org/10.1037/a0030354

Gavrila, V., Garrity, A., Hirschfeld, E., Edwards, B., & Lee, J. M. (2019). Peer Support Through a Diabetes Social Media Community. *Journal of Diabetes Science and Technology*, *13*(3), 493–497. https://doi.org/10.1177/1932296818818828

Goodman, B. (2022, December 28). *As the market for new weight loss drugs soars, people with diabetes pay the price*. CNN. https://www.cnn.com/2022/12/28/health/weight-loss-diabetes-drug-shortages/index.html

Heitkemper, E. M., Wilcox, G. B., Zuñiga, J., Kim, M. T., & Cuevas, H. (2023). A Text-Mining Analysis to Examine Dominant Sources of Online Information and Content on Continuous Glucose Monitors. *The Science of Diabetes Self-Management and Care*, *49*(2), 101–111. https://doi.org/10.1177/26350106231158828

Hoare, J. K., Lister, N. B., Garnett, S. P., Baur, L. A., & Jebeile, H. (2022). Mindful and Intuitive Eating Imagery on Instagram: A Content Analysis. *Nutrients*, *14*(18), Article 18. https://doi.org/10.3390/nu14183834

Huang, G., & Zhou, E. (2019). Time to Work Out! Examining the Behavior Change Techniques and Relevant Theoretical Mechanisms that Predict the Popularity of Fitness Mobile Apps with Chinese-Language User Interfaces. *Health Communication*, *34*(12), 1502–1512. https://doi.org/10.1080/10410236.2018.1500434

Hubspot. (2022). *Instagram Engagement Report 2022*. https://www.hubspot.com/hubfs/Instagram_Engagement_Report_2022_CXD_V2.pdf

Hubspot. (2023). *Instgram Engagement report 2023*. https://mention.com/pardot-2/files/instagram-engagement-report-2023-en.pdf

Innovation Milestones. (2012, December 14). Medtronic Diabetes. https://www.medtronicdiabetes.com/about-medtronic-innovation/milestone-timeline

Instagram. (2023). *About Instagram Insights | Instagram Help Center*. https://help.instagram.com/788388387972460/?helpref=related_articles

Jiang, S., & Beaudoin, C. (2016). *Smoking Prevention in China: A Content Analysis of an Anti-Smoking Social Media Campaign*. https://www.tandfonline.com/doi/full/10.1080/10810730.2016.1157653?casa_token=XSsiK9Hy4AMAAAAA%3ApExXAKlylm-NWDkDBW4EanvrHwRipkJVWFioCWRI1V9fu4EKRAgeh4mZkMVdi9p74rfT5DAS5nregQ

Kashian, N., & Liu, Y. (2020). Posting Exercise Activity on Social Media for Self-Efficacy and Well-Being. *Southern Communication Journal*, *85*(2), 73–84. https://doi.org/10.1080/1041794X.2019.1658801

Khang, H., Han, E.-K., & Ki, E.-J. (2014). Exploring influential social cognitive determinants of social media use. *Computers in Human Behavior*, *36*, 48–55. https://doi.org/10.1016/j.chb.2014.03.038

Klonoff, D. C., Nguyen, K. T., Xu, N. Y., Gutierrez, A., Espinoza, J. C., & Vidmar, A. P. (2022). Use of Continuous Glucose Monitors by People Without Diabetes: An Idea Whose Time Has Come? *Journal of Diabetes Science and Technology*, 19322968221110830. https://doi.org/10.1177/19322968221110830

Krippendorff, K. (2003). *Content Analysis: An Introduction to Its Methodology* (2nd edition). Sage Publications, Inc.

Krippendorff, K., & Craggs, R. (2016). The Reliability of Multi-Valued Coding of Data. *Communication Methods and Measures*. https://www.tandfonline.com/doi/abs/10.1080/19312458.2016.1228863

Laerd Statictics—Testing for Normality using SPSS Statistics. (n.d.). Retrieved April 19, 2024, from https://statistics.laerd.com/spss-tutorials/testing-for-normality-using-spss-statistics.php

Malik, A., Khan, M. L., & Quan-Haase, A. (2021). Public health agencies outreach through Instagram during the COVID-19 pandemic: Crisis and Emergency Risk Communication perspective. *International Journal of Disaster Risk Reduction*, *61*, 102346. https://doi.org/10.1016/j.ijdrr.2021.102346

MD, R. H. S. (2023, February 21). *What happens when a drug goes viral?* Harvard Health. https://www.health.harvard.edu/blog/what-happens-when-a-drug-goes-viral-202302212892

Mian, Z., Hermayer, K. L., & Jenkins, A. (2019). Continuous Glucose Monitoring: Review of an Innovation in Diabetes Management. *The American Journal of the Medical Sciences*, *358*(5), 332–339. https://doi.org/10.1016/j.amjms.2019.07.003

Nabi, R. L., & Oliver, M. B. (2009). *The SAGE Handbook of Media Processes and Effects*. SAGE.

Newman, J. D., & Turner, A. P. F. (2005). Home blood glucose biosensors: A commercial perspective. *Biosensors and Bioelectronics*, *20*(12), 2435–2453. https://doi.org/10.1016/j.bios.2004.11.012

Olczuk, D., & Priefer, R. (2018). A history of continuous glucose monitors (CGMs) in self-monitoring of diabetes mellitus. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *12*(2), 181–187. https://doi.org/10.1016/j.dsx.2017.09.005

Peng, C.-T., Wu, T.-Y., Chen, Y., & Atkin, D. J. (2019). Comparing and modeling via social media: The social influences of fitspiration on male instagram users' work out intention. *Computers in Human Behavior*, *99*, 156–167. https://doi.org/10.1016/j.chb.2019.05.011

Peruta, A., & Shields, A. B. (2018). Marketing your university on social media: A content analysis of Facebook post types and formats. *Journal of Marketing for Higher Education*, *28*(2), 175–191. https://doi.org/10.1080/08841241.2018.1442896

Presseller, E. K., Parker, M. N., Lin, M., Weimer, J., & Juarascio, A. S. (2020). The application of continuous glucose monitoring technology to eating disorders research: An idea worth researching. *International Journal of Eating Disorders*, *53*(12), 1901–1905. https://doi.org/10.1002/eat.23404

Putranto, H. A., Rizaldi, T., Riskiawan, H. Y., Setyohadi, D. P. S., Atmadji, E. S. J., & Nuryanto, I. H. (2022). Measurement of Engagement Rate on Instagram for Business Marketing (Case Study: MSME of Dowry in Jember). *2022 International Conference on Electrical and Information Technology (IEIT)*, 317–321. https://doi.org/10.1109/IEIT56384.2022.9967851

Razak, A. A., Mansor, N. A., Razak, R. A., Nawi, N. M. M., Yusoff, A. M., & Din, N. (2020). *Changing Awareness about Health Behavior: A Study among Young Instagram Users*.

Riffe, D., Lacy, S., Watson, B., & Fico, F. (2019). *Analyzing Media Messages: Using Quantitative Content Analysis in Research* (4th ed.). Routledge. https://doi.org/10.4324/9780429464287

Rozaq, M., Hastjarjo, S., & Slamet, Y. (2020). *Digital Modeling through Observation of Content on Social Media in the Learning Process of Novice Entrepreneurial Communication Strategies*. 153–161. https://doi.org/10.2991/assehr.k.201219.023

Scharrer, E. S., Srividya, & Ramasubramanian, S. (2021). *Quantitative Research Methods in Communication: The Power of Numbers for Social Justice*. Routledge. https://doi.org/10.4324/9781003091653

Schunk, D. H., & DiBenedetto, M. K. (2020). Motivation and social cognitive theory. *Contemporary Educational Psychology*, *60*, 101832. https://doi.org/10.1016/j.cedpsych.2019.101832

Sehl, K. (2023). Engagement Rate Calculator + Guide for 2023. *Social Media Marketing & Management Dashboard*. https://blog.hootsuite.com/calculate-engagement-rate/

Simpson, C. C., & Mazzeo, S. E. (2017). Skinny Is Not Enough: A Content Analysis of Fitspiration on Pinterest. *Health Communication*, *32*(5), 560–567. https://doi.org/10.1080/10410236.2016.1140273

Stein, J.-P., Krause, E., & Ohler, P. (2021). Every (Insta)Gram counts? Applying cultivation theory to explore the effects of Instagram on young users' body image. *Psychology of Popular Media*, *10*(1), 87–97. https://doi.org/10.1037/ppm0000268

Tadayon Nabavi, R., & Bijandi, M. (2023). *Bandura's Social Learning Theory & Social Cognitive Learning Theory*.

Velasquez, A., & Rojas, H. (2017). Political Expression on Social Media: The Role of Communication Competence and Expected Outcomes. *Social Media + Society*, *3*(1), 2056305117696521. https://doi.org/10.1177/2056305117696521

Velasquez, S. E. (2021). *An Exploratory Study of Weight Loss Information Seeking on Instagram* [Ph.D., Emporia State University]. https://www.proquest.com/docview/2584285583/abstract/95C3E350BC014454PQ/1

White, K., Gebremariam, A., Lewis, D., Nordgren, W., Wedding, J., Pasek, J., Garrity, A., Hirschfeld, E., & Lee, J. M. (2018). Motivations for Participation in an Online Social Media Community for Diabetes. *Journal of Diabetes Science and Technology*, *12*(3), 712–718. https://doi.org/10.1177/1932296817749611

Xie-Carson, L., Benckendorff, P., & Hughes, K. (2023). Keep it #Unreal: Exploring Instagram Users' Engagement With Virtual Influencers in Tourism Contexts. *Journal of Hospitality & Tourism Research*, 10963480231180940. https://doi.org/10.1177/10963480231180940

Yang, C.-H., Maher, J. P., & Conroy, D. E. (2015). Implementation of Behavior Change Techniques in Mobile Applications for Physical Activity. *American Journal of Preventive Medicine*, *48*(4), 452–455. https://doi.org/10.1016/j.amepre.2014.10.010

Zafar, H., Channa, A., Jeoti, V., & Stojanović, G. M. (2022). Comprehensive Review on Wearable Sweat-Glucose Sensors for Continuous Glucose Monitoring. *Sensors*, *22*(2), Article 2. https://doi.org/10.3390/s22020638